AquaBot: Assistive Drinking Robot for the Mobility-impaired

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***Abstract*—A shared autonomy based assistive system which uses mouth tracking and path navigation to deliver water to the mobility impaired has been implemented in this project. The end goal of this project is to automate the water delivery task for the mobility-impaired population. We implemented the mouth tracking algorithm and the path navigation algorithm on commercial robot STRETCH RE1. Finally, we evaluated the implementation of these two algorithms and demonstrated the shared autonomy based system is robust in performing the water delivery task.**

***Index Terms*—assistive drinking; computer vision; navigation; human robot interaction**

I. Introduction

The task of providing feeding and drinking assistance to the mobility impaired is arduous. According to the data from the US census in 2014, The total number of people having severe disabilities is 95 million [1]. Of which there are around 19 million people who need assistance with Activities in Daily Living (ADLs). In this population, nearly 5 million people have difficulties in drinking and they need assistance from a caregiver.

Mobility limitations can occur due to different causes such as cerebral palsy, amputations, and spinal cord injuries [2]. The severity of the mobility limitation varies from individual to individual. People with severe disabilities need assistance to do basic ADLs. One of the most important basic ADLs is eating and drinking, aiding patients to participate in activities as much as they can is essential for their mental health and helps them build self-esteem [3]. Quadriplegic is a form of paralysis caused by injury in the cervical spine. Patients with quadriplegia tend to lose the ability to control the torso and limbs [4].

People with these physical limitations commonly experience dehydration [5], because they cannot drink on their own and need assistance from caregivers . Drinking enough water is essential for patients because they need water to maintain body temperature and avoid constipation. Their skin conditions, metabolism, and kidney functions can get worse if they do not get enough water. Thus, it is a very challenging task for caregivers to provide drinking assistance to patients i.e 2-3 liters per day. It can take a caregiver up to 5 minutes for a hot drink per serving, and they have to repeat this 7-8 times per day[6].

Drinking and feeding assistance tasks for patients are mostly provided by human caregivers today. These daily routine activities can be fulfilled by assistive devices or robots, thus helping both patients and caregivers who get involved in the task. Having support systems that work mostly autonomously will encourage independence [7] and reduce the workload for caregivers. However, the device will not be acceptable and successful, if it requires more effort and time than the caregivers themselves performing the assistive tasks.

Assistive robots are the robots that were developed to help caregivers to provide help to users who have difficulties in performing ADLs [7]. Drinking assistance robots play an important role in assistive robotic research helping caregivers address the dehydration problem in patients. Many types of drinking assistance robots were built in the past decade to help solve the dehydration problem. The most common type of drinking assistance robot is the robot arm with the base mounted to the wheelchair or tabletop with an EEG controller or face recognition for the user interface. The drawbacks of using this kind of device are that it cannot move to different positions and EEG controllers require high mental effort to control the movement of the robotic effectors to a target position in 3-dimensional space.

The fixed base robots restrict the robot from providing water to the intended people. Whereas mobile base robots will enable users to move the robot from one place to another, such as from the kitchen area to the bedroom. It would be highly beneficial for caregivers especially when they are away from the people to whom they provide assistance.

The drinking assistance provided by many robots involves the delivery of water with a cup directly to a person's mouth. It would be beneficial for patients who have lost mouth muscle control because of which they cannot use a straw [9]. This task requires high robust control of the end effector of the robot.

In our research, we have developed a system that involves the Stretch robot to provide drinking assistance. The Stretch robot is a mobile base robot, thus users can move the robot to provide water at different locations. The stretch receives the destination of a person as an input. Then, it drives to the provided target position and provides water to the mobility impaired persons. The robot's arm has a cup with a straw, which is utilized by it to provide fluids.

Fully autonomous systems for drinking assistance are extremely difficult to develop, and almost any system will definitely require some inputs from humans to function correctly. Thus, we have aimed to implement a shared autonomy-based system, which involves sharing of responsibilities between the caregiver, care receiver, and the robot. From the caregiver's end, they first turn on the robot and set it up. Then, a cup filled with water with a straw in it is given to the gripper of the Stretch. After preparing the robot for water delivery, the caregiver provides the target position to the robot via the RVIZ interface. The robot will now move to the target position after receiving the command and autonomously deliver water to the mobility impaired person.The user interface of RVIZ is very simple, thus, the caregivers can quickly learn to use it. This interface also helps caregivers to deliver water to mobility impaired persons even when they are far away from the house. Our novel autonomous mobile base robot providing assistance to people in drinking can fill the research gap and reduces the problem of dehydration in mobility impaired.

II. Related work

This paper investigates previous studies related to the assistive drinking tasks in three main fields.These three fields are assistive drinking robots, visual sensing systems for mouth detection, and navigation systems.

A. Assistive drinking robots

There are several robotic arms developed in the past to address dehydration problem in people. These include two main types of robotic arms based on their functionality, which are the wheelchair-based robots and the workstation-type robots. The Wheelchair mounted robot arms enable users to manually control the robot arm movement by using the wheelchair controller, to interact with the surrounding objects and the environment. On the other hand, the workstation-type robot is a fixed base robot intended to do a specific task at the location where it has been installed.

1) Wheelchair Mounted Robot Arms (WMRA) - Manual control : The initial versions of wheelchair-mounted robot arms include the Manus robot arm and Raptor robot arm which were developed in 2000. JACO robot is the next version of WMRA introduced in 2010. The JACO has been very popular since its inception.

Manus robot arm is a wheelchair-mounted robot manipulator developed by Exact Dynamics and commercialized in the Netherlands [8]. It has an arm attached to wheelchair which has six degrees of freedom. It can grasp objects with a weight up to 2.2kg and can perform drinking assistance to people. The rotating wrist gripper with 2 fingers can grasp the cup, and bring it close to the person's mouth using the turn-on and turn-off commands which control the wrist rotation for water delivery[8].

Raptor is the first FDA-approved rehabilitative robot [8] developed by Phybotics (Applied Resources corporation) [21]. Raptor is another wheelchair-mounted robot arm with the Torque Transmission gearbox mechanism to provide high torque strength with lightweight objects[22]. The robot can be manually controlled by using the simple controller in the wheelchair. The robot gripper has two fingers, allowing users to grasp various objects. Although it is mostly similar to the Manus in terms of functionality, it differs in its unique mechanical design which enables the user to pick up the objects from the ground.

JACO robot is the next version of WMRA introduced in 2010 by Kinova and commercialized in 25 countries[21].The JACO has been very popular since its inception, as it is mounted on an electronic wheelchair. The JACO has six DOF motions with Kinova's gripper that is attached to the rotational actuator of the robot arm. There are two types of Kinova's gripper that users can select, which are the two finger gripper and three finger gripper. The two finger gripper allows the user to pinch a small object, while the three fingers gripper has a stronger grasp, enabling the user to grasp the bigger objects[21]. The robot controller is the Cartesian controller that enables the user to manually control the basic movements of the robot end-effector including three translation motions, three rotational motions, and open /close operations[21]. For the drinking assistance task, the Jaco robot has a drinking mode algorithm that shifts the center of rotation of the gripper in height and radius to set the bottle close to the mouth. Later the wrist is rotated to deliver water to a person[21]. However, most users prefer drinking through the straw rather than from a cup directly.

Fig. 1. JACO mounted on a wheelchair

Controlling these robots to perform drinking assistance is a complex and delicate task. It requires accurate controlling skills, and requires a lot of time, and effort from users to accomplish this task [21]. Thus, several studies regarding autonomous drinking were developed to resolve this problem.

2) Workstation-type robots - Autonomous drinking assistance feature: In this section we have studied three different work station type robots, which relatively are more autonomous than the wheel chair mounted robots described earlier. All of them display autonomy in different tasks, which are responsible for their unique nature.

In 2006, Neural signals controlled robotic arms were proposed by Hochberg et al [23] In this work, people with tetraplegia utilized a neural interface system to move and click a computer cursor. These movements in turn triggered physical movements in the robotic arms. Thus, the robotic arms performed grasping and reaching tasks, helping participants to drink coffee from a bottle.

In 2015, Schroer et al. developed the Brain-Machine Interface (BMI) on the Kuka omniRob platform with the Schunk three fingers gripper [24]. The robot uses the Kinect sensor and the external RGB-D camera to measure the position of the cup and the location of the mouth of the user in the local coordination frame. The robot then receives electroencephalography (EEG) signal from the user's brain, with which it determines when to deliver water. In 2021, Try et al developed the drinking assistance systems using Jaco II robot arms, a three fingers Kinova gripper with the camera, BME 680 sensor, and a Tof sensor attached to the gripper [25]. This system involves a cup with Tacterion Pylon medium sensor which can detect when the cup touches the user's lip. Thus this sensor acts as a vital component which adjusts the cup to deliver water to people. The movements of the end effector and its speed are controlled by the user through a contact which can be measured by changes in capacitive and resistive values received as an input.

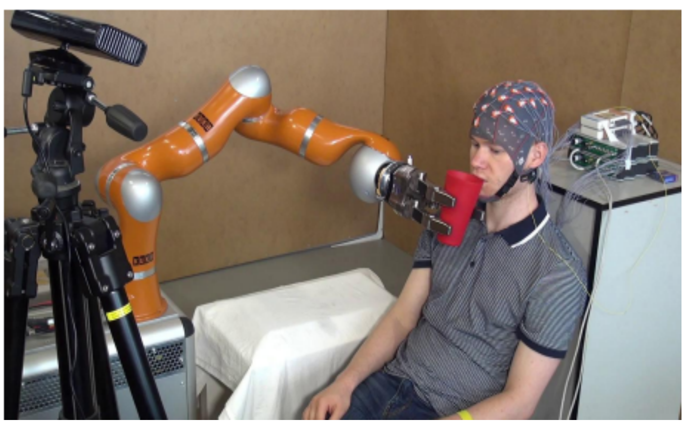

Fig. 2. Drinking assistance robot developed by Schroer

B. Visual sensing systems for Mouth Detection

Mouth detection is a vital part of our solution. The higher the accuracy in detecting the mouth of the person, the higher will be the success rate of our robot in providing water to that person. Thus, we have studied several works from the past which have been significant milestones in mouth detection. One such work is by Jones and Viola [10][11]. Their VJ framework for real-time face detection involved applying Haar-like features in a cascaded Adaboost classifier. Though this approach has given good and acceptable performance compared to prior works, there are significant drawbacks to their approach. First of all, the feature size in the 24x24 detection window is 160,000 which is relatively large. Moreover, the VJ framework was not effective enough to handle the non-frontal faces.

The issue of large feature size has later been a challenging research aspect. The methods like NPD[12] SURF[13] and ACF [14] have been proposed to address this issue. The approach by Pham and Cham in fast training and selection of Haar features with help of statistics boosting based face detection helped to significantly reduce computational expenses.[15] The method presented by them to train a weak classifier by using statistics from weighted input data decreased training time from minutes to seconds and helped to achieve good accuracy. Another approach by Charles, Jianxin, Jie, Matthew, and James has produced the detector which is significantly faster standard VJ method.[16] They have achieved this by recycling the outputs of the early stages of the training phase along with a retracing method that inserted early rejection points in cascades. This helped in increasing the overall accuracy and the performance of the face feature detector.

The popular Dlib library for face feature detection wherein the SVM classifier was used has also been the main driver for our work.[17] This library is an open-source library intended to be used for real-time problems and for research as well. It has been written in C++ language. This library consists of several machine learning tools which can be utilized for various different purposes. Among these tools, one such tool that particularly aligns with our research is the facial landmark detector. This is an SVM-based detector, which uses 68 coordinates to detect and represent a face in an image, as shown in Figure 2. A modified version of this concept has been used by us for mouth detection in our project which would detect the mouth of a person in the live video feed.

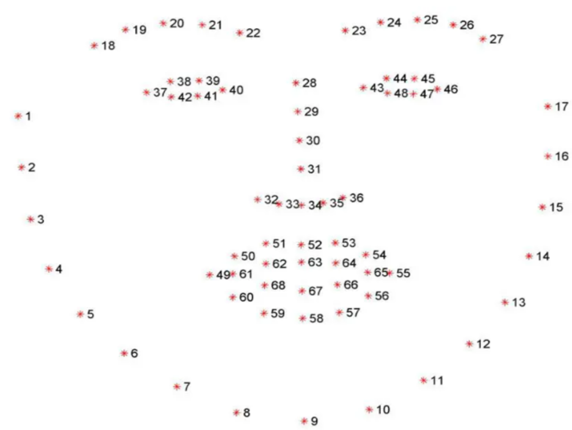

Fig. 3. Representation of Face by SVM classifier in DLib

Other facial feature detection methods include using Convolutional Neural networks and variations of them. For example, an integration of ConvNet and 3D face model in an end-to-end discriminative learning framework has been presented by Li to detect faces in the wild[18]. Another approach of applying faster RCNN for face detection has achieved very good accuracy and performance over regular CNN.[19]. Based on this work the authors of [20] have moved a step further by proposing Region Proposal network along with Fast RCNN for face detection. They have used WIDER FACE dataset to train the model and generate hard negatives. The resulting model was further trained on the FDDB dataset. They have also fine tuned the model by applying multi-scale training process and feature concatenation strategy to boost its performance. This approach has been recognised as one of the best published approaches for real-time face detection.

C. Navigation system

The navigation system is necessary for our robot to move from one location to other. The implementation of the navigation system starts with the creation of a map by the mobile robot with the help of sensors like Lidar, camera, and lasers. The procedure is facilitated by SLAM techniques which help the robot to create a map while localizing itself. There are several SLAM techniques proposed in the past like the Cartographer, Gmapping, HectorSLAM, TinySLAM, and VinySLAM. Kohlbrecher's work on Hector SLAM has been used to assist a rescue robot while navigating to different places to perform various rescue actions[26]. The ROS (Robot Operating System) has been used as a platform to generate a highly accurate metric based map for exploration of unseen and uneven environments, highly essential for a rescue robot. Thus, the robot could provide better rescue facilities.

The gmapping is another popular and most widely used algorithm. One application of this algorithm to a mobile robot is discussed in [27]. The robot in this paper uses a Hokuyo Laser Range Finder sensor and netbook for indoor mapping. The Rao-Blackwellized Particle Filter has been used to collect data from the sensors which is combined with the data of the pose of the robot to create a 2D grid map. This map is further used by the robot for navigating to a given destination in an indoor environment.

Improving over gmapping, Li et al proposed the usage of FastSLAM along with the Jacobian Neural network.[28]. The authors have used the third-degree Cubature rule for Gaussian Weighted integral to estimate the SLAM state accurately. The algorithm was simulated using the Ackermann model. This approach suffered from a limitation which is accumulating errors with incorrect odometry model.

From the previous works by others, we can conclude that each SLAM algorithm has its own benefits and limitations. However, it is very difficult to completely overcome all the limitations of the SLAM techniques, we can definitely fine tune different parameters to mask the limitations to some extent. Few such parameters and their effect on Gmapping technique are discussed in [27]. These options have guided us to build a robust navigation system for our approach.

III. Method

The system that we have developed to provide assistive drinking consists of Stretch robot. It has an arm that can hold a cup filled with water as shown in Fig.1.

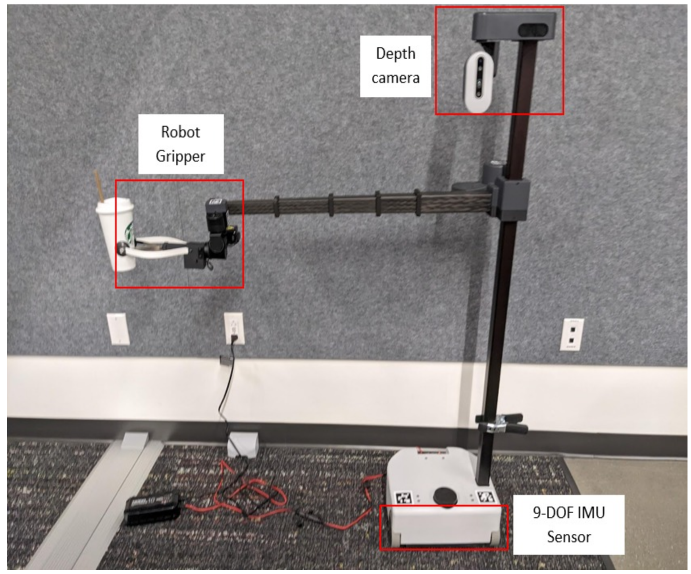

Fig. 4. Stretch robot with the cup and straw at the end effector. The robot has three main components including (i) The depth camera. (ii) The robot gripper on adjustable robot arm (iii) The 9 DOF IMU sensor in the robot base.

There are mainly two important steps involved in delivery of water by the robot, which are mentioned below.

A. Navigation System

In the navigation system, we have provided the robot with a destination position that is close to the person who needs to be provided assistance with drinking. After which the robot, can autonomously drive itself to the destination provided. To achieve this, we initially created a rough map of the room where the robot needs to navigate autonomously using Gmapping SLAM technique. This map is created by letting the robot to move around the environment where it needs to provide assistance. The robot utilizes the camera mounted on it to map its environment and different objects in its environment. The

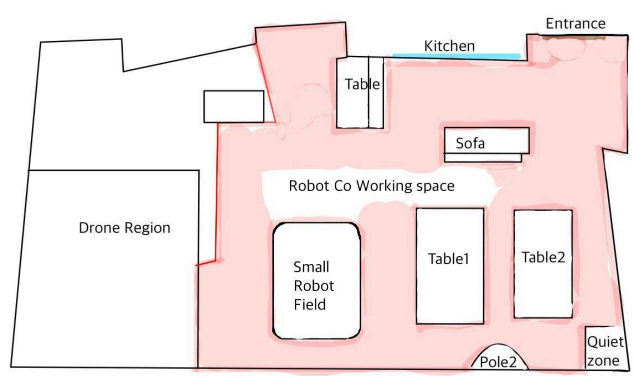

Fig. 5. Human drawn map of the Indoor environment

robot's view of the environment can be viewed using a tool called RVIZ which is provided by the ROS(Robot Operating System). This tool helps to visualise the robot's perspective of the environment along with safety distances associated with the different objects in the environment. The safety distances are set so that the robot will not get very close to any object in the environment and also prevents it from colliding with any object. The map of the environment where we have used the robot is shown in Figure 6.

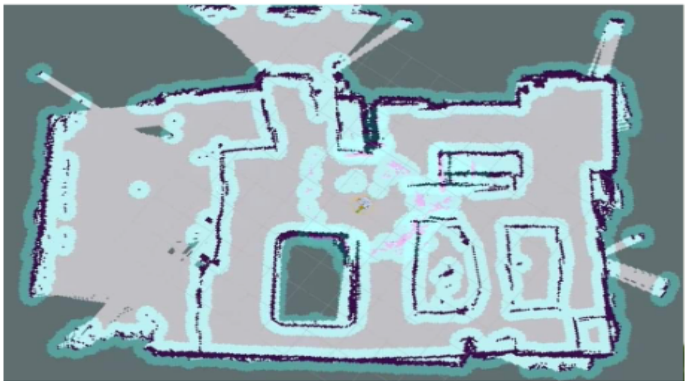

Fig. 6. Map that Robot created by itself in RViz Tool

The initial map helps the robot to understand its environment and also helps the caregiver to provide navigation goals to the robot. Once the navigation goal is given to the robot it creates a path from its current location to the destination using A* algorithm. The global path created by the robot to a destination is shown in Figure 7.

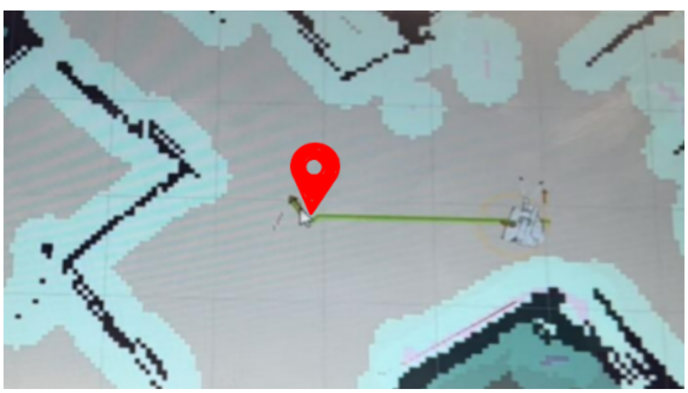

Fig. 7. Global path created by the Robot to a given destination

Then the robot follows along the global path and reaches the destination. During its travel, it continuously localizes so that the robot can understand its location with respect to its environment and destination. If the robot encounters an obstacle during its travel, then it stops automatically to avoid collisions and any potential damage. Upon reaching the destination, the robot localizes for the final time to orient itself to the destination given. This helps the robot to get to a pose that is comfortable for a mobility impaired person to drink water from the robot's arm.

B. Visual Based Assisted Drinking System

After reaching very close to a point where the robot needs to provide drinking assistance, it activates its computer vision based mouth tracking system. This system helps the robot to get the exact location of the person's mouth so that it can adjust its arm to provide water to them. Our system is very robust, as it detects both closed and open mouth situations. The closed and open mouth detection by the robot can be seen in Figure 8.

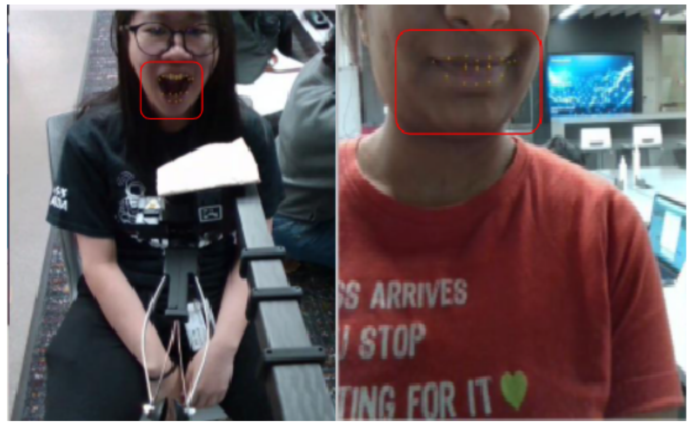

Fig. 8. Mouth detection by robot: Left - Open Mouth Right - Closed mouth

The camera of the robot helps with the detection of the person's mouth. This camera acts as a medium for providing the robot with continuous feed of its environment so that it can always keep a track of the person's mouth. A modified version of facial landmark detector from the DLIB library has been used by us to get the coordinates of the mouth from live video feed of the camera. Once the robot gets the location of the person's mouth, it estimates the coordinates of the mouth. These coordinates are used by the arm of the robot to adjust itself. The x coordinate of the mouth helps the robot to adjust its arm horizontally and y coordinate helps it to adjust vertically. All these adjustments are done to minimize the distance between the arm of the robot and the person's mouth, so that the person can easily drink water from the arm of the robot.

Once the arm of the robot gets close to the mobility impaired person, the person can use the straw provided with the cup in the arm of the robot to drink water or any other fluid. We have also considered the fact that the person might move their head or their base leading to change in the coordinates of the mouth. In such a case, the robot immediately detects a change in the coordinates of the mouth in both horizontal and vertical directions, and repeats the process of adjusting its arm close to the person's mouth. This is why our robot is very dynamic with respect to the changing positions of the person. But for this system to work correctly, we always assume that even though the position and orientation of the person changes, the new coordinates are always in the vision of the camera of the robot. Thus, this system gives us the power of hydrating people with multiple poses and locations.

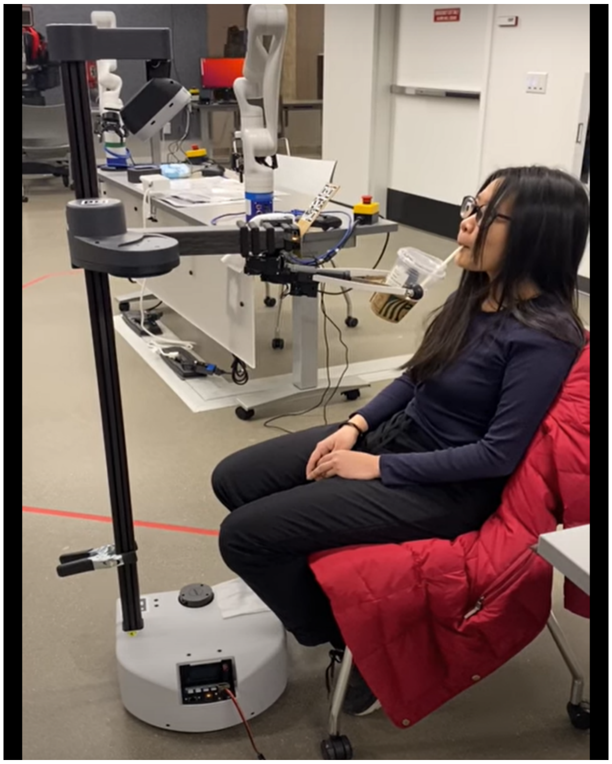

Fig. 9. Robot providing water to a person after navigation and mouth detection

IV. Evaluations

We have conducted several rounds of experiments to evaluate our approach to solve the hydration problem. With the several experiments conducted we demonstrate how our solution involving the robot is reliable and appropriate for hydration. The evaluation methods are also broken down into two separate divisions, one which focuses on evaluation of Navigation system and other which focuses on Visual mouth tracking system. All the evaluations performed build confidence on our system, and will help us to make the system even more safer and reliable.

A. Navigation System

As the navigation system involves providing a destination to the robot and letting it plan its path from its current location to the destination, we have performed three different kinds of experiments to build confidence in the navigation system. The three experiments are as follows:

1) Experiment 1: Distance of Destinations that the robot can reach: This experiment involves providing destinations to the robot at different distances from its current location and evaluating if the robot can reach those destinations. Every destination was given to the robot about five times and in every case we have seen that the robot reaches the given destination. We have given destinations to our robots only up to 10m, because the average size of an indoor room is roughly 10 by 10 meters, and we have constrained our robot to hydrate only indoors. The Table I summarizes the experiment results.

TABLE I
EXPERIMENT1: DESTINATIONS GIVEN AT DIFFERENT DISTANCES

Destination *Distance*	Average Time *to Destination*	Did robot reach *destination?*
1m	55 secs	Yes
3m	78 secs	Yes
5m	180 secs	Yes
7m	350 secs	Yes
10m	558 secs	Yes

2) Experiment 2: Accuracy of the Robot in reaching a destination of 1m set at different orientations from the current location of the robot: This experiment involves providing a destination that is roughly a meter away from the robot's current location and testing if the robot can reach the destination within 100 seconds. The destinations given to the robot orient at 0°, 30°, 60° and similar such increments of 30° from the axis to which the robot is currently aligned. Also, the threshold for the robot has been set to 100 seconds because we believe 100 seconds is an acceptable time for the robot, and if takes beyond that time, then the people using the robot might get impatient. The results of experiment 2 are summarized in Table II. From the several rounds of experiments that we have conducted, we have concluded that the robot succeeded in reaching the destination of 1m in less 100 seconds every 11 out of 12 times. Thus, a success rate of 92% has been attained with our approach.

TABLE II
EXPERIMENT2: DESTINATION OF 1M GIVEN IN DIFFERENT ORIENTATIONS

Orientation of Destination from the robot's axis (degrees)	Time taken by robot to reach the destination (secs)
0	22
30	28
60	50
90	63
120	83
150	98
180	125
210	95
240	89
270	73
300	45
330	37

3) Experiment 3: Error rate in reaching the destination: This experiment involves calculating the error rate of the robot in reaching the destination given to it. For every destination given to the robot, we have noted the distance between the position reached by the robot after navigation and the actual destination. This helped us to determine the accuracy of the navigation system. The comparison between the final robot's position and the actual destination is depicted in Graph I. Based on the information from the test results, we have calculated the Error rate according to Formulae 1 and 2.

$$\text{MSE} = \frac{1}{n}\Sigma(\text{X - Y})^2 \tag{1}$$

MSE = Mean Squared Error of Deviations in distances
X = Actual Destination Distance

Y = Distance reached by the robot from it's current position
n = Total no.of experiments

$$\text{Error rate} = \sqrt{\text{MSE}} \tag{2}$$

From our 20 trials, we have computed that the error rate(Standard Deviation) in the robot reaching a position is 1.9%, and MSE value is 0.00037.

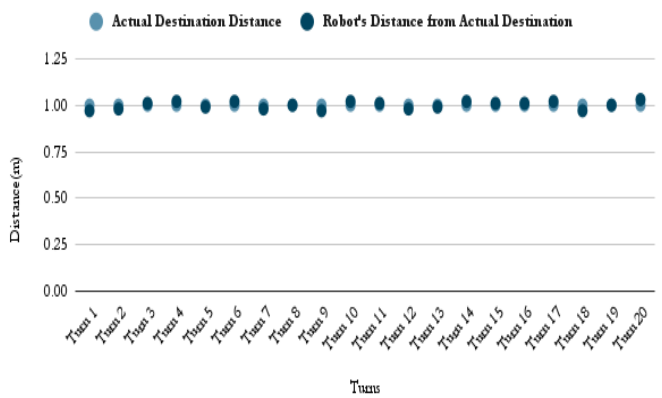

Fig. 10. Graph I: Comparison between Actual destination and Robot's position

B. Visual Based Assisted Drinking System

[h] The visual based assisted drinking system must track the mouth of the person and provide water by adjusting the end effector of the robot to get it close to the mouth of the person. To build confidence in this system we have performed several rounds of experiments by providing different locations of the person's mouth as an input to the system. We have defined a threshold that the robot's end effector must reach a position that is 10cm away from the person's mouth to consider it a successful trial. With this experiment, we can conclude that our robot had successfully reached a position close to the person's mouth every 9 out of 10 times.

V. Conclusion

Our approach to resolving the dehydration problem in the mobility impaired though is not a fully autonomous system, we believe that we have still made a significant contribution in this field. With our novel approach, we have not only decreased the caregivers' responsibilities of delivering water to the mobility impaired but also have developed a system where the caregivers can deliver fluids from anywhere and everywhere.

The field of assistive robots is very vast, and we have tried to address a small problem in it. Though we have given a permissible solution for assistive drinking, we believe there is still a lot of scope for improvement. Few such potential improvements include developing a voice-based interface for providing the navigation goals to the robot and implementing a system where a robot can autonomously grab a cup of water from a location and deliver it to the intended person. When such improvements are made, the caregiver's responsibilities decrease further and helps mobility-impaired people to be more independent and hydrated.

Fig. 11. Different positions of the person given as an input to the robot

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