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Abstract— **Individuals with tetraplegia are severely limited in terms of independence, which can lead to depression and premature death. The field of robotics has sought to create solutions for increased independence by enabling individuals with tetraplegia to perform physical activities. This includes semi-automatic solutions. The use case of an assistive robotic manipulator (ARM) and thus increased independence could be expanded by allowing remote control, e.g. when the user is lying in bed. This study presents and evaluates semi-autonomous intra-oral tongue-based control of a seven degree of freedom ARM/gripper in a near and remote setting. The system consists of a tongue control interface (iTongue), a semi-automatic framework based on YOLOv5 and adaptive levels of automation, an Intel Realsense D435i camera and a JACO robotic manipulator. Two study participants completed ten rounds of controlling the JACO ARM to reach and pick up a soda bottle and pour from it in a cup. The semi-automation improved the grasping performance for both of the study participants, particularly when controlling in a remote setting, decreasing the cognitive load and the overall task completion time. The presented system has the potential to increase the independence and quality of life for individuals with tetraplegia, by enabling the user to perform physical activities even when lying in bed. Future work should include expanding the semi-automation to other activities of daily living and evaluating the system in a greater population and by individuals with tetraplegia.**

Keywords—iTongue, Tetraplegia, ARM, semi-automation, remote control

I. Introduction

In America, it is estimated that around 100,000 people suffer from tetraplegia, a physical condition where arms legs and torso are paralyzed [1]. Individuals with tetraplegia are severely limited in terms of independence. The lack of independence can cause individuals with spinal cord injuries to be more prone to depression and premature death compared with people without [2]. Therefore, the primary goal for individuals with tetraplegia is improved independence and that said, it has been found that upper-body functionality is the most important priority for improved independence [3].

The field of robotics has sought to create solutions for assisting individuals with tetraplegia. Despite the already existing research projects [4]–[6] and commercially available robotic devices for assisting with daily activities[7]–[9], there is room for further development and improvements. Chung et al. [10] found that it would be beneficial to manage the high dexterity in robotic assistive manipulation by fewer commands/clicks from the user by developing a two-way user interface. Hence, the implementation of computer vision can improve the control of a robotic manipulator with autonomous path and grasp planning by lessening the amount of readjustment commands from the user.

Solutions based on automation of assistive robotic manipulators are increasingly becoming a reality and there are several solutions available that aim to decrease the cognitive burden associated with the control in a dexterous workspace [6], [11]. Furthermore, automatic control aims to improve the experience of using ARMs and increase the performance for actions, but autonomy can also decrease the feeling of independence and result in decreased satisfaction [12]. Parasuraman et al. [13] suggest that a system can have varying levels of automation, depending on the situational demands when operating. This adaptive automation is relevant to implement to give the user full control in certain scenarios, while also allowing for increased level of automation when the user demand is high.

Due to their condition, individuals with tetraplegia have specific requirements for human-robot interfacing. The limited amount of applicable interface solutions are based on movement of the head [14], eyes [15], or tongue [16], [17], voice recognition [18], or brain activity [19]. As individuals with tetraplegia often maintain the dexterity and the ability to move the tongue, it makes a good candidate for providing input to a device. One such system is the inductive tongue control interface (ITCI) proposed in [17], which has 18 available sensors and is therefore suitable for control of a high DOF system such as an ARM. The ITCI has been used in several studies to control a six DOF ARM [5], [20]–[22], one of which in a remote setting [21], demonstrating the potential of the solution to improving the quality of life and level of independence of individuals with tetraplegia. However, in all of the studies the accuracy of task completion, both in terms of time and success rate, could potentially be improved by the integration of semi-autonomous assistance when controlling the robot.

Therefore, this study presents and evaluates semi-autonomous intra oral tongue-based control of a seven DOF ARM in a near and remote setting. The study is a further evaluation of methods from our unpublished report [23].

II. Method

The main part of the system developed for this study consisted of a tongue interface, a controls system with adaptive semi-automation, and a JACO ARM [23] (Fig. 1). The system was evaluated in a one-day human experiment with two abled-bodied individuals.

A. System Overview

The system consists of the following hardware components: an ITCI (iTongue by TKS A/S, Denmark), a JACO ARM (by Kinova, Canada), a wheelchair (by Permobil, Sweden), a depth camera (Intel RealSense D435i), an RGB camera (no-name 1080p), and a PC (Lenovo Legion 5). The software components consisted of sensor-robot mapping, a graphical user interface (GUI), a semi-automation framework, and robot control. The software was programmed using C++ and Python programming languages and the communication between the different components was done through the robot operating system (ROS melodic). The JACO ARM and the two cameras were mounted on the wheelchair, as shown in Fig. 1. The GUI was provided on a computer screen, showing the visual feedback from the two cameras and what sensor on the iTongue was being activated.

The communication between the hardware and software components is seen in Fig. 2 where nodes are represented by blue ovals and the hardware components by yellow boxes. The arrows illustrate the published and subscribed topics (output/input) of each node. The iTongue sends serial data to the "iTongueTalker" node through a USB connection, which then publishes what sensor is being activated. The "Camerasplitter" splits the RealSense camera´s data into a depth data stream and an RGB data stream. The "Image converter" node converts the RGB data stream from the "Camerasplitter" node to a V4L2 stream, a format that is required by the "Object detection". The "Object detection" outputs bounding boxes which are used by the "Shape detection" to output the Cartesian location of the object of interest. This position is used by the "Jaco control" to assist the user in grasping a desired object. The "GUI" visualizes the bounding boxes from "Object detection", RGB streams from the two cameras, and the activated sensor from "iTongueTalker".

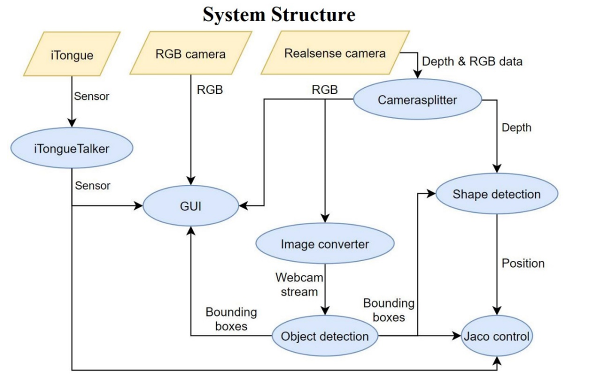

Fig. 2. System structure diagram of the communication between nodes (blue ovals) and the hardware components (yellow boxes). The arrows illustrate the published and subscribed topics (output/input) of each node. Adapted from [23]

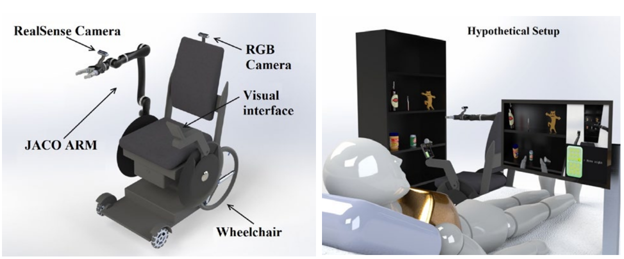

Fig. 1. Left: The wheelchair setup. Right: Hypothetical setup where the user can control the wheelchair and ARM in a remote setting. Adapted from [23].

B. Camerasplitter

Depth and RGB data from the Intel RealSense camera were read using the Intel RealSense SDK 2.0 [24]. Both the depth sensor and the RGB stream were configured to run at a low resolution (480x270 pixels and 640x480 pixels, respectively) to reduce execution time of following nodes and to improve the depth stream accuracy. The depth stream and the RGB stream were aligned, such that each pixel in the RGB image corresponded to the pixel at the same position in the depth frame. This was done by cropping and up-scaling the depth stream to ensure the same field of view and resolution as the RGB image stream. Thereafter, the depth and RGB data were published to their respective topics.

C. Object Detection

To train, classify, and locate objects in the video stream the You Only Look Once version 5 (YOLOv5 [25]) framework was implemented. YOLOv5 is a real time object detection model that utilizes convolutional neural networks (CNNs) and anchor boxes to identify and locate objects in an image [25].

In this study, a customized data set was utilized. The data set was based on a variety of different beverages, including six classes: a 50cl soda, a 150cl soda, apple juice, fruit juice, rosé wine, and a thermal mug. 100 images of each object and 200

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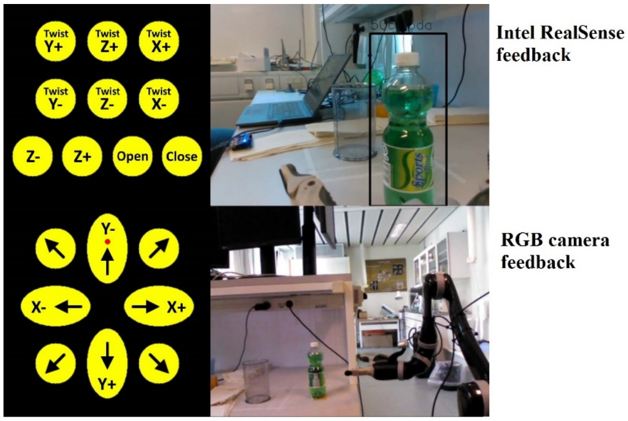

Fig. 3. The GUI showing the iTongue activation and the visual feedback from the two camera streams. Adapted from [23]

images with multiple or all objects in the image at once were captured and labeled with bounding boxes and the respective class. Prior to considering the custom data set complete and passing it to the CNN for training, the data set was extended with augmentations using third party service provider Roboflow [26]. The following augmentations were applied: rotation, shear, hue, and brightness, creating three additional images for each of the original data set image. When training the model in the YOLOv5 framework, the filters gradually adjusted through each pass of the CNN, also denoted an epoch. This data set was trained on 400 epochs.

D. Shape Detection

The goal of the shape detection node was to extract the position of the object based the bounding box received from the “Object detection” node. The position was estimated using the center of the bounding box and extracted depth from the depth cloud. As the estimated position was located at the surface of the object, the detected position was shifted away from the camera by the radius of the object. Each object’s radius was manually measured beforehand and connected to the classification of the bounding boxes. The classification and radius were used to shift the estimated position of an object so it corresponded to the object center.

E. Tongue Interface

The iTongue consist of the following components: a mouthpiece unit (MPU), an activation unit (AU), a control unit (CU), and a charger. The MPU consist of inductive sensors on a printed circuit board. The activation unit is made of titanium and can either be pierced or glued to the tongue. When the activation unit is close to one of the sensors, the voltage across the sensor changes which can be interpreted as an activation. The MPU samples the voltage in each of the sensors and sends it through radio frequency to the CU. The CU gives the potential to connect to external devices, such as a computer or a wheelchair. In this study, the raw data from the iTongue was read and sent to the computer through a USB connection. The data was processed in the “iTongueTalker” node using a weighted average of neighboring sensors [27] and thereafter, the placement of the AU on the MPU and the activated sensor were published to the respective topic.

F. Graphical User Interface

The GUI (Fig. 3) provides the user with visual feedback of the position of the AU on the MPU and the robot mapping of each iTongue sensor. Moreover, the GUI provides visual input from the RGB camera mounted on the backrest of the wheelchair and from the Intel RealSense camera mounted on the robot’s end-effector.

G. Jaco Control

The purpose of the “Jaco control” node was to interpret the input from the “iTongueTalker”, “GUI”, and “Shape Detection” nodes to control commands for the robotic ARM. The JACO ARM was controlled in 3D space using velocity control and an adaptive level of assistance depending on the estimated intention of the user.

Due to a minimum depth distance of the Intel RealSense camera and limitations of the YOLOv5, measurements of the object position in 3D space were not always available. To compensate for this, the objects were tracked based on past measurements and saved as transforms. Each entry of a transform corresponded to a single object and was represented by the 3D transformation and the time of detection within a vector. For each transform in the object array, the algorithm checked if the timestamp of the transform was older than a specified threshold (Fig. 4) to decide if it should be deleted from the array. The vectors were restricted to contain a maximum of 50 transforms to keep the execution time and delay of the system low.

In case the “Camerasplitter” node returned faulty depth measurements (due to errors during format transformation and memory operations of the data), RANSAC [28] was implemented for removing outliers by calculating the position of tracked objects based on the previously stored transforms in the object array. A scoring was performed to evaluate if the transform lay within a certain distance from the tracked object. Based on the scoring, the transform with the highest score was copied to a tracked objects vector, which was used to semi-automatically assist in performing pick-and-place operations. After receiving data from the iTongue, the node initiated the semi-autonomous control, which moved the robot based on the location of the tracked objects.

In this study, a control system with adaptive levels of assistance was implemented by estimating a level of assistance, which indicates the likelihood that the user wants to pick up an object. In order for the end-effector of JACO to approach an object, a pre-grasp position was defined (as an offset in the XY-

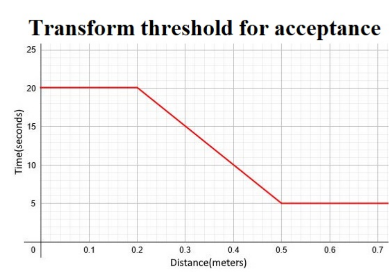

Fig. 4. The relation between allowed transform time limit and distance to the transform. Adapted from [23]

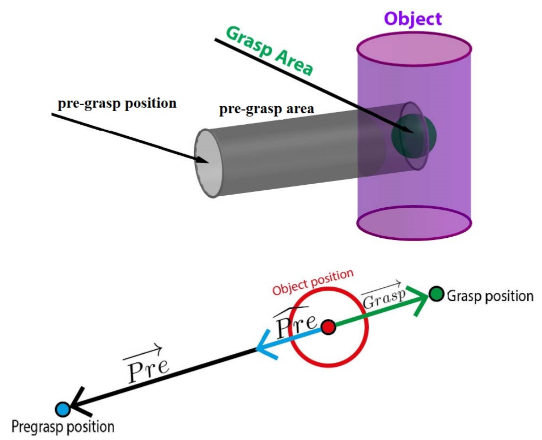

Fig. 5. Top: Illustration of the pre-grasp and grasp area. Bottom: Illustration of the pre-grasp and grasp position vector relative to the center of an object. Adapted from [23]

plane in direction of the end-effector, described from the center of the object) and served as the initial trajectory goal when grasping an object. According to the estimated likelihood of the user's intention, the user was either not assisted, partially assisted (0-100% assistance), or fully assisted in directing the end-effector towards the pre-grasp position. When the user had controlled the end-effector to a pre-grasp position, the end-effector entered a pre-grasp area and was fully guided towards a grasp area (Fig. 5). After reaching the grasp area, a command was initiated to close the end-effector fingers around the object.

To determine whether the semi-automation should assist in controlling the end-effector of the JACO towards an object, a function for the level of assistance (LoA) was defined as

$$LoA = 0.3d + d^2 \cdot \theta + 0.003 \cdot \theta^4 \quad (1)$$

where d is the distance from the end-effector to the trajectory goal and θ is the angle between the direction activated by the user and the object position with respect to the end-effector position. Based on equation 1 the level of assistance was divided into three levels: fully automatic (LoA < 0.05), shared control (0.05 < LoA < 0.1), and full manual control (LoA ≥ 0.1). Experimental Procedure

H. Success Rate of Semi-automation when Reaching Objects of Interest

Prior to evaluating the system in a remote setting, a test of the semi-autonomous system was conducted [23]. The purpose of this test was to evaluate the success rate of semi-automation when reaching for each of the objects in the data set. Here, one of the manuscript authors participated (P1, 20-year-old able-bodied male) who had no prior experience using the iTongue. During this test, the iTongue was used in a handheld setup.

An object was placed on a marked spot on a table within the workspace of the JACO ARM. P1 directed the JACO towards the object from different positions until grasping was initialized, a collision occurred, or the system was deemed to have a wrongful target location when semi-autonomously assisting. This process was repeated 10 times for each of the six objects.

I. Pouring Water Task

In order to evaluate the semi-autonomous system in a near and remote setting, one of the objects from the list was chosen to be picked up. A 50cl soda bottle was placed 50 cm from the base of the robot and a cup was placed 30 cm from the soda bottle. The experimental task was to pick up the soda bottle and pour from it into the cup and then place the soda bottle on the table. At the beginning of each trial, the JACO robot was set to "home position".

The local ethical committee: The North Denmark Region Committee on Health Research Ethics approved this study. Two abled-bodied individuals participated in this test, both of which belong to the authors list. One of the participants (P2, 31 years old female) had approximately two weeks experience (distributed over three years) using the iTongue device but the other (P3, 21-year-old male) had never used it before. The MPU of the iTongue was attached to the palate of the mouth using a dental putty mold (ImpressA Putty, TopDent) and the AU was glued to the tongue using Histoacryl® (B.Braun Surgical S.A., ES) tissue glue.

The participants were seated to the left of the JACO robot in front of a computer screen, which provided the visual feedback (Fig 3). Each participant performed the task ten times (two sessions of five rounds) in each condition (near, remote, with and without semi-automation). During the remote session, a curtain was placed between the participant and the robot to simulate remote operation by blocking the direct line of sight. Both participants started the experiment by picking up the object using semi-automation and direct vision five times, followed by picking up the object using manual control and direct vision five times. Thereafter, the test was repeated in reverse order where the line of sight to the robot was blocked. After 30 minutes break, session two started with manual control and direct vision, followed by picking up the object with the help of the semi-automation. As in the first session, the experimental task was performed using direct vision first and second where the vision was blocked using a curtain.

Prior to performing this experimental task, the participants were allowed to get familiar with the device. As P2, had great experience using the iTongue, 15 minutes of training and learning how to use the semi-automatic system was considered enough. P3 was allowed to train for approximately 60 minutes prior to the start of the experiment.

In order to evaluate the system task completion time, gripping time, and trajectory length were compared between the manual and the semi-automatic control. The subjects were asked to perform 10 successful trials of the experimental task. A trial was said to be unsuccessful and repeated if the bottle or the cup fell down, otherwise successful. The task completion time was measured from when the robot started moving until the fingers did not open more after placing the bottle on the table. Gripping time was defined from when the robot started moving and until the robot had closed the fingers around the bottle. The trajectory length was measured as the Euclidean distance between the data points (x,y,z) published by the JACO robot.

III. Results

A. Semi-automation when Reaching Objects of Interest

P1 managed to grasp and clear all the specified objects from the table with a mean success rate of 85%. The highest success rate of 100% was attained when reaching for the 150cl soda and the Apple Juice, whereas the lowest success rate of 60% was attained by the Fruit Juice, as shown in Table I. [23]

B. Pouring Water Task

Both participants were successful in completing ten rounds of the experimental task. P2 performed three failed rounds using the semi-automatic system: one because of knocking the bottle over when picking it up and two because of releasing the bottle too early resulting in it to fall down on the table. P3 performed two failed trials: one when using the semi-autonomous system and one using the manual control. Both failed attempts were caused by knocking the bottle over when picking it up.

The mean task completion time, gripping time and trajectory length are shown in table II. The semi-autonomous system was only active during the first part of the experimental task; that is, when picking up the bottle. The semi-autonomous system decreased the gripping time in six out of ten trials for P2 when controlling using direct vision of the robot and seven out of the ten trials in a remote setting (Fig. 7). For P3, the difference in gripping time between controlling using manual versus semi-automatic system is evident; that is, decrease in the gripping time in all except for one trial (Fig. 7). The semi-autonomous system performs well in terms of trajectory length during picking up of the bottle in a remote setting, resulting in a shorter trajectory than for the other control conditions. This is especially true for P3.

Table I: The success rate in percentage of the overall trials per object for one subject. Adapted from [23].

TRIAL	50cl Soda	150cl Soda	Rosé Wine	Thermal Mug	Apple Juice	Fruit Juice
SUCCESS RATE	90	100	80	80	100	60
MEAN %	85					

Table II: Mean task completion time (TCT), mean gripping time (GT) and mean trajectory length (TL) during session 1 (S1) and session 2 (S2) for the four different conditions: manual control using direct vision, manual control in a remote setting, semi-automatic control using direct vision and semi-automatic control in a remote setting

		TCT		**GT**		**TL**	
		S1	S2	S1	S2	S1	S2
P2	manual	73.46	80.90	25.22	27.78	0.67	0.88
	manual_remote	92.12	93.98	29.92	30.62	0.76	0.85
	semi_auto	84.34	76.74	25.12	25.08	0.72	0.86
	semi_auto_remote	99.90	98.08	23.22	25.32	0.76	0.84
P3	manual	78.70	78.58	26.87	26.56	0.66	0.75
	manual_remote	100.04	100.14	29.62	26.34	0.61	0.78
	semi_auto	75.88	78.22	15.89	20.48	0.59	0.68
	semi_auto_remote	56.32	83.54	16.66	20.56	0.56	0.66

IV. Discussion

The JACO robotic arm, iTongue, and computer vision are among components that present great opportunities for assisting individuals with tetraplegia in performing activities of daily

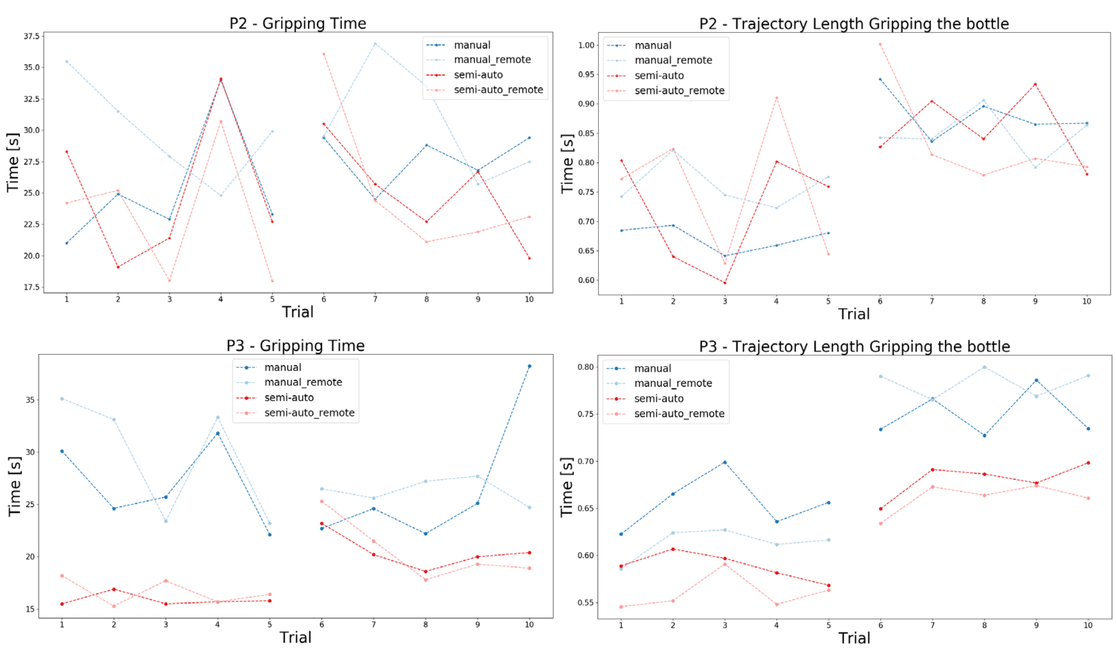

Fig. 7. **Top Left:** Time it took to pick up the bootle for P2. The semi-automatic system performes better in seven out of ten trials in remote setting. **Top Right:** The trajectory length for picking up the bottle for P2. **Bottom Left:** Time it took to pick up the bootle for P3. The semi-automatic system performes better in all except one trial. **Top Right:** The trajectory length for picking up the bottle for P3.

living and thus increasing quality of life. Kim et al. (17) has emphasized the importance of feeling in control and that increased autonomy can have a negative effect on the user satisfaction. In this study, a semi-automatic system was implemented with adaptive level of assistance (as suggested by Parasuraman et al. (70)). The presented study shows the possibility of increasing the performance and decreasing the cognitive load for individuals with tetraplegia while also maintaining the feeling of control, independence and thus satisfaction for the user. The semi-automation improved the performance for both of the study participants, particularly when controlling grasping in a remote setting. One of the challenges presented when controlling an ARM in a remote setting are the missing depth information from the visual feedback, which results in increased cognitive load and time for completing a task. Both subjects expressed decreased cognitive load when semi-automatically tongue-controlling the robot to pick up the bottle in a remote setting and the results show that the time it took to pick up the bottle was decreased compared with manual control. The results emphasize the potential of the system for increased independence for the user. Future work will include improving the customized data set by expanding it with more images and possibly training the CNN using more than 400 epochs. Furthermore, the system could be improved by expanding the semi-automation to apply in other parts of the experimental task and other activities of daily living. Lastly, the system should be evaluated in a higher number of study participants and by individuals with tetraplegia.

V. Conclusion

The study presented an intra-oral tongue control semi-automatic system that improves the performance when controlling a robotic manipulator in a pick and place operation, particularly when controlling it in a remote setting. The tongue-based interface used in this study (iTongue) is suitable for individuals with tetraplegia and therefore, the combined system has the potential to increase the independence and quality of life, by enabling the user to perform physical activities, even when lying in bed. Future work should include expanding the semi-automation to other activities of daily living and evaluating the system in a greater population and by individuals with tetraplegia.

References

[1] C. M. Curtin, J. P. Wagner, D. R. Gater, and K. C. Chung, “Opinions on the treatment of people with tetraplegia: Contrasting perceptions of physiatrists and hand surgeons,” *J. Spinal Cord Med.*, vol. 30, no. 3, pp. 256–262, 2007.

[2] World Health Organization, “Spinal cord injury.” [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/spinal-cord-injury. [Accessed: 05-Jul-2021].

[3] P. J. Manns and K. E. Chad, “Components of Quality of Life for Persons With a Quadriplegic and Paraplegic Spinal Cord Injury,” 2001.

[4] E. K. Gordon, X. Meng, T. Bhattacharjee, M. Barnes, and S. S. Srinivasa, “Adaptive Robot-Assisted Feeding: An Online Learning Framework for Acquiring Previously Unseen Food Items.”

[5] L. N. S. Andreasen Struijk, L. L. Egsgaard, R. Lontis, M. Gaihede, and B. Bentsen, “Wireless intraoral tongue control of an assistive robotic arm for individuals with tetraplegia,” *J. Neuroeng. Rehabil.*, vol. 14, no. 1, pp. 1–8, 2017.

[6] S. Iregui, C. Vergara, J. De Schutter, and E. Aertbeliën, “Generating Reactive Virtual Guidance Fixtures for Assisted Telemanipulation Tasks.”

[7] “Obi – The first dining robot of its kind.” [Online]. Available: https://meetobi.com/. [Accessed: 19-Mar-2021].

[8] “Assistive Innovations - iARM.” [Online]. Available: https://www.assistive-innovations.com/en/robotic-arms/iarm. [Accessed: 19-Mar-2021].

[9] “Robotics company | Robotic assistive technology | Kinova.” [Online]. Available: https://www.kinovarobotics.com/en. [Accessed: 16-Jun-2020].

[10] C.-S. Chung, H. Wang, and R. A. Cooper, “Functional assessment and performance evaluation for assistive robotic manipulators: Literature review,” *J. Spinal Cord Med.*, vol. 36, no. 4, pp. 273–289, 2013.

[11] M. Gualtieri, J. Kuczynski, A. M. Shultz, A. Ten Pas, H. Yanco, and R. Platt, “Open World Assistive Grasping Using Laser Selection.”

[12] D. J. Kim *et al.*, “How Autonomy Impacts Performance and Satisfaction: Results from a Study with Spinal Cord Injured Subjects Using an Assistive Robot,” *IEEE Trans. Syst. Man, Cybern. Part A Syst. Humans*, vol. 42, no. 1, pp. 2–14, 2012.

[13] R. Parasuraman, T. B. Sheridan, and C. D. Wickens, “A model for types and levels of human interaction with automation,” *IEEE Trans. Syst. Man, Cybern. Part ASystems Humans.*, vol. 30, no. 3, pp. 286–297, 2000.

[14] “Permobil Egg Switch For Head Array.” [Online]. Available: https://www.permobil.com/en-us/products/accessories/drive-controls/permobil-egg-switch-for-head-array. [Accessed: 05-Jul-2021].

[15] R. M. Aronson and H. Admoni, “Eye gaze for assistive manipulation,” in *ACM/IEEE International Conference on Human-Robot Interaction*, 2020, pp. 552–554.

[16] X. Huo and M. Ghovanloo, “Evaluation of a wireless wearable tongue–computer interface by individuals with high-level spinal cord injuries,” *J Neural Eng.*, vol. 7, no. 2, 2010.

[17] L. N. S. A. Struijk, “An Inductive Tongue Computer Interface for Control of Computers and Assistive Devices,” *IEEE Trans. Biomed. Eng.*, vol. 53, no. 12, pp. 2594–2597, 2006.

[18] S. Poirier, F. Routhier, and A. Campeau-lecours, “Voice Control Interface Prototype for Assistive Robots for People Living with Upper Limb Disabilities,” 2019.

[19] M. Palankar *et al.*, “Control of a 9-DoF wheelchair-mounted robotic arm system using a P300 brain computer interface: Initial experiments,” *2008 IEEE Int. Conf. Robot. Biomimetics, ROBIO 2008*, pp. 348–353, 2008.

[20] M. Hildebrand *et al.*, “Semi-Autonomous Tongue Control of an Assistive Robotic Arm for Individuals with Quadriplegia,” 2019.

[21] Á. A. Pálsdóttir, S. Dosen, M. Mohammadi, and L. N. S. A. Struijk, “Remote Tongue Based Control of a Wheelchair Mounted Assistive Robotic Arm – a proof of concept study,” in *2019 IEEE International Conference on Mechatronics and Automation*, 2019, pp. 1300–1304.

[22] M. Mohammadi, H. Knoche, and L. N. S. Andreasen Struijk, “Continuous tongue robot mapping for paralyzed individuals improves the functional performance of tongue-based robotic assistance,” *IEEE Trans. Biomed. Eng.*, 2021.

[23] J. K. Mortensen, J. W. Knudsen, E. T. Pedersen, A. B. Mortensen, and M. H. Bøgestrand, “Semi-autonomous Tongue Control of the Jaco Robotic Manipulator.” Unpublished report Aalborg University, 2021.

[24] “Intel RealSense SDK 2.0 – Intel RealSense Depth and Tracking cameras.” [Online]. Available: https://www.intelrealsense.com/sdk-2/. [Accessed: 05-Jul-2021].

[25] “GitHub - ultralytics/yolov5: YOLOv5 in PyTorch > ONNX > CoreML > TFLite.” [Online]. Available: https://github.com/ultralytics/yolov5. [Accessed: 05-Jul-2021].

[26] “Roboflow: Give your software the power to see objects in images and video.” [Online]. Available: https://roboflow.com/. [Accessed: 12-Jul-2021].

[27] M. Mohammadi, H. Knoche, M. Gaihede, B. Bentsen, and L. N. S. Andreasen Struijk, “A high-resolution tongue-based joystick to enable robot control for individuals with severe disabilities,” *IEEE Int. Conf. Rehabil. Robot.*, vol. 2019-June, pp. 1043–1048, 2019.

[28] M. A. Fischler and R. C. Bolles, “Random Sample Paradigm for Model Consensus: A Apphcatlons to Image Fitting with Analysis and Automated Cartography,” *Graph. Image Process.*, vol. 24, no. 6, pp. 381–395, 1981.