Turning Assistive Machines into Assistive Robots

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ABSTRACT

For decades, the potential for automation—in particular, in the form of smart wheelchairs—to aid those with motor, or cognitive, impairments has been recognized. It is a paradox that often the more severe a person's motor impairment, the more challenging it is for them to operate the very assistive machines which might enhance their quality of life. A primary aim of my lab is to address this confound by incorporating robotics autonomy and intelligence into assistive machines—turning the machine into a kind of robot, and offloading some of the control burden from the user. Robots already synthetically sense, act in and reason about the world, and these technologies can be leveraged to help bridge the gap left by sensory, motor or cognitive impairments in the users of assistive machines. This paper overviews some of the ongoing projects in my lab, which strives to advance human ability through robotics autonomy.

Keywords: Rehabilitation Robotics, Assistive Robots, Machine Learning, Robot Autonomy

1. INTRODUCTION

Assistive machines—like powered wheelchairs, assistive robotic arms, upper or lower limb prostheses, and exoskeletons (Fig. 1)—are crucial in facilitating the independence of those with severe motor impairments. However, there are those for whom the control of these devices remains a challenge; in some cases, an insurmountable hurdle. It is a paradox that often the more severe a person's motor impairment, the more challenging it is for them to operate the very assistive machines which might enhance their quality of life.

When issuing the appropriate control signals to operate an assistive machine is a challenge for a user, there exists an opportunity for robotics technologies. Robots already synthetically sense, act in and reason about the world, and these technologies can be leveraged to help bridge the gap left by sensory, motor or cognitive impairments in the users of assistive machines. By endowing the assistive machine with some amount of autonomy—so that the machine itself is able to accomplish tasks autonomously, in some capacity—some of the control burden might be transferred from the user to the machine.

An important observation is that users of assistive devices overwhelmingly prefer to cede only a minimum amount of control authority to the machine.[1,2] Thus, while at one end of the control spectrum lies full manual control (i.e. direct teleoperation), and at the other lies fully automated control (i.e. an autonomous robot), in between lies a continuum of *shared control* paradigms, that blend—whether by fusion or arbitration—the inputs from manual control and automated controllers. Within robotics, typically the goal of shared human-robot control paradigms is to find a sweet spot along this continuum;[3–6] ideally, where sharing control makes the system more capable than it is at either of the continuum extremes.

Achieving a balance in control sharing that is both *effective* at accomplishing tasks and *accepted* by the human user is crucial for autonomous assistive robots—particularly those that provide physical assistance to the user. A founding principle of the *a*ssistive and *r*ehabilitation robotics *lab*oratory (*a*rgall*lab*) at the Rehabilitation Institute of Chicago (RIC) is to contribute to the advancement of human-assistive machines that make the human *more able* through the introduction of robotics-inspired autonomy, but still ultimately *in control*, through shared control paradigms that leverage machine learning to be customizable to and teachable by the user.

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[*]RIC is a rehabilitation hospital, ranked #1 in the United States by World & News Report for 24 consecutive years, and with the largest physical rehabilitation research center in the world.

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Figure 1. Examples of commercially available assistive machines. *Clockwise from top left:* The JACO wheelchair-mounted robotic arm from Kinova Robotics,[7] operated via a foot-controlled 3-axis joystick (inset). The Quantum 600 powered wheelchair from Pride Mobility,[8] that provides the base for our mobile robot platform (Fig. 2). The Ekso Hope lower limb exoskeleton from Ekso Bionics.[9] The i-limb ultra prosthetic hand from TouchBionics.[10]

This paper provides a high-level overview of assistive machines endowed with partial autonomy, as well as ongoing projects within the *ar*gal*lab*. The following section outlines the process of turning an assistive machine into an assistive robot. Section 3 then discusses the importance of the assistive robot appropriately sharing control with the human user. The detection and interpretation of control signals from the user are then discussed respectively in Sections 4 and 5, followed by the autonomous detection of task goals in Section 6. A relatively unexplored topic—that of leveraging machine learning within assistive and rehabilitation robotics—is presented in Section 7. Throughout the text, opportunities for advancements in sensing technologies to play a role within this domain are highlighted.

2. ASSISTIVE MACHINES AS ROBOTS

To endow the machine with autonomy typically requires the addition of sensors and an autonomous control paradigm. Sensors are used to detect the current state: where *state* in this case is broad in scope, ranging for example from the presence or absence of control signals from the user, to the location of the machine within the world, to the detection of high level goals within the world. Typical extrinsic sensors used within robotics to detect external state include image sensors (visual image, infrared (IR)), time-of-flight sensors (IR, sonar, ultra-sonic, laser) and structured light sensors (e.g. the Microsoft Kinect, Asus Xtion). There also are intrinsic sensors, used to detect the internal state of the robot, through which information about the state of the world might be inferred—for example, force-torque sensors at the joints or current spikes in the motors of a robotic arm can indicate contact between the arm and an object. Based on the inferred state of the world, the control algorithm—which might be high-level artificial intelligence or low-level motion controllers—dictates which control action the machine should take.

The development of novel technologies to sense external state would benefit the field of robotics as a whole, including but not limited to assitive robotics.

The two main robot platforms used and developed within the *ar*gal*lab* are a partial autonomy (smart) wheelchair and assistive robotic arm (Fig. 2). The smart wheelchair platform is built on a Pride Mobility Quantum 600 base,[11] modified to be drive-by-wire (including inverter and wheel encoders) by Sensible Machines.[12] To this we have added computing components and IR, ultrasonic and Kinect (RGB-D) sensors.[†] The robotic arm is the MICO from Kinova Robotics,[7] a 6 degree-of-freedom (DoF) robotic arm with a 2-finger gripper. It is the research edition sibling of the JACO wheelchair-mounted assistive robotic arm, already adopted by hundreds of users throughout the world and evaluated via subject studies.[13] The MICO features a smaller frame, lower cost, additional sensing (torque, accelerometer, joint position, current, temperature) and out-of-the-box interfacing

[†]Full specifications: *mini-PC* = Shuttle XH61 mini-PC with Intel i7-2600S processor, 16GB DDR3 SDRAM, 40GB solid state hard drive; *IR range sensor* = Sharp GP2Y0A02YK IR distance sensors (×10); *Ultra-sonic range sensor* = Maxbotix LV-MaxSonar-EZ1 Ultra-sonic range sensors (×4); *Sensor interface board* = Arduino Mega2560.

 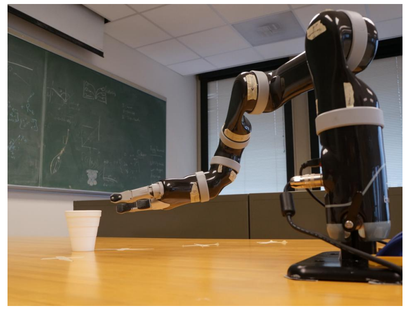

Figure 2. *Left:* Smart wheelchair platform under development in the *ar*gal*lab*, which includes a ring of IR and ultrasonic sensors and a top-mounted Kinect RGB-D sensor. *Right:* The MICO robotic arm in our lab, a 6+1 DoF robotic arm (6 arm joints + 1 gripper), which observes the external world through a single Kinect sensor.

tools (C++ API and ROS driver). The MICO observes the external world through a single Kinect RGB-D sensor.

By far the most ubiquitous powered assistive machine is the powered wheelchair. Accordingly, the development of partial-autonomy wheelchairs has also received the most attention within the academic community. The potential for "smart" wheelchairs—which incorporate robotics autonomy—to aid the mobility of those with motor, or cognitive, impairments has been recognized for decades.[14] Using epidemiological data from the research literature, one survey[15] estimates that between 1.4 and 2.1 million individuals would benefit from a smart wheelchair at least some of the time. For reasons of user, bystander and wheelchair safety, collision avoidance is one of the most common behaviors implemented within smart wheelchair systems.[2,16–20] To achieve autonomous navigation, early smart wheelchairs relied on modifications to their environment, such as fiducial landmarks[21,22] or visual/magnetic lines,[23] As sensors and algorithms improved however, so did the autonomous navigation behaviors. Autonomy behaviors developed to help with spatially-constrained maneuvers[24] or to address user fatigue include person following,[25] wheelchair convoying,[26] automated docking,[27] sidewalk following,[28] wall following,[29,30] assisted doorway traversal,[16,31,32] and trajectory playback[33] and rewind.[34]

As assistive machines become more complex—for example, robotic arms that are controlled within 6-D (position+orientation of the end-effector), compared to the 2-D control of powered wheelchairs (heading, speed)—the control requirements to operate them also will become more complex. Thus the need for and gains from endowing assistive machines with partial autonomy will become only greater.

3. SHARING CONTROL BETWEEN THE HUMAN AND ROBOT

The introduction of partial autonomy makes an assistive machine into a sort of robot, that shares control with the human user. Our shared-control framework assumes the existence of a set $\mathcal{F}$ of automated controllers $f(\cdot)$. Each controller dictates the motion of an autonomous behavior for the assistive robot. Formally, a vector of control signals $\boldsymbol{u}_t$ is generated by a function $f(\cdot)$

$$\boldsymbol{u}_t \leftarrow f(\boldsymbol{x}_t)$$

while control signals $\boldsymbol{q}_t$ are generated by the human. These two signals then are reasoned about within a blending function $\beta(\cdot)$

$$\hat{u}_t \leftarrow \beta(\boldsymbol{u}_t, \boldsymbol{q}_t)$$

which generates a shared-control signal $\hat{u}_t$. This control signal $\hat{u}_t$ is executed by the robot platform.

For the wheelchair-base robot in our lab, the state $\boldsymbol{x}_t$ consists of environment information like nearby obstacles, objects of interest or goal positions, and robot information like the current 2-D ground position, speeds or accelerations. The wheelchair-base robot operates within the space of translational ν_t and rotational ω_t wheel speeds. Thus, the control signal is $\boldsymbol{u}_t = \langle \nu_t, \omega_t \rangle$.

For the robotic arm in our lab, the state $\boldsymbol{x}_t$ consists of environment information like the location of objects of interest, and robot information like joint angle positions $\boldsymbol{\varphi}_t$, speeds $\dot{\boldsymbol{\varphi}}_t$, accelerations $\ddot{\boldsymbol{\varphi}}_t$, and/or time τ, depending on the specific control law employed. The robotic arm operates within the space of velocity control for each joint $\varphi_{t,i}$ individually, or velocity control of the position $\boldsymbol{p}_t \in \Re^3$ and orientation $\boldsymbol{o}_t \in \Re^3$ of the end-effector. In the latter case, an inverse kinematic controller $IK(\cdot)$ resolves the mapping from end-effector position+orientation to joint angles, $\boldsymbol{\varphi}_t \leftarrow IK(\langle \boldsymbol{p}_t, \boldsymbol{o}_t \rangle)$. Thus, for an arm with m joints (for our robotic arm, $m = 6$) with angles $\boldsymbol{\varphi} = \langle \varphi_1, \varphi_2, ..., \varphi_m \rangle$, the joint velocity control signal is $\boldsymbol{u}_t = \langle \dot{\varphi}_{t,1}, \dot{\varphi}_{t,2}, ..., \dot{\varphi}_{t,m} \rangle$, while the end-effector velocity control signal is $\boldsymbol{u}_t = \langle \dot{\boldsymbol{p}}_t, \dot{\boldsymbol{o}}_t \rangle$.

On our smart wheelchair robot, the most fundamental role control sharing plays is for the machine to assume control when a collision is eminent. Our approach[35] has the machine take over control iteratively, leaving control with the user for as long as—and returning control as soon as—is possible (Fig. 3).

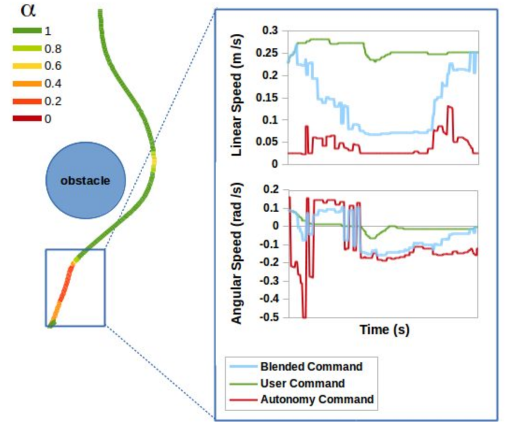

Figure 3. Command blending to maintain safety. As the forward projection of the user's commands (green in graphs) generate a path which collides with an obstacle, control is iteratively shifted from the user to the autonomy (by reducing the value of α). The resultant blended command (light blue in graphs) prioritizes foremost safety, but also keeping as much control as possible with the user. Robot ground path shown with colors that reflect the value of the control blending parameter α at that time. Image and caption from Argall 2014.[35]

Other work capitalizes on the inherent flexibility seen during multiple instances of a task's execution.[36] In particular, the approach extracts task variance from a set of demonstrations, based on the key insight that *variance* in the demonstration data equates to *allowable flexibility* in the task execution. The allowable flexibility inherently encodes spatial constraints of the task. Demonstrations are encoded within a Gaussian Mixture Model (GMM), and task variance is extracted via Gaussian Mixture Regression (GMR).[37] The human and autonomy inputs are then blended as a smooth function of *(i)* the learned variance and *(ii)* the distance between user-generated and autonomy-generated control commands (Fig. 4a,c).

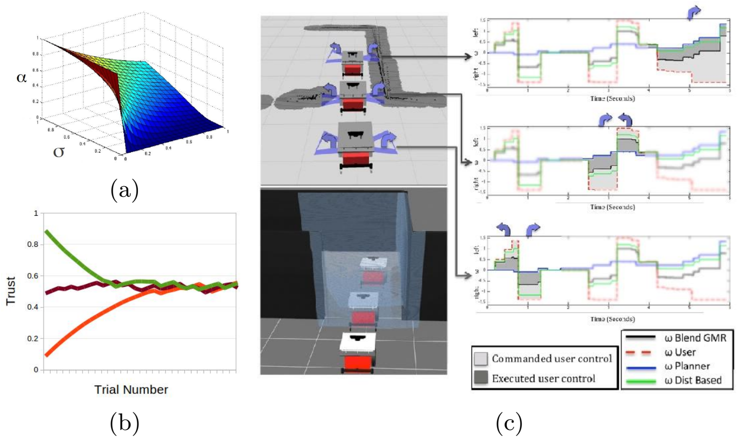

Figure 4. Preliminary studies with control sharing. *(a)* Blending parameter α is a function of demonstrated variance σ.[36] *(b)* Evolution of a measure of trust that informs α. *(c)* Snapshots of stress testing shared control.[36] Plots show user-commanded rotational speeds (blue arrows), and amount of executed (dark gray) and unexecuted (light gray) user-commanded control. Image from Goil, *et al.*, 2013.[36]

A collaboration with Todd Murphey at Northwestern University proposes a framework based on a *computable measure of trust* in the *human*, and uses this measure to modulate how control is allocated between the human and the robot.[38] The trust measure is autonomously computed and updated online—as the user interacts with and shares control of the machine—based on past task performance and agreement between the user and automated controller commands. A preliminary case study with 3 subjects performing a virtual balancing task support the appropriateness of the trust measure formulation (Fig. 4b), and future work will apply this approach to our assistive robots.

Lastly, work under development in collaboration with Siddhartha Srinivasa at Carnegie Mellon University targets a formalization for the split between human and robot control. The application domain of particular interest for this work is high-DoF assistive robots. In their prior work with assistive teleoperation[39] an arbitration function allocates control between an automated controller and human input. Our collaboration will apply this framework to the domain of a wheelchair-mounted robotic arm (the MICO), and will look at learning these arbitration functions, as well as customizing them to the needs and preferences of severely paralyzed users.

The majority of related literature on shared control with assistive devices lies within the realm of wheelchair automation. Many shared-control smart wheelchair platforms place the high-level control (e.g. goal selection, route planning) with the user, and the low-level control (e.g. motion control commands, obstacle avoidance) with the machine.[40–43] Other approaches do automate the route planning as well,[44,45] which can be especially appropriate for users with cognitive impairments.[46] Recognizing that the user is often dissatisfied when the machine takes over more control than is necessary—effectively forcing the user to cede more control authority to the machine than needed—many approaches offer a variety, often a hierarchy, of autonomous and semi-autonomous control modes within their shared control schemes.[47–49] Others explicitly target low-profile automation,[50,51] create new customized levels of autonomy,[52] or blend the user's control commands with the autonomy's control commands.[2,53,54] There are approaches that take this consideration of user input even further and aim to explicitly estimate user intent, in order to decide when the automation should step in,[16,55] smoothly blend with the autonomy controls,[56] or filter noisy input signals.[57]

Automation for wheelchair-mounted robotic arms typically has the user at a minimum select the task or object of interest,[58–60] and possibly also intervene to provide pose corrections[61–63] or assist the automation.[64] A driving factor in much of the partial automation for arms is the difficulty in higher-DoF control: the human is brought into the loop to offload part of this burden. A handful of examples allocate the manual and automated control to handle different portions of a low-level control space (e.g. Cartesian,[65] position-force[66]), in an attempt to scale a lower-DoF interface (e.g. 2-axis joystick) to control a higher-DoF system (e.g. 6-DoF arm).

4. CAPTURING CONTROL SIGNALS FROM THE HUMAN

Human motor limitations often translate into limitations—in bandwidth, in duration, in strength—in the control signals that the person can produce. Many traditional interfaces, like a 2-axis joystick, are inaccessible to those with severe motor impairments like paralysis (e.g. high Spinal Cord Injury), bradykinesia (slowness of motion, from, e.g., MSA, Parkinson Disease, Severe Traumatic Brain Injury), visual impairments (when paired with other motor impairments) or degenerative conditions (e.g. ALS, MS). The control interfaces which are accessible—for example, a Sip-N-Puff or headrest switch array (Fig. 5)—are limited in both the *dimensionality* of the control signals they are able to simultaneously issue (generally 1-D, occasionally 2-D), and also the *continuity* of that control signal. While a proportional control interface generates control signals that scale with the magnitude of the user input (e.g. amount of joystick deflection), with non-proportional control interfaces the generated control signals are preset amounts that do not scale. According to a survey of 200 clinicians, more than 50% of powered wheelchair users reported complaints with wheelchair control,[69] while a survey of 1,575 prosthesis users points to a want for better control mechanisms (including less visual attention).[70] Reports of prosthesis rejection rates are extremely variable (6%-100%), with unsatisfactory control being cited as a major reason.[1‡] Factors like fatigue also can be huge for those with physical impairments; who might, for example, trade a reduction in control precision for an interface that is less fatiguing.

Figure 5. Examples of non-proportional control interfaces. *Left:* The Sip-N-Puff[67] issues commands by blowing and sucking on a straw. *Right:* A switch-based electronic head array with three proximity sensors.[68]

The majority of work done within the *argallab* to date intentionally makes use of only commercially available interfaces already used to teleoperate assistive machines (i.e. powered wheelchairs). The motivation for constraining the problem in this way is two-fold. 1) For common machines like powered wheelchairs, the interfaces used to generate control signals for teleoperation are currently available, broadly employed and their operation is

[‡]Arguably the most fundamental challenges to user acceptance of myoelectric prostheses relate to hardware design; a user simply will not use a device if it is too heavy or if the socket connection is uncomfortable.[71] The issue of satisfactory control however is still significant.

familiar to users. (And *feasible* for users—which is important for assistive domains.) 2) These interfaces do not divert user attention from the task execution. (The estimation of user intent from such interfaces is a challenge discussed in Section 5.)

An exception is work under development in collaboration with Ferdinando Mussa-Ivaldi at RIC, which merges the Body-Machine Interface (BMI) invention of his Robotics Laboratory with robotics autonomy technologies developed within our lab. The BMI approach[72,73] maps residual upper body motions (of those with, for example, high spinal cord injury) to 2-D control points, offering a novel control interface to those with severe paralysis. In our collaborative work, the control signals issued by the BMI will be scaled up to control higher-DoF assistive robots—specifically, a 6+1-DoF robotic arm (Fig. 6). This scale-up will be facilitated by an adaptive shared control paradigm, that iteratively has the user take over more and more of the control as they become more skilled at issuing higher-dimensional control signals.

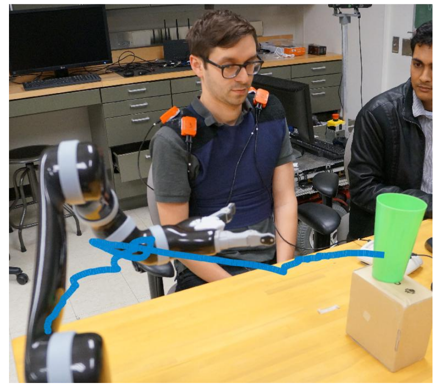

Figure 6. Proof-of-concept teleoperation of 2-D of the 6-DoF MICO robotic arm using the BMI (the remaining 4-D are fixed). Execution path in blue.

The development of novel sensing modalities to detect control signals from a human—moreover, when that person has limitations in the control signals and motions that they are able to produce—has the potential to make enormous impact within the domain of assistive technologies.

5. ESTIMATION OF USER INTENT

The estimation of user intent is fundamental to robotic systems operating in collaboration with, in close proximity to, sharing control with or assisting humans. To appropriately share control with a human, a robot requires a notion of the human's intentions or goals—which must be estimated, if they are unknown. Our work currently focuses on estimating user intent exclusively from the control signals used to teleoperate the robot, which moreover may be constrained by limitations on the control interface. An example of a limited interface accessible to those with severe motor impairments controls wheelchair translational or rotational motion separately—but never simultaneously.

Our research in intent estimation aims to develop algorithmic approaches that explicitly encode crucial aspects of the task domain—like limited control interfaces—while expecting no additional information from the user other than the control signals used to teleoperate the robot. Our framework for intent estimation, developed in preliminary work,[74] combines an analysis of the environment via Voronoi graphs with a probabilistic model of the commands a user might issue to achieve local goals, which are the nodes of the graph. Specifically, the joint probability distribution $\mathcal{P}(\boldsymbol{u}, \xi_g)$ of issued commands $\boldsymbol{u}$ and candidate goal configurations ξ_g is modeled within a Gaussian Mixture Model $\boldsymbol{\theta}$, whose parameters are estimated from general examples of driving behavior. Gaussian Mixture Regression is used to estimate the probability $\mathcal{P}(\xi_g|\boldsymbol{u};\boldsymbol{\theta})$ of a local goal configuration given the issued command, and this probability then is propagated to the global goals. The framework thus estimates the intended goal of a user, without requiring user-specific models or an *a priori* map. The types of goals under consideration within the context of wheelchair driving assistance might include doorways for traversing, tables for docking, or ramps for boarding a vehicle (Sec. 6).

Related approaches that estimate user intent, plans, or goals take a probabilistic approach to model relationships between user actions, states, and intention;[75–78] while others build models of influences within the environment[79] or specific behaviors of the user,[80,81] including driving.[82] Within the specific application domain of smart wheelchairs, user intent is estimated to decide which shared autonomy paradigm to use,[83] when the autonomy should step in[16] and to smoothly blend with the autonomous control.[56]

6. AUTONOMOUS PERCEPTION OF GOALS

If the machine is able to autonomously perceive candidate goals within the environment, this can reduce the requirements on the interface through which the user indicates their intent. With a set of candidate goals, the process simplifies to inferring *which* element from this finite set—rather than needing to perform inference over

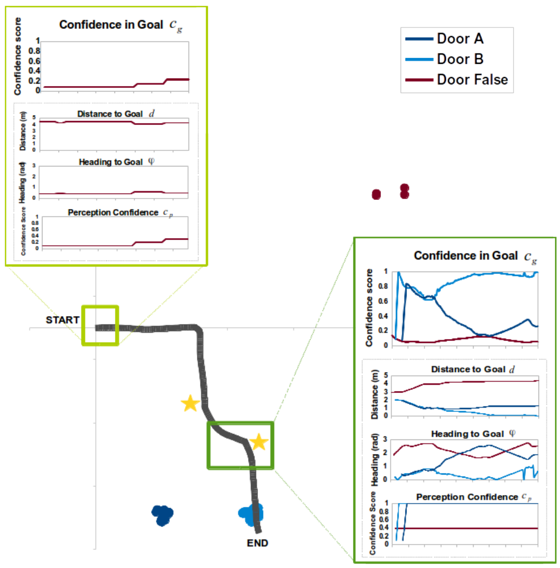

Figure 7. Confidence associated with autonomously observed goals. Two doors (light and dark blue dots) are observed within the environment; a third (red dots) is falsely identified. Plot panels show (top→bottom) goal confidence c_g, distance d and heading ϕ to the navigation goal and perception confidence c_p. At the start of the run, the false positive door is observed, however the low perception confidence keeps the overall confidence c_g also low. As the robot turns towards the actual doors, both are identified with high confidence. As the user issues commands that show preference for Door B (first star), its confidence rises and it becomes the active goal. The user retains control until she ceases issuing commands (second star), and the autonomy takes over in full. Robot ground path in dark gray. Image and caption from Argall 2014.[35]

the (infinite) set of all possible goals (e.g. all 2-D locations within the environment). The aim is to simplify the interaction between the user and the machine, which now autonomously also has an idea of where might be candidate locations of interest to visit, or objects of interest to manipulate.

Figure 8. Autonomous doorway detection (red box) and traversal using only depth information from a Kinect and our autonomous doorway detection algorithm.[84]

In Section 3, the topic of control sharing was discussed largely within the context of low-level control. When the robotic system is autonomously perceiving navigation or manipulation goals however, the concept of arbitrating between the signals of the human and the robot comes into play at a higher level as well. On our wheelchair robot, goal arbitration considers the confidence in the autonomous goal perception, as well as agreement between control commands that would achieve that goal versus control commands being issued by the human user.[35] An example of this arbitration is shown in Figure 7.

In our lab, autonomous goal perception contributes to the aim of having the user interact with the robot—including indicating their intent—using only the interface already used to teleoperate the machine. One of the assistance modules on our smart wheelchair is doorway traversal: a task frequently cited as challenging for powered wheelchair drivers, due to tight spatial constraints. Our algorithm[84] for doorway perception takes a geometrical approach, using depth data from an RGB-D sensor and searching first for (wall) planes perpendicular to the floor, then gaps within the plane constrained in width by specifications in the Americans with Disabilities Act. The algorithm provides both the location and orientation of an identified door, which then may be provided as a navigation goal to an autonomous path planner (Fig. 8).

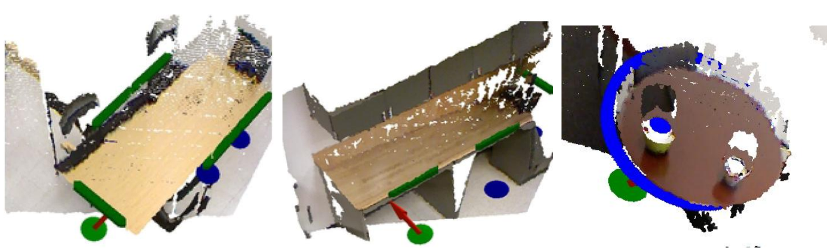

Figure 9. Autonomous docking location detection (green and blue circles) on example docking structures (left to right: rectangular conference table, desk, circular table). On the circular table, the docking location is anchored to the detected place setting (bowl). Image from Jain, *et al.*, 2014.[85]

Another available assistance module is docking the wheelchair at desks and tables, which also can require dexterous maneuvering if the open space at the desk/table is constrained or the surrounding environment is cluttered (e.g. a crowded restaurant). Our algorithm[85] again takes a geometrical approach using RGB-D data, this time searching for planes parallel to the floor and constrained to be a height at which a person seated in a wheelchair would be able to interact with the surface. Both rectangular and circular surfaces are identified, using machine vision techniques. A search for candidate docking locations is then performed along the edges of these surfaces, and each candidate location is checked for clearance (free space below). One variant of the algorithm additionally checks for circular objects like plates and bowls on the detected surface, and anchors the docking locations to them—with the insight that when such objects are place settings, often this is where a person seats him/herself at a table (Fig. 9).

The autonomous perception of navigation and manipulation goals falls under the broad category of sensing the external world. As noted in Section 2, the development of novel technologies through which a robot is able to perceive the external world have impact throughout the field of robotics, including assistive robot domains.

7. MACHINE LEARNING WITH ASSISTIVE AND REHABILITATION ROBOTS

Within the clinical context of assistive devices, machine learning plays a limited, nearly absent, role.[§] Our premise is that machine learning can help with making assistive machine autonomy both customizable to the preferences of a user, and teachable by them. There is an opportunity here for machine learning to facilitate a superior human-robot team, which here is heterogeneous in the fullest sense: the very need for the assistive device means there are capabilities which only the machine can fulfill.

A large portion of machine learning algorithms depend on some form of feedback signal (e.g. state reward, an error value). Especially for learning goals that relate to user preference, it is reasonable to expect that at least some feedback would (or should) be provided by the user. In this case, not only will the feedback be provided by a person who is not a robotics or control expert—which is a challenge for robotics applications in general—this person furthermore will have limitations in their sensory, motor and/or cognitive capabilities, which need to be accounted for.

This topic presents a relatively unexplored challenge, and also a unique opportunity for advances in sensing technologies. The ability to unobtrusively detect rich feedback from the user about the suitability of the machine autonomy and/or how it shares control with them, and moreover from those with motor impairments, would have enormous impact within the domain of assistive robot autonomy.

In the end, the gold standard in rehabilitation is not to devise clever and useful assistive machines, but rather for the motor-impaired person to *recover lost motor function*, whenever possible. In a collaboration with Ferdinando Mussa-Ivaldi at RIC, we hypothesize that machine learning can be used to encourage motor learning by the human, and thus to elicit a rehabilitation response. In particular, we propose to modulate the control split between the human and robot with the goal of encouraging human motor learning. This is an exciting area—using *robot machine learning* to elicit a *human motor learning* response—which to our knowledge is previously unexplored within the rehabilitation and machine learning fields.

8. CONCLUSION

Robotics automation holds enormous potential to aid in the control of assistive machines, and by doing so impact the lives of those with motor, sensory and/or cognitive impairments. This paper has provided a high-level overview of some of the fundamental technical topics with the field of autonomous assistive and rehabilitation robotics, as well as ongoing work within the *ar*gal*lab* at the Rehabilitation Institute of Chicago. Opportunities for advances in sensing technologies to play a role within the domain of assistive robot autonomy were highlighted, including most notably superior mechanisms for detecting signals—signals for control, and also as feedback for machine learning algorithms—from those with severe motor impairments.

[§]With the exception of classifiers that decode EMG signals for the control of myoelectric prostheses.

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