CAREER: Robot Learning from Motor-Impaired Instructors and Task Partners

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Overview

Advances in robotics technologies are well-poised to make major contributions in the area of human assistance. Robots which do not adapt to the variable needs of their users when providing physical assistance will however struggle to achieve widespread adoption and acceptance. Not only are the physical abilities of the user very non-static—and therefore also is their desired or needed amount of assistance—but how the user operates the robot too will change over time. The fact that there is always a human in the loop offers an opportunity: to learn from the human, transforming into a problem of robot learning from human teachers. Which raises a significant question: how will the machine learning algorithm behave when being instructed by teachers who not only are not machine learning or robotics experts, but moreover have motor impairments that influence the learning signals which are provided?

The proposed work contributes algorithmic approaches tailored specifically to the unique constraints of learning from motor-impaired users, and an evaluation of these algorithms in use by end-users. The core pillars of the PI's education plan include course development, mentorship, a student exchange and outreach. The PI's teaching mission is to found a curriculum of courses that intersect robotics with machine learning and artificial intelligence (novel to Northwestern).

Intellectual Merit

There has been limited study of robot learning from non-experts, and the domain of motor-impaired teachers is even more challenging: their teleoperation signals are noisy (due to artifacts in the motor signal left by the impairment) and sparse (because providing motor commands is more effort with an impairment), and filtered through a control interface. Rather than treat these constraints as limitations, the proposed work puts forth multiple hypotheses for how such constraints can become *advantageous* for machine learning algorithms that exploit unique characteristics (like problem-space sparsity) of the control and feedback signals provided by motor-impaired humans.

Towards this end, the proposed work develops multiple novel machine learning algorithmic techniques, (1) that reason explicitly about the *control interface* to the robot and how it interacts with the full control space; (2) that derive information about the human's control patterns and the task requirements, from *variability* in the human's teleoperation commands; and (3) which include the design of *adaptation cues* informed by reward- and example-based feedback from the motor-impaired teacher. Note that items (1) and (2) are of general utility to any domain that involves interaction between a human and a controlled system, and item (3) advances the ability to learn from imperfect or otherwise limited teachers.

The proposed work also will investigate a number of the hypotheses via subject studies with motor-impaired end-users operating a robotic arm, both to explore this problem space and to assess the functionality and user acceptance of the contributed algorithmic techniques.

Broader Impacts

The PI's teaching and mentoring activities will train a next generation of robotics researchers with a passion for human rehabilitation and assistance. An outreach program will target older autism spectrum children and annual demos at the Museum of Science and Industry will educate K-12 children on assistive robotics.

A significant part of the broader impact of the proposed and future work of the PI's lab is to make humans more able through the introduction of robotics-inspired automation and adaptation to human-assistive devices. Situated at the Rehabilitation Institute of Chicago—with ready access to a patient population, therapists, clinicians, and opportunities for clinical collaborations—her lab is uniquely poised, as an academic robotics research group, to make clinically-relevant contributions.

The proposed work will also impact the larger field of humans interacting with controlled machines. Within the context of motor-impaired users and robots, the work is poised to *transform rehabilitation science*: by treating the motor impairments as an advantage, rather than a constraint, for machine learning algorithms—and enabling the customization of the machine's control by the end-users themselves.

The potential for robotics technologies to transform the field of human health and rehabilitation is considerable. Autonomous robots already synthetically sense the world, synthetically generate motion, and synthetically compute cognition—any of which might be adapted to help address sensory, motor and cognitive impairments in humans. Patient populations who are poised to benefit from such advances include those with Amyotrophic Lateral Sclerosis (ALS), Muscular Dystrohpy (MD), Multiple Sclerosis (MS), high level Spinal Cord Injury (SCI), Spinal Muscular Atrophy (SMA), Cerebral Palsy (CP), Traumatic Brain Injury (TBI), Parkinson Disease and stroke survivors, among others.

The premise of this work is that in order to achieve widespread adoption and acceptance, robots which attach to or support humans to provide physical assistance *must* adapt to the varied and variable needs of their users. The fact that there is *always* a human in the loop—that these sorts of robots are fundamentally shared-control systems—moreover offers an opportunity to learn from the human user. Which raises a significant question: how will machine learning algorithms behave when being instructed by teachers who not only are not machine learning experts, or robotics experts, but moreover have motor impairments that influence the learning signals which are provided? Our thesis is that the adaptation of robot autonomy by motor-impaired end-users frames the machine learning problem in a way that not only introduces challenges (like data noise and sparsity), but also offers unique advantages (like constraining the targeted behavior).

1 Introduction

Assistive machines—like power wheelchairs, robotic arms, exoskeletons, electric prostheses—are crucial in facilitating the independence of those with severe motor impairments. Such machines can extend and enable mobility and manipulation abilities of persons with motor limitations in their own legs and arms.

However, there are circumstances under which the control of assistive machines remains a challenge—to the point even of making use of the machine entirely inaccessible. In addition to the motor *impairments of the user*, these circumstances include the *limited control interfaces* which are available to those with severe impairments, and also the *complexity of the machine* to be controlled.

To illustrate, the most ubiquitous assistive machine is the powered wheelchair, and there are many impairments for which driving a powered wheelchair can be a challenge (such as upper-body *physical* impairments like ataxia or bradykinesia, *cognitive* impairments like deficits in executive reasoning, and *visual* impairments like limitations in head, neck or eye movement [72]. According to a survey of 200 clinicians, more than 50% of powered wheelchair users reported complaints with wheelchair control [40]. In another assistive domain, a survey of 1,575 prosthesis users points to a want for better control mechanisms [25]. Factors like fatigue and pain 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.

It is a founding premise of my lab's work that the introduction of robotics autonomy can be used to help overcome many of the challenges in operating assistive machines. The introduction of autonomy transforms an assistive machine into a kind of robot, that shares control with the human user and so offloads some of the control burden from them. *We anticipate that such physically assistive robots must adapt both their autonomy formulations and control-sharing paradigms to the varied and variable needs of their users—and that if they fail to do so, they also will fail to achieve widespread acceptance and adoption.*

- **Changing human ability.** For one, it is expected that the user's needed or desired amount of assistance will be extremely *non-static*: hopefully due to successful rehabilitation, but also possibly due to the degenerative nature of a disease.
- **Changing human preference.** A given user may even prefer different levels of assistance on different days or throughout the day, depending on factors like level of pain or fatigue.
- **Changing environments.** The performance of the robot certainly will change as it is introduced into new scenarios. If we want the robot to go where the human goes, it will encounter novel environments.
- **Changing robot capability.** We furthermore expect that users will want to specify new behaviors for the robot, without needing to call in an expert engineer.

There is an opportunity here to learn from human as s/he operates the robot—to learn about their preferences in control sharing, and how the robot autonomy should behave. Furthermore, the *human* naturally will also be learning and adapting to the machine; changing how they behave as an operator as they become more familiar with the robot. We thus can expect *co-adaptation* and *co-learning* from this human-robot team.

Today people are surrounded by technology that adapts to them—which is often simple, like learning spelling preferences in autocorrect, but certainly is ubiquitous. Technology that does *not* do so is perceived as unintelligent. Assistive robotics technology that *repeatedly* performs the same "mistakes"—incorrectly infers user intent, fails in task execution, takes control when unwelcome—will be perceived as unintelligent. Compound this with the fact that to allow a machine attached to or supporting one's body to take over control, to act with autonomy, demands a tremendous amount of trust in that autonomy. Unintelligent autonomy, that does not adapt, we believe simply will not be tolerated.

Robot Learning from Motor-Impaired Teachers

There has been limited study of robot learning from non-experts, who do not understand the details of how a given machine learning algorithm is working.[1] The proposed domain is even more challenging—not only are the instructors not machine learning experts, they might not even be task experts. They *are*, however, who the robot should be learning from—their preferences are precisely what the system is meant to optimize.

Challenges. While there will be some cases where machine learning algorithms work out of the box, we anticipate that that for the majority of cases *existing machine learning paradigms naively run will be found wanting*—that to be effective within the domain of motor-impaired teachers and task partners, machine learning paradigms will need to take the signature of the user's signals explicitly into account, and be robust to noise in these signals and variable levels of expertise in the teacher. We identify three ready options for accomplishing machine learning: (1) to have the human provide an explicit feedback signal, (2) to extract learning signals from the human's control signals used to operate the machine, or (3) to compute feedback signals autonomously from performance metrics. (Item 3 is no different than in other robot learning domains, and so we defer its discussion.)

- **Information content, sparsity and noise.** If providing control signals is an effort (and it likely is for impaired users), or if the control paradigm allows for very intermittent control signals, we can expect fewer signals to be issued and so a sparser dataset. The user's motor impairments also very possibly produce control signals with large amounts of noise and trial-by-trial variations. Moreover, the control interface effectively filters the user's signals—and so also their abilities. This filtering might have a positive (e.g. smoothing tremor) or negative (e.g. damping intended control signals) effect, but in either case it reduces the information content of the user's control signal. Thus, teleoperation signals provided by motor-impaired users are expected to be *noisy* and *sparse*, and in some manner *filtered* through the control interface—which all boils down to fewer control signals encoding less information.

- **Learning from poor examples.** Whether providing feedback or control examples, we expect that motor-impaired users will be less able to accommodate the needs of the machine learning algorithm—because their motor impairment fundamentally acts in some ways as a constraint. Humans typically providing signals to machine learning algorithms most certainly (even if unconsciously) provide "good" data to the algorithm, especially when they understand the operation of that algorithm. Most machine learning algorithms also inherently assume expertise in the teacher, and do not reason explicitly about poor quality data or feedback signals (though many do implicitly handle dataset noise).

- **Variable rates of adaptation.** There are various motivations for adapting a control-sharing paradigm, for

[1] Machine learning algorithm abbreviations. GMM: Gaussian Mixture Models, GMM-GMR: Gaussian Mixture Models Gaussian Mixture Regression, GPR: Gaussian Process Regression, IOC: Inverse Optimal Control, IRL: Inverse Reinforcement Learning, LWR: Locally Weighted Regression, NN: Neural Networks, PCA: Principle Components Analysis, QP: Quadratic Programming, RL: Reinforcement Learning, SVM: Support Vector Machines

which different rates of adaptation may be appropriate—rapid for within-day changes (fatigue), moderate for between-day changes (pain) and slower for less dynamic changes (improvement due to rehabilitation).

- **Lifelong learning.** There is a very clear need for lifelong learning; for the robot to continually learn from its experiences and environment. Lifelong learning is a challenge for many machine learning algorithms—those that remember and optimize over all learning instances (e.g. LWR, SVM) run up against storage and processing constraints, while those that bias their optimization towards more recent examples often forget earlier learning instances (e.g. NN).

Thus, a suitable machine learning algorithm must be able to extract information from *sparse* and *noisy* signals provided by *non-experts*, to adapt alternately *swiftly and slowly* depending on the reason for adaptation, and be *judicious* in deciding what is temporary variability and what are actual changes in need, ability or preference—in short, to adapt appropriately to the changing needs and wants of the user, without overfitting to trial-by-trial variations and noise.

Our central thesis is that, while many of the above characteristics of impaired operators make the machine learning problem harder, many of these same characteristics become advantageous to an algorithm that exploits unique characteristics of the (impaired) teacher's control and feedback signals—and thus make the learning problem easier *than it would be for a general-purpose machine algorithm that does not take into account the sparse nature of the teacher-provided signals.* Moreover, we believe that the study of algorithms (that do exploit the user's signal characteristics) in use by real end-users is a *crucial step in the development of deployable adaptive assistive robots*.

Advantages. In fact, there are many ways in which machine learning algorithms can benefit from constraints and characteristics of the learning signals provided by motor-impaired users. A number of our hypotheses on this topic are presented next, with concrete plans to tackle the hypotheses in Section 3.

Target performance. The flip side of many of the constraints listed above is that these constraints may *recast the problem* into one that is *more focused and tractable*. Specifically, the target system performance to reach is known, and feasible—nothing superhuman, but rather to match the capabilities of unimpaired (and unaugmented) human motion. Which provides very well-defined upper and lower bounds: what able-bodied humans can do (upper bound) and what the user can do without the machine (lower bound). Many machine learning formulations naturally encode constraints (e.g. within their optimization, QP) and flexible bounds on those constraints (e.g. slack variables in SVMs).

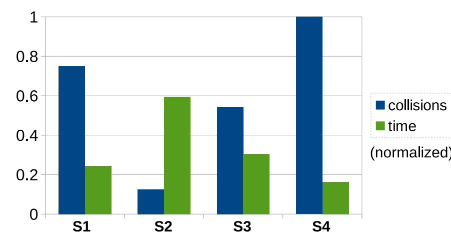

Figure 1: Unimpaired subjects performing a dynamic control-sharing task in our prior work. Within similar task expertise, some prioritize minimizing the number of collisions (S1, S3, S4) and others minimizing time (S2).

We hypothesize that the spectrum of what the user wants to achieve is narrower than in other human-robot team domains, and that this narrowness of scope makes the learning problem easier (**H0**).

There effectively is *sparsity in what the user wants the human-robot team to accomplish*; or equivalently, unimpaired subjects are so capable the space of what a human-robot team is meant to accomplish is broader, and thus *harder* to learn. In Figure 1 we see an example where the experimenters do specify the task, but do not instruct subjects how to solve the task—and what each subject chooses to optimize varies. By contrast, physical therapists typically instruct patients also on how to solve the task, because the space of solutions is so limited. We anticipate lower variance in the space of task solutions offered by motor-impaired subjects.

Information content. The *information content* encoded within the user's control signals has interesting characteristics and implications for machine learning. For one, as the amount of noise goes up, the information content of the signal goes down—and there are machine learning algorithms which in fact benefit from this (e.g. sparse coding algorithms [55], compressed sensing algorithms [39]). Very likely the more motor-impaired a person is, the more judicious they will be with the motions that they do make, and this can highlight particularly important parts of the task or state space. Also, while the data may be noisy and sparse, we can expect that over time there is a lot of it, if the machine is used daily.

We hypothesize that actionable policies will emerge with demonstrated examples, but only when machine learning algorithms intended for sparse data sets—e.g. sparse coding, compressed sensing—are used (**H1**).

We further hypothesize that variability in the control signal provides useful information about task, user and robot constraints, which can be encoded within machine learning models (**H2**).

Suboptimal but task-feasible areas of the state space—that is, where the control policy can visit and still accomplish the task (even if suboptimally)—may be used to help to infer user control constraints or resolve robot-configuration constraints during path planning, for example; and has been used in the PI's own work to inform when control sharing should be restricted [42]. It is possible to encode within a machine learned model (e.g. using GMM, GPR) acceptable flexibility in the task execution [22]. Without noisy executions, the utility of these parts of the state space would simply be unknown.

We additionally hypothesize that because the motor signals which are realized encode less information—by the very virtue of the motor impairment—that these signals may encode more clearly the motor intent (**H3**). For instance, if the motor intent is to move the body forward, and instead of executing the complex and high-dimensional motor commands for walking the user deflects a joystick along a single axis, this is a much simpler signal from which to decode intent.[2]

New behavior formulations. We anticipate that instruction by motor-impaired users will give rise to *new formulations for robot behaviors.* Both the signature of the teleoperation signals and how a user operates the robot are dependent on characteristics of the control interface used for operation—which for those with motor impairments, can detect a limited range of signals, perform extreme filtering and differ based on motor impairment.

We hypothesize that robot behaviors demonstrated by motor-impaired teachers in many instances will be optimizing something other than our traditional cost functions—for example, the high cost of switching between which control dimensions of the robot a limited interface map to (i.e. mode switching)—and that the application of particular machine learning techniques (like IOC, IRL) will reveal these differences (**H4**).

Student-teacher interaction. Characteristics of the interaction between the *human teacher and robot learner* are notable. We can assume that the teacher is always available, and always co-located with the robot learner, including when in new areas of the state space. This is reminiscent of the concept of an oracle in the world of Partially-Observable Markov Decision Processes (POMDPs), however applied to revealing information about which action to take rather than which is the true state. In our domain the oracle in effect is omnipresent, but is not omniscient—since it is subject to the same limited expertise and constraints in providing supplemental information as the original data source (i.e. the motor-impaired human).

We hypothesize that regular, sparse access to noisy feedback can be just as effective as dense noise-free feedback within a machine learning algorithm that specifically expects this type of feedback (**H5**).

Here again if the teacher is judicious and sparse in providing feedback, this tells us something about how important policy exactness is in that part of the state space—that is, if the teacher does not bother to provide a correction, likely that area of the state space is not critical for achieving (or failing) the task, or the necessary control fidelity is not so fine in that part of the state space (i.e. multiple equally good action choices). Our work will leverage the techniques developed to address hypothesis **H4** to represent this information.

Control sharing. We also expect to learn something about *control sharing* within human-robot teams. For one, this human-robot team is truly heterogeneous: the robot is fulfilling functionality absent in the human.

[2]In this case, the projection to a lower-dimensional space is done by the joystick interface. One role for machine learning within a rehabilitation setting would be to *discover* this lower dimensional intent.

Moreover, the function filled by the robot is present in able-bodied humans, and we do not intend for the robot to adopt any of the functionality which is comfortably covered by the motor-impaired user—it has been widely observed that humans prefer to retain as much control authority as possible [27, 54].
We hypothesize that the overlap of teammate responsibilities when control sharing is lower than in other human-robot teams, and that the division of labor is dictated by the user's impairment (**H6**).
We expect moreover that this overlap is extremely non-static, as the abilities and preferences of the user change—and that so too must the control-sharing be adapted. Even if the user is not a task expert, their control signals *do* still encode information about their preferences—for instance, a consistent disagreement between their signals and those generated by the robot autonomy is a cue that the autonomy is doing something undesirable. It is reasonable to expect that an optimal control sharing strategy will be unique to (1) a user's sensory-motor capabilities, (2) their personal preferences, and (3) possibly also the task at hand.
We therefore hypothesize that adapting the control-sharing strategy to the user's changing capabilities and preferences will increase the acceptance and utility of the assistive robot (**H7**).
Lastly, *we hypothesize* that the adaptation of a control-sharing paradigm may be used proactively to encourage rehabilitation, by taking into consideration also rehabilitation goals set by a therapist clinician (**H8**).

Scope of Work and Intellectual Merit

Linking concretely back to the requirements and expectations of machine learning algorithms, these hypotheses are concerned with the dimensionality and spread of both the input space and the prediction space (**H0**), and the information content encoded within the training data (**H1-H4**) and other learning feedback signals (**H5**)—which are the crucial concerns for any machine learning domain. By advancing the ability to learn from imperfect or otherwise limited teachers, our contributed work is of general utility to machine learning within real world domains. These hypotheses also cover aspects of the interaction between the robot and human, within the context of both learning and regular operation (**H6-H8**)—which apply more broadly to Cyber-Physical Systems, and is of general utility to *any* domain that involves interaction between a human and a controlled system.

The proposed work will take steps towards the advancement and assessment of hypotheses **H1**-**H5** and **H7**.[3] Major contributions of this work will be to innovate in multiple algorithmic areas—including noise mining, interface awareness and feedback signals—in order to realize the evaluation the above hypotheses (Sec. 3). Our remaining major contributions will be to provide concrete insight into this problem domain and proposed solutions through subject studies with motor-impaired and unimpaired volunteers, that assess many of the above hypotheses (Sec. 4).

2 Background

Figure 2: Example non-proportional control interfaces. *Left:* The Sip-N-Puff [1] issues commands by blowing and sucking on a straw. *Right:* A switch-based head array with three proximity sensors [2].

Interfaces. Human motor limitations often translate into limitations—in bandwidth, in duration, in strength—in the control signals that person can produce. Many traditional interfaces, like a 2-axis joystick, are inaccessible to those with severe motor impairments like paralysis (e.g. high SCI), bradykinesia (slowness of motion from, e.g., SMA, Parkinson Disease, Severe Traumatic Brain Injury), visual impairments (when paired with other motor impairments) or degenerative conditions (e.g. ALS, MS). Accessible commercial control interfaces 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. These interfaces typically are based on switching finite-state

[3]Hypotheses **H0** and **H6** would require extensive evaluation of other human-robot team domains, which given the time and budget constraints is beyond the scope of the proposed work. Hypothesis **H8** is very exciting, and large enough to merit an entire grant of its own—which we do plan to pursue as follow-up work.

devices, such as the Sip-N-Puff, head-operated joysticks, switch-based head arrays and limited-throw joysticks (Fig. 2). These sort of interfaces already struggle with 2 degree-of-freedom (DoF) control problems like a powered wheelchair (speed, heading), and are nearly untenable for more complex (e.g. 6-DoF control) machines like robotic arms.

Figure 3: Autonomous assistive robots in our lab. *Left:* The MICO 6+1-DoF robotic arm, commercially available and developed for human assistive applications. *Right:* A wheeled mobile robot, built on the base of a powered wheelchair.

Complexity. For many candidate assistive robots (e.g. dexterous robotic arms, hands), control occurs in higher dimensional spaces. To issue a high dimensional control signal already is a limitation when using traditional control interfaces like a 2- or 3-axis joystick, and becomes only further complicated when using the specialized interfaces accessible to limited mobility users. The typical control solution with such interfaces is far from optimal: to partition the control space and operate only a subset of the controllable DoF at a time (a *mode*), and cycle between different control subsets (*mode switching*).

The work in the PI's lab addresses this challenge using robot autonomy and control-sharing with the human. *Our prior and ongoing work* develops asssitive robotic arm and wheelchair platforms (Fig. 3).

Control Sharing. An important observation is that users of assistive devices overwhelmingly prefer to *retain as much control as possible*, and cede only a minimum amount of control authority to the machine [27, 54]. While at one end of the shared control spectrum lies full manual control and at the other lies fully automated control, 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 control paradigms is to find a sweet spot along this continuum [34–36, 41, 43, 56, 71, 77, 83]; ideally, where sharing control makes the system more capable than it is at either of the extremes. Dynamically changing how control is shared is reminiscent of the field of adaptive control [24, 48, 80], which adapts a control law or system model in response to observable changes in a system's behavior. Control sharing autonomy for assistive robotic arms typically has the user select the task or goal, and possibly also intervene to provide pose corrections [28, 58, 78] or assist the automation [79]. Many smart wheelchairs place the high-level control with the human and the low-level control with the machine [30, 60, 61, 68, 82], or blend the human's control commands with the autonomy's control commands [54, 73, 75].

Prior work in the PI's lab has designed and evaluated novel control sharing strategies for the smart wheelchair [11, 12, 42] and robotic arm [50] platforms. An approach based on demonstrations of a behavior provided by the user him/herself (or an aide) encodes within the demonstration variance spatial task constraints that inform control sharing (Fig. 4a). Another approach (Fig. 4c) iteratively shifts control from the user to the autonomy (by reducing the value of α) as the forward projection of the user's commands (green in graphs) generate a path which collides with an obstacle. The resulting blended command (light blue in graphs) prioritizes foremost safety, but also keeping control with

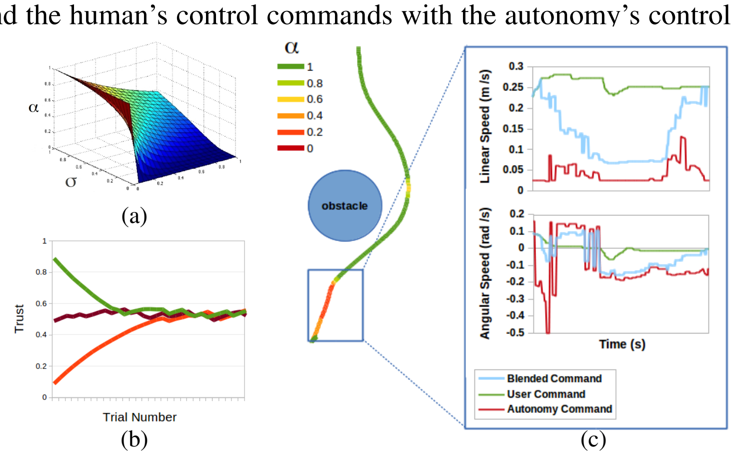

Figure 4: Our prior work in control sharing. *(a)* Blending parameter α is a function of demonstrated variance σ. *(b)* Evolution of a measure of trust that informs α. *(c)* Control sharing for safety monitoring on a smart wheelchair. Robot ground path colors reflect the value of α at that time.

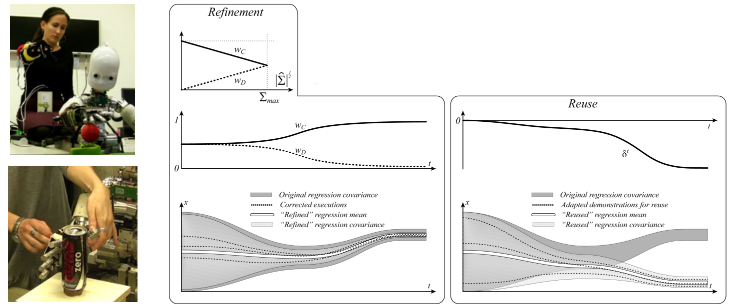

Figure 5: PI's prior work that teaches a humanoid through demonstration and tactile correction. Plots: Adaptation for policy refinement (left) and reuse (right). Datapoint weights (w_C, w_D) are set based on the covariance envelope ($\hat{\Sigma}$) of the original demonstration dataset [22, 23, 70].

the user. Our approach to shared autonomy for myoelectric prosthesis control [38] had the human shape the output of an automated controller with EMG signals, which allowed for much sparser input from the human and enabled otherwise infeasible motions.

A novelty in the proposed work is that the formulation of the control-sharing will be *adapted*, to optimize the interaction between the human and robot, as the human's needs and abilities change.

Robot Learning. In many domains it is desirable for those who are not software or control experts to develop and adapt robot behaviors. The focus of Learning from Demonstration (LfD) has historically (past ∼15 years) been on the reproduction of task behaviors demonstrated by a teacher [20, 29]. More recently (past ∼5 years) a parallel focus has developed on continued learning, often using demonstration to seed other forms of learning [9, 14, 22, 26, 31, 33, 45, 53, 63, 70, 76]. There has been comparatively little work however on learning from bad teachers or poor quality data [15, 51]. Historically the use of Reinforcement Learning (RL) has been limited for systems with complex real-world dynamics, though recent advances in algorithmic approaches are facilitating the wider adoption of RL by real-world robots [52].

The perspective of robot autonomy and learning has limited representation within the clinical rehabilitation community to date. Closest are works that adapt how much control assistance is provided during physical therapy exercises with rehabilitation robots [64, 81]. The PI is positioned unqiuely as someone trained in robot autonomy and learning (her survey article on robot learning from demonstration has been cited over 850 times) and now directing a robotics lab situated in a hospital. *The PI's prior work* focused in particular on the development of novel mechanisms to provide feedback to robot platforms with different form factors, and algorithmic approaches for how to interpret these corrections (e.g. Fig. 5)—including behavior refinement [13, 14, 17, 19, 21–23, 70], scaffolding motion primitives [16, 18], tempering multiple information sources [15], and bootstrapping policies to accomplish new tasks [22, 23, 70].

In the proposed work motor-impaired teachers will instruct robot learners, including in the design of new robot behaviors. There has been little study to date on non-expert teachers, or algorithms that reason explicitly about teacher ability. We know of no robot learning studies with motor-impaired teachers.

Results from Prior NSF Support. Argall is PI on the grant *SCH: EXP: Collaborative Research: A Formalism for Customizing and Training Intelligent Assistive Devices,* 1R01EB019335-01, $686,956, 09/01/14 - 8/31/2017, an NSF Smart and Connected Health grant funded as an R01 by the NIH. *Intellectual merit:* The focus is on assistance that augments human control signals to bridge the dimensionality gap for a variety of devices (powered wheelchairs, robot arms). The grant has just started and to date has one conference publication [50] and several submitted works. *Broader impacts:* The grant has funded 1 PhD student and 1 undergraduate student at Northwestern. The work was featured in an interactive National Robotics Week demo at Chicago's Museum of Science and Industry, with thousands of visitors (primarily K-12 children).

3 Algorithm Design and Development

Our technical formulation assumes the existence of a set $\mathcal{F}$ of automated controllers $f(\cdot)$, and a set $\mathcal{B}$ of control sharing strategies β. Each controller dictates the motion of an autonomous behavior for the assistive robot. Formally, behavior function $f(\cdot)$ generates a vector of control signals $\boldsymbol{u}_f^t \in \mathbb{R}^m$ is generated from observed state $\boldsymbol{x}^t$, $\boldsymbol{u}_f^t \leftarrow f(\boldsymbol{x}^t)$ Control signals $\hat{\boldsymbol{u}}_h^t \in \mathbb{R}^n$ from the human are mapped onto the space of robot control, $\boldsymbol{u}_h^t \leftarrow h(\hat{\boldsymbol{u}}_h^t)$, generating control vector $\boldsymbol{u}_h^t \in \mathbb{R}^m$. The signals from the human and robot autonomy then are reasoned about within control sharing strategy $\beta(\cdot)$ which generates the signal $\boldsymbol{u}^t$ executed by the robot platform, $\boldsymbol{u}^t \leftarrow \beta(\boldsymbol{u}_f^t, \boldsymbol{u}_h^t)$.

Our algorithmic work will reason about characteristics of the user's signal ($\hat{\boldsymbol{u}}_h$) and how it is mapped to the space of robot control ($h(\cdot)$), and how input from motor-impaired users adapts the control blending ($\beta(\cdot)$) and defines new robot behaviors ($f(\cdot)$).

3.1 Noise-Mining Algorithms

Noise in the signals generated by the user will be mined for information about their motor habits and also to uncover task constraints. Our work will look at noise within both the original control-generation space $\hat{\boldsymbol{u}}_h$, before being mapped by $h(\cdot)$, as well as the post-mapped space $\boldsymbol{u}_h$.

Task T2:[4] To develop algorithms that derive information about the human's control patterns and the task requirements, from noise in the human's teleoperation commands. (Addresses hypothesis **H2**.)

For instance, to extract information about a person's motor habits, there are dimensionality reduction algorithms that generate basis functions which span an alternative space in which the majority of the signal content is captured (e.g. PCA). Additionally, statistical machine learning algorithms which output a measure of covariance (e.g. GMM-GMR, GPR) tell us something about the task constraints. *The PI's prior work* has extracted information about spatial task constraints in robot manipulation [22] and driving [42] (Fig. 4a) domains, and also about mechanical flexibility in the robot hardware [70] from the variance observed in multiple demonstrations of task execution by a human teacher. These techniques will be leveraged and built upon in the proposed work.

3.2 Interface-Aware Algorithms

There very likely are differences in the spaces spanned by control signals generated by the human ($\boldsymbol{u}_h$) and those spanned by the robot's autonomy ($\boldsymbol{u}_f$).[5] Consider for example that $n < m$ covers a subspace of the control dimensions covered by m—that is, the mapping is one-to-one for $n \in m$, and the dimensions $\neg n \in m$ are left undefined by the human's control signals (until the mode switches to map n to a different subspace of m). The question for control sharing (or intent prediction) is how to interpret the undefined control signal dimensions? An option which seems a reasonable choice for blending is to only blend the subset of the autonomy signal $\boldsymbol{u}_f$ that spans n. However to consider the history of earlier human signals $\boldsymbol{u}_h$ when n mapped to a different control subspace (in prior control modes) could be more informative for trying to infer human intent, for example.

Task T3: To develop algorithms that explicitly consider the control interface in use (e.g. and its filtering characteristics) and how it interacts with the full control space of the robot.

One idea is to explicitly model constraints on $\hat{\boldsymbol{u}}_h$ with a path planner. Consider the example of driving a powered wheelchair, and a head-operated array of switches that have the user select various actions (forward, backward, turn, stop) by first accessing a menu (displayed on a small screen mounted on the arm rest). The menu-access constraint might influence the state formulation S, actions A or state transition function $T_{s,a}^{s'}$—being represented as a "menu access" action (A) which must be selected before a different motion action can be selected, or by augmenting the state-space definition (S) to include the current action and constraining state transitions ($T_{s,a}^{s'}$). That the menu-access mode of operation is cumbersome to use can be represented within the cost function $C(s,a)$ that penalizes switches between motion actions. Thus, we can model

[4]Tasks **T0** and **T1** are described in Section 3.5. (The notation is ordered by plan of work rather than presentation in the text.)

[5]There also may be differences in command frequency (of $\hat{\boldsymbol{u}}_h$ and $\boldsymbol{u}_f$), e.g. if $h(\cdot)$ maps from a more abstract space (e.g. "go forward") to a lower-level higher-frequency space (e.g. $1\frac{m}{s}$ issued at $20Hz$). This translation captured notationally through $h(\cdot)$.

constraints on the feasible state transitions $T^{s'}_{s,a} : s \xrightarrow{a} s'$ as imposed by limitations on the control interface, and encode within the planner's cost function $c \leftarrow C(s, a)$ difficulties in operating the interface. The space of viable plans generated by such a constrained planner could then be considered when blending control, or to what extent they agree with the the user's control signal when reasoning about user intent.

3.3 Adaptation Algorithms

We formulate each behavior $f \in \mathcal{F}$ and control-sharing strategy $\beta \in \mathcal{B}$ so as to have an associated set of parameters θ_f and θ_β which are available for modulation. For example, a path planner [62] used on our mobile robot platform has parameters to modulate how much curvature is in the generated trajectory, and how aggressively the robot attempts to reach the goal position. Exactly what influence the parameters θ_f (θ_β) have on associated behavior f (strategy β) varies greatly across behaviors (and strategies). How to modulate the parameters might employ any number of machine learning algorithms [47, 74]—the crucial factor is the *feedback signal* received by the machine learning algorithm. In the proposed work, signals include (1) a reward/cost (e.g. for use within a Reinforcement Learning (RL) algorithm) or (2) an example/correction (e.g. for use within a Supervised Learning algorithm).

Task T4: To design adaptation cues informed by reward- and example-based (including corrections) feedback from a motor-impaired teacher for use by machine learning algorithms.

One option we will pursue is *to have the human explicitly provide feedback* about their preference or the robot performance. Such a signal might be provided through the control interface (e.g. a button press), and take the form of a reward/cost (e.g. a post-hoc binary valuation on performance) or correction.

Another option we will pursue is *to infer the feedback signal from the human's control signals*, by assessing *agreement* between signals produced by the human versus by the autonomy. Specifically, we will compute running measure of agreement $\lambda \in [0, 1]$, where $\tilde{\lambda}_h$ and $\tilde{\lambda}_\ell$ are respectively upper and lower thresholds on (dis)agreement.

Reinforcement. In the case of *agreement* between the human signal and the autonomy, the learning response is to *reinforce* the autonomy selection. We quantify agreement as $\tilde{\lambda}_h < \lambda$. Reinforcement can be accomplished by generating a positive reward within an RL formulation, for example.

Correction. In the case of *disagreement* between the human signal and the autonomy, the human signal is interpreted as a *correction* for the autonomy. This could be accomplished by treating the execution trace as an example within a Learning from Demonstration paradigm, for instance (and building on the prior work of the PI [13–19, 21–23, 42, 70], Figs. 4a, 5). Disagreement is quantified as $\lambda < \tilde{\lambda}_\ell$.

Penalization. We also consider *penalization* in the case of *disagreement*. Specifically, by generating negative rewards within RL formulations or by treating the execution trace as a negative example of what *not* to do—information which certain machine learning algorithms, including probabilistic representations (e.g. [44]) and cost-learning formulations (e.g. margin maximization [66]), are able to incorporate.

We additionally will design learning cues *computed from metrics of human-robot team performance*, ρ, to see if the user prefers to have the adaptation be entirely autonomous (i.e. with no feedback signals from the human). We define a lower threshold $\tilde{\rho}$ on poor performance. (We consider only a lower threshold on performance—when performance is good, we interpret this as no need to change anything.) In the case of continued poor performance, $\rho < \tilde{\rho}$, we can issue a *penalization* as described above.

3.4 Variable Rates of Adaptation

Within our formulation there are different types of adaptation, because there are different reasons for why the adaptation is happening. Specifically, we can: (1) to shift between control-sharing formulations, (2) to update the control-sharing formulations and (3) to update the autonomy behavior formulations. For temporary changes in the needs or abilities of the user (fatigue, pain), simply selecting a different control-sharing paradigm, that has the robot assume or cede more of the control authority, is appropriate (1). For more permanent changes in the needs or abilities of the user (due to successful rehabilitation, disease progression), or equivalently for control-sharing that has not been optimized to the preferences of the user, actually changing the formulation of the control-sharing paradigm is appropriate (2). For circumstances when the robot autonomy is behaving suboptimally (e.g. due to execution in a new environment), with respect to either the user's preferences or task goals, then updating the autonomy behavior itself is necessary (3).

Task T5: To design adaptation cues for when to shift between control-sharing paradigms.

The proposed work will begin to explore the topic of variable rates of adaptation by having users assess static versus dynamic control-sharing paradigms (i.e. a first pass at item 1) under study **S4**. The question of *which* adaptation type to perform—that is, whether disagreement should simply change which paradigm is selected, or change the paradigm itself—is a major research question that will be addressed in future work.

Adaptation cues for shifting between control-sharing paradigms will be informed by the *frequency* of the user's control signals, and their *agreement* with the autonomy signals. The frequency at which the signal is provided encodes information about the willingness or ability of the user to provide control commands, while agreement with the autonomy can give clues about the quality of that autonomy formulation. Thus, we compute a running measure Ω_h to encode the human signal frequency and interpret a *decrease* in Ω_h as the human feeling it is no longer necessary to provide as fine-grained information to the robot—that the autonomy is doing the right thing, and can take over more control. (And correspondingly, an increase in Ω_h is a cue to cede authority.) Similarly, the case of continued *agreement* between the human and autonomy—that is, $\tilde{\lambda}_h < \lambda$—we also interpret as a cue that the autonomy doing the right thing and can take over more control. (And correspondingly to take over less control in the case of disagreement.)

3.5 Data Characterization

The first step in our plan of work will be to characterize the control signals generated by users with motor impairments during robot teleoperation. The data will be gathered under study **S0** (described next, Sec. 4), and will inform the algorithmic work just described in Sections 3.1-3.4.

We will take a dual-pronged approach to the analysis of the data gathered under study **S0**. The first prong will *analyze the data according to statistical techniques* commonly employed by machine learning algorithms—such as projections (e.g. computation of eigenvectors), statistical descriptors (e.g. means, covariances), application of signal filters (e.g. low band-pass) and sparse reduction (e.g. compressed sensing).

Task T0: To stastically characterize the data from motor-impaired and control subjects gathered under **S0**.

The second prong will *apply established machine learning algorithms* to this data. Algorithms[6] will include those based on: (1) statistical measures (e.g. GMM-GMR, GPR); (2) projections to lower dimensional representations (e.g. PCA and its derivatives); (3) projections to higher dimensional representations (e.g. SVM); (4) error feedback during model learning (e.g. LWR, NN); and (5) learning reward/cost functions (e.g. IRL, IOC, structured prediction [66]).

Task T1: To learn autonomous robot behaviors from the data gathered under study **S0** (addresses hypothesis **H1**), and compare the resulting policies (addresses hypotheses **H4**).

4 Evaluation Plan

Subject studies will investigate the development of novel behaviors (study **S0**, **S1** and **S3**) and the adaptation of existing behaviors (studies **S2** and **S3**) and control-sharing paradigms (study **S4**).

Hardware and Software. The proposed work will extensively leverage existing hardware and software already developed in the PI's lab.

Mobile Robot. The smart wheelchair (Fig. 3, left) developed in our lab is built on a Pride Mobility Quantum 600 base [4], and modified to be drive-by-wire (inverter, wheel encoders) by Sensible Machines [5]. To this

[6]Machine learning packages like scikit-learn [3] will allow many of these algorithms to be implemented with low overhead.

we have added sensing and computing components (including RGB-D, IR and ultra-sonic sensors). The software suite we have developed for this platform is extensive, and already structured autonomy behaviors and control-sharing paradigms as described in Section 3 [11]. We are currently porting this system to a full Permobil platform complete with seat and Omni interface. The first platform will be used for software development and testing, and the second for subject studies. The study tasks with the mobile robot platforms will consist of navigation tasks derived from the clinical Wheelchair Skills Test for Power Wheelchair Users [6], like getting through a hinged door or avoiding moving obstacles.

Robotic Arm. The MICO (Fig. 3, right) is a 6-DoF robotic arm from Kinova Robotics with a 2-finger gripper. It is the research edition sibling of the JACO assistive robotic arm, already adopted by hundreds of users throughout the world and evaluated via subject studies [59]. The MICO features a smaller frame, lower cost, additional sensing (torque, accelerometer, joint position, current, temperature) and out-of-the-box interfacing tools (C++ API and ROS driver). The software suite already in place on this platform likewise is extensive, with tools for trajectory planning and with a framework already in place for control sharing. The study tasks with this platform will consist of object grasping and manipulation tasks, for example a multi-step feeding task.

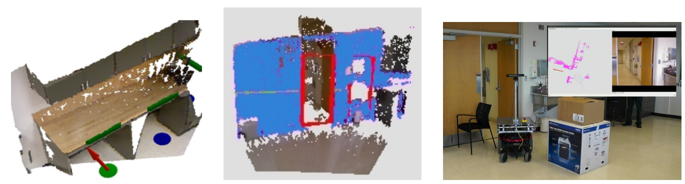

Figure 6: Perception algorithms developed for our mobile robot. Left to right: Perception of safe locations for docking [49] and doorways [37], and autonomous doorway navigation with perception data inset.

Perception: Objects and locations of interest for manipulation tasks will be autonomously identified. The perception system running on our MICO employs an RGB-D sensor (Kinect) and a 3-D geometric approach to object detection using ViewPoint Feature Histogram (VFH) descriptors [69]. Goal perception for mobile robot tasks will build (as needed) on our prior work (Fig. 6), for example that detects the location and orientation of doorways [37] and safe locations for docking at desks and tables [49].

Control Interfaces. For each robot platform, we will evaluate performance with one limited and one richer control interface. For the mobile robot platform, the *limited interface* will be *non-proportional*—for example, a Sip-N-Puff or headrest switch array (Fig. 2)—which makes dexterous maneuvering more difficult. The *richer interface* will be a 2-axis joystick. For the robotic arm platform, the *richer interface* is a 3-axis joystick, and the *limited interface* will use only one or two of these axes (the third axis (twist) is infeasible for many candidate users to operate).

Subjects. For the characterization study (**S0**), we plan to include 35 volunteers who are potential users of physically assistive robots, and 35 subjects without motor impairments. Candidate patient populations include late stage ALS and MD, MS, high-level SCI and CP. Inclusion criteria will require consistent voluntary movement of the body parts used to operate the control input device. Exclusion criteria will limit the participation of those with cognitive deficits.

For studies **S1**-**S4**, we expect to include 20 subjects without and 16 subjects with motor impairments, for each study (80 without and 64 with impairments in total; the actual numbers will be informed by the results study **S0**). This sample size was set based on a pilot study performed by our collaborators [50] with 8 uninjured and 6 SCI subjects using a specially designed control interface to control a cursor in 2-D [32]. Based on a 2-sample t-test (matched pairs), the data suggests 16 SCI subjects would be sufficient to observe over a single one hour session a learning effect with a power of .95 and $\alpha = 0.05$ (0.71 error-units reduction, STD =0.73 error units). We include uninjured subjects, who are easier to recruit, to first vet the system and increase statistical significance.

Subjects with motor impairments will be recruited by Jessica Presperin Pedersen, MBA, OTR/L, ATP, who is a Clinical Occupational Therapist in the Wheelchair and Seating Program, and Research Coordinator for its Assistive Technology Module, both at RIC. Subjects without impairments will be recruited from the visitors, student and staff at RIC and Northwestern University, through posted advertisements. All subjects will receive an honorarium for participation, and IRB approvals will be sought from Northwestern.

Metrics. Assessment in studies **S1**-**S4** will include quantifiable performance metrics and also subjective user reports. *Execution Performance* will be measured by task completion, path efficiency and execution time. *User Preference* will be measured according to (1) acceptance, by asking subjects to rate on a Likert scale [65] the automation, control-sharing and adaptation system, its capability and utility to them, and also (2) cognitive load, based on the users' subjective rating (e.g. using the NASA TLX [46]), and (3) self-reported level of pain and fatigue, and desired amount of assistance.

Study S0: Characterization. To observe and characterize differences between motor-impaired and unimpaired subjects while teleoperating assistive robot platforms. (Addresses hypothesis **H3**.)
Protocol. Data will be gathered during robot teleoperation under two tasks. Hardware. Both robot platforms, operated with both limited and complex interfaces. Task. Half of the subjects will evaluate both manipulation tasks, and the other half both driving tasks, in counter-balanced order to avoid ordering effects. Metrics. Data will be characterized according to tasks **T0** and **T1**, as described in Section 3.5.

Evaluation E0: Noise-Mining Algorithms. We will compare the performance of the noise-mining algorithms developed under task **T2** to algorithms that do not reason explicitly about information encoded within the data noise, when operated by motor-impaired users. (Addresses hypothesis **H2**.)
Evaluation. The data gathered under study **S0** will be used for this evaluation. The algorithms compared will include those implemented under task **T1**, compared to those developed under task **T2**.

Study S1: Interface-Aware Algorithms. To compare the performance of the interface-aware algorithms developed under task **T3** to naive algorithms that do not model the control interface. (To be used for the agreement calculations that will inform task **T4**.)
Protocol. One interface-aware algorithm and one interface-unaware (naive) algorithm will be evaluated for their ability to infer user-intent during control sharing. Hardware. Robotic arm platform, operated with both limited and complex interfaces. Task. Each subject will evaluate two tasks and both algorithms, using one interface. The allocation of which interface, and the ordering of tasks and algorithms, across subjects will be uniform and counter-balanced to avoid ordering effects. Manipulated variables. The interpretation of the user's control signal (i.e. which algorithm) will be manipulated, using a *within-subjects* design.

Study S2: Adaptation Cues. To assess which adaptation cues developed under **T4** are more effective for task performance and more preferred by motor-impaired teachers. (Preparation for study **S3**.)
Protocol. One explicit (reward) and two implicit (correction and reward, inferred from control signals) adaptation cues will be evaluated to adapt existing autonomy behaviors. Hardware. Both robot platforms, operated with complex interfaces. Task. One task per platform. Each subject will evaluate all cues using one robot platform and one interface performing one task. The allocation of which platform, and the ordering of cues, across subjects will be uniform and counter-balanced to avoid ordering effects. Manipulated variables. The adaptation cue will be manipulated, using a *within-subjects* design.

Study S3: Comparison to Existing Algorithms. To compare the performance of machine learning algorithms developed under task **T4** versus algorithms that are provided with dense noise-free feedback. (Addresses hypothesis **H5**.)
Protocol. The best-performing adaptation algorithm under study **S2** (policy P0) will be compared to the best-performing algorithm implemented under task **T1** (policy P1). P0 will be seeded with the same autonomy behavior used in study **S2**, and then adapted with user input. P1 will be learned *a priori* from data gathered from *unimpaired* subjects under **S0**. Hardware. Both robot platforms, operated with complex interfaces. Task. One task per platform. Each subject will first provide feedback to adapt and develop policy P0. Then both policies P0 and P1 will be evaluated, in counter-balanced order to avoid ordering effects. Manipulated variables. The policy development algorithm will be manipulated, using a *within-subjects* design.

Study S4: Adaptation Acceptance. To investigate the relative performance and user acceptance of static versus dynamic control sharing paradigms. (Addresses hypothesis **H8**.)
Protocol. Autonomously adapted versus user-adapted control-sharing paradigms will be evaluated. Three control-sharing paradigms (that provide *little*, *moderate* or *much* assistance) will be available. When user-adapted, the user chooses whether and when to change paradigms by indicating "less assistance" or "more assistance". (Note that if the user never chooses to change paradigms, this amounts to a static control-sharing paradigm.) When autonomously-adapted, the change is computed in software using techniques developed under task **T5**. Hardware. Robotic arm platform, operated with a complex interface. Task. Two tasks, with differing levels of difficulty. Each subject will evaluate both adaptation paradigms and both tasks. The ordering of paradigms and tasks will be counter-balanced to avoid ordering effects. Manipulated variables. The adaptation paradigm will be manipulated, using a *within-subjects* design.

5 Education Plan

Coursework. The principal objectives of the PI's teaching agenda are the following:

O1: To introduce into the Northwestern University curriculum courses that intersect robotics with ML and AI—a fusion area essential for an innovating engineering curriculum. While mechatronics and robot control have been excellently covered within Mechanical Engineering (ME), and AI and ML within Electrical Engineering & Computer Science (EECS), prior to the arrival of the PI at Northwestern, their intersection was a gap. *Metric:* Incorporation into the Northwestern curriculum,[7] course assessments.

O2: To introduce students to the practical challenges faced when working with real robots, and ignite passion for robotics research. *Metric:* Number of students who engage in robotics research.

O3: To draw students from outside of and across engineering disciplines—including but not limited to EECS, ME and Biomedical Engineering (BME). *Metric:* Distribution of student affiliations.

The PI furthermore is a faculty member of the curriculum committees for Computer Science and the M.S. in Robotics program, which offers a forum to promote robotics within Northwestern's engineering curriculum.

EECS 301 Introductory Robotics Laboratory. First taught in Winter 2013, this undergraduate course aims to expose early-stage students to the basic foundations for pioneering robotics, through a focus on AI and ML (O1). The PI won an internal grant to purchase for the course 14 robot platforms (see Facilities). Course assessments include lab reports, code reviews, quizzes and in-class team competitions (O1). The laboratory assignments require constructing the robots and programming their behaviors, providing students with a firsthand understanding of challenges like noisy sensor data and uncertain actuation, and the thrill in overcoming these challenges (O2). All of these aspects are intended to foster an interest in research. A total of 11 undergraduate students have continued research studies with the PI after taking this course (O2). To facilitate a draw of students from across engineering disciplines, the programming component of the course is intentionally accessible to those with a limited computer science background (O3).

EECS 469 Machine Learning and Artificial Intelligence for Robotics. First offered in the Spring Quarter of 2012 (and twice since), this graduate-level course provides a coverage of the artificial intelligence, machine learning and statistical estimation topics especially relevant for robot operation and robotics research (O1). Course assessments include algorithm implementations, results write-ups, code reviews, class presentations and a final exam (O1). The coursework is project-based. Students work with real robot datasets and are expected to reason about which ML/AI technique is most appropriate to apply to various scenarios, and then to implement it (O2). All teachings saw equal parts representation from EECS, ME and BME (O3). This course will undergo significant *restructuring* in its next teaching. The aim is to (1) reduce the amount of class time spent writing equations on the board, (2) encourage students to come to class with the necessary prior preparation complete, (3) design a larger set of salient and instructive examples to be worked through

[7] As of the Fall 2015 quarter, both courses have been assigned permanent course numbers (O1).

during class time, (4) allow for more in-class group discussion about the homeworks and (5) better align students' expectations with the workload requirements [57, 67]. *The restructuring will be assessed* through (1) entry/exit surveys about core robotics knowledge and how time is spent inside and outside of class [10], (2) progress checks after the submission of each homework assignment [10] and (3) a comparison to exam performance in past teachings. The PI will collaborate with Northwesern's Searle Center for Advanced Learning and Teaching to perform these assessments. (*Please see the attached letter of collaboration.*)

Mentorship. The PI is committed to training a next generation of robot machine learning and rehabilitation experts, through mentorship at the post-graduate, graduate, undergraduate and high school levels. The PI previously ran the mentorship program for all of the ($\sim$50) postdoctoral fellows at RIC.

Independent Study. The PI has advised multiple undergraduate (15) and masters (5) students in independent study research projects taken for course credit. High school students (3) have spent time in her lab, and she is a founding faculty member and student advisor for Northwestern's recently established cross-departmental M.S. in Robotics program. Independent study students design their project scope and milestones in collaboration with the PI, and are assessed via an oral presentation to her lab members and final written report.

Research Group. Argall's research group currently has 1 postdoctoral fellow, 4 PhD students and 4 undergrad students; with plans to grow to 7-8 PhD students and 2 postdoctoral fellows, and to continue to recruit undergraduate researchers from her laboratory course. Currently (summer 2015) her lab is hosting two undergraduate interns. Each undergraduate in her lab is assigned a PhD student mentor. The PI holds individual weekly research meetings with each of her lab members to discuss progress and goals. Weekly lab meetings first update on the status of the major robot platforms in the lab, and then alternate between research presentations and reading group sessions led by lab members on a rotating schedule.

Undergraduate Internship. Each summer an undergraduate student intern will be recruited for a full time 12 week position. ***Primary Goal:*** To expose the student to a CPS area with high societal impact (rehabilitation robotics), and fueling interest in research. The *Summer Research Opportunity Program* (SROP) at Northwestern facilitates undergraduate research internships for underrepresented minorities and disadvantaged groups (open to students across all US universities), providing stipend and housing. Argall pledges to work with the SROP office to recruit for this undergraduate position. Interns will meet weekly with their dedicated PhD mentor to set and assess goals, meet bi-weekly with the PI to discuss progress, participate in weekly lab meetings and present their work to the lab. ***Expected Outcomes:*** The intern gains professional experience and research motivation; the PI identifies candidate PhD students.

International Student Exchange. Every other year, one graduate student from the PI's lab will participate in a student exchange with the Learning Algorithms and Systems Laboratory (LASA) at the École Polytechnique Fédérale de Lausanne (EPFL) in Switzerland, directed by Prof. Aude Billard. (*Please see the attached letter of collaboration.*) ***Primary Goal:*** The exchange will serve as *a strategic resource in training the PI's students*, and thus in building her research group. The LASA lab [7] is a world leader in robot machine learning, with multiple high-end robotic arms and humanoids. Students will be immersed in group of robot machine learning experts (11 PhD students, two postdoctoral fellows). The opportunities offered through this collaboration are unavailable within the Northwestern community—Argall is the only faculty whose research lies at the intersection of ML/AI and robotics. ***Expected Outcome:*** For the students, a deepened understanding of machine learning and appreciation for how research is performed in another country, and a piece of work suitable for publication at top conferences. In turn, Prof. Billard's students will be immersed in a rehabilitation environment and have access to a mobile robot platform.

Robotics Club Outreach. The PI will partner with the non-profit Giant Steps therapeutic day school [8] to found a robotics outreach program that targets older K-12 students on the autism spectrum. (*Please see attached letter of collaboration.*) Giants Steps provides education, therapeutic and recreational programs for K-12 students with Autism Spectrum Disorders in the Chicagoland area. ***Primary Goal:*** is to provide an engaging context (building and programming robots) for ASD children to identify skills useful for future jobs for which they may be well-suited, and moreover in STEM areas. People with ASD often have difficulty with social interactions, and the largely asocial skills of mechanical construction and computer programming can be a good match. The program will operate once a month, with sessions led by rotating groups of people from the PI's lab, and potentially training Giant Steps faculty. ***Expected Outcomes:*** An increased interest in programming and/or mechanical construction from the ASD students (measured by entry/exit surveys [10]), as well as a rich mentoring experience for the PI's lab members. The PIs additionally will coordinate an annual "research day" event, that will be a special educational session on assistive robotics and demo at Giant Steps hardware from the PI's lab.

Museum of Science and Industry. Multiple Northwestern University robotics faculty participate in a large National Robotics Week event held annually at the Museum of Science and Industry in Chicago. This event brings in over 12,000 people—largely children—over the course of 2 days. Demonstrations by Northwestern labs are featured in the main rotunda of the building. ***Primary Goal:*** To educate on the theme of assistive robotics, using our MICO robotic arm and wheelchair-base mobile robot. We will feature results from the proposed work annually in this demo. ***Expected Outcome:*** Increased K-12 awareness of assistive robotics.

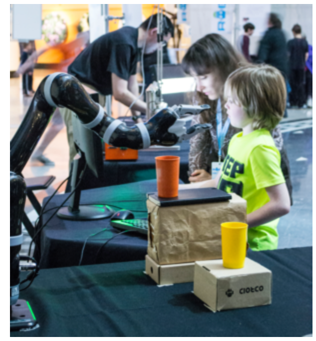

Figure 7: *Museum of Science & Industry* visitor during National Robotics Week, interacting with our MICO arm.

6 Broader Impacts of the Proposed Work

Public Health Impact. The proposed work is an exemplar of the overarching theme of research performed in the PI's lab—current, and projected—which lies at the intersection of artificial intelligence and rehabilitation robotics. Its foremost focus is on the *introduction of autonomy to assistive machines*, that is *able to be customized and designed* by a user who is not a control expert. *The work of the PI's lab is poised to make significant contributions to the areas of shared human-machine control, interactive robot learning and assistive technologies*. The likelihood of real societal impact is raised by direct daily access therapists and clinicians which keeps the lab's work focused on solutions with concrete clinical viability.

Partnership with Industry. The PI is a regular collaborator with Kinova Robotics, who make the MICO robotic arm. Kinova also is very keen to introduce machine learning into their assistive robots, and is interested in incorporating the results of the proposed work into their software suite for dissemination, if successful. (*Please see the attached letter of collaboration.*)

Cyber-Physical Systems. Impact on the larger field of humans interacting with controlled machines will be particularly salient for motor-impaired users interacting with robots. By treating motor impairments as an *advantage* for machine learning algorithms, rather than a *limitation*, customization of the machine's control *by the end-users themselves* is made possible. The work is poised to *transform rehabilitation science*.

Mentorship, **Robotics Club Outreach** and **Museum of Science and Industry.** As described in Section 5.

Plan of Work. In Year 1 the data characterization study (**S0**) and evaluation (**T0**, **T1**) will occur, including hardware and software development to support this study and evaluation. The **S0** data will inform the development (**T2**) and evaluation (**E0**) of noise-mining algorithms in Year 2, and the development (**T3**) and assessment (**S1**) of interface-aware algorithms in Year 3. The design (**T4**) and assessment (**S2**) of adaptation cues will occur in Year 4, and the comparison to other machine learning algorithms (**S3**) will begin (13 subjects). In Year 5 the comparison study will conclude (13 subjects), and the assessment of adaptation acceptance study (**S4**) will be run. The restructuring of course EECS 469 will occur in Year 1. Starting in Year 1 and continued annually, each summer an undergraduate research intern will be recruited, and each spring the team will participate in the National Robotics Week event at the Museum of Science and Industry. Foundations for the Giant Steps outreach program will be laid in Year 1, and launched in Year 2.

References

[1] Therafin Corporation: http://www.therafin.com.

[2] Adaptive Switch Laboratories: http://www.asl-inc.com.

[3] The scikit-learn machine learning toolkit: http://scikit-learn.org/.

[4] The Quantum 600 powered wheelchair from Pride Mobility: http://www.pridemobility.com.

[5] The MR-100 drive-by-wire wheelchair-base robot from Sensible Machines: http://www.sensiblemachines.com/enabling-modules.php.

[6] The Wheelchair Skills Test (WST) for Power Wheelchair Users: http://www.wheelchairskillsprogram.ca.

[7] The LASA laboratory at EPFL: http://lasa.epfl.ch.

[8] The Giant Steps therapeutic day school: http://mygiantsteps.org.

[9] P. Abbeel and A. Y. Ng. Exploration and apprenticeship learning in reinforcement learning. In *Proceedings of the 22nd International Conference on Machine Learning (ICML'05)*, 2005.

[10] T. A. Angelo and K. P. Cross. *Classroom Assessment Techniques*. Jossey-Bass, San Francisco, 1993.

[11] B. D. Argall. Modular and adaptive wheelchair automation. In *Proceedings of the International Symposium on Experimental Robotics (ISER)*, 2014.

[12] B. D. Argall. Turning assistive machines into assistive robots. In *Proceedings of the SPIE Photonics West Congress*, 2015. Keynote presentation.

[13] B. D. Argall, B. Browning, and M. M. Veloso. Learning from demonstration with the critique of a human teacher. In *Proceedings of the ACM/IEEE International Conference on Human-Robot Interactions (HRI)*, 2007.

[14] B. D. Argall, B. Browning, and M. M. Veloso. Learning robot motion control with demonstration and advice-operators. In *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2008.

[15] B. D. Argall, B. Browning, and M. M. Veloso. Automatic weight learning for multiple data sources when learning from demonstration. In *Proceedings of the IEEE International Conference on Robotics and Automation (ICRA)*, 2009.

[16] B. D. Argall, B. Browning, and M. M. Veloso. Learning mobile robot motion control from demonstrated primitives and human feedback. In *Proceedings of the 14th International Symposium on Robotics Research (ISRR)*, 2009.

[17] B. D. Argall, B. Browning, and M. M. Veloso. Mobile robot motion control from demonstration and corrective feedback. In J. Peters and O. Sigaud, editors, *From Motor to Interaction Learning in Robots*, pages 431–450. Springer, New York, NY, 2009.

[18] B. D. Argall, B. Browning, and M. M. Veloso. Teacher feedback to scaffold and refine demonstrated motion primitives on a mobile robot. *Robotics and Autonomous Systems*, 59(3-4):243–255, 2011.

[19] B. D. Argall, B. Browning, and M. M. Veloso. Feedback for the refinement of learned motion control on a mobile robot. *International Journal of Social Robotics*, 4(4):383–395, 2012.

[20] B. D. Argall, S. Chernova, M. M. Veloso, and B. Browning. A survey of robot learning from demonstration. *Robotics and Autonomous Systems*, 57(5):469–483, 2009.

[21] B. D. Argall, E. L. Sauser, and A. G. Billard. Policy adaptation through tactile correction. In *Proceedings of the 36th Annual Convention of the Society for the Study of Artificial Intelligence and Simulation of Behaviour (AISB)*, 2010.

[22] B. D. Argall, E. L. Sauser, and A. G. Billard. Tactile guidance for policy adaptation. *Foundations and Trends in Robotics*, 1(2), 2010.

[23] B. D. Argall, E. L. Sauser, and A. G. Billard. Tactile guidance for policy refinement and reuse. In *Proceedings of IEEE Conference on Development and Learning (ICDL)*, 2010.

[24] K. Åström and B. Wittenmark. *Adaptive Control: Second Edition*. Dover Publications, Inc., 2008.

[25] D. Atkins, D. Heard, and W. Donovan. Epidemiologic overview of individuals with upper-limb loss and their reported research priorities. *Journal of Prosthetics and Orthotics*, 8:2 – 11, 1996.

[26] J. A. Bagnell and J. G. Schneider. Autonomous helicopter control using reinforcement learning policy search methods. In *Proceedings of the IEEE International Conference on Robotics and Automation (ICRA'01)*, 2001.

[27] E. A. Biddiss and T. T. Chau. Upper limb prosthesis use and abandonment: A survey of the last 25 years. *Prosthetics and Orthotics International*, 31(3):236–257, 2007.

[28] Z. Bien, M.-J. Chung, P.-H. Chang, D.-S. Kwon, D.-J. Kim, J.-S. Han, J.-H. Kim, D.-H. Kim, H.-S. Park, S.-H. Kang, K. Lee, and S.-C. Lim. Integration of a rehabilitation robotic system (kares ii) with human-friendly man-machine interaction units. *Autonomous Robots*, 16(2):165–191, 2004.

[29] A. Billard, S. Callinon, R. Dillmann, and S. Schaal. Robot programming by demonstration. In B. Siciliano and O. Khatib, editors, *Handbook of Robotics*, chapter 59. Springer, New York, NY, USA, 2008.

[30] G. Bourhis, O. Horn, O. Habert, and A. Pruski. An autonomous vehicle for people with motor disabilities. *IEEE Robotics & Automation Magazine*, 8(1):20–28, 2001.

[31] S. Calinon and A. Billard. Incremental learning of gestures by imitation in a humanoid robot. In *Proceedings of the 2nd ACM/IEEE International Conference on Human-Robot Interactions (HRI'07)*, 2007.

[32] M. Casadio, A. Pressman, S. Acosta, Z. Danzinger, A. Fishbach, and F. Mussa-Ivaldi. Body machine interface: remapping motor skills after spinal cord injury. In *Proceedings of the IEEE International Conference on Rehabilitation Robotics*, 2011.

[33] S. Chernova and M. Veloso. Confidence-based learning from demonstration using Gaussian Mixture Models. In *Proceedings of the International Conference on Autonomous Agents and Multiagent Systems (AAMAS'07)*, 2007.

[34] J. W. Crandall and M. A. Goodrich. Experiments in adjustable autonomy. In *Proceedings of the IEEE International Conference on Systems, Man and Cybernetics*, 2001.

[35] J. W. Crandall and M. A. Goodrich. Characterizing efficiency of human robot interaction: A case study of shared-control teleoperation. In *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS '02)*, 2002.

[36] J. W. Crandall, M. A. Goodrich, D. R. Olsen, Jr., and C. W. Nielsen. Validating humanâĂŞrobot interaction schemes in multitasking environments. *IEEE Transactions on Systems, Man and Cybernetics*, 35(4):438–449, 2005.

[37] M. Derry and B. Argall. Automated doorway detection for assistive shared-control wheelchairs. In *Proceedings of the IEEE International Conference on Robotics and Automation (ICRA)*, 2013.

[38] M. Derry and B. Argall. Extending myoelectric prosthesis control with shapable automation: A first assessment. In *Proceedings of the ACM/IEEE International Conference on Human-Robot Interactions (HRI)*, 2014.

[39] D. L. Donoho. Compressed sensing. *IEEE Transactions on Information Theory*, 52:1289–1306, 2006.

[40] L. Fehr, W. E. Langbein, and S. B. . Skaar. Adequacy of power wheelchair control interfaces for persons with severe disabilities : A clinical survey. *Journal of Rehabilitation Research & Development*, 37(3):353–360, 2000.

[41] T. Fong, C. Thorpe, and C. Baur. Advanced interfaces for vehicle teleoperation: Collaborative control, sensor fusion displays, and remote driving tools. *Autonomous Robots*, 11(1):77–85, 2001.

[42] A. Goil, M. Derry, and B. Argall. Blending user and robot controls using machine learning for assisted wheelchair doorway navigation. In *Proceedings of the IEEE International Conference on Rehabilitation Robotics (ICORR)*, 2013.

[43] W. Griffin, W. Provancher, and M. Cutkosky. Feedback strategies for telemanipulation with shared control of object handling forces. *Presence: Teleoperators and Virtual Environments*, 14(6):720–731, 2005.

[44] D. Grollman and A. Billard. Donut as i do: Learning from failed demonstrations. In *Proceedings of IEEE International Conference on Robotics and Automation*, 2011.

[45] D. H. Grollman and O. C. Jenkins. Dogged learning for robots. In *Proceedings of the IEEE International Conference on Robotics and Automation (ICRA'07)*, 2007.

[46] S. G. Hart and L. E. Stavenland. Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. In P. A. Hancock and N. Meshkati, editors, *Human Mental Workload*, chapter 7, pages 139–183. Elsevier, 1988.

[47] T. Hastie, R. Tibshirani, and J. Friedman. *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. Springer, New York, NY, USA, 2001.

[48] P. Ioannou and J. Sun. *Robust Adaptive Control*. Dover Publications, Inc., 2012.

[49] S. Jain and B. D. Argall. Automated perception of safe and oriented docking locations with alignment information for assistive wheelchairs. In *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2014.

[50] S. Jain, A. Farshchiansadegh, A. Broad, F. Abdollahi, F. Mussa-Ivaldi, and B. Argall. Assistive robotic manipulation through shared autonomy and a body-machine interface. In *Proceedings of the IEEE International Conference on Rehabilitation Robotics (ICORR)*, 2015.

[51] M. Kaiser, H. Friedrich, and R. Dillmann. Obtaining good performance from a bad teacher. In *Programming by Demonstration vs. Learning from Examples Workshop at ML'95*, 1995.

[52] J. Kober, J. A. Bagnell, and J. Peters. Reinforcement learning in robotics: A survey. *International Journal of Robotics Research*, 32:1238–1274, 2013.

[53] J. Kober and J. Peters. Learning motor primitives for robotics. In *Proceedings of the IEEE International Conference on Robotics and Automation (ICRA '09)*, Kobe, Japan, 2009.

[54] A. Lankenau and T. Röfer. A versatile and safe mobility assistant. *IEEE Robotics & Automation Magazine*, 8(1):29–37, 2001.

[55] H. Lee, A. Battle, R. Raina, and A. Y. Ng. Efficient sparse coding algorithms. In *Advances in neural information processing systems*, 2006.

[56] A. Leeper, K. Hsiao, M. Ciocarlie, L. Takayama, and D. Gossow. Strategies for human-in-the-loop robotic grasping. In *Proceedings of the International Conference on Human-Robot Interactions (HRI '11)*, 2011.

[57] Light, Cox, and Calkins. *Learning and Teaching in Higher Education: The Reflective Professional*. Sage.

[58] T. Luith, D. Ojdanić, O. Friman, O. Prenzel, and A. Graser. Low level control in a semi-autonomous rehabilitation robotic system via a brain-computer interface. In *International Conference on Rehabilitation Robotics (ICORR '07)*, 2007.

[59] V. Maheu, J. Frappier, P. S. Archambault, and F. Routhier. Evaluation of the jaco robotic arm: clinico-economic study for powered wheelchair users with upper-extremity disabilities. In *International Conference on Rehabilitation Robotics (ICORR '11)*, 2011.

[60] M. Mazo. An integral system for assisted mobility. *IEEE Robotics & Automation Magazine*, 8(1):46–56, 2001.

[61] I. naki Iturrate, J. M. Antelis, A. Kübler, and J. Minguez. A noninvasive brain-actuated wheelchair based on a p300 neurophysiological protocol and automated navigation. *IEEE Transactions on Industrial Electronics*, 25(3), 2009.

[62] J. J. Park, C. Johnson, and B. Kuipers. Robot navigation with model predictive equilibrium point control. In *Intelligent Robots and Systems (IROS '12), Proceedings of IEEE/RSJ International Conference on*, 2012.

[63] P. Pastor, M. Kalakrishnan, S. Chitta, E. Theodorou, and S. Schaal. Skill learning and task outcome prediction for manipulation. In *Proceedings of IEEE International Conference on Robotics and Automation (ICRA)*, 2011.

[64] A. Pehlivan, F. Sergi, and M. OMalley. A subject-adaptive controller for wrist robotic rehabilitation. *IEEE Transactions on Mechatronics*, 20:1338 – 1350, 2015.

[65] R. R. Likert. A technique for the measurement of attitudes. *Archives of Psychology*, 22(140):1–55, 1932.

[66] N. Ratliff. *Learning to Search: Structured Prediction Techniques for Imitation Learning*. PhD thesis, Robotics Institute, Carnegie Mellon University, Pittsburgh, PA, 2009.

[67] J. Reeve. A self-determination theory perspective on student engagement. In *Handbook of Research on Student Engagement*, pages 149–172. Springer, USA, 2012.

[68] T. Röfer, C. Mandel, and T. Laue. Controlling an automated wheelchair via joystick/head-joystick supported by smart driving assistance. In *Proceedings of the IEEE International Conference on Rehabilitation Robotics*, 2009.

[69] R. Rusu, G. Bradski, R. Thibaux, and J. Hsu. Fast 3d recognition and pose using the viewpoint feature histogram. In *Proceedings of the IEEE/RSJ International Intelligent Robots and Systems (IROS)*, 2010.

[70] E. L. Sauser, B. D. Argall, G. Metta, and A. G. Billard. Iterative learning of grasp adaptation through human corrections. *Robotics and Autonomous Systems*, 60(1):55–71, 2012.

[71] T. Sheridan. *Telerobotics, Automation, and Human Supervisory Control*. MIT Press, 1992.

[72] R. Simpson, E. LoPresti, and R. Cooper. How many people would benefit from a smart wheelchair? *Journal of Rehabilitation Research & Development*, 45(1):53–72, 2008.

[73] R. C. Simpson, D. Poirot, and F. Baxter. The hephaestus smart wheelchair system. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 10(2), 2002.

[74] R. S. Sutton and A. G. Barto. *Reinforcement Learning: An Introduction*. The MIT Press, Cambridge, MA, London, England, 1998.

[75] T. N. A. W. N. System. Simon p. levine and david a. bell and lincoln a. jaros and richard c. simpson and yoram koren and johann borenstein. *IEEE Transactions on Rehabilitation Engineering*, 7(4), 1999.

[76] M. E. Taylor and S. Chernova. Integrating human demonstration and reinforcement learning: Initial results in human-agent transfer. In *Proceedings of the AAMAS 2010 Workshop on Agents Learning Interactively from Human Teachers*, 2010.

[77] J. G. Trafton, N. L. Cassimatis, M. D. Bugajska, D. P. Brock, F. E. Mintz, and A. C. Schultz. Enabling effective human-robot interaction using perspective-taking in robots. *IEEE Transactions on Systems, Man and Cybernetics*, 35(4):460–470, 2005.

[78] D. Valbuena, M. Cyriacks, O. Friman, I. Volosyak, and A. Graser. Brain-computer interface for high-level control of rehabilitation robotic systems. In *International Conference on Rehabilitation Robotics (ICORR '07)*, 2007.

[79] I. Volosyak, O. Ivlev, and A. Gräser. Rehabilitation robot FRIEND II - the general concept and current implementation. In *International Conference on Rehabilitation Robotics (ICORR '05)*, 2005.

[80] B. Widrow and S. D. Stearns. *Adaptive signal processing*. Prentice-Hall, Inc., 1985.

[81] E. T. Wolbrecht, V. Chan, D. J. Reinkensmeyer, and J. E. Bobrow. Optimizing compliant, model-based robotic assistance to promote neurorehabilitation. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 16:286–297, 2008.

[82] H. A. Yanco. *Shared User-Computer Control of a Robotic Wheelchair System*. PhD thesis, Department of Electrical Engineering and Computer Science, Massachusetts Institute of Technology, Boston, MA, 2000.

[83] E. You and K. Hauser. Assisted teleoperation strategies for aggressively controlling a robot arm with 2D input. In *Proceedings of Robotics: Science and Systems (RSS '11)*, 2011.