My research explores how to develop technologies and systems for flexible human-robot teaming across a range of applications, particularly for contact-rich and physically-demanding tasks. While collaborative robotics (i.e., cobots) have been around for almost twenty years, recent ethnographic studies have shown that their deployment in industry is still limited to basic tasks, such as machine tending (i.e., pick and place) [1]. However, even in the manufacturing context, there exist other opportunities for cobots, such as in physically-demanding tasks that are injuring workers (e.g., sanding, grinding, torquing fasteners). Though deep learning approaches to robot autonomy have made significant advances in the past decade, current methods are far from generalizing in a way that enables flexible tasking, particularly in complex, contact-rich tasks [2]. As an alternative to fully autonomous systems, I believe that advancing techniques that combine iterative learning and human-in-the-loop interactions can drive further adoption of collaborative robots.

For example, imagine you are a worker in a factory trying to configure a robot to perform a repetitive sanding task (such as in Figure 1c). Autonomous methods require access to large datasets or accurate simulations. Conversely, manual programming methods require arduous specification and refinement phases that are sensitive to the variability of the physical processes. Instead, I envision a paradigm that leverages Learning from Demonstration (LfD), human feedback, and iterative learning. For example, a worker can naturally demonstrate the task a handful of times; the robot learns a task model that reasons about uncertainty; the robot assesses and explains its task understanding; and the human shifts to a collaborative or supervisory role, providing feedback and corrections as the robot executes the task. Ultimately, the robot refines its task understanding and requires decreased supervision.

Realizing this vision in a generalizable way will require advances in many individual technologies, from how to effectively encode robot behaviors to how to develop intuitive real-time interactions between robots and human teammates. Much of my previous work has focused on developing foundational methods necessary for creating effective-human robot teaming. Specifically, the main areas I have explored are (1) methods for informed shared autonomy during the execution of contact-rich tasks and (2) approaches to acquire and parameterize robot behaviors. Moving forward, it will be equally important to study how human-robot teaming is enabled by combinations of these technologies and the interaction effects between technologies.

Previous and Current Research

Shared Autonomy for Contact-Rich Tasks

My doctoral research has primarily focused on developing shared autonomy methods for contact-rich tasks. Shared autonomy methods arbitrate control between a user and robot for tasks that are difficult to automate [3]. Recent work has looked at using human inputs as corrections to the robot policy and focused on inferring necessary changes to the weights of a robot's reward signal [4]. Notably, past research only addresses inferring kinematic augmentations through physical human-robot interaction, such as inferring desired end-effector orientation or distances from obstacles. However, the types of useful corrections vary depending on the task and often extend beyond kinematic variables, particularly in contact-rich tasks. *My key insights were to generalize the notion of human corrections to arbitrary robot state variables and to shift the focus of*

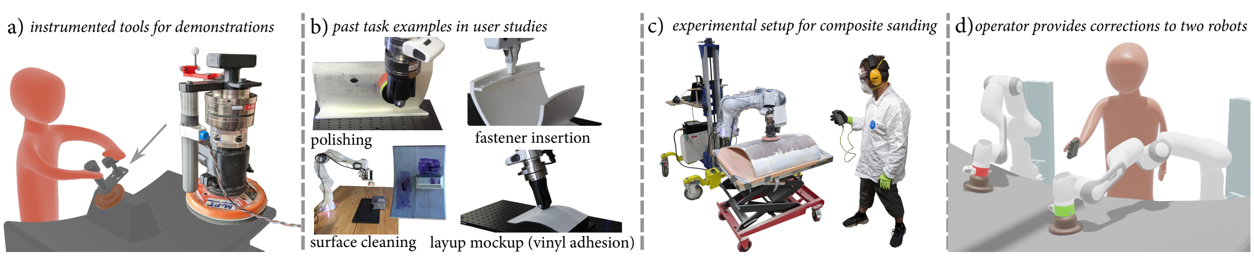

Figure 1: Past and current work in shared autonomy. (a) Learning from Demonstration approach to extract nominal behavior and corrections using instrumented tools. (b) Example tasks assessed using corrective shared autonomy. (c) Platform for future sanding evaluations with representative end users. (d) Current work where an operator provides corrections to two robots with staggered executions to offset periods of task variability.

learning from rewards to inferring task-relevant corrections an operator may wish to provide. For example, the relevant corrections during sanding often involve modifications to the abrasiveness, which is a combination of the applied force, tool pitch, and tangential velocity. In my method, *Corrective Shared Autonomy* [5], a robot executes a nominal policy and an operator layers corrections on an as-needed basis using a joystick-like haptic input. I proposed an approach to provide corrections to any controllable state variable using a decoupled input and showed the approach enabled users to complete physical tasks (e.g., layup, polishing, and fastener insertion) when the nominal policy lacked the robustness to complete the task.

In follow-up work, I showed how variability in expert demonstrations can be used as an indicator for the types of corrections an operator may wish to provide [6]. As a simple example, large variations in force during one section of the demonstrations may indicate that operators may need to provide corrections to force during that section. Through experimental investigation, I demonstrated a principal-component-analysis (PCA) based method that can extract a latent space of corrections, including coordinations of state variables, from within the demonstration variability and automatically provide a spatially-grounded input mapping for operators to provide the corrective input. Through a user study, I showed that this method enabled the completion of surface-cleaning tasks using two different degree-of-freedom inputs and that the automatically inferred input mappings scored high usability ratings [7]. To my knowledge, my methods were the first shared autonomy methods enabling human-robot teaming on tasks involving significant interaction with the environment.

Acquisition and Parameterization of Robot Behaviors

Learning from Demonstration is one promising approach for encoding robot behaviors where experts perform multiple demonstrations of a task from which a robot learns a task model [8]. Ideally, such demonstrations can be performed in a way that is natural for the user, such as through video [9] or instrumented tools [10]. One major challenge in this paradigm is the transfer from human demonstrations to robot behaviors, given the differences in dynamics and kinematics between humans and robot platforms. To facilitate informed transfer of skills, I collaborated with *Guru Subramani (now at Intuitive Surgical)* to develop methods for extracting common geometric constraints from demonstration (e.g., planar motions when writing on a surface, revolute motions when opening hinges and doors) using a pair of instrumented tongs. Through a user study, my method achieved high-percentage accuracy across eight geometric primitives and showed how knowledge of the constraint can inform a control and impedance strategy during robot execution [11]. In follow-up work, I investigated how to identify and leverage common human strategies during natural demonstrations. Specifically, I demonstrated that orientation slip, for example when a person lets a handle rotate within their hand when opening an oven door, can be recognized and parameterized from kinematic and wrench data during constraint inference and leveraged for robot execution [12] (see Figure 2a/b).

In collaboration with *Emmanuel Senft (now at Idiap Research Institute)*, I have also explored end-user programming methods to task robots in remote and collaborative settings using tablet-based augmented reality (AR) interfaces (see Figure 2c/d). The motivation is to allow novices to program complex chains of primitive behavior by leveraging abstractions (e.g., move all objects in a region) and the visual grounding of an AR in-

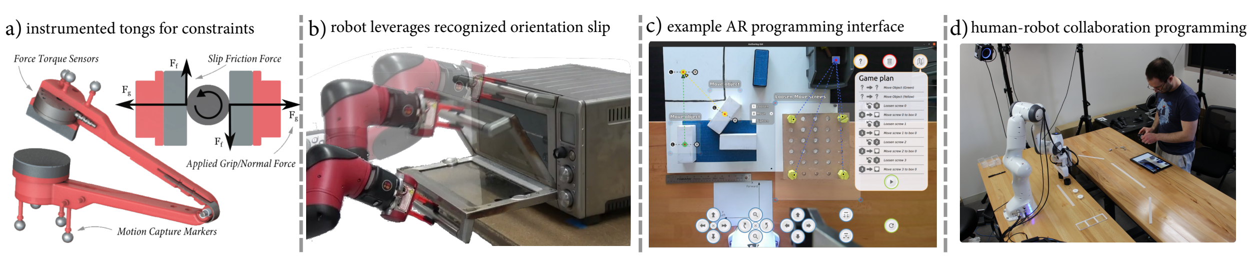

Figure 2: Past work in specifying robot behaviors. (a) Instrumented tongs that capture kinematics and interaction wrenches during demonstrations for use in inferring constraints. (b) Example task where a robot leverages slip that was parameterized from expert demonstrations to improve its kinematics while opening a toaster oven (c) Augmented reality interface for programming sequences of high-level robot actions (d) Example scenario of applying tablet-specified trigger-action programs to quickly configure a collaborative assembly task.

terface. Specifically, by adding an RGB-D camera to the end effector of a robot manipulator, I demonstrated that novice users can remotely task robots to perform complicated multi-step tasks, such as kitting or sorting [13]. In follow-up work, I showed how similar interfaces can be combined with trigger-action programming rules to quickly specify human-robot collaborations such as collaborative-assembly tasks [14].

Overall, I have demonstrated several new mechanisms for creating robot programs across multi-step and contact-rich tasks. My work in LfD introduced the notion of parameterizing and leveraging human strategies during learning and my work in remote programming has enabled programming of long-horizon and collaborative tasks using a fraction of the required operator input of previous methods.

Current Efforts

Recently, I have focused on efforts to assess my previous work in relevant real-world applications and to increase operator utilization during shared autonomy. Specifically, I am investigating (1) a more realistic test bench to assess the shared autonomy and end-user programming work in sanding tasks and (2) methods to scale my shared autonomy approach across multiple robot agents (see Figure 1c/d).

Working with engineers at Boeing, I created a robot sanding platform to assess combinations of my previous work. The setup is motivated by composite sanding tasks in aviation manufacturing and combines tablet-based end-user programming [13], human-in-the-loop registration of task geometry [15], and real-time corrections using a custom haptic input [16]. This system was shipped to Boeing in Washington and demonstrated to project stakeholders, Boeing engineers, and executives. I am currently planning an expert evaluation to investigate the *usability, ergonomics, and performance of the system*.

In collaboration with *Dylan Losey at Virginia Tech*, I am investigating opportunities to scale my current shared autonomy approach to the multi-agent setting where one operator provides corrections across multiple homogeneous robot executions. The motivation for this project is that many tasks have small regions of variability that require intermittent operator intervention but leave the operator idle otherwise. For example, during fastener insertion, the overall process requires fetching, prepping, and installing fasteners, however, there may only be uncertainty during installation from poor registration between the robot and workpiece. By scaling and scheduling multiple executions around robot uncertainty, it may be possible to significantly improve operator utilization and engagement.

Future Research Agenda

In the absence of robust and flexible automation, there is a need for human-robot teaming systems that can quickly be tasked, refined, and work effectively alongside humans. In my past work, I have developed techniques for acquiring robot behaviors and methods for shared autonomy that allow an operator to interact with mostly-autonomous systems. Going forward, I will continue to develop techniques for advanced human-robot teaming and to build and assess end-to-end systems that combine techniques. I look forward to building a long-term research program in these areas, continuing to develop new foundational paradigms for effective human-robot-teaming, and ultimately leading the field towards impact in society. In this section, I describe both my short-term research agenda as well as some long-term research questions.

Short-Term Research Focus

To move towards my goal of flexible human-robot teaming, I will extend my research in several directions in the next two to three years, mainly focusing on the area of shared autonomy. In my previous work in shared autonomy, learning is leveraged to define the subset of corrections that an operator can provide during tasks with a high-dimensional state space. Much of the other work in learning and corrections has focused on inferring changes to robot behavior based on operator corrections. One natural question is *how to combine* *these approaches into a two-stage learning framework for corrections* where both the space of admissible corrections and robot behavior evolve with continued use of the system.

Additionally, much of the work in robot corrections focuses on *real-time interactions* with a robot policy. However, in realistic teacher-student scenarios, feedback often spans different levels of interaction. For example, a teacher may provide low-level feedback (i.e., signal level), higher-level strategic feedback, or post-hoc feedback after a task has been completed. Extending recent mixed-feedback methods [17], I will investigate *what combinations of feedback can be used to effectively complete contact-rich tasks*.

Finally, to further increase scalability and utilization of humans, I will continue investigating multi-robot shared autonomy. Instead of using explicit scheduling, I plan to generalize to the setting of inverse reinforcement learning [18] where the robot can *learn a reward-based task representation and state-based confidence metric that can be used to sequence multiple agents while an operator provides oversight and feedback*.

Human-centric Robot Skill Acquisition and Refinement

There are many challenges in moving state-of-the-art Learning from Demonstration and programming methods from the lab to use with the intended target populations. In Learning from Demonstration, some of these challenges include addressing the heterogeneity of demonstrations, personalization for different end-users, and the balance between expressiveness and generality of task models [19]. In end-user programming, some challenges include levels of abstraction, prior knowledge, and the knowledge representation [20]. Furthermore, when considering robot skill acquisition in the context of human-robot teaming systems, it is important to consider the legibility and explainability of the resulting behaviors.

I am interested in exploring *how combinations of these tools can be used to effectively define and refine robot behaviors for complex tasks*. In particular, I am interested in studying the impact of different levels of task abstraction (e.g., task primitives, hierarchical models, reward-based models) on policies for human-robot teaming. I am also interested in exploring how multiple modalities of input (e.g., natural demonstrations, AR programming, haptics, natural language) can be leveraged and combined to define, visualize, and refine a policy. As policies become more advanced, there is also a need to couple behavior-learning techniques with emerging methods for AI explainability to increase bidirectional communication in human-robot systems.

Inter-domain Formalisms for Shared Autonomy

Shared autonomy offers opportunities for assistive robot policies across a wide range of applications. However, many of the current systems and assistance policies are designed and evaluated in context-specific scenarios [21]. While inevitably there will be context-specific decisions in systems, I believe there are opportunities to develop more general methods and guidelines for deploying shared assistance in systems.

Many factors influence the requirements of a shared autonomy system, including the level of operator skill, the criticality of the task, and environmental factors (e.g., collocated vs remote, delay, visual context). I am interested in exploring *how task and operator factors correlate with desired features in a shared autonomy system* (e.g., level of input, input method, arbitration). Ultimately, I want to develop evidence-based guidelines for developing shared autonomy systems for a given context and end user. I plan to systemically investigate these relationships alongside domain experts that I have collaborated with previously (e.g., aerospace manufacturing, space robotics, medical robotics) to develop and assess solutions in realistic environments with realistic end users. I will also establish new partnerships in other relevant domains (e.g., home care, rehabilitation). Techniques will be deployed and evaluated across different domains to avoid overfitting of solutions. I also believe that investigating a large range of domains will help to expose domain-specific problems and to create varied datasets that benefit the larger shared autonomy community.

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