Toward Active Robot-Assisted Feeding with a General-Purpose Mobile Manipulator: Design, Evaluation, and Lessons Learned

Daehyung Park, Yuuna Hoshi, Harshal P. Mahajan, Wendy A. Rogers, Charles C. Kemp

Healthcare Robotics Lab, Georgia Institute of Technology, Atlanta, GA, USA
Georgia Institute of Technology, Atlanta, GA, USA
University of Illinois Urbana-Champaign, Champaign, IL, USA

Abstract

Eating is an essential activity of daily living (ADL) for staying healthy and living at home independently. Although numerous assistive devices have been introduced, many people with disabilities are still restricted from independent eating due to the devices’ physical or perceptual limitations. In this work, we introduce a new meal-assistance system using a general-purpose mobile manipulator, a Willow Garage PR2, which has the potential to serve as a versatile form of assistive technology. Our active feeding framework enables the robot to autonomously deliver food to the user’s mouth. In detail, our web-based user interface, visually-guided behaviors, and safety tools allow people with severe motor impairments to benefit from the robotic assistance. We evaluated our system with 10 able-bodied participants and 9 people with motor impairments. Both groups of participants successfully ate various foods using the system and reported high rates of success for the system’s autonomous behaviors in a laboratory environment. Then, we performed in-home evaluation with Henry Evans, a person with quadriplegia, at his house in California, USA. In general, Henry and the other people who operated the system reported that it was comfortable, safe, and easy-to-use. We discuss learned lessons and design insights through user evaluations.

Keywords: Assistive Robots, Manipulation, Assistive Feeding

1. Introduction

Activities of daily living (ADLs), such as eating, toileting, and dressing, are important for quality of life [1]. Yet for many people with disabilities, including people with upper limb impairments, such tasks prove challenging without assistance from a human caregiver. However, shortages of healthcare workers and rising healthcare costs create a pressing need for innovations that make assistance more affordable and effective.

Technology interventions can be a solution by bridging the gap between physical capability and necessary functional ability [2]. Numerous specialized assistive devices, including robots, have been developed to help people with disabilities perform ADLs on their own [3]. Each device typically provides a narrow form of assistance suitable for people with particular impairments. Alternatively, researchers have applied general-purpose mobile manipulators to a variety of applications, such as rescue, assistance, and residential service [4, 5]. The robots often have a mobile base and human-like arms (e.g., PR2 robot from Willow Garage [6] and Jaco arm with a mobile base from Fattal et al. [7]), and help users to overcome their physical or perceptual limitations (e.g., remote manipulation [8]). Although the robots have the potential to provide a wide variety of assistance with tasks [9], their complexity creates challenges, including the risk of low usability.

A representative assistive task is meal assistance, which is an essential ADL for staying healthy. People with upper-body/limb impairments often have difficulty feeding themselves. Although a number of specialized meal-assistance robots are commercially available (e.g., My Spoon [10], Bestic arm [11], and Mealtime partner [12]), these robots provide limited meal assistance. Notably, we refer to the type of assistance these robots provide as passive feeding assistance, where the robot delivers food to a predefined location outside the users’ mouth and users take the food by using their upper body/limb movement. This is due in part to the robots’ (desk-mountable) fixed bases, low degree-of-freedom (DoF) arms, and limited sensing capabilities.
Instead, we use a general-purpose mobile manipulator to provide active feeding assistance that autonomously delivers food inside a user’s mouth, taking advantage of the robot’s greater physical and sensing capabilities.

In this paper, we introduce a meal-assistance system that enables a general-purpose mobile manipulator, a PR2 robot, to provide safe, easy-to-use assistance with feeding. The system provides active feeding assistance in which the PR2 delivers food inside a user’s mouth after scooping (or stabbing) food using visually-guided movements. The system can perform three independent subtasks: scooping (or stabbing), spoon-wiping, and delivering. A user can command a task via a graphical user interface (GUI). Our previous work that is a part of this paper introduced a proto-type of a feeding system with ARTags to find the food or the user’s mouth location [13]. We improved the system, particularly by adding subtasks, detectors, interfaces, and a monitoring framework. Note that we group the scooping and stabbing subtasks in terms of their similar functionality (i.e., food acquisition), but the subtasks use different tools, motions, and foods.

Our primary contribution is that instead of a specialized meal-assistance device, our system uses a general-purpose mobile manipulator to provide active feeding assistance that addresses considerations found in the literature: convenience, comfortability, speed, and safety as well as food grasping and delivery functions [14, 15]. For convenience, we enabled the system to autonomously delivery various soft or solid foods using 5 utensils and 2 types of bowls. The system allows caregivers to register and replace the utensil and the bowl through software and hardware interfaces. The system also allows users to access its interface from web browsing devices. For comfortable and safe deliveries, we designed the system to use a low-gain controller and a multimodal execution monitor to detect failures during assistance [16, 17, 18].

Another contribution is the evaluation of the system. As a step towards use by people with motor impairments, we first evaluated our system with 10 able-bodied participants. Also, Henry Evans, a person with quadriplegia, operated the system evaluated our system with 10 able-bodied participants. Also, Henry Evans, a person with quadriplegia, operated the system during assistance [16, 17, 18]. Our previous work that is a part of this paper introduced a proto-type of a feeding system with ARTags to find the food or the user’s mouth location [13]. We improved the system, particularly by adding subtasks, detectors, interfaces, and a monitoring framework. Note that we group the scooping and stabbing subtasks in terms of their similar functionality (i.e., food acquisition), but the subtasks use different tools, motions, and foods.

The rest of this paper is organized as follows: Section 2 shows related work including the examples of assistive robots, particularly assistive feeding devices. Section 3 presents the outline of our meal-assistance system. Section 4 describes the individual components of the system. Then, Sections 5 and 6 show our experimental setup and results, respectively. Finally, we present design insights and conclusions in Sections 7 and 8, respectively.

2. Related Work

Assistive robots are a type of device that can provide physical, mental, or social assistance to people with disabilities or seniors [19, 20]. In this section, we review assistive robots, particularly manipulators, for ADLs. We then go over meal-assistance devices including feeding robots.

2.1. Assistive Manipulators

Researchers have introduced a wide variety of assistive manipulators—such as 7-DoF arms mounted on a wheelchair or desk—to provide general assistance near the human [29, 30, 31, 32, 33]. We categorize the types of manipulators in terms of mobility: fixed- and mobile-base manipulators.

Fixed-base Robots. Fixed-base assistive robots are often placed near a user or a targeted workspace. Researchers mounted early assistive robots to desktops for assistance with feeding, cosmetics, and hygiene. The professional vocational assistive robot (ProVAR) is a representative desktop manipulator placed in an office workspace [30]. Handy-1 is another adjustable table-mounted manipulator for ADLs such as eating, drinking, and washing applications [34]. The mounted robots were designed to perform various ADLs using a general-purpose manipulator. However, the limited workspaces of the robots restricts the range of available activities. Alternatively, researchers have introduced various wheelchair-mounted robotic arms (WMRAs). For meal assistance, Maheu et al. showed that people with disabilities can feed themselves using a manually controlled JACO arm mounted on a wheelchair [35]. Schroer et al. showed drinking assistance using a 7-DoF KUKA arm [24]. For object fetching, Kim et al. introduced the UCF-MANUS robot, consisting of a wheelchair-mounted manipulator and interface [36].

Mobile-base Robots. The absence of mobility is an important issue in robotic assistance. Hawkins et al. found that movement of a mobile manipulator’s base was needed to provide assistance with a shaving task, since the PR2 that they used could not otherwise reach the relevant locations [37]. In feeding, the fixed robot base often requires the relocation of the robot or user by caregivers in the beginning or during the task. A fixed base restricts the scope of assistive tasks [38]. Without mobility, robots are restricted to a narrow set of tasks and are unable to leave the immediate vicinity of the human to provide assistance elsewhere. Recent studies have introduced general-purpose mobile manipulators for various assistive robotic tasks, including shaving [9, 37], dressing [39, 40, 41], fetch-and-carry [42, 43, 44, 45], and guiding tasks [46]. Our meal-assistance system has a mobile base that has the potential to enhance the quality of feeding assistance.

2.2. Meal-Assistance Devices

Researchers and companies have introduced various assistive devices for feeding. We focus on stabilizing handles, arm supports, and robots.
Table 1: A survey of recent robot-assisted feeding systems.

| Platform               | Interfacea | Toolb | Teaching/Movement Type | Base       | Safety Tool          |
|------------------------|------------|-------|------------------------|------------|----------------------|
| Commercial             |            |       |                        |            |                      |
| My Spoon [10]          | Joystick   | sf    | Predefined             | Fixed      | -                    |
| Bestic arm [11]        | Button     | s     | Predefined             | Fixed      | -                    |
| Meal Buddy [21]        | Joystick   | s     | Predefined             | Fixed      | -                    |
| Mealtime [12]          | Button     | s     | Predefined             | Fixed      | A shatterproof spoon |
| Obi [22]               | Button     | s     | Predefined Kinesthetic | Fixed      | Collision detection  |
| Yamazaki and Masuda [23]| GUI(H)     | sc    | User-selectedc        | Predefined | Fixed                |
| Song and Kim [15]      | Joystick & Button | sg | Predefined             | Predefined | Fixed                |
| Schroer et al. [24]d  | BCF        | N/A   | N/A Vision             | Movable    | -                    |
| Kobayashi et al. [25]  | Touch sensor | sc  | Vision                 | Fixed      | Spring joint         |
| Perera et al. [26, 27] | BCI        | s     | Predefined             | Fixed      | -                    |
| Admoni and Srinivasa [28]| Joystick & Gaze | f  | User-selected          | Predefined | Fixed                |
| Our Work               | GUI(H) & Gesture(H) | sf | Vision                 | Vision     | Movable Execution monitor |

a: H: A head tracker is used as a pointing device, E: An eye tracker is used as a pointing device.
b: s: spoon, f: fork, c: chopstick, g: gripper.
c: A user manually selects a target location on a screen.
d: Drinking task only.
e: Brain-computer interface (BCI).

Stabilizing Handle. Tremor often causes spilling food or drink. Stabilizing handles can be used for holding and smoothly transferring food on an attached spoon by aligning it with gravity (e.g., Liftware [47]). Pathak et al. reported an electronically controlled handle could improve holding, transferring, and eating during tremor-induced motions [48]. The self-stabilizing device is beneficial to people with Parkinson’s disease. However, the hand-handle device may not be available for people with severe tremor or other motor impairments.

Arm Support. Alternatively, arm support devices enable users to use their upper limb by supporting their weak arm, suppressing tremor, or expanding their limited arm movement. Several makers have developed wheelchair- or table-mounted arm supports: Neater [49] and Nelson [50]. By moving a spoon on the devices’ tip, users can scoop food and feed themselves while suppressing tremor or uncontrolled movements. The devices can be powered or underpowered but require users’ manual movements using their upper limb. Thus, depending on individuals with disabilities, the comfortableness and efficiency of feeding varies largely.

Robot. The use of meal-assistance robots is an alternative solution for various levels of people with motor impairments. A number of commercially available solutions exist: Handy-1 [34], Winsford feeder [51], My Spoon [10], Bestic arm [11], Mealtime partner [12], and Meal buddy [21]. These robots are designed for a particular purpose (i.e., meal assistance), often having a desk-mountable fixed base and a low DoF arm. A user can command a sequence of scooping-feeding motions via a joystick or a button. The robots follow predefined trajectories where food and mouth locations are hard coded. A recently released robot, Obi [22], uses kinesthetic teaching from caregivers, but it still provides passive assistance in that it only moves to the specified location rather than adapting to the location of the user’s mouth. To the best of our knowledge, there is no commercial robot which provides teaching the locations or locating the base for a person with upper limb disability.

Researchers have introduced advanced meal assistance systems with various functionalities [52]. Our previous work introduced a multimodal anomaly detector to detect anomalous feeding executions for safety [53]. Song and Kim designed a feeding robot with a specialized gripper for cultural food [15]. Yamazaki and Masuda introduced a 5-DoF chopstick-equipped robot that provides various motions to pick various characteristics of foods [23, 54]. The robot also allows each user to select a desired food-taking location via a graphical user interface (GUI). Recently, Admoni and Srinivasa introduced a gaze-based shared autonomy framework to predict a user’s target piece of food and retrieve it [28]. Javdani et al. presented a shared-control teleoperation approach to orient the utensil [55]. Unlike these manual or semi-autonomous systems, Kobayashi et al. introduced an automatic remnant food scooping method using a laser range finder [25]. Similarly, our system selects a scooping location using an RGB-D camera and autonomously retrieves it.

In terms of delivering food, most robotic systems use passive feeding executions in which a robot conveys food to a predefined location, typically in front of the user’s mouth. These systems depend on the users’ upper body movement to reach the food. Takahashi and Suzukawa, on the other hand, introduced an in-
interface enabling a user with quadriplegia to manually adjust feeding locations [56]. Similar to our work, Schroer et al. proposed an adaptive drinking assistance robot that finds the user’s mouth location with an external vision system [24]. We leverage such visual input to detect gestures and anomalies as well as the user’s mouth. In addition, researchers have adapted feeding task movements to users’ preferences by incrementally updating movement primitives [57, 58]. Table 1 shows a comparison result of features in currently available meal assistance robots that provide both food grasping and feeding functions.

3. Outline of System

3.1. System Configuration

Our robot-assisted feeding system hardware consists of a PR2 robot, tool holders, and additional sensors. Fig. 2 shows an overview of the system. The PR2 holds a bowl and a utensil while providing visually-guided feeding assistance. A user can command a preferred task via a graphical user interface (GUI) (see Fig. 3). The PR2 is a 32-DoF mobile manipulator that consists of an omni-directional mobile base, a 1-DoF telescoping spine, and two 7-DoF back-drivable arms that are controlled by 1 kHz low-gain PID controllers. Its maximum payload and grip force are listed as 1.8 kg and 80 N, respectively. These are enough to firmly hold a bowl or a utensil during assistance.

The system can perform three independent tasks: scooping (or stabbing), feeding, and spoon wiping. For scooping, the system finds the highest food location using a head-mounted RGB-D camera, Microsoft Kinect V2, to scoop a spoonful of food in a bowl held by its right arm. For active feeding, the system estimates the user’s face and mouth pose using an Intel SR300 RGB-D camera mounted on top of the right wrist. While running the tasks, the system runs a multimodal execution monitor to detect anomalous behaviors using 6 different sensors. We will discuss how to use these multimodal sensory signals to detect anomalous behaviors in Section 4.4. We run all software components on top of the Robot Operating System (ROS) [59]. All our source code is opened on www.github.com/gt-ros-pkg/hrl-assistive.

3.2. Operating Procedure

We will explain the operating procedure when a person with motor impairments wants to eat yogurt. We assume the robot is placed at a location from which it can reach the user’s mouth while holding a utensil and a bowl. We also assume the user can move and click a mouse pointer using a finger or a head (or eye) tracker. The typical operations follow:

- **Scooping**: The user clicks the Scooping button on the GUI. The robot then scoops a spoonful of yogurt from a randomly or visually selected location in the bowl adapting primitive movements.

- **Wiping**: The user clicks the Wiping button if the scooping task brings excessive food on the top of the spoon or a residue at the bottom of the spoon. The robot wipes off the surface of the spoon using the wiping bar on the bowl (see Fig. 5).

- **Feeding**: The user clicks the Feeding button when an adequate amount of yogurt is present on the spoon. The user turns his or her head toward the camera on the robot’s right wrist. The robot then estimates the pose of the user’s mouth and delivers yogurt inside the mouth. It then pulls the spoon back from the mouth.

During the operations, the user can stop and run the robot again whenever he or she wants using the provided interfaces.

Our multimodal execution monitor runs in parallel with the scooping and feeding tasks. When it detects an anomalous execution that largely differs from typical non-anomalous executions, the system pauses the current task execution and then moves the arm back to the initial pose of the current task. Note that the robot keeps the spoon’s level to avoid food spills during the returning motions.

4. System Components

4.1. User Interface

Our system uses a web-based GUI platform developed for self-care tasks around the users’ head [37]. We modify the platform to transmit task commands, display visual outputs from the cameras, and collect feedback from users (see Fig. 3). The GUI uses a rosbridge ROS library [60] that allows web browsers to interact with ROS using ROS topics and services over websockets. We developed the interfaces using HTML5, CSS3, and JavaScript. Users can access the interface using web-browsing devices such as a tablet or a laptop with their own input devices such as a mouse or a head tracker. The interface consists of a live video screen that displays the video output from the head- or wrist-mounted camera and a task tab that provides buttons or bars to command a task or adjust internal parameters of the system.

In the feeding task tab, the users can select one of three task buttons: Scooping/Stabbing, Clean spoon, and Feeding. The system then executes the selected task until finishing the task or receiving a stop command. The user can force the robot to stop at any moment by clicking a full-screen stop button that appears during task executions. The stop command is treated as an anomalous event which triggers a corrective action following transition $T_A$ in the finite-state machine (FSM) described in Section 4.2. After task completion, the users may then enter feedback (i.e., success or failure). We used the feedback to label the current execution data to train/test the execution monitor and tune the performance of the system.

In addition, users can select a comfortable feeding location where the robot places the entire spoon or fork with food inside the user’s mouth. By default, the robot places the tip of a utensil 4 cm inside from the center of the estimated mouth plane (Red-Green plane in Fig. 8). Fig. 3 Right shows a feeding-position calibration tab with 6 arrow buttons to add ±1 cm offsets to the target location in the selected direction.

4.2. Task Planners

**Finite-state Machine.** Fig. 4 shows the flow of the overall task sequence using a finite-state machine (FSM). To perform the
Scooping/Stabbing Task. The scooping and stabbing tasks aim to pick and hold food. The system produces either scooping (or stabbing) motions using a sequence of motion primitives. It adapts (i.e., translates) its motion with respect to the estimated food location. In this work, the robot can vary the scooping location by visually estimating a scoopable (or stabbable) point or randomly selecting it inside the bowl. For visual selection, we use a food location estimator described in Section 4.3. Otherwise, the robot approaches a random location inside the bowl. Note that we preregistered the size of the bowl so the system is able to estimate the scooping/stabbing area and restrict its motions to this region.

Caregivers can mount a pair of utensil and bowl for various type of foods. Fig. 5 Right shows 5 representative utensils we used in our evaluation: a silicone spoon, small/large plastic spoons, a plastic fork, and a metal fork. A user (or a caregiver) is able to mount a preferred utensil on the 3D-printed tool-changer after registering the transformation information from the changer to the utensil tip. Currently, the system provides a YAML file for a caregiver or expert to register a new utensil. There is also a 3D-printed handle the robot can firmly grasp. Fig. 5 Left shows a bowl our robot typically held during our evaluation. We also attached a handle to the bowl to enable a PR2 to grasp and hold it.

Food spilling can occur during scooping or stabbing due to
excessive amounts of food and imperfect manipulation. To prevent spilling from the bowl, we mounted a 3D-printed bowl guard (see Fig. 5 Left). We also place a cylindrical bar to wipe off excessive food from the bottom of the spoon.

**Feeding Task.** The feeding task aims to provide easily accessible and safe meal-assistance to a wide range of users, such as people with quadriplegia. Unlike conventional passive feeding systems in the literature, our active feeding system does not require a user’s upper body/limb movements to take food on the utensil. In other words, our system automatically delivers food inside the user’s mouth.

To put food inside the mouth, we use a 3D mouth-pose estimator using the wrist-mounted RGB-D camera that allows the robot to observe the user’s frontal face. We provide details in Section 4.3. After estimating the mouth pose, the system selects a feeding position inside the mouth with a predefined or user-selected offset (i.e., 4 cm in default). After the first delivery, the robot stores and re-uses the estimated mouth pose to shorten the delivery time. Our system also provides a button to re-estimate the mouth pose when the user wants (see Fig. 3 Right). We will explain available options for users in Section 4.1.

Our system does not require pose teaching by users or caregivers. The system has a set of predefined trajectories, linearly interpolating predefined poses in a predefined mouth coordinate frame visualized in Fig. 8. After estimating the new mouth pose, the system transfers the trajectories from the new mouth coordinate system to the world coordinate system. Note that our system provides spoon tilting motions for the large plastic spoon since users can have difficulty scraping the stiff and deep spoon against their upper lips to take food off.

For safety, the system observes the user’s face and the utensil during feeding. However, the robot may not fully observe the face due to occlusion by the other end-effector and the utensil it holds. Our system lifts up the camera to avoid occlusion, which enables the landmark estimator to predict points on the small occluded area (see Fig. 6).

**Wiping Task.** The scooping task often brings an excessive amount of food on the top of the spoon or a residue left at the bottom of the spoon. Both may result in food spills during the delivery. This requires a larger mouth opening or re-positioning to avoid food being on the user’s skin or body. A number of commercial robots use the edge of a bowl to clean excess food. Meal Buddy uses a wiping bar to wipe off excess food from the spoon and wipe drips from the bottom (see Fig. 5 Left). The guard is 3 cm high. It is used to block food spills from the bowl while performing the scooping motions. Likewise, the bar is 13.5 cm long. It is used to remove residue at the bottom of the spoon when the user commands the wiping task by clicking a Clean Spoon button on the system’s GUI. The robot drags the bottom surface of the spoon on the bar following a predefined linear trajectory. Note that the relative displacement between the right end effector and the bar is fixed due to the robot rigidly grasping the bowl.

4.3. Estimators
A Food-location Estimator. Our food-location estimator attempts to find a location where the robot can scoop or stab a large amount of food from the bowl. After repeated scooping or stabbing executions, the robot may fail to take the remaining food. At this point, either the feeding session can end or a caregiver can refill or redistribute the food. A commercial feeding robot, iEAT [61], rotates its food plate to adjust the scooping point. Alternatively, we addressed this issue by developing a vision-based estimator.

Our estimator determines the best scooping (or stabbing) location by selecting a location with the highest point-cloud density around five candidate locations, \( S = \{ s_1, s_2, s_3, s_4, s_5 \} \) displayed as yellow markers in Fig. 7, in the bowl. Given the estimated center and predefined diameter of the bowl, the estimator collects a point cloud \( X \) that corresponds to food inside the bowl using the head-mounted RGB-D camera. To exclude irrelevant points like the curvature of the bowl, we use a binary decision function, \( \Psi : x \rightarrow \{ 0, 1 \} \), that returns 0 if a point location \( x \in \mathbb{R}^3 \) is outside an ellipsoidal area in the bowl. Then, at each candidate location \( s_i \), the estimator computes a density score that is the sum of multivariate Gaussian probability density function values, \( p(x) = N(x; \mu = s_i, \Sigma = \bar{\Sigma}(X)) \) where \( x \in X \) and \( \bar{\Sigma}(X) \) is a sample co-variance matrix. It finally selects a location \( s^* \) with the highest density and sends it as the scooping or stabbing location to the robot,

\[
s^* = \arg\max_{s_i \in S} \sum \Psi(x)N(x; \mu = s_i, \Sigma = \bar{\Sigma}(X)). \tag{1}
\]

A Mouth-pose Estimator. The estimation of a user’s mouth pose plays an important role in enabling the robot to provide active feeding assistance to diverse users. In our previous work [13], the robot first estimated the location of an ARTag attached to the user’s forehead and then estimated the location of the user’s mouth through a predefined rigid transform from the ARTag’s pose. In this work, we introduce a mouth-pose estimator that does not require an ARTag and rigid transform. Instead, it directly estimates the location of the user’s lips from an RGB-D image.

Our estimator first extracts facial landmarks, key points of interest to localize facial regions such as the mouth, nose, left eye, right eye, and jaw, using the open source dlib library [62, 63]. This process localizes a user’s face from an RGB image and detects 68 landmarks for a frontal face. We then convert these 2D locations to 3D points by projecting them onto a depth image. This process can produce large errors due to the noise in the depth data and poor time-synchronization between the RGB and depth images. Thus, our algorithm rejects landmarks that 1) have large 3D distances from frontal-face reference landmarks defined with respect to the current mouth coordinate frame and 2) have large displacements (\( \leq 5 \text{ cm} \)) over time (\( \leq 10 \text{ Hz} \)). Then, following the model-based face localization method in [64], our algorithm also rejects a set of false positive landmarks that largely differ from pre-modeled landmarks located near eyes. After this rejection process, our algorithm computes a Delaunay triangulation of the landmarks to approximate the model of face surface and then groups the landmarks in the model into three groups: cheek, eye, and mouth. The estimator finally estimates the position and orientation of the mouth at the center of the mouth groups and perpendicular to the plane defined by the three groups, respectively.

4.4. Safety

Safety is an important consideration for feeding assistance system. Ideally, a user with impairments should be able to safely use the system without a caregiver monitoring the system. When compared to a simple specialized assistive feeding device, the greater autonomy and complexity of our active feeding system increases the chance of an error occurring. In this section, we describe aspects of our system that we have designed to increase safety.

Hardware. The PR2 arms are backdrivable and controlled by a low-gain PID controller to reduce the forces applied in the event of a collision. The PR2 also provides an emergency stop button that a user or a caregiver can press to cut off power to the PR2’s motors. In the event that the system loses power, the PR2’s passive spring counterbalance system helps to keep the arms from descending rapidly due to gravity.

Software. Our GUI provides a full-screen stop button (see Fig. 3 Middle) for people with motor impairments to conveniently and quickly cancel the current task and stop the robot’s current motion. During task executions, the button expands to the entire web browser and, if the user clicks anywhere on the browser, the roshbridge server for the GUI sends a stop command to the system. The command then triggers the \( T_A \) transition on FSM. In the end, the robot returns to the initial pose of the current task.
5. Experimental Setup

As a step towards use by people with motor impairments, we first performed a preliminary evaluation of the meal-assistance system with 10 able-bodied participants (N = 10) and Henry Evans, our main collaborator with severe motor impairments. The aim of the preliminary evaluation was to confirm the usability and safety of the active feeding system. We then performed evaluation of the system with 8 people with motor impairments that restricted their self-feeding ability (N = 8) in the Healthcare Robotics Lab at Georgia Tech, Georgia, USA. We also deployed the system in Henry’s home in California and performed a three-day evaluation. We conducted the evaluations with approval from the Georgia Tech Institutional Review Board (IRB).

Participants controlled the robot to scoop (or stab) and feed themselves through a 7 inch Google Tango tablet with a Chrome browser. Before starting this evaluation, we briefly trained the participants to use the meal-assistance system. As part of this training, they practiced using the system three times. Each practice run took about one minute. They freely controlled the robot to wipe off the bottom of the spoon before they ate food.

5.1. Preliminary Evaluations

Able-bodied Participants. We recruited 9 able-bodied participants and performed evaluations in the Healthcare Robotics Lab from April 30th to May 12th, 2017. They were all Georgia Tech students consisting of 1 female and 8 males, aged 22-29. We divided the participants into 3 groups of equal size where each group of participants used a different utensil and type of food: cottage cheese and silicone spoon, watermelon chunks and metal fork, and fruit mix and plastic spoon. Each participant performed 60 non-anomalous and 36 anomalous feeding executions (= (20 + 12) x 3 sessions) for a total time of less than 3 hours, where each participant completed a session within one hour. In this work, we only used the non-anomalous feeding executions to evaluate the system. The participants performed 540 non-anomalous executions and 19 extra executions. The participants also answered 11 post-experiment questions (five-point Likert type questionnaire items) after the experiment.

We also designed a long-term evaluation to observe the system’s daily assistance capability. The first author, an able-bodied participant, conducted a total of 428 feeding executions for 22 days between April 3th and July 28th, 2017. The first author ate 6 types of foods (i.e., yogurt, rice, fruit mix, watermelon chunks, cereal, and cottage cheese) and used 5 utensils (i.e., small/large plastic spoons, a silicone spoon, and plastic/metal forks) for lunch or dessert after lunch at the Healthcare Robotics Lab at Georgia Tech. Each session completed within 30 minutes, but there was no time restriction. Fig. 11 shows the 6 examples of foods we used in this evaluation. We used the system until each day’s food ran out so the number of executions varied. We determined the success and failure of an individual task.

A Person with Motor Impairments. We performed a remote test with Henry Evans, who became quadriplegic and mute after a stroke in 2003. As our main collaborator, he has participated in our assistive robot studies from 2010. From his home in California, USA, he used the web-based GUI to command a PR2 robot in Georgia, USA to feed an able-bodied person. Henry used an off-the-shelf head tracker and a mouse button to operate the web-based GUI. While using the system, he had visual feedback from the web-based GUI and a Beam+ (a separate telepresence robot). Fig. 12 shows a photograph of the remote test. Henry answered survey questions and provided design insights.
5.2. Evaluation with People with Motor Impairments

In-lab Evaluation. After confirming the usability and safety of the system through the preliminary evaluations in Sec. 6.1, we recruited 8 potential end users who have difficulties in eating using hand-held utensils over 5 months starting in November, 2017. 4 participants were male, and 4 participants were female. The age range was 23-72 (avg. = 49.4, std. = 21.4, N = 7). Participants had self-reported motor impairments that caused difficulties when feeding themselves and were comfortable with operating a touchscreen tablet. They participated in the study on their power wheelchairs and fed themselves through the tablet able-bodied participants used. For each participant, we conducted 1 session lasting approximately 2 hours. After safety training and 3 practice trials, the participants were asked to use the robot to freely feed themselves 10 spoons of yogurt (or forks of mixed fruit) and then 10 forks of mixed fruit (or spoons of yogurt). Experimenters refilled the bowl with food after every 5 feeding executions. At the end of the experiment, we administered questionnaires based on the NASA TLX subjective workload measure [66] and five-point Likert type questionnaire items as well as 2 open-ended questions. In addition to the formal questionnaires, we engaged participants in free discussion about the design of the meal-assistance system to gain insights from the targeted user group. Fig. 14 shows photographs from this in-lab evaluation.

In-home Evaluation. We also deployed the system to Henry’s home in California, USA (see Fig. 1). He used the meal-assistance system for two sessions per day, from February 11th through February 13th, 2017. He performed over 130 feeding executions over six sessions. We designed this study to observe if he could use the system without assistance from experimenters or caregivers. For this evaluation, we used a distinct PR2 robot from Georgia Tech in his home and mounted the same equipment that we used in the laboratory. We used yogurt and a silicone spoon. During the evaluation, we located the robot holding a bowl and a spoon beside his wheelchair. He used a head tracker to move the mouse cursor and a one-button mouse to click it. By manipulating the buttons on our GUI, he successfully controlled the system. We asked him to freely eat yogurt using the Scooping, Wiping, and Feeding buttons. At the end of our evaluation, we asked Henry to fill out a survey with 22 questions (five-point Likert type questionnaire items) based on [67], and 2 open-ended questions.

6. Results

6.1. Preliminary Evaluation

In the preliminary evaluation, we confirmed the usability and safety of the prototype meal-assistance system with 9 able-bodied participants. Table 2 shows 11 five-point Likert type questionnaire items. The third item shows 9 able-bodied participants successfully fed themselves using the prototype system with an average score of 4.67 and 7.14% relative standard error (RSE)\(^2\). Participants also reported that the system was safe and easy-to-use with scores of 4.22 and 4.0, respectively. Note that the participants were mostly familiar with robotic applications with a score of 4.89, so the answers may not be similar to the acceptance of the end-user group. An interesting result is that the participants neither agreed or disagreed with the amount of food the system delivers and its delivery speed. However, people with motor impairments mostly agreed with the speed in the in-lab evaluation. There was system improvement between the evaluations with two participant groups, but there was no change in speed.

Henry also successfully used the system to feed yogurt to an able-bodied participant. His answers, shown in Table 3, were similar to the able-bodied participants’. In response to an open-ended question at the end of the survey, he wrote “overall, worked well, although the PR2 video did not work.” In a later email with the subject line “feeding feedback”, he wrote “it is ready for field testing!”\(^3\), indicating he was prepared to try out the system in person.

\(^2\)The RSE that equals or less than 25% indicates the answer shows reasonable accuracy.

\(^3\)The PR2 camera shows the participant’s face only. To observe the entire experiment, he had to use additional teleconference robot.
6.2. Evaluation with People with Motor Impairments

We then conducted evaluations with 8 people with motor impairments. The system succeeded at feeding 99 times out of a total of 100 attempts (task success). The only failure was due to a participant’s accidental stop button click. The participants also reported that the system successfully fed them with an average score of 4.52 out of 5 (user success). Participants’ responses suggest that the robotic system could increase their perceptions of comfort and independence over their current feeding systems. They gave average scores of 2.88 and 3.25 to comfort and independence questions about their current feeding systems versus 4.75 and 4.5 for the robotic system (see Table 4). The participants agreed that the system helps feeding significantly with an average score of 4.88. Further analyses are in Section 6.3.

6.3. We additionally measured NASA TLX subjective workload to assess the participants’ mental, physical, temporal, effort, and frustration while using the system (see Table 5). The result indicates that our system requires an overall low workload. In particular, the simple interface of system resulted very low mental demand. However, the average of frustration is higher than other demands. We remain the investigation of the relation between the frustration and the degree of motor impairments as...
Table 2: Five-point Likert type questionnaire items for 9 able-bodied participants. The last column provides the average and standard deviation of scores with 1=strongly disagree, 2=disagree, 3=neither, 4=agree, and 5=strongly agree. When relative standard error (RSE) is 25% or less, results have reasonable accuracy.

| Questionnaires                                      | Score          |
|-----------------------------------------------------|----------------|
| I am familiar with engineering.                     | 4.78 0.67 4.65%|
| I am familiar with robotic applications.            | 4.89 0.33 2.27%|
| I successfully ate food using the system.           | 4.67 1.00 7.14%|
| I am satisfied with using the system.               | 3.89 0.93 7.95%|
| The system was easy-to-use.                         | 4.00 1.00 8.33%|
| I felt safe while using the system.                 | 4.22 0.83 6.58%|
| I was comfortable while using the system.           | 4.33 0.71 5.44%|
| The system delivered an adequate amount of food.    | 3.00 1.58 17.57%|
| The system delivered food with adequate speed.      | 3.11 1.69 18.12%|
| The system accurately placed food in my mouth.      | 4.00 0.87 7.22%|
| The system provides sufficient safety tools or functions to prevent hazards. | 4.56 0.89 6.45% |

Table 3: Five-point Likert type questionnaire items for the remote test with Henry Evans. The last column provides answers with strongly disagree (sd), disagree (d), neither (n), agree (a), and strongly agree (sa).

| Questionnaires                                      | Answer |
|-----------------------------------------------------|--------|
| The system was easy and intuitive to use.           | sa     |
| The web interface layout and icons were intuitive.  | sa     |
| I was satisfied with the time it took to complete the task. | d      |

Figure 16: Distributions of meal-assistance completion time from 3 able-bodied participants and 8 people with motor impairments (p-value = 0.0004 with a two-sided Welch’s t-test). The participants ate yogurt with a silicone spoon.

6.3. Analyses

6.3.1. Able-bodied People vs People with Motor Impairments

Completion Time. Fig. 16 shows the distributions of meal-assistance completion time from 3 able-bodied participants and 8 participants with motor impairments. In this graph, each participant ate yogurt using a silicone spoon. The completion time is an elapsed time that has passed between the click of the scooping button and the end of feeding motion including spoon wiping executed by individuals’ preference. There was no speed-relevant system change between two experiments. Able-bodied participants and those with motor impairments took about $39 \pm 4.5$ sec and $41 \pm 5.2$ sec, respectively. We performed Welch’s t-test, also known as unequal variances t-test, to test whether two samples differ significantly. The test resulted in $p-value = 0.0004$, which indicates the difference between two participant groups’ completion times is statistically significant. A likely cause is the difficulty of GUI manipulation due to upper-limb impairments.

Henry Evans also took about 78 seconds for one time of meal assistance that is about 39 seconds longer than the able-bodied participants’ duration. A likely cause was from mouse pointing time using the head tracker and the use of the wiping task, since Henry Evans used it 0.85 times per meal assistance but other participants mostly did not use it. Note that the wiping task usually took 17 seconds and there were adjustments in motion between the in-home and in-lab evaluations. However, there was our future work.

Finally, from the in-home evaluation, an end user, Henry Evans, successfully fed himself with the robot for all consecutive trials, where we turned off the execution monitor during 20 trials in the first session out of the six sessions to measure the feeding performance only. Table 6 provides the questionnaire results that we found most informative. As can be seen from the table, Henry reported that he found the system to be effective, safe, and easy to use. His responses to the 22 questions indicate that the anomaly detection function positively contributed to his experience of using the robot, helping him feel safer, and effectively alerting him of problems. In an email following the experiment, Henry also recommended several ways to improve the system, such as increasing the rate at which it feeds yogurt and giving the user the ability to finely adjust where the spoon moves with respect to the mouth.
Table 4: Five-point Likert type questionnaire items for 8 people with motor impairments. The last column provides the average and standard deviation of scores with 1=strongly disagree, 2=disagree, 3=neither, 4=agree, and 5=strongly agree.

| Questionnaires | Score                  | Avg. | Std. | RSE   |
|----------------|------------------------|------|------|-------|
| I feel comfortable using my current feeding system. | 2.88 | 1.64 | 20.19% |
| I feel independent using my current feeding system. | 3.25 | 1.49 | 16.19% |
| I expect this meal-assistance system to increase the independence of the user. | 4.14 | 0.90 | 7.68% |
| I expect this meal-assistance system to be satisfactory. | 4.38 | 0.74 | 6.01% |
| I expect this meal-assistance system to be comfortable. | 4.38 | 0.74 | 6.01% |
| I am comfortable with using technology. | 4.57 | 0.53 | 4.13% |
| I felt comfortable using the meal-assistance system. | 4.75 | 0.46 | 3.45% |
| I felt independent using the meal-assistance system. | 4.50 | 1.07 | 8.40% |
| The meal-assistance system provided significant help in eating. | 4.88 | 0.35 | 2.56% |
| The meal-assistance system successfully accomplished tasks. | 4.38 | 0.52 | 4.18% |
| The meal-assistance system was simple and easy to use. | 4.75 | 0.71 | 5.26% |
| I felt safe while using the meal-assistance system. | 4.50 | 0.76 | 5.94% |

Table 5: Questionnaire items based on NASA-TLX for 8 people with motor impairments. Participants chose a number between 1 and 20 for each question. 1 indicates “Very Low” for Mental, Physical, Temporal, Effort, and Frustration, and “Perfect” for Performance. 20 indicates “Very High” for Mental, Physical, Temporal, Effort, and Frustration, and “Failure” for Performance.

| Questionnaires | Score                  | Avg. | Std. | RSE   |
|----------------|------------------------|------|------|-------|
| Mental demand  | How mentally demanding was the task? | 2.88 | 2.03 | 23.55% |
| Physical demand| How physically demanding was the task? | 4.00 | 5.01 | 41.79% |
| Temporal demand| How hurried or rushed was the pace of the task? | 2.25 | 2.38 | 35.17% |
| Performance    | How successful were you in accomplishing what you were asked to do? | 2.25 | 2.38 | 35.17% |
| Effort         | How hard did you have to work to accomplish your level of performance? | 3.38 | 4.34 | 32.17% |
| Frustration    | How insecure, discouraged, irritated, stressed, and annoyed were you? | 5.25 | 5.31 | 33.73% |

Table 6: Five-point Likert type questionnaire items for an in-home evaluation with Henry Evans. The last column provides answers for strongly disagree (sd), disagree (d), neither (n), agree (a), and strongly agree (sa).

| Questionnaires | answer |
|----------------|--------|
| The system successfully accomplished tasks. | sa      |
| I felt safe while using the system. | sa      |
| The system was simple and easy to use. | sa      |
| The anomaly detection helped me feel more safe. | a       |

no change in speed.

**Ease of Use.** To assess ease of use, we asked a question about ease of use to both able-bodied people and those with motor impairments. Fig. 17a shows their responses where the median responses are ‘agree’ for able-bodied people and ‘strongly agree’ for those with motor impairments. The Welch’s t-test resulted in $p-value = 0.901$, so we cannot conclude that their agreements significantly differ.

**Comfortable Assistance.** We assessed agreement with ‘the system is comfortable to perform self-feeding task.’ Fig. 17b shows the participants’ responses where the median responses are ‘agree’ for able-bodied people and ‘strongly agree’ for those with motor impairments. The Welch’s t-test resulted in $p-value = 0.897$, so we cannot conclude that their agreements significantly differ.

**Successful Assistance.** Self-assessment of success was measured with the item ‘the system is successful to perform self-feeding task.’ Fig. 17c shows the participants’ responses where the median responses are ‘agree’ for both. The Welch’s t-test resulted in $p-value = 0.879$, so we cannot conclude that their agreements significantly differ.

**Safety.** Safety concerns were measured with the statement ‘the system is safe to perform self-feeding task.’ Fig. 17d shows the participants’ responses where the median responses are ‘strongly
agree’ for both. The Welch’s t-test resulted in \( p-value = 0.907 \), so we cannot conclude that their agreements significantly differ.

Throughout the evaluations, our meal-assistance system successfully fed foods to both able-bodied participants and those with motor impairments. Participants agreed that the system comfortably, successfully, and safely provides the meal assistance with easy-to-use interface. Overall, our results suggest that it is feasible for general-purpose mobile manipulators to provide meal assistance.

7. Discussion

7.1. Design Insights

We discuss learned lessons and insights about the design of potential meal-assistance systems for people with motor impairments that result in a self-feeding disability.

- **Robot Appearance**: Participants responded that they felt safe after the evaluation. However, several participants were overwhelmed or intimidated at first by the large size of the robot (a PR2). A participant with motor impairments stated that she felt threatened when the thick arm approached her in the beginning of the evaluation. Another participant said that a robot which is bigger than herself is intimidating. As for possible solutions to this problem, one participant suggested to make the robot look more “friendly”, such as by using more natural colors rather than the current metallic exterior.

- **User Interface (UI)**: Having multiple types of user interfaces the user can choose from would be a useful function to add to this system. A participant with numbness in her fingers often had trouble using the touchscreen, and preferred physical buttons. A number of participants clicked the touchscreen multiple times due to no button feedback. However, another participant did not have much strength in her hands, and therefore preferred the touchscreen to other methods.

- **Slicing food**: Many participants with motor impairments stated that slicing/cutting food is something that could be improved about their current feeding method, since they have difficulty applying sufficient force and dexterously manipulate knives. An assistive robot that slices food can not only reduce the burden of caregiving but also provide independent eating with a variety of foods.

- **Amount of Food**: Serving an adequate amount of food will help to increase the satisfaction of users and the efficiency of task executions. In the evaluations, the amount of food the robot scooped (or stabbed) varied. An excessive amount of food was usually connected to food spills while delivering food. Other times, the system scooped a very small amount of solid food (e.g., fruit) or failed to scoop. Participants showed difficulties in eating an excessive amount of fruit and had to command the last task execution again.
7.2. Assistive Robots

- **Speed:** Providing adjustable speed may be beneficial. The desired speed varied across participants and participant groups. Able-bodied participants neither agreed nor disagreed with the current system’s speed (about 40 sec per cycle). In contrast, the responses from people with motor impairments indicated they were satisfied with the speed on average, although Henry Evans desired a faster rate of feeding. That is because he is an expert user but had to spend a longer time to manipulate the user interface. Note that there was a small difference in motion but no change in speed.

- **Feeding Motion:** Tilting a spoon when it is going out from a user’s mouth could be beneficial. Depending on the spoon’s depth and the user’s disability, a horizontal retracting motion may not be sufficient to move all of the food from the spoon into the user’s mouth. For example, in the first author’s long term evaluation, we had to apply a human-like spoon feeding motion (i.e., tilting and retracting) to comfortably take food on the large plastic spoon in Fig. 5.

8. Conclusion

We introduced a proof-of-concept of meal-assistance system using a general-purpose mobile manipulator, a PR2 robot. The system can perform three independent tasks: scooping (or stabbing), spoon-wiping, and feeding, where a user can command a preferred task via a web-based GUI. Unlike conventional feeding devices, our novel system design enabled the mobile manipulator to provide visually-guided active feeding assistance that autonomously delivers food inside a user’s mouth after visually-guided scooping (or stabbing) of food. We also designed the system to provide safer assistance using various hardware and software tools including a high-level execution monitor. Overall, the design improved the accessibility and usability of the meal-assistance system for people with motor impairments that led to self-feeding disability.

We evaluated the prototype system with 10 able-bodied participants and 9 participants with motor impairments. In our preliminary evaluation with 9 able-bodied participants, the system successfully performed roughly 2,000 feeding executions with 5 utensils and 6 types of food items. Throughout our longer term evaluation, we confirmed the safety and usability of the system. In our evaluation with the end-user group, the participants with motor impairments were able to use the system successfully to feed themselves. Their responses were generally positive and similar to those of able-bodied participants to questions about the ease-of-use, comfortableness, safety, and success of the system. We also deployed the system at Henry Evans’ house in California, USA. He was able to use the system to feed himself successfully with 70 non-anomalous feeding executions for three days in his residential home setting. We demonstrated the feasibility of the new meal-assistance system. Finally, we shared design insights and lessons we learned through the design and evaluation. Our robot-assisted feeding system has the potential to reduce the disability experienced by individuals with motor impairments by providing them the support they need to perform feeding tasks.

9. Appendix: Supplementary data

The evaluation process and interview scenes are attached as a supplementary video.

Acknowledgements

We thank Hokeun Kim and Zackory Erickson for their assistance throughout this project. This work was supported by NSF Award IIS-1150157, NIDILRR grant 90RE5016-01-00 via RERC TechSAge, and a Google Faculty Research Award. Dr. Kemp is a cofounder, a board member, an equity holder, and the CTO of Hello Robot, Inc., which is developing products related to this research. This research could affect his personal financial status. The terms of this arrangement have been reviewed and approved by Georgia Tech in accordance with its conflict of interest policies.
Eclipse Automation, Meet obi, a robot that helps disabled individuals eat

Y. Kobayashi, Y. Ohshima, T. Kaneko, A. Yamashita, Meal support system with spoof using laser range finder and manipulator, International Journal of Robotics and Automation 31 (2016).

References

[1] J. M. Wiener, R. J. Hanley, R. Clark, J. F. Van Nostrand, Measuring the activities of daily living: Comparisons across national surveys, Journal of Gerontology 45 (1990) S229–S237.

[2] T. L. Mitzner, J. A. Sanford, W. A. Rogers, Closing the capacity-ability gap: Using technology to support aging with disability, Innovation in Aging 2 (2018) igy008.

[3] P. Rashidi, A. Mihailidis, A survey on ambient-assisted living tools for older adults, IEEE journal of biomedical and health informatics 17 (2013) 570–590.

[4] M. Schwarz, T. Rodehutskors, D. Droeschel, M. Beul, M. Schreiber, N. Araslanov, I. Ivanov, C. Lenz, J. Razlaw, S. Schüller, et al., Nimbro rescue: Solving disaster-response tasks with the mobile manipulation robot momaro, Journal of Field Robotics 34 (2017) 400–425.

[5] P. Deegan, R. Grupen, A. Hanson, E. Horrell, S. Sen, B. Thibodeau, A. Williams, D. Xie, Mobile manipulators for assisted living in residential settings, Autonomous Robots 24 (2008) 179–192.

[6] Willow Garage, Pr2 robot system, 2010. http://www.willowgarage.com/ [Accessed: 2018-04-14].

[7] C. Fattal, V. Leynaert, I. Laffont, A. Baillet, M. Enjalbert, C. Leroux, Sam, an assistive robotic device dedicated to helping persons with quadriplegia: Usability study, International Journal of Social Robotics (2018) 1–15.

[8] P. M. Grice, C. C. Kemp, In-home and remote use of robotic body surrogates by people with profound motor deficits, arXiv preprint arXiv:1803.01477 (2018).

[9] D. Park, Y. Kim, Z. Erickson, C. C. Kemp, Towards assistive feeding with a general-purpose mobile manipulator, in: Robotics and Automation, 2016. ICRA’16. IEEE International Conference on - workshop on Human-Robot Interfaces for Enhanced Physical Interactions, 2016.

[10] N. Tejima, Rehabilitation manipulator for eating, Journal of the Robotics Society of Japan 14 (1996) 624–627.

[11] W.-K. Song, J. Kim, Novel assistive robot for self-feeding, INTECH Open Access Publisher, 2012.

[12] D. Park, H. Kim, C. C. Kemp, Multimodal anomaly detection for assistive robots (submitted).

[13] D. Park, H. Kim, Y. Hoshi, Z. Erickson, A. Kapusta, C. C. Kemp, A multimodal execution monitor with anomaly classification for robot-assisted feeding, in: Intelligent Robots and Systems (IROS), 2017 IEEE/RSJ International Conference on, IEEE, 2017.

[14] D. Park, Y. Hoshi, C. C. Kemp, A multimodal anomaly detector for robot-assisted feeding using an lstm-based variational autoencoder, IEEE Robotics and Automation Letters (2018).

[15] D. Feil-Seifer, M. J. Mataric, Defining socially assistive robotics, in: International Conference on Rehabilitation Robotics (ICORR), IEEE, 2005, pp. 465–468.

[16] P. Maciejasz, J. Eschweiler, K. Gerlach-Hahn, A. Jansen-Troy, J. Frappier, F. Routhier, Evaluation of the handy 1, a rehabilitation robot-assisted feeding system, International Journal of Social Robotics (2015) 1–15.

[17] C. C. Kemp, D. A. Lazewatsky, H. Nguyen, et al., Robots for humanity: A case study in assistive mobile manipulation, 2013.

[18] Secom, Meal-Assistance Robot, My Spoon, 2017. https://www.secom.co.jp/english/mysoon/ [Accessed: 2017-07-15].

[19] Camanio Care AB, Bestic. Increase your mealtine independence, 2017. http://www.camanio.com/ [Accessed: 2017-07-15].

[20] Mealtime Partners, Specializing in Assistive Dining and Drinking Equipment, 2017. http://www.mealtimepartners.com/ [Accessed: 2017-07-15].

[21] D. Park, Y. K. Kim, Z. Erickson, C. C. Kemp, Towards assistive feeding with a general-purpose mobile manipulator, in: Robotics and Automation, 2016. ICRA’16. IEEE International Conference on - workshop on Human-Robot Interfaces for Enhanced Physical Interactions, 2016.

[22] S. Topping, An overview of the development of handy 1, a rehabilitation robot to assist the severely disabled, Journal of intelligent and robotic systems 34 (2002) 253–263.

[23] V. Maheu, P. S. Archambault, J. Frappier, F. Routhier, Evaluation of the jaco robotic arm: Clinico-economic study for powered wheelchair users with upper-extremity disabilities, in: Rehabilitation Robotics (ICORR), 2011 IEEE International Conference on, IEEE, 2011, pp. 1–5.

[24] D.-J. Kim, Z. Wang, N. Paperno, A. Behal, System design and implementation of ucfl-manusail intelligent assistive robotic manipulator, IEEE/ASME Transactions on Mechatronics 19 (2014) 225–237.

[25] P. Kr. Hawkins, P. M. Gruen, T. L. Chen, C.-H. King, C. C. Kemp, Assistive mobile manipulation for self-care tasks around the head, in: Computational Intelligence in Robotic Rehabilitation and Assistive Technologies, 2014 IEEE Symposium on, IEEE, 2014, pp. 16–25.

[26] A. Kapusta, D. Park, C. C. Kemp, Task-centric selection of robot and system configurations for assistive tasks, in: Intelligent Robots and Systems (IROS), 2015 IEEE/RSJ International Conference on, 2015, pp. 1480–1487. doi: 10.1109/IROS.2015.7385683

[27] K. Yamaazaki, R. Oya, K. Nagaahama, K. Okada, M. Inaba. Bottom dressing by a life-sized humanoid robot provided failure detection and recovery functions, in: System Integration (SII), 2014 IEEE/SICE International Symposium on, IEEE, 2014, pp. 564–570.

[28] S. D. Klee, B. Q. Ferreira, R. Silva, J. P. Costeira, F. S. Melo, M. Veloso, Personalized assistance for dressing users, in: International Conference on Social Robotics, Springer, 2015, pp. 359–369.

[29] Z. Erickson, M. Collier, A. Kapusta, C. Kemp, Tracking human pose during robot-assisted dressing using single-axis capacitive proximity sensing, IEEE Robotics and Automation Letters (2018).

[30] A. Kargov, T. Asfour, C. Pylatiuk, R. Oberle, H. Klosek, S. Schulz, K. Regenstein, G. Breithauer, R. Dillmann, Development of an anthropomorphic hand for a mobile assistive robot, in: Rehabilitation Robotics, 9th International Conference on, IEEE, 2015, pp. 182–186.

[31] H. Nguyen, C. Anderson, A. Trevor, A. Jain, Z. Xu, C. C. Kemp, El-e: An assistive robotic device dedicated to helping persons with quadriplegia: Usability study, International Journal of Social Robotics 11 (2014) 3.

[32] H. M. Van der Loos, J. F. Van Nostrand, Measuring the capacity-ability gap: Using technology to support aging with disability, Innovation in Aging 2 (2018) igy008.

[33] C. J. Perera, I. Naotunna, C. Sadarunuw, R. A. R. C. Gopura, T. D. Lalithatharne, Ssvep based bmi for a meal assistance robot, in: Systems, Man, and Cybernetics (SMC), 2016 IEEE International Conference on, IEEE, 2016, pp. 002295–002300.

[34] C. J. Perera, T. D. Lalithatharne, K. Kiguchi, EGG-controlled meal assistance robot with camera-based automatic mouth position tracking and mouth open detection, in: Robotics and Automation (ICRA), 2017 IEEE International Conference on, IEEE, 2017, pp. 1760–1765.

[35] H. Admoni, S. Srinivasa, Eye gaze reveals intentions in shared autonomy, in: In Proceedings of Intenions in HRI Workshop at HRI, ACM/IEEE, 2017.

[36] J. Hammel, K. Hall, D. Lees, L. Leifer, M. Van der Loos, I. Perkash, R. Crigler, Clinical evaluation of a desktop robotic assistant, J Rehabil Res Dev 26 (1989) 1–16.

[37] M. Hillman, K. Hagan, S. Hagan, J. Jepson, R. Orpwood, A wheelchair mounted assistive robot, in: Proceedings of the RESNA’99 Annual Conference: Spotlight on Technology, ERCIC, 1999, p. 125.

[38] J. Dietesch, A. Jardon, A. Jimenez, R. Correal, R. Cabas, S. Martinez, C. Balaguer, A portable light-weight climbing robot for personal assistance applications, Industrial Robot: An International Journal 33 (2006) 303–307.

[39] Y. Wakita, W.-K. Yoon, N. Yamanobe, User evaluation to apply the robotic arm rapuda for an upper-limb disabilities patient’s daily life, in: Robotics and Biomimetics (ROBIO), 2012 IEEE International Conference on, IEEE, 2012, pp. 1482–1487.

[40] M. Topping, An overview of the development of handy 1, a rehabilitation robot to assist the severely disabled, Journal of intelligent and robotic systems 34 (2002) 253–263.

[41] V. Maheu, P. S. Archambault, J. Frappier, F. Routhier, Evaluation of the jaco robotic arm: Clinico-economic study for powered wheelchair users with upper-extremity disabilities, in: Rehabilitation Robotics (ICORR), 2011 IEEE International Conference on, IEEE, 2011, pp. 1–5.
[46] Y. Jia, Y. Liu, N. Xi, H. Wang, P. Stürmer, Design of robotic human assistance systems using a mobile manipulator, International Journal of Advanced Robotic Systems 9 (2012) 165.

[47] Liftware, Liftware, 2014. https://www.liftware.com/ [Accessed: 2017-07-15].

[48] A. Pathak, J. A. Redmond, M. Allen, K. L. Chou, A noninvasive handheld assistive device to accommodate essential tremor: a pilot study, Movement Disorders 29 (2014) 838–842.

[49] Neater Solutions, Neater Eaters, 2017. http://www.neater.co.uk/ [Accessed: 2017-07-15].

[50] Focal Meditech, Nelson, 2010. https://www.focalmeditech.nl/ [Accessed: 2018-08-04].

[51] R. P. Herrmann, A. C. Phalangas, R. M. Mahoney, M. Alexander, Powered feeding devices: an evaluation of three models, Archives of physical medicine and rehabilitation 80 (1999) 1237–1242.

[52] J. Naotunna, C. J. Perera, C. Sandaruwan, R. Gopura, T. D. Lalitharatne, Meal assistance robots: A review on current status, challenges and future directions, in: System Integration (SII), 2015 IEEE/SICE International Symposium on, IEEE, 2015, pp. 211–216.

[53] D. Park, Y. Hoshi, C. C. Kemp, A multimodal anomaly detector for robot-assisted feeding using an lstm-based variational autoencoder, IEEE Robotics and Automation Letters 3 (2018) 1544–1551.

[54] A. Yamazaki, R. Masuda, Autonomous foods handling by chopsticks for meal assistant robot, in: ROBOTIK 2012, 7th German Conference on Robotics, VDE, 2012, pp. 1–6.

[55] S. Javdani, H. Admoni, S. Pellegrinelli, S. S. Srinivasa, J. A. Bagnell, Shared autonomy via hindsight optimization for teleoperation and learning, CoRR abs/1706.00155 (2017).

[56] Y. Takahashi, S. Suzukawa, Easy human interface for severely handicapped persons and application for eating assist robot, in: Mechatronics, IEEE International Conference on, IEEE, 2006, pp. 225–229.

[57] G. Canal, G. Aleya, C. Torras, Personalization framework for adaptive robotic feeding assistance, in: International Conference on Social Robotics, Springer, 2016, pp. 22–31.

[58] T. Rhodes, M. Veloso, Robot-driven trajectory improvement for feeding tasks, in: Proceedings of IROS’18, the IEEE/RSJ International Conference on Intelligent Robots and Systems, Madrid, Spain, 2018.

[59] M. Quigley, K. Conley, B. Gerkey, J. Faust, T. Foote, J. Leibs, R. Wheeler, A. Y. Ng, Ros: an open-source robot operating system, in: ICRA workshop on open source software, volume 3, Kobe, Japan, 2009, p. 5.

[60] C. Crick, G. Jay, S. Osentoski, B. Pitzer, O. C. Jenkins, Rosbridge: Ros for non-ros users, in: Robotics Research, Springer, 2017, pp. 493–504.

[61] Assistive Innovations, Ieat feeding robot, 2016. https://www.assistive-innovations.com [Accessed: 2017-12-06].

[62] D. E. King, Dlib-ml: A machine learning toolkit, Journal of Machine Learning Research 10 (2009) 1755–1758.

[63] V. Kazemi, J. Sullivan, One millisecond face alignment with an ensemble of regression trees, in: 2014 IEEE Conference on Computer Vision and Pattern Recognition, 2014, pp. 1867–1874. doi:10.1109/CVPR.2014.241.

[64] G. Garcia-Mateos, A. Ruiz, P. E. L. de Teruel, A. L. Rodriguez, L. Fernandez, Estimating 3d facial pose in video with just three points, in: Computer Vision and Pattern Recognition Workshops, 2008. CVPR’08. IEEE Computer Society Conference on, 2008, pp. 1–8. doi:10.1109/CVPRW.2008.4563050.

[65] D. Park, Z. Erickson, T. Bhattacharjee, C. C. Kemp, Multimodal execution monitoring for anomaly detection during robot manipulation, in: Robotics and Automation, 2016. ICRA’16. IEEE International Conference on, IEEE, 2016.

[66] S. G. Hart, L. E. Staveland, Development of nasa-tlx (task load index): Results of empirical and theoretical research, in: Advances in psychology, volume 52, Elsevier, 1988, pp. 139–183.

[67] A. Weiss, R. Bernhaupt, M. Lankes, M. Tscheligi, The ushs evaluation framework for human-robot interaction, in: AISB2009: proceedings of the symposium on new frontiers in human-robot interaction, volume 4, 2009, pp. 11–26.