CPS: Synergy: Collaborative Research:
Learning control sharing strategies for assistive cyber-physical systems

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Overview

We propose a new paradigm for controlling complex assistive Cyber-Physical Systems (CPSs), like robotic arms mounted on wheelchairs, via simple low-dimensional control interfaces that are accessible to persons with severe motor impairments, like 2-D joysticks or 1-D Sip-N-Puff interfaces. In our formalism, the system anticipates when to switch between modes that operate on only a portion of the control space, and the user issues the lower-dimensional control signals within that subspace. We propose methods for how to learn assistive mode-switching strategies and how to perform this assistance under goal uncertainty. We test these methods in user studies with high Spinal Cord Injury (SCI) patients as well as uninjured subjects, evaluating the expense of mode-switching (Q1), the need for and approach to learning mode-switching assistance (Q2, Q3) and how this assistance should act under goal uncertainty (Q4).

Intellectual Merit

Assistive machines promote independence and ability in those with severe motor impairments. However, as these machines become more capable, they often also become more complex. Traditional interfaces cover only a portion of the control space, and during teleoperation it is necessary to switch between different control *modes* to access the full control space. Robotics automation may be leveraged to anticipate *when* to switch between different control modes. This approach is a departure from the majority of control sharing approaches within assistive domains, which either partition the control space and allocate different portions to the robot and human, or augment the human's control signals to bridge the dimensionality gap. How to best share control within assitive domains remains an open question, and an appealing characteristic of our approach is that the user is kept maximally in control since their signals are not altered or augmented.

We introduce a formalism for assistive mode-switching that is grounded in hybrid dynamical systems theory, and aims to ease the burden of teleoperating high-dimensional assistive robots. By modeling this CPS as a hybrid dynamical system, we model assistance as optimization over a desired cost function. We also model the system's uncertainty over the user's goals via a POMDP. This model provides the natural scaffolding for learning user preferences. Through user studies, we aim to address the following research questions:

(Q1) **Expense:** How expensive is mode-switching?

(Q2) **Customization Need:** Do we need to learn mode-switching from specific users?

(Q3) **Learning Assistance:** How can we learn mode-switching paradigms from a user?

(Q4) **Goal Uncertainty:** How should the assistance act under goal uncertainty? How will users respond?

Crucially, we will collaborate with therapists at the Rehabilitation Institute of Chicago to evaluate our framework via extensive user studies both on able-bodied users and SCI users.

Broader Impacts

Applications. The public health impact is significant, by increasing the independence of those with severe motor impairments and/or paralysis. Multiple efforts will facilitate large-scale deployment of our results, including a collaboration with Kinova, a manufacturer of assistive robotic arms, and a partnership with Rehabilitation Institute of Chicago.
Undergraduate education. The primary contribution will be through direct involvement in research. We both have a track record of integrating undergraduates in our labs.
Public and K-12 outreach. The PIs will demo in outreach programs for area schools and a National Robotics Week exhibit at the Museum of Science & Industry in Chicago. We will use our press offices to disseminate research results.
Underrepresented groups. Srinivasa is a mentor for the Robotics Summer Scholars Program for underrepresented students. His group teaches regularly at all-girls schools.
Industrial impact. We have a collaboration plan in place with Kinova Robotics, for transfer of research results to industry research labs and potential distribution with industry products.

1 Introduction

Assistive machines—like powered wheelchairs, myoelectric prostheses and robotic arms—promote independence and ability in those with severe motor impairments [32,33,59,66,92]. As the state-of-the-art in these assistive Cyber-Physical Systems (CPSs) advances, more dexterous and capable machines hold the promise to revolutionize ways in which those with motor impairments can interact within society and with their loved ones, and to care for themselves with independence.

However, as these machines become more capable, they often also become more complex. Which raises the question: how to control this added complexity? The aim of our proposed work is to address this question.

Control of Complex Assistive Machines. A confounding factor is that the more severe a person's motor impairment, the more limited are the control interfaces available to them to operate. The control signals issued by these interfaces are lower in dimensionality and bandwidth. Thus, paradoxically, a greater need for sophisticated assistive devices is paired with a diminishing ability to control their additional complexity.

Traditional interfaces often cover only a portion of the control space of more complex devices like robotic arms [83]. For example, while a 2-axis joystick does fully cover the 2-D control space (heading, speed) of a powered wheelchair, to control the end-effector of a robotic arm is nominally a 6-D control problem. This already is a challenge with a 2-D control interface, which is only exasperated if limited to a 1-D interface like a Sip-N-Puff or switch-based head array [23,25,44,49,55,58,68,85,86].

Help from Autonomy. The potential for robotics autonomy to ease control burden within assistive domains has been recognized for decades. While full autonomy is an option, it removes all control from the user. When this is not desired by the human, the assistive technology in fact has made them *less* able. It also discards useful input the human might provide, leveraging for example their superior situational awareness, that would add to system robustness.

Control sharing is a way to offload some control burden, without removing all control authority, from the human [10,16,20,56,87,93]. The most common paradigms augment or adjust control signals from the human (e.g. to bridge the gap in control signal dimensionality), or partition the control problem (e.g. high-level decisions like which task to execute lie with the human, and low-level execution decisions lie with the robot).

Here, we propose an alternative role for the autonomy: to assist the user in transitioning between different subsets of the control space—that is, to autonomously remap signals from the user interface to different control *modes* (e.g. subsets of the control dimensions).

A Framework for Assistive Mode-Switching. The operation of an assistive device via different control modes is reminscient of upper-limb prosthesis control [3, 12, 54, 63, 67, 77, 78]. In this case control is diverted between different "functions" (e.g. elbow, wrist). The parallel for a robotic arm is to divert control between different subsets of the joint-control space. (Modes that operate subsets of the end-effector control space of course are equally viable.) Within the field of prosthetics, function switching is known to be cumbersome, and the opportunity for autonomous switching to ease this burden has been identified [57] (though it is not yet feasible to implement on today's prosthetic hardware).

We introduce a formalism for assistive mode-switching that is grounded in hybrid dynamical systems theory. The user issues low-dimensional control signals, and these signals are not

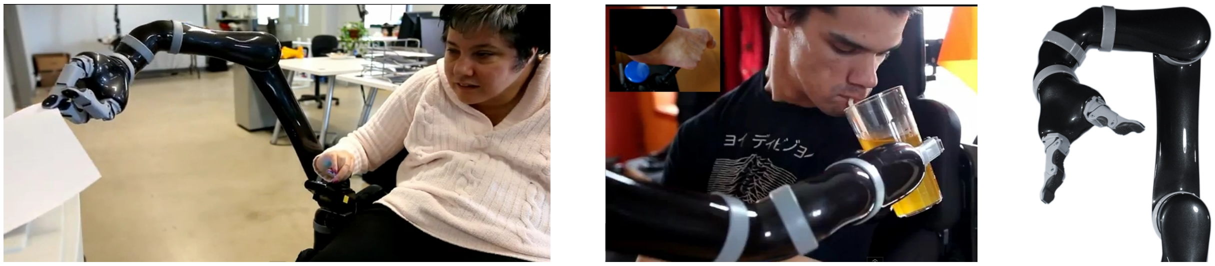


Figure 1. Users controlling the Kinova JACO arm through a hand-operated (left) and foot-operated (middle) joystick. Our platform (right), the Kinova MICO arm, is kinematically identical but smaller, lighter and cheaper, with a two-fingered hand.

augmented or modified by the autonomy. What the autonomy *is* changing is what these low-dimensional signals map to.

More formally, we model this CPS as a hybrid dynamical system, where each mode has its own dynamics, and we can switch modes anytime. The user has some optimal control policy, where they are noisily optimizing a joint cost function over continuous state and discrete mode switches. With knowledge of this cost function, the autonomy can anticipate these mode switches and perform the switch for the user. Uncovering this cost function is a major research activity of the proposed work.

Mode-switching assistance has the key benefit that it is low-bandwidth and intermittent, and hence possibly easier to learn. We also hypothesize that it acheives a sweet-spot of assistance: helping them with tedious parts of the task while still giving them full control over continuous motion. Furthermore, we believe that because of these benefits, users will be more tolerant to errors in mode-switching assistance.

Our work furthermore proposes to learn optimal paradigms for mode switching through interactions with the user. Our subject studies with uninjured subjects and volunteers with high Spinal Cord Injury (SCI) will evaluate the following research questions: (1) How expensive is mode-switching? (2) How well can the fixed policy of time-optimal mode-switching perform? (3) How can we learn mode-switching policies? (4) How can we generalize to goal uncertainty?

We will also to work closely with Occupational Therapists at the Rehabilitation Institute of Chicago to develop evaluation scenarios for our work.

Significance. Robotic arms have the potential to greatly increase the independence of wheelchair users, and reduce cost of care. A recent survey [46] of 31 powered wheelchair users dependent on caregivers estimates that a robotic arm would reduce caregiving time by 41% (1.5 hours/day). A study [15,26] of long-term (>4 years) robotic arm users corroborates this estimate, with users carrying out 40% more activities of daily living (ADL) independently and an average reduction in care of 1.2 hours per day. Additional cost-benefits include [62] to optimize ADL assistance, move out of 24/7 assistance facilities or the user (or caregiver) being able to return to work.

The proposed work targets the easier operation of robotic arms by severely paralyzed users (Fig.1). The need to control many degrees of freedom (DoF) gives rise to mode-switching during teleoperation. The switching itself can be cumbersome even with 2- and 3-axis joysticks, and becomes prohibitively so with more limited (1-D) interfaces. Easing the operation of switching not only lowers this burden on those already able to operate robotic arms, but may open use to populations to whom assistive robotic arms are currently inaccessible.

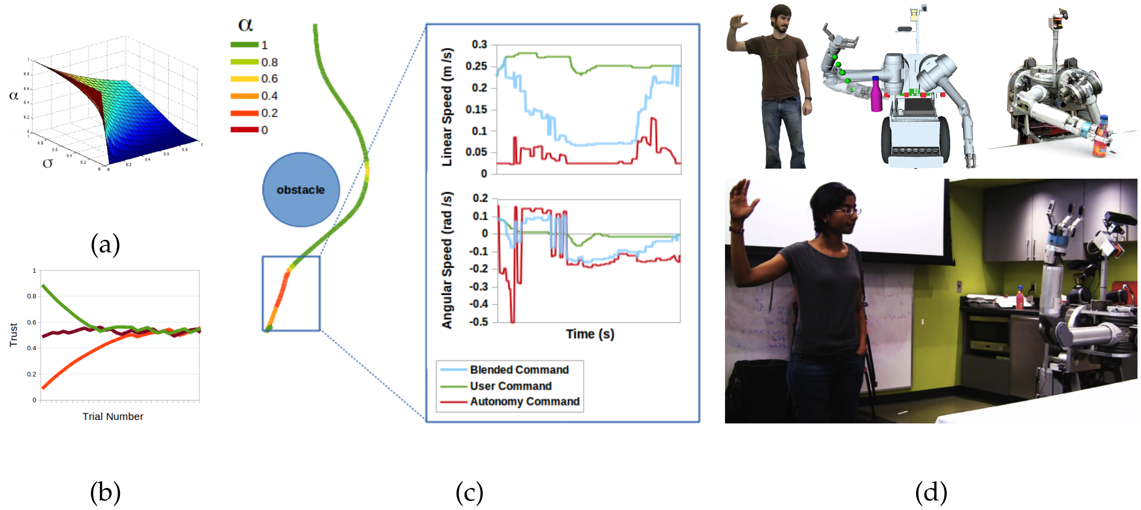


Figure 2. Prior work in control sharing. *(a)* Blending parameter α is a function of variance σ in demonstrated task executions. *(b)* Evolution of a measure of trust in the user that informs α. *(c)* Control sharing for safety monitoring on a smart wheelchair. Robot ground path shown with colors that reflect the value of the control blending parameter α at that time. *(d)* Assistive teleoperation with able-bodied users.

Research Team. The proposal leverages the PIs' shared expertise in manipulation, algorithm development, and deploying real-world robotic systems. The proposal also leverages the PIs' complementary strengths: Srinivasa's focus on deploying advanced manipulation platforms, robotic motion planning and manipulation, and human-robot comanipulation, and Argall's focus on robot learning from human demonstration, control policy adaptation, and human rehabilitation.

For seamless collaboration, PIs will use identical setups: the Kinova MICO (Fig.1(right)), a commercial assistive robotic arm, and perception hardware, and software. The team will also work closely with clinical staff at the Rehabilitation Institute of Chicago, the nation's premier rehabilitation hospital, and will have unparalleled access to SCI clinicians and their patients.

Relevance to CPS. Our work is clearly *synergistic*: at the intersection of robotic manipulation, human rehabilitation, control theory, machine learning, human-robot interaction and clinical studies. We address the *science* of CPS by developing new models of the interaction dynamics between the system and the user, the *technology* of CPS by developing new interfaces and interaction modalities with strong theoretical foundations, and the *engineering* of CPS by deploying our algorithms on real robot hardware and extensive studies with able-bodied and SCI users.

2 Prior Work

Argall prior work in control sharing. PI Argall has developed a smart wheelchair platform for which the design and evaluation of novel control sharing strategies is a major thrust [5, 6, 27]. An approach based on demonstrations of a behavior that the user themselves (or an aide) provides encodes within the demonstration variance the spatial task constraints that inform control sharing (Fig. 2a). A different approach iteratively shifts control from the user to the autonomy (by reducing the value of α) as the forward projections of the user's commands (green in graphs) generate a path which collides with an obstacle (Fig. 2c). The blended command (light blue in graphs) prioritizes foremost safety, but also keeping as much control as possible with the user. Another approach computes an evolving measure of trust in the user, based on past performance, which dictates how much control authority is granted to them (Fig. 2b).

Srinivasa prior work in assistive teleoperation. PI Srinivasa has developed a formalism for assistive teleoperation based on *policy blending* [16–18]. Here, the user's input and the robot's policy are blended continuously via a hand-coded arbitration function (Fig. 2d).

Shared autonomy paradigms. Paradigms for controlling such high dimensional systems with much lower dimensional interfaces like a joystick [83], sip-and-puff [55], or a brain-computer interface [86] fall into two categories.

The first treats the user as an *indicator of goals* by reducing the user's input to one of a finite set of predefined configurations or goals. While these systems are easy to operate, removing autonomy from the user often decreases their satisfaction with the system [36,37].

The second treats the user as a *provider of motion* by mapping the lower dimensional input to some subset of the arm's degrees of freedom, called a *mode*. Users then *switch* modes to control a different subset [47,48,57,61,65,88,89], a method known as *modal control*. Thus the user is able to move the arm everywhere, but not using all of the degrees of freedoms at the same time. Studies with people with disabilities revealed that the numerous and frequent mode switches required for performing everyday tasks made such systems difficult to operate [21].

Shared control in robotics. Many robot systems share control between manual operation by a human and automated operation by a controller. Typically, the goal is to find a sweet spot along the continuum spanning from fully manual to fully automated control [24,28,42,64,96]; ideally, where sharing control makes the system more capable than at either extreme of the continuum.

Goal Prediction. Maximum entropy inverse optimal control (MaxEnt IOC) methods have been shown to be effective for goal prediction [19,98–100]. In this framework, the user is assumed to be an intent-driven agent approximately optimizing a cost function. By minimizing the worst-case predictive loss, Ziebart et al. derive a model where trajectory probability decreases exponentially with cost, and show how this cost function can be learned efficiently from user demonstrations [99]. They then derive a method for inferring a distribution over goals from user inputs, where probabilities correspond to how optimal the inputs are for each goal [100].

Other techniques to address the prediction problem include conditional random fields [39], Gaussian Process Dynamical Models (GPDMs) [90], or Gaussian mixture model over tasks types [31].

Assistance Methods. Many prior works assume the user's goal is known, and use methods such as potential fields [2,14] and motion planning [97] to assist in reaching that goal.

For multiple goals, many works follow a predict-then-blend approach of predicting the most likely goal, then assisting for that goal. These methods range from taking over when confident [22,38], to virtual fixtures that help follow paths [1], to blending with a motion planner [19]. Many of these methods [8,39,41] can be thought of as an *arbitration* between the user's policy and a fully autonomous policy for the most likely goal [19]. These two policies are blended, where prediction confidence regulates the amount of assistance.

Fern and Tadepalli have studied MDP and POMDP models for assistance [75] with an interactive assistant which suggest actions to users, who then accept or reject the action. They show that optimal action selection even in this simplified model is PSPACE-complete. However, a simple greedy policy has bounded regret [75]. Nguyen et al. [53] and Macindoe et al. [45] apply similar models to creating agents in cooperative games, where autonomous agents simultaneously infer human intentions and take assistance actions.

Results from Prior NSF Support. Argall and Srinivasa have been funded by *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 grant focuses on assistance that augments control signals from the human to bridge the gap in control signal dimensionality for a variety of devices including powered wheelchairs and robot arms, and on customizing system components based on user data that can generalize to new situations. The grant has just started and has several submitted works but no publications to date. **Broader impacts.** The grant has funded 2 PhD students and 1 undergraduate student at CMU and 1 PhD student at NU. Two of those students are women, and the research performed under the grant has enabled them to win the Hertz and NSF Fellowships, and the CRA Outstanding Undergraduate Female Researcher Finalist award. The work also was featured at interactive National Robotics Week demos at CMU and at Chicago's Museum of Science and Industry, with thousands of visitors (primarily K-12 children).

3 A Framework for Mode Switching Assistance

In this section, we formalize mode-switching assistance as switching over a hybrid dynamical system. This also provides us a sound scaffold for machine learning user-specific strategies.

3.1 Mode switching as a hybrid dynamical system

We work with a robot with configuration $q \in \mathcal{Q}$ defined over a configuration space $\mathcal{Q}$. Following standard terminology used in hybrid dynamical systems, we define a *mode space* that contains a finite set of modes $m \in M$. We now define the state space X as the Cartesian product $X = \mathcal{Q} \times M$. Each state is represented as (q, m) where $q \in \mathcal{Q}$ and $m \in M$.

Each state x has a finite *action space* $U(x)$, and we define U as the set of all possible actions. A state transition function $T : X \times U \to X$ governs the deterministic dynamics of the system.

We distinguish between two types of actions: (1) Continuous actions $u_q \in U_{\mathcal{Q}}(x)$ that change configuration in a fixed mode, $T : (q, m) \times u_q \mapsto (q', m)$, and (2) Discrete mode switching actions $u_m \in U_M(x)$ that change mode in a fixed configuration, $T : (q, m) \times u_m \mapsto (q, m')$. Given a sequence of actions σ and a start state x_s, we can compute the *trajectory* $\xi(x_s, \sigma)$ as the sequence of states that the system transitions through starting from x_s by applying the actions in σ.

In our problem, the set of reachable configurations from a given state by applying only continuous actions U_q is a subspace of $\mathcal{Q}$. Also note that the product of all of such subspaces is a foliation [34] and covers $\mathcal{Q}$. This essentially means that because the reachable subspace in any given mode does not cover $\mathcal{Q}$, the action trajectory from a start to a desired goal will likely involve an interleaving of continuous and mode-switching actions.

3.2 A model for mode switching

We model the human operator as a rational agent who wishes to control the robot such that the operator is noisily optimizing a cost function $C : X \times U \to \mathbb{R}^+$. Thus, given a sequence of actions σ and a trajectory ξ, we can compute the cost of the trajectory as

$$C(x_0, \sigma) = \sum_{i}^{n} C(\xi_i, \sigma_i) \tag{1}$$

where ξ_i and σ_i index the i-th element in the respective sequence. The optimal action sequence from a start x_s to a goal x_g is then given by:

$$\sigma^* = \arg\min_{\sigma} C(x_s, \sigma) \qquad \text{s.t. } \xi_n = x_g \tag{2}$$

We then define the value function $V : X \to \mathbb{R}^+$ as $V(x) = C(x, \sigma^*)$, the cost of the optimal trajectory from x, and the optimal policy $\pi^* : X \to U$ as $\pi^*(x) = \sigma_0^*$, the optimal action at x. Note that there might be several optimal actions at a given state x. In that case, choosing any of them will be, by definition, optimal.

We can now define the *optimal mode set* $\mathcal{Q}(m) \subseteq \mathcal{Q}$ as the set of all configurations where m is the optimal mode:

$$\mathcal{Q}(m) = \{q \in \mathcal{Q} | T(x, \pi^*(x)) = (\cdot, m) \text{ where } x = (q, m)\} \tag{3}$$

Note that $\cup \mathcal{Q}(m) = \mathcal{Q}$ but also that $\mathcal{Q}(i) \cap \mathcal{Q}(j)$, $i \neq j$, need not always be empty, i.e. every configuration has at least one optimal mode, but might have more than one.

We can now define *mode switching assistance* as the automated switching to the optimal mode(s). Formally, it is the subset of actions in the optimal policy that switch modes:

$$\pi_M^*(x) = \begin{cases} u & \{u\} \subseteq U_M(x) \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

Central to our proposal is the hypothesis that mode switching is expensive in terms of user effort and time, and qualitatively stressful to the user. Our first research question (Section 4 **Q1**) proposes to validate this hypothesis.

3.3 The time-optimal motion assumption

Much of our formulation above hinges on knowing the user's cost function C. Although this setup begs for learning C from demonstration, we propose to try something much simpler (Section 4 **Q2**): to hypothesize that users are moving time-optimally.

We have two key reasons for testing this hypothesis: (1) learning often requires significant amounts of near-optimal and noise-free training data, which would be challenging to obtain from SCI patients, and (2) since mode switching assistance is intermittent, we believe that it might be more tolerant to differences between the user's actual cost function and the one we hypothesize.

We also believe that the time-optimal policy can act as the scaffolding for machine learning. As more data is obtained via interaction, the learned policy can gradually update the cost function to one that is customized for the user and task.

3.4 Learning mode switching assistance

Even in the case where the time-optimal mode-switching is effective, there still may be utility to updating and customizing the assistance over time to the user's personal preferences. A key research question we will address (Section 4 **Q3**) is to collect data from able-bodied and SCI users and learn the cost function.

Before we describe the theory, we would like to make a pragmatic statement about our user group. Getting any demonstration data from SCI users is challenging. We are deeply aware of that. However, the key to mode-switching assistance is that: (1) the mode switch does not happen on a fast timescale, and (2) it is a selection from a discrete set. This is completely unlike traditional continuous assistance paradigms. We believe this compression of input required for learning will enable practical machine learning

We propose to model the user's cost function as some linear combination of several (here, k) features $f(x,u) \in \mathbb{R}^k$ of a given state and action weighted by $\theta \in \mathbb{R}^k$ as $C(x) = \theta^T f(x,u)$. We propose a linear combination of features, as linear learning methods have been shown to very efficient in terms of both data and computation [74]. Thus, given a trajectory ξ, we can compute its cost as:

$$C(x_0,\sigma) = \sum_i^n C(\xi_i,\sigma_i) = \sum_i^n \theta^T f_i = \theta^T \sum_i^n f_i = \theta^T f_\xi \tag{5}$$

where f_ξ is the *feature count* of the trajectory as it sums feature values over the entire trajectory.

We can then define $\xi^*(\theta)$ as the optimal trajectory for a given θ

$$\xi^*(\theta) = \arg\min_\xi \theta^T f_\xi \tag{6}$$

Given that the user demonstrates m individual trajectories $\widetilde{\xi}$ over several scenarios, the goal of *inverse reinforcement learning* is to learn the optimal weights θ^* such that the optimal trajectory given those weights minimizes loss function $L(\cdot)$when compared to the user's demonstration [60]

$$\theta^* = \arg\min_\theta \sum_m L(\xi_i^*(\theta), \widetilde{\xi}_i) \tag{7}$$

Unfortunately, recovering the user's exact weights is an ill-posed problem as many reward weights, including degeneracies (e.g. all zeroes), make demonstrated trajectories optimal [99].

The maximum margin principle overcomes this problem by building in a degree of robustness where it attempts to make the user's demonstration $\widetilde{\xi}_i$ look significantly better than any alternative trajectory ξ under the weight θ by a margin that scales with the size of the loss of ξ. This ensures that the correct policy looks much more attractive than very bad policies.

In case of noise or inconsistencies in the human demonstrations, we propose to use the principle of maximum entropy, which derives a loss function which chooses the distribution that does not exhibit any additional preferences beyond matching the expectation over feature counts. Under this model, plans with equivalent rewards have equal probabilities, and plans with higher rewards are exponentially more preferred:

$$P(\xi|\theta) = \frac{1}{Z(\theta)} \exp(-\theta^T f_\xi) \tag{8}$$

where $Z(\theta)$, called the partition function, normalizes the distribution. We note that the principle of maximum entropy also resolves ambiguity of which distribution to choose that satisfies feature matching, as noted in the beginning of this subsection.

3.5 Mode switching under goal uncertainty

The final piece to our formalism is to represent, and reason explicitly about, goal uncertainty. If the user's desired goal is unknown to the system, the problem breaks down into two parts: (1) maintaining a probability distribution over the possible goals $g \in G$ given the trajectory $\xi_{0\to t}$ until time t, and (2) assisting via mode switching optimally under this goal uncertainty.

We can decompose $\xi_{0\to T}$ into two components, the trajectory $\xi_{0\to t}$ until the current time t and the future trajectory $\xi_{t\to T}$ until completion at time T, the final time-step of the trajectory. This allows us to use (8) as:

$$P(\xi_{0\to t}|g) = \frac{1}{Z(\theta)} \exp(-\theta^T (f_{\xi_{0\to t}})) \int_{\xi_{t\to T}} \exp(-\theta^T f_{\xi}) d\xi \tag{9}$$

We can then use Bayes rule to compute the probability distribution over goals as [16]:

$$P(g|\xi_{0\to t}) = \frac{P(\xi_{0\to t}|g)p(g)}{\sum_{g'} P(\xi_{0\to t}|g')p(g')} \tag{10}$$

Knowing the distribution over goals, our challenge now is to derive an optimal assistance policy. We propose to formulate this problem as a partially-observable Markov decision process (POMDP) [35], where the unknown state is the user's desired goal. Our goal is to minimize the expectation over the cost of the entire trajectory.

Solving POMDPs, i.e. finding the optimal action for any belief state, is generally intractable. We utilize the QMDP approximation [43], also referred to as hindsight optimization [11, 95] to select actions. The idea is to estimate the cost-to-go of the belief by assuming full observability will be obtained at the next time step. The result is a system that never tries to gather information, but can plan efficiently in the deterministic subproblems [94, 95].

We believe this method is suitable for shared autonomy for many reasons. Conceptually, we assume the user will provide inputs continuously at all states, and therefore we gain information without explicit information gathering. In this setting, works in other domains have shown that QMDP performs similarly to methods that consider explicit information gathering [40]. Computationally, QMDP is efficient to compute even with continuous state and action spaces, enabling fast reaction to user inputs. Finally, explicit information gathering where the user is treated as an oracle would likely be frustrating [4, 29], and this method naturally avoids it.

We denote $V_g(x)$ as the value function at state x given goal g. We can then write the QMDP policy as:

$$u^* = \arg\min_{u\in U} \sum_{g\in G} P(g|\xi_{0\to t}) \left(C(\xi(t), u) + V_g(T(\xi(t), u)) \right) \tag{11}$$

The QMDP policy trades off optimality for computational efficiency. As a consequence, it performs no information-gathering actions. A key research question is to address if this approximation produces satisfactory performance with real users (Section 4 **Q4**).

4 Research Questions

Our framework for mode switching assistance provides the foundation for addressing the following key questions.

Q1 How expensive is mode-switching?

Our central hypothesis is that mode switching is indeed expensive. Our own interviews with current users of the Kinova arm pinpointed that the struggles with modal control relate back to the need to constantly change modes. Users noted that there were "a lot of modes, actions, combination of buttons". Each of these mode changes requires the user to divert their attention away from accomplishing their task to consider the necessary mode change [80,81]. The cognitive action of shifting attention from one task to another is referred to as *task switching.* Task switching slows down users and can lead to increased errors regardless of the interface they are using to make this switch [7,51,52,72,91]. Thus there is much evidence to suggest that the need to change modes is a harmful distraction that impedes efficient control.

We propose to run our first user study, both with able-bodied and SCI users, to quantify the cost of mode switching. Section 5 outlines our evaluation scenarios, and Section 6 details our user studies and metrics.

Q2 Do we need to learn C? How well will a time-optimal policy perform?

An interesting aspect of mode-switching assistance is that it is intermittent: giving the operator full control within a mode and only assisting by switching. Because of this intermittence, we hypothesize that users might not feel like they are *fighting* the system if the cost function C being used is not exactly what they would like to optimize. This is in contrast to continuous assistance, where the system constantly provides input, where we believe user tolerance to discrepancy in the cost function might not be as generous.

To explore this question, we propose to develop time-optimal mode switching, where we assume that the operator is attempting to minimize total task completion time. We then propose to run our second user study, both with able-bodied and SCI users, to quantify the effects of time-optimal mode switching. We suspect that our results will be mixed based on the user group (some users might really want the robot to move the way they want it to) and task complexity (some tasks might be so hard that users would accept any form of assistance).

Q3 How should we learn C?

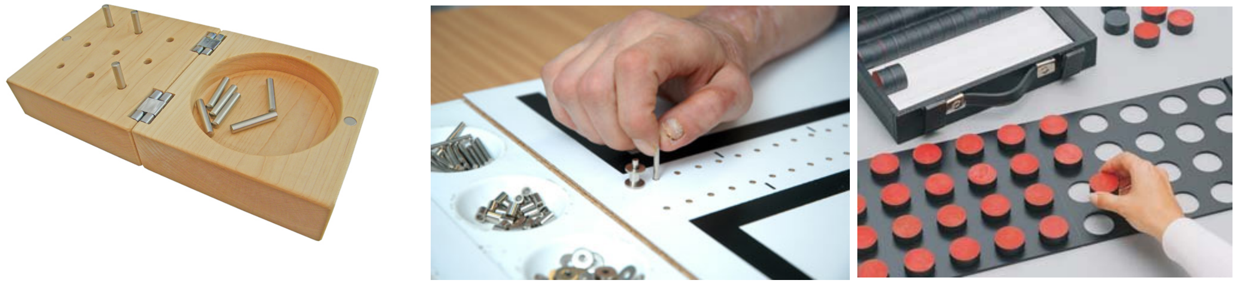
Whether we need to address this question or not depends on the answer to **Q2**. We suspect that the answer to **Q2** will not be unanimous: there will always be users and task where a fixed time-optimal policy might not be desirable. Hence, it is indeed worthwhile to ask this question.

At first blush, one might assume that the best way to learn C is from user demonstration. However, what C really captures is not how the operator moves the robot but how they *want* to move the robot. And since *expert* demonstrations are not available, learning C becomes all the more challenging. For example, we certainly do not want to learn a C that captures all the hand tremors of the operator.

One possible way to address this challenge is to learn C interatively *with* assistance. Here, we hypothesize a C, and run a trial where the system assists with that C. We then measure how much the user agreed with the assistance (quantitatively via control effort) and update C accordingly. We propose to explore the theoretical and practical issues with such an iterative learning method.

Q4 How should the assistance act under goal uncertainty? How will users respond?

We outlined a strategy where the system models the user as a POMDP and simultaneously predicts their desired goal and assists them. This QMDP policy trades off optimality for efficiency by explicitly avoiding information-seeking actions. This is provably suboptimal, as there might be information-gathering actions that can efficiently disambiguate between goals and enable efficient assistance. Our reasoning for selecting this approximation is grounded in two tenets: (1)



(a) 9 Hole Peg Test (b) Purdue Pegboard Test (c) Minnesota Test

Figure 3. Functional tests that repeat specific motion primitives.

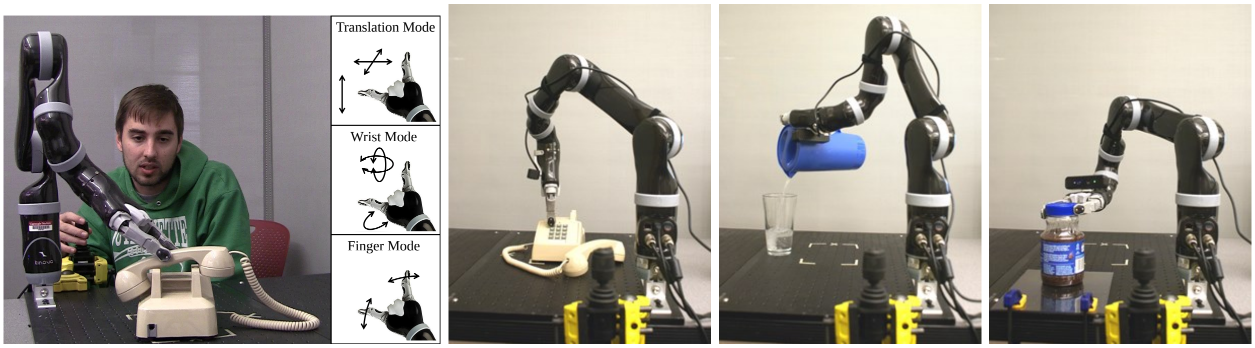
the observation that grasping actions are naturally information-gathering, i.e. there is often little reason to stray far away from the desired goal to gain information (of course, this is not a general statement), and (2) the hypothesis that users might actually not prefer actions that are excessively information-seeking as they might be hard to interpret. Our proposed study will evaluate user response to the QMDP policy.

5 Evaluation Scenarios

There are advantages to evaluating our assistive robot arm system with the same standardized tests that Occupational Therapists (OT) use with human patients. Standard OT tests are already validated, have years of application, provide a metric that can be used across robots and people, and makes our results more transparent to a larger community. Manipulation tests can be divided into strength tests, which measure the muscular ability of the human hand and upper limbs, and functional tests, which measure the ability to perform particular tasks or motions. Because the robot's hardware will exclusively determine its performance on strength tests and will not change drastically over time, we will evaluate using functional tests.

A survey of functional tests shows that functional tests fall into two categories: repeated tasks that test specific motion primitives, and tasks that are based on daily living and cover a several motion primitives per task. The Purdue Pegboard test [79], 9 Hole Peg Test [73], and Minnesota rate of manipulation test, shown in Fig.3, ask the user to provide a number of short repeated tasks and use the overall task time as the primary evaluation metric. Tests based on daily activities include the Motor Activity Log (MAL) [76, 84], the Jebsen Taylor Hand Function Test [82], the Action Research Arm (ARA) test [50], Sollerman hand function test [69], and the Chedoke Arm and Hand Activity Inventory (CAHAI) [9].

Our prior work (Section 6.2) has used tasks from the CAHAI test (Fig.4), which has the advantage of including both qualitative and quantitative metrics for evaluation. It is however optimized for evaluating stroke recovery, which is not the target population for this work. We therefore will collaboration with OTs at RIC in the selection of tests used to assess function in SCI patients (e.g. the ARA, Sollerman and Jebsen). Our *task set* will derive from the selected tests.



(a) Mode switching evaluation (b) Dialing 911 (c) Pouring water (d) Unscrewing a jar

Figure 4. Three modified tasks from the Chedoke Arm and Hand Activity Inventory, which able-bodied users performed through teleoperating the MICO robot.

6 Evaluation Plan

We plan four studies to evaluate the importance of mode-switching, as well as the impact of our assistance methods.

Robot platform. We will use the MICO robotic arm from Kinova Robotics at both RIC and CMU, thus enabling the immediate transfer of technologies between the two groups and *reducing the confound of experimental differences between the two sites*. The MICO is a 6-DoF robotic arm 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 [46]. 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).

We will leverage our existing software for motion planning, perception, learning, and control, developed on our existing platform HERB [70,71] that performs autonomous manipulation tasks. ***Perception:*** We plan for the necessary *sensory augmentation to be low cost and low profile*, consisting of RGB-D sensors (e.g. Creative Senz3D, $150) on the robot and in the environment to monitor the environment. To recognize and register objects, which provide the goal locations G for our system, we will leverage our previous perception research (the MOPED system [13]).
Control Interface: We will use a standard 2-axis joystick (Fig.4a). Standardizing the input device eliminates a confound, but does require a longer training period to combat learning effects.

6.1 Subject Studies

Participants. We will run each study on 28 able-bodied participants, address potential pitfalls, and only then test each on 8 SCI patients (depending on availability from this much smaller participant pool). We obtained a sample size of 28 based on a power analysis using the standard deviation from user ratings in our preliminary study from Section 6.2, a power value of 0.8, and an expected difference of 1 on a 1-7 Likert scale. The sample size of 8 SCI patients was calculated with the same power analysis, except with two 1-7 Likert scales for preference instead of a single forced choice scale, effectively increasing the sensitivity of the measurement to allow for an expected difference of 2, which reduces the required number of patients to a reasonable scale. SCI subjects will be recruited in collaboration with Jessica Pedersen, OTR/L, ATP.

Study 1: Mode-Switching Behavior. To investigate **Q1**, we evaluate user performance on three tasks from the *task set*, using a 2-axis joystick to control the MICO arm.
Manipulated Variables: We will manipulate which task is performed.
Subject Allocation: This study will be run first with able-bodied users, in which we will use a *within-subjects* design, in which each user will perform each of the tasks. The study will be repeated with for users with SCI, but with only a single task: the task that mode-switching incurred the greatest impact on performance for the able-bodied users.
Protocol: The study will consist of *three phases*: (1) the user will *train* on the system in order to alleviate learning effects; (2) the user will perform each of the three tasks in a counterbalanced order; and (3) the user will provide subjective feedback on the difficulty of each of the tasks.
Objective Metrics: We will measure number of mode switches, and total task (task efficiency) and mode-switching time.
Subjective Metrics: We will ask users to evaluate, in a post-hoc questionnaire, the difficulty of each of the tasks, modeled around the NASA TLX [30].
Hypothesis: We expect that mode-switching will take up a significant portion of the time and effort spent on the tasks, and that more difficult tasks will require more frequent mode-switching.

Study 2: User Reaction to Time-optimal Automatic Mode-Switching. To investigate **Q2**, we will automatically change modes according to a time-optimal policy. While the time-optimal policy is not learned directly from the users, it is an intuitive strategy which was effective in a simplified experiment during our preliminary work (Sec. 6.2).
Manipulated Variables: We will manipulate whether the robot uses automatic mode switching according to a time-optimal policy or no automatic mode switching.
Subject Allocation: We will use a *within-subjects* design, in which each user evaluates both options, without being informed of which option the current system is using. This study will first be performed with able-bodied users and then with SCI users.
Protocol: The study will consist of *three phases*: (1) the user will *train* on the system in order to alleviate learning effects; (2) the user will perform the required tasks with and without the automatic mode-switching with a counterbalanced ordering; and (3) the user will provide subjective feedback on each of the two conditions. The tasks that the user is required to perform will be the same as those in Study 1—multiple tasks for able-bodied users, and in expectation of fatigue and limited session duration, the SCI users will perform only a single task.
Objective Metrics: We will use the same objective measures as in Study 1, and we will also measure the number of times users changed modes immediately after an automatic mode-switch under the automatic switching condition as an indicator of resistance to the robot's policy.
Subjective Metrics: We will ask users to evaluate, in a post-hoc questionnaire, their preference between the two conditions and how in control they felt. We will also ask about their perceptions of task performance and cognitive load, again using the NASA TLX as a model.
Hypothesis: We expect that able-bodied users will prefer automatic mode switching based on our preliminary work, but that SCI users will prefer automatic mode changing less due to a feeling of losing independence. Further, we expect that the objective metrics will show faster task times, fewer mode switches, and shorter mode switching times for automatic mode switching.

What is good enough? If automated mode-switching is perfect, then users would *never* have to mode-switch themselves. Thus, the number of user mode switches is a good quantitative metric for how good the assistance is. In addition, we propose to use task completion time, and results from our questionnaire to evaluate if time-optimal mode-switching assistance is good enough.

Study 3: User Reaction to Learned Mode-Switching. To investigate Q3, we will compare time-optimal mode-switching to one learned from user demonstration. A key concern is the challenge of gathering sufficient data from SCI patients. We propose to use a model learned from able-bodied users to assist SCI patients. The efficacy of this model will inform us whether we need to learn models specifically for each SCI patient. We will use the exact same setup as Study 2.
Hypothesis: We expect that both able-bodied and SCI users will prefer the learned assistance model. Further, we expect that the objective metrics will show faster task times, fewer mode switches, and shorter mode switching times in the learned mode switching condition.

Study 4: Learned Mode-Switching Under Goal Uncertainty. To investigate Q4, we will compare mode switching using the QMDP policy under goal uncertainty with direct user teleoperation, with both able-bodied and SCI users. Our key concern is how well users would be able to interpret the system's assistance given that it only has a distribution over possible goals. We will use the same exact setup as Study 2.
Hypothesis: We expect, again, that both able-bodied and SCI users will prefer the learned assistance model. Further, we expect that the objective metrics will show faster task times, fewer mode switches, and shorter mode switching times in the learned mode switching condition.

Timeline. We have carefully organized the four studies such that they can be completed at the end of each of the four proposed years. We will repeat the pattern of running able-bodied user studies first, followed by SCI user studies at RIC.

Y	Question 1		Question 2		Question 3		Question 4	
1	S1-A	S1-S						
2			S2-A	S2-S				
3					S3-A	S3-S		
4							S4-A	S4-S

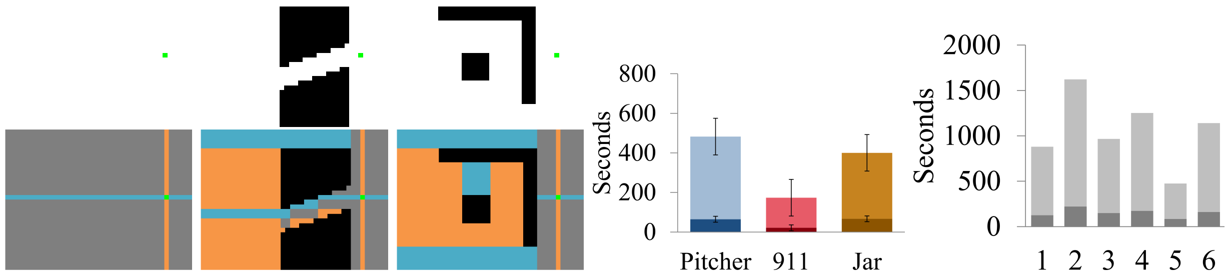
A: able-bodied users, S: SCI users

6.2 Preliminary Findings

We have already performed preliminary work on mode switching in the context of a 2D simulated robot. In these experiments, two control modes were used, where the subjects could only move along the x-axis or the y-axis, can could change between modes by pressing a button. Able-bodied users were asked to maneuver the goal shown in green on in three different tasks shown in Fig.5. We found that by identifying for each location of the robot which mode would give a faster path to the goal, we could correctly predict the mode in on average 85.7% of the time.

Using this model to perform automatic mode-switching with able-bodied users, we asked users to rate their preference between no assistance and assisted mode-switching on a 7-point Likert scale. We found users significantly preferred automatic time-optimal mode-switching to manual mode switching, $t(154)=2.96$, $p=.004$, and responded that they felt comfortable about the robot's switching and thought it did so at the correct time and location. Both responses were significant, with $t(24)=4.72$, $p<.001$ and $t(24)=2.34$, $p=.028$ respectively.

We also started to look into the impact of mode-switching on performance with the MICO arm. Using 6 able-bodied users, we objectively measured the task time and mode-switching time for each of three CAHAI tasks (Fig.4). The results showed on average a startling 17.4% of the task time was spent changing modes and not actually moving the robot. Further, this ratio was fairly consistant among users and tasks, as shown in Fig.5e.



(a) Task 1 (b) Task 2 (c) Task 3 (d) (e)

Figure 5. In the top row are three tasks that the users performed with a 2D robot. The green square is the goal state and the black polygons are obstacles. In the bottom row, regions are colored with respect to the optimal control mode: in blue regions it is better to be in `x` mode, in orange regions it is better to be in `y` mode, and in gray regions `x` and `y` mode yield the same results. Comparison of time spent moving the robot (lighter shade) and time spent changing the robot's control mode (darker shade) both between tasks (5d) and between users (5e).

7 Broader Impacts of the Proposed Work

Applications. The public health impact of the proposed work is significant, by increasing the mobility and independence of those with severe motor impairments and/or paralysis. We will facilitate large-scale deployment within the general public through the following efforts: *(i) The additional components will be almost exclusively software*; additional hardware will be minimal (e.g. a Kinect for RGB-D sensing) and of negligible cost. *(ii) We will partner with Kinova Robotics*, maker of the JACO and MICO arms, to explore the future inclusion of our technology in their software distribution, hugely increasing the number of users reached.

Collaboration with Kinova. We have a collaboration plan in place with Kinova Robotics, to explore the future inclusion of our technology in their software distribution. Kinova furthermore commits to providing technological support for interfacing with their products. (See letter.)

Collaboration with National University of Singapore (NUS). We also have a collaboration plan in place with Prof. David Hsu at NUS whose expertise on machine learning and POMDPs is directly relevant. He also has identical hardware as the PIs, the Kinova MICO arm. (See letter.)

Collaboration with the Rehabilitation Institute of Chicago (RIC). The proposal offers a unique opportunity to collaborate closely with clinicians at the RIC, facilitated by the location of PI Argall's lab. Our unique access to high spinal-cord injury users combined with our commitment to clinically proven hardware has the potential for great societal impact.

Further opportunities for international collaboration. The PIs believe in international experience for their students, to enhance quality of the research and to develop a broad view of robotics research. Srinivasa's PhD student Dmitry Berenson worked on the HRP2 robot at Prof. Satoshi Kagami's lab at AIST Japan under NSF EAPSI 2007-08, which led to Berenson's thesis. Furthermore, Argall was a postdoc at Prof. Aude Billard's Learning Algorithms and Systems Laboratory at EPFL Switzerland, and continues to publish with this lab.

Graduate education. This project will also significantly impact graduate and undergraduate students. Graduate students will have the opportunity to work closely with faculty and facilities at both CMU and NU through student exchange, teleconferences, and group meetings. Students in the PIs courses will be encouraged to participate in this research and be exposed to its results:

EECS-495 Machine Learning and AI for Robotics at NU, and 16662 Robot Autonomy and 16863 Manipulation Algorithms at CMU. Student projects will use and enhance the Kinova MICO arms.

Undergraduate education. The primary contribution to undergraduate education is through direct involvement in research. The CMU project NSF IIS-0916557 and the lab of PI Argall have engaged 7 undergraduates at CMU and 5 undergraduates at NU, including students from underrepresented groups, through class projects, independent projects, workstudies during the school year, and REU summer research. Both labs have developed a self-sustaining culture of attracting top undergraduate students in CS, ME, EECS and BME, and many of these students continue on to graduate school, some with NSF fellowships.

Participation of underrepresented groups. Srinivasa is a mentor for the Robotics Summer Scholars Program for underrepresented students, and has mentored 7 students since 2012 (2 female). His group works with Gwen's Girls (underprivileged girls), and the Tech. Leadership Initiative (underrepresented students). Argall speaks to women in STEM groups at NU and attracts considerable interest from female graduate and undergraduate students in particular.

Public and K-12 outreach: Press Srinivasa generates significant interest from the general public, with features in National Geographic, Scientific American, Popular Science, Wired Magazine, PBS, and the BBC. HERB was named one of the "World's most advanced robots" in Businessweek. Srinivasa's work was featured on the nsf.gov website and on NSF Science Nation. We will use the press office at both NU and CMU to disseminate research results quickly to a broad technical and non-technical audience, and raise awareness about the work of women in science and to stimulate public interest in STEM.

K-12 outreach: Lab tours and talks. Robot projects like ours generate great interest in the community and are frequently targeted by outreach programs in local area high schools. HERB is a magnet for lab tours, with almost one tour a week. PI Srinivasa has hosted kindergarten, elementary, and high school groups, and given talks at local schools. We will add assistive robotic arm scenarios to our existing demo suite. We will demo these research results at CMU at the annual National Robotics Week event for area high schools, which brings over 300 students for a day of lab tours and talks; and at the Museum of Science and Industry in Chicago, which brings in over 12,000 people—largely children—over the course of 2 days.[1]

Dissemination. Research will be published in a timely fashion at conferences and in journals. Code developed will run under ROS and be distributed to the ROS community. Past work by Srinivasa's group contributed significantly to Barrett Technology "puck" motor controller, and to open-source robot control software (the Open WAM Driver). In fact, the HERB robot inspired the NRI WAM+BarrettHand+Segway package. The proposed work will continue to contribute software and impact the extensive research community using the WAM. Srinivasa's group maintains other open-source code including COMPS, a constrained planning framework for manipulation planning; MOPED, for object recognition and pose estimation; CHOMP, a gradient algorithm for trajectory optimization; and GATMO, for navigation among movable objects. The software is used by over 20 research groups around the world.

[1]The Museum of Science and Industry in Chicago is generally considered one of the best technology museums in the world. Demos by NU robotics faculty during the museum's National Robotics Week event are featured in the main rotunda of the building.

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Collaboration Plan

The work of our project will span PI Srinivasa's Personal Robotics lab at Carnegie Mellon University, in Pittsburgh, and co-PI Argall's Assistive & Rehabilitation Robotics Lab (**ar**gall**lab**) at the Rehabilitation Institute of Chicago (RIC), in Chicago.

Collaboration with an Occupational Therapist. Jessica Presperin Pedersen, MBA, OTR/L, ATP, is a Clinical Occupational Therapist in the Wheelchair and Seating Program, and Research Coordinator for its Assistive Technology Module, at the Rehabilitation Institute of Chicago. She has over 35 years experience as an Occupational Therapist, and is clinical staff within the Midwest Regional Spinal Cord Injury Care System (MRSCICS) at RIC. Ms. Pedersen will provide provide clinical expertise on the design of experimental protocols and results analysis, and also clinical support for the participation of volunteers with Spinal Cord Injury. Ms. Pedersen also will participate in the bi-weekly teleconferencing meetings described below. The **ar**gall**lab** lab of co-PI Argall is located at RIC, facilitating this collaboration.

Intellectual collaboration. The PIs propose to use student exchange and co-authored papers as the main means of intellectual collaboration. We propose to exchange graduate students during the summers, and visit each other.

Experimental collaboration. We propose to develop code under the Robot Operating System (ROS) framework developed by Willow Garage. The MICO, HERB and the wheelchair robot of the PIs' groups already run ROS. Our goal is to run the same software stack on all of our robot platforms, thereby demonstrating generality of our algorithms.

Coordination across sites. In order to facilitate tight collaboration on our software development we will hold group meetings via teleconferencing every two weeks, throughout the project. We will additionally hold a co-located project retreat meeting annually, likely in conjunction with a conference that many project members plan to attend (IROS, ICRA, RSS, HRI).

Facilities, Equipment, and Other Resources

Personal Robotics Lab, Carnegie Mellon University Srinivasa founded and directs the Personal Robotics Laboratory. The lab presently contains 9 PhD, 2 Masters, and 3 undergraduate students, and 3 fulltime staff. The lab space, of over 600 square feet, contains student desks; an electronics workbench; over 20 workstations, some outfitted with multiple GPUs for vision processing; a NextEngine commercial 3D laser scanner; a 15 camera Natural Point motion capture system; a StarGazer commercial localization system; a full kitchen with a refrigerator built for HERB; and HERB, a bimanual mobile manipulator outifted with 2 Barrett WAM arms on a Segway base with a suite of sensors including a custom-build 3D spinning laser. The lab also routinely accesses the CMU Big Data computing cluster and the CMU machine shop and 3D printer.

Heterogeneous Distributed Computing The Carnegie Mellon University (CMU) School of Computer Science (SCS) research facility has a large number and wide variety of computers available for faculty and graduate student use approximately 4000 machines. About one-third are Linux/Unix on Intel and AMD platforms, 60% are Windows systems, and Macintosh computers make up the remainder. Every incoming graduate student is provided with a new, high-powered personal computer; some receive a dual-boot configuration - both Windows and Linux. SCS facilities include a rich variety of computing infrastructure services of very high quality: email, shared file service (AFS), authentication, remote access services (VPN, iPass), backup, printing, software licensing, hardware repair, and so on. The SCS environment also includes a growing number of high-performance compute clusters; support services are available for the entire lifecycle of the cluster, including help for specification and purchasing. For all aspects of computing, there is a dedicated support (Help) staff within the facility, which provides full support for users, applications, machines, and services, via a menu of premium support services. Beyond these college resources, the University maintains computation facilities of various kinds for general use. The Pittsburgh Supercomputing Center (PSC) is a joint effort of Carnegie Mellon and the University of Pittsburgh together with Westinghouse Corporation. It is supported by several federal agencies, the Commonwealth of Pennsylvania and private industry. It is a leading partner in the TeraGrid, the National Science Foundation's cyberinfrastructure program. It operates several supercomputing-class machines, including an SGI UV shared memory machine with 4096 cores and 32TBytes of shared memory.

Networking Carnegie Mellon operates a fully-interconnected, multimedia, multiprotocol campus network. The system incorporates state-of-the-art commercial technology and spans all campus buildings in a redundant 10Gbps backbone infrastructure that enables access to all campus systems, including the PSC supercomputers. The University also provides Wi-Fi connectivity in all campus buildings; it has recently upgraded to equipment that supports the 802.11n standard, which provides wireless speeds in excess of 100Mbps. SCS has redundant 10Gbps links to the Carnegie Mellon campus network. The University has redundant 1Gbps links to a combination of providers for internet connectivity. These include Sprint and Level3 for commodity internet traffic, and the Three Rivers Optical Exchange (3ROX) for connections to a number of high-speed research and education networks, including Internet2, National Lambda Rail, ESnet, and Teragrid. The University can also arrange advanced point-to-point research connectivity through services such as Internet2's Dynamic Circuit Network.

General Facilities Information Carnegie Mellon's School of Computer Science is the largest academic organization devoted to the study of computers. Its seven degree-granting departments — the Computer Science Department, the Human-Computer Interaction Institute, the Institute for Software Research, the Lane Center for Computational Biology, the Language Technologies Institute, the Machine Learning Department, and the Robotics Institute — include over 250 faculty, 700 graduate students, and a 250-member professional technical staff. SCS also collaborates with other University Research Centers, including the Software Engineering Institute (SEI), the Pittsburgh Supercomputing Center (PSC), the Information Networking Institute (INI), the Institute for Complex Engineered Systems (ICES), the Center for the Neural Basis of Cognition (CNBC), and the Entertainment Technology Center (ETC).

Data Management Plan

Source code All code produced by this project will be open source, including code for trajectory optimization, generating legible motion, and low-level robot control. The most useful code will be distributed under an open source BSD license at the ROS (www.ros.org) and OpenRAVE (openrave.programmingvision.com) websites. Such code will be developed throughout the course of the project and posted when it has reasonably matured. This code will be further advertised and disseminated through focused workshops. Code will be developed using standard collaborative code development and version control tools, providing automatic backup. Other potential intellectual property produced by the project will be governed by the standard policies of CMU and Northwestern.

Plans for archiving and preservation of access The project team will only use university-authorized servers for long-term storage of raw data, and will rely on archiving and security procedures developed by the respective universities. Each university maintains several terabytes of secondary storage with regular back-up. Another mechanism we will use for archiving data will be analysis and publication or results in the open scientific literature which is archival.

User studies Our data will be generated using up-to-date IRB Protocols as established by CMU and Northwestern and will be HIPAA compliant if patient data should be involved.

Raw data will be automatically generated by computers or retrieved from sensor devices. Raw data include task performance, subjective ratings, questionnaires, and psycho-physiological data. Various formats for data files are developed by different instrument manufacturers, but all files can be converted to a common format (xls, csv or txt) for analysis, manipulation or comparison with other data sets. We may collect audio or video files through use of common video cameras or voice recorders; however this data collection will be optionally conducted based on participants' consent. The data files will contain records of participants' task execution states and interviews, and will be converted to a general format (wav or mov). The faces of participants will be graphically blurred in publications and presentations in images or videos. Data from experiments will be extracted in tabular form to a general format (csv, xls or txt) for import into analysis or spreadsheet software. Contextual details (metafiles) will be written in text-based 'readme files' for explanation of variables, file structure, etc.

Policies for Access and Sharing, and Provisions for Appropriate Projection/Privacy All data will remain anonymous - this includes all information that we collect. To maintain anonymity, each participant will be assigned a number and will be referred to as participant #X. No link will exist between consent forms and data. Only members of the research project will access and view the data in detail. No other researchers will have access to these files.

All participant data, including physiological data and consent forms will be kept separate. The consent forms will be stored in a locked location on university property and will not be disclosed to third parties. Participant name, address, contact information and other direct personal identifiers in consent forms will not be mentioned in any publication or dissemination of research data and/or results by the university. If participants give consent to have their interviews recorded; these recordings will be used by the project team and not otherwise disclosed.

Policies and provisions for re-use, re-distribution Any confidential data related to health issues or physical/mental disorders will not be re-used or re-distributed for the purpose of retrieving and sharing further information beyond this research scope.

Project Personnel and Partner Institutions

1. Siddhartha S. Srinivasa, Ph.D.; Carnegie Mellon University; Principal Investigator.
2. Brenna Argall, Ph.D.; Northwestern University; co-Principal Investigator.
3. Jessica Presperin Pedersen, MBA, OTR/L, ATP; Rehabilitation Institute of Chicago; Other Professional.

Past and Present Collaborators

Collaborators for Siddhartha S. Srinivasa, Ph.D.; Carnegie Mellon University; Principal Investigator.

1. Pieter Abbeel; Berkeley
2. Brenna Argall; Northwestern University
3. Drew Bagnell; CMU
4. Tim Barfoot; UToronto
5. Howie Choset; CMU
6. Aaron Dollar; Yale
7. Michael Erdmann; CMU
8. Jodi Forlizzi; CMU
9. Dieter Fox; UWashington
10. Geoffrey Gordon; CMU
11. Aaron Johnson; CMU
12. Ross Knepper; Cornell
13. Andreas Krause; ETH Zurich
14. Max Likhachev; CMU
15. Kevin Lynch; Northwestern University
16. Pyry Matikainen; CMU
17. Matthew Mason; CMU
18. Nancy Pollard; CMU
19. Alberto Rodriguez; MIT
20. Daniela Rus; MIT
21. Brian Scassellati; Yale
22. Stefanie Tellex; Brown
23. William Townsend; Barrett Technologies
24. Andrea Thomaz; GTech
25. Garth Zeglin; CMU

Collaborators for Brennna Argall, Ph.D.; Northwestern University; co-Principal Investigator.

1. Julie Adams; Vanderbilt University
2. Katherine Barsness; Northwestern University
3. Aude Billard; École Polytechnique Fédérale de Lausanne
4. Brett Browning; Carnegie Mellon University
5. John Burke; SA Technologies
6. David Chen; Rehabilitation Institute of Chicago
7. Sonia Chernova; Worcester Polytechnic Institute
8. Edward Colgate; Northwestern University
9. Henriette Cramer; Mobile Life Centre
10. Kerstin Dautenhahn; University of Hertfordshire
11. Matthew Derry; Northwestern University
12. Magnus Egerstedt; Georgia Institute of Technology
13. Kris Hauser; Duke University
14. Siddarth Jain; Northwestern University
15. Odest Chad Jenkins; Brown University
16. Peter Kahn; University of Washington
17. Kevin Lynch; Northwestern University
18. Giorgio Metta; Italian Institute of Technology
19. Todd Murphy; Northwestern University
20. Ferdinando Mussa-Ivaldi; Rehabilitation Institute of Chicago / Northwestern University
21. Bilge Mutlu; University of Wisconsin
22. Ana Lucia Pais; École Polytechnique Fédérale de Lausanne
23. Adriana Tapus; ENSTA-ParisTech
24. Greg Trafton; US Naval Research Laboratories
25. Eric Sauser; École Polytechnique Fédérale de Lausanne
26. Siddhartha Srinivasa; Carnegie Mellon University
27. Manuela Veloso; Carnegie Mellon University

28. Ying Wu; Northwestern University

Collaborators for Jessica Presperin Pedersen, MBA, OTR/L, ATP; Rehabilitation Institute of Chicago; Other Professional.

1. Farnaz Abdollahi; Rehabilitation Institute of Chicago
2. Tim Caruso; Shriners Children's Hospital
3. David Chen; Rehabilitation Institute of Chicago
4. Ali Farshchian; Northwestern University
5. Ishmael Gonzoles; Northwestern University
6. Denise Harmon; National Seating and Mobility Company
7. Kristi Kirshner; Northwestern University / Schwab Rehabilitation Hospital
8. Mei-Hua Lee; Michigan State University
9. Allison Lichy; National Rehab Hospital
10. Ferdinando Mussa-Ivaldi; Northwestern University
11. Camilla Pierella; Rehabilitation Institute of Chicago
12. Lisa Rosen; Rehabilitation Institute of Chicago
13. Elliot Roth; Northwestern University
14. C. Smith; Craig Hospital
15. Elias Thorpe; Northwestern University
16. Jill Sparacio; Sparacio Consulant
17. Diane Thomson; Rehabilitation Institute of Michigan