Machine Learning for Shared Control with Assistive Machines

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***Abstract*— The focus of this paper is to present a very relevant robotics application domain and its challenges, and to highlight how machine learning might be used to help resolve them. The domain in question is the shared control of partial automation assistive machines (e.g. powered wheelchairs, electric prostheses); where control is shared with the motor-impaired human user of the machine. A variety of challenges particular to this domain are outlined, for example appropriate control interfaces and user acceptance. A founding principle of the recently established Laboratory of Adaptive and Autonomous Rehabilitation Robotics is that machine learning can be used to address at least some of these challenges. This short paper elaborates on these ideas, identifying promising avenues for machine learning with the domain of shared control with assistive robots, and introduces a handful of projects within the lab beginning to address them.**

Keywords*—*Rehabilitation Robotics; Machine Learning; Shared Human-Machine Control

I. INTRODUCTION

Within the clinical context of assistive devices, machine learning plays a limited, nearly absent, role.[1] 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 an insurmountable hurdle. A hurdle that partial automation holds some promise to overcome, and it is our premise that machine learning can help.

The introduction of partial automation makes an assistive machine into a sort of robot, that shares control with the human user. An important observation is that users of assistive devices overwhelmingly prefer to cede only a minimum amount of control authority to the machine [12], [32]. 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. Typically, the goal of shared human-robot control paradigms is to find a sweet spot along this continuum [28], [33], [43]; ideally, where sharing control makes the system more capable than it is at either of the continuum extremes.

However, when the human-robot system consists of an assistive device (robot) and its user (human), the goal is somewhat different. In this case the goal of the automation is to fill a gap left by the sensory/motor impairment of the user, and user's acceptance of the system—rather than quantifiable performance metrics—is the final word on how the balance in shared control is achieved. This is a key distinction, with a host of repercussions discussed further in Section II-B. Moreover, while the system as a whole may not itself be fully autonomous—though for reasons of user preference, rather than a lacking robustness—the very need for the assistive device means there are capabilities which only the machine can fulfill. The human-robot team thus is heterogeneous, in the fullest sense. There is an opportunity here for machine learning to facilitate a superior human-robot team, and in this case we argue that a very relevant form of machine learning by an autonomous system is in fact taking place.

There are many challenges particular to the shared control of assistive devices (Sec. II-B) and, in aiming to address them, there accordingly are a variety of target outcomes and goals a machine learning formulation might take on (Sec. II-C). This paper will share some ideas about learning goals applicable to this topic, and their incorporation into a handful of projects (Sec. III) just starting at the recently founded Laboratory of Adaptive and Autonomous Rehabilitation Robotics (A^2R^2 *Lab*) at the Rehabilitation Institute of Chicago (RIC).[2] The founding principle of the A^2R^2 *Lab* is to facilitate the advancement of human-assistive devices, that make the human *more able* through the introduction of robotics-inspired automation, but still ultimately *in control*, through shared control paradigms that are customizable and adaptable by the user. The intent is to *leverage machine learning* to achieve this goal.

II. SHARED CONTROL WITH ASSISTIVE DEVICES

Here we begin with an overview of related literature on shared control within the domain of assistive machines. Challenges in this domain are then highlighted, and opportunities for machine learning to provide solutions to some of these challenges are identified.

A. Background

The majority of the shared control work with assistive devices lies within the realm of wheelchair automation—"smart" wheelchairs—whose potential to aid the mobility of those with motor, or cognitive, impairments has been

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

[2]RIC is a rehabilitation hospital, ranked number one in the United States by World & News Report for 20 years running, and with the largest physical rehabilitation research center in the world.

Fig. 1. Examples of commercially available assistive machines. *Clockwise from top left:* The JACO wheelchair-mounted robotic arm from Kinova Robotics [1], operated via a foot-controlled 3-axis joystick (inset). The Ekso Hope lower limb exoskeleton from Ekso Bionics [2]. The i-limb ultra prosthetic hand from TouchBionics [3]. The Quantum 600 powered wheelchair from Pride Mobility [4], that provides the base for our mobile robot platform (Fig. 2).

recognized for decades [45]. 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 [15], [38], [42], [52]. Other approaches do automate the route planning as well [41], [51], which can be especially appropriate for users with cognitive impairments [37].

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 [14], [36], [39]. Others explicitly target low-profile automation [29], [53], create new customized levels of autonomy [22], or blend the user's control commands with the automation's control commands [32], [46], [47]. 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 [17], [40], smoothly blend with the automation controls [49], or filter noisy input signals [20].

Automation for wheelchair-mounted robotic arms typically has the user at a minimum select the task or object of interest [25], [31], [34], and possibly also intervene to provide pose corrections [13], [35], [48] or assist the automation [50]. A driving factor in much of the partial automation for arms is the difficulty in higher degree-of-freedom (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 [24], position-force [44]), 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).

Shared control between the human and robot thus is acknowledged to be an elemental topic within the domain of assistive machines and rehabilitation. Little to no machine learning has been introduced within this domain however.

B. Challenges and Special Considerations

Here we review a handful of high priority issues that are particular to shared control within an assistive domain.

Interfaces for control. 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). According to a survey of 200 clinicians, more than 50% of powered wheelchair users reported complaints with wheelchair control [26], while a survey of 1,575 prosthesis users points to a want for better control mechanisms (including less visual attention) [11]. Reports of prosthesis rejection rates are extremely variable (6%-100%), with unsatisfactory control being cited as a major reason [12].[3] Factors like fatigue also can be huge for those with physical impairments; who might, for example, trade a reduction in control precision as an acceptable price for an interface that is less fatiguing.

Interfaces for providing feedback. 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.

User acceptance. While user acceptance is always a factor in the adoption of new technologies, users of assistive devices rely very intimately on this machine—it is physically supporting, or attached to, their bodies—and accordingly can be very particular in their tolerance for innovation. Many

[3] 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 [27]. The issue of intuitive control however is still significant.

imaginative academic research projects in assistive robotics sadly never make it past the laboratory; in fact, to our knowledge, very few of the technologies developed for the systems listed in the prior section have made the jump to widespread access and adoption (e.g. through commercialization).[4]

Flow of control authority. For reasons of user acceptance in particular, it is a priority that the user does not feel as though they are giving up an undue amount of control [12], [32]. This needs to be balanced with the goal of execution success (and machine learning, discussed further in Sec. II-B). From the standpoint of the user, transfers of control authority should be seamless and anticipated.

Performance measures. User acceptance and satisfaction is the number one factor of import in measuring the performance of the shared control scheme. The ultimate goal is for users to benefit from the technology, which is impossible to achieve if they are disinclined to adopt it. However, user satisfaction may or may not account for (or coincide with) measures of control/execution success. Further complicating matters is the inertia often associated with a user's familiarity with their current compensatory mechanism; needing to relearn this is understandably daunting and unappealing. (Even if the current mechanism is to use no device, this inertia still can prove a challenge.)

C. Opportunities for Machine Learning

We proposed that machine learning is well poised to contribute to solutions for many of these challenges. A few approaches of interest are identified here.

Facilitate a superior human-robot interaction. The are many ways by which to define what *superior* might mean within the context of interactions between humans and assistive robots. For example, a superior interaction might optimize the control flow between the user and the machine, or the performance of the human-robot team. One qualitative measure used in some of our preliminary work is an intuitive blending of manual and automated control commands (more in Section III-A).

Customize the automation to the user. The formulation of the automated behaviors themselves might be customized, or even the control paradigm as a whole—that is, where the split between human and machine control happens. Machine learning is a natural candidate to accomplish such customization, that is responsive to the user's physical needs and preferences. *We hypothesize* that an optimal split in human-robot control will be unique to *(i)* a user's sensory-motor capabilities, *(ii)* their personal preferences, and *(iii)* possibly also the task at hand. The worth in flexible control splits is echoed in the sliding scale autonomy formulation of Desai & Yanco [22], that arbitrates between manual and automated wheel speed inputs to smoothly transition between preset modes with fixed manual/automation splits. Our current work in collaboration with Siddartha Srinivasa at Carnegie Mellon University (CMU) aims to learn and customize the arbitration functions handling the allocation of manual and automated control (more in Section III-C).

The topic of shared control with assistive devices is peculiar within the larger domain of human-robot teams—in comparison to, for example, search-and-rescue teams or manufacturing teams—when one considers how willing the human is to adapt to limitations of the machine: usually a necessity in any human-robot interaction. With assistive machines, this willingness is potentially very low. (As seen, for example, with electric prosthesis rejection [11], [12].) Through customization, machine learning is a prime candidate to facilitate device operation that is more intuitive, in the hopes of garnering greater user acceptance.

Elicit a rehabilitation response. 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. *We hypothesize* that machine learning can be used to encourage motor learning by the human, and thus to elicit a rehabilitation response. In particular, in a collaboration with Ferdinando Mussa-Ivaldi at RIC, we propose to modulate the control split between the human and robot with the goal of encouraging human motor learning (more in Section III-B). 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.

Before concluding, a comment on a topic important to the application of learning to assistive human-robot systems: the learning rate. Ideally, this rate should be fast enough to be responsive to opportunities for improvement and adaptation; but not so fast that it disrupts the flow of control authority—that is, the user should still be able to predict the automated behaviors' functioning and anticipate transfers of control authority. This point takes on a particular relevance with users of assistive devices, where frustrations with unintuitive control have a history of leading to device rejection.

III. WORKS IN PROGRESS

This section provides a brief overview of works and collaborations recently underway in the A^2R^2 *Lab* at RIC. These works aim specifically to expand upon machine learning opportunities, within the domain of assistive machines, identified in the previous section.

A. Inferring Appropriate Blending from Demonstration

One approach to blending low-level controls that we are pursuing—with the goal of a natural flow of control authority—capitalizes on the inherent flexibility seen during multiple instances of a task's execution. 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, as observed in [10]. Here the allowable flexibility inherently encodes spatial constraints of the task. Demonstrations are encoded within a Gaussian Mixture Model (GMM), and

[4]We are aware of the following commercial smart wheelchair endeavors: the Smart Wheelchair [5], the TAO-7 Intelligent Wheelchair Base (marketed for research, not for users) [6], the Wheelchair Pathfinder (discontinued) [7], and the RoboChariot (discontinued) [8].

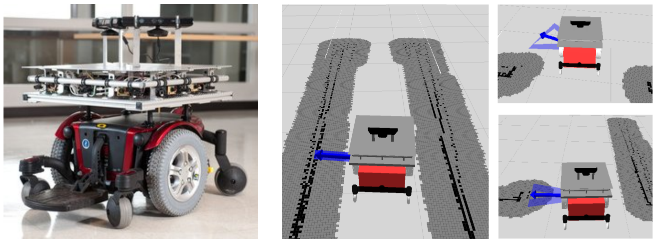

Fig. 2. *Left:* Our wheelchair-based differential drive mobile robot, with a ring of IR and ultrasonic sensors, and two top-mounted Kinects. *Right:* The simulated robot in a ROS-Gazebo environment, with examples of learned variance. Blue arrows represent the user-commanded controls (angular speed), and the magnitude of the variance is represented by the width of the blue triangle around an arrow; narrower triangles mean the user's control is more restricted. Occupancy grid obstacles (doorways and walls) in dark gray. Full details in [30].

task variance is extracted via Gaussian Mixture Regression (GMR) [16]. The human and automation inputs are then blended as a smooth function of *(i)* the learned variance and *(ii)* the distance between user-generated and automation-generated control commands. Of note is that the approach uses demonstration *only* in order to decide how much control authority to cede to the user—that is, only to learn task variances for blending control—and *not* to learn generalized motion trajectories or understand user intent.

A first validation [30] within a simulated environment considers doorway navigation: a task frequently cited as challenging for powered wheelchair drivers, due to tight spatial constraints. The automation controller is a local planner distributed with ROS [9], which is provided with a navigation goal from our doorway detection algorithm [21] that autonomously estimates doorway position and orientation from depth data. The blended control command is angular speed. Example results shown in Figure 2.

B. Inducing Motor Learning with Sliding Shared Autonomy

Work under development in collaboration with Ferdinando Mussa-Ivaldi at RIC will merge the Body-Machine Interface (BMI) work of his Robotics Laboratory with automation technologies developed within the A^2R^2 Lab. The BMI approach [18], [19] maps residual upper body motions to 2-D control points, offering a novel interface for wheelchair operation by those with severe paralysis. In our collaborative work, partnered with the BMI interface will be a variety of automated driving and path planning modalities, customized to the user via machine learning techniques. Moreover, by shifting where the split between manual and automated control occurs, the automation will aim to induce a motor learning learning response from subjects with high Spinal Cord Injury.

C. Formalizing Shared Human-Machine Control

Work under development in collaboration with Siddhartha Srinivasa and Anca Dragan of the Personal Robotics Laboratory at CMU targets a formalization for the split between human and robot control. In their prior work with assistive teleoperation [23] an arbitration function allocates control between an automated controller and human input, with the key insight to modulate arbitration based on the system's confidence in the inferred user's goal. Our collaboration will apply this framework to the domain of a wheelchair-mounted robotic arm, and will look at learning these arbitration functions, as well as customizing them to the needs and preferences of severely paralyzed users.

IV. CONCLUSION

In lieu of a particular algorithm formulation or application, in this paper a robotics application domain—the shared control of partial automation assistive machines—with a very relevant and compelling societal impact has been identified as ripe for intersection with machine learning. Pertinent challenges were overviewed, a handful of potential learning applications identified, and first project formulations introduced. The A^2R^2 Lab will leverage machine learning heavily in its pursuit to advance human-assistive devices, that make a user more able through the introduction of robotics-inspired automation that shares control with the human user.

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