My research explores how to develop technologies and systems for flexible human-robot teaming across a range of applications. While collaborative robots (i.e., cobots) have been deployed in industry for fifteen years, recent field studies have shown that their use is still limited to basic tasks, such as machine tending (i.e., pick and place) [1]. In the face of a US labor shortage [2], there is an urgency to unlock new opportunities for cobots, including for physically demanding tasks that exacerbate labor issues by injuring workers (e.g., sanding, grinding, torquing fasteners). Though deep learning approaches to robot autonomy have made significant advances in the past few years, current methods are not yet enabling flexible tasking, particularly in complex, contact-rich tasks [3]. Furthermore, there are many domains where human presence is desired, such as when tasks are undefined, critical, or require collaboration between humans and robots. **My research vision is to develop interfaces that integrate human knowledge and robot autonomy**. To realize this vision, I aim to advance many technologies, from how to effectively encode robot behaviors to how to develop intuitive real-time interactions between robots and human teammates. I will also study how the quality of human-robot teaming solutions is impacted by *different combinations* of technologies.

Past Contributions: Toward Effective Interactions in Contact-Rich Tasks

Much of my previous work has focused on developing the foundational methods necessary for creating effective-human robot teaming. In particular, I have focused on contact-rich tasks that are difficult on people and difficult to fully automate. Specifically, the main areas I have explored are (1) methods for *informed shared autonomy* during the execution of variable tasks and (2) approaches to *acquire and parameterize robot behaviors*.

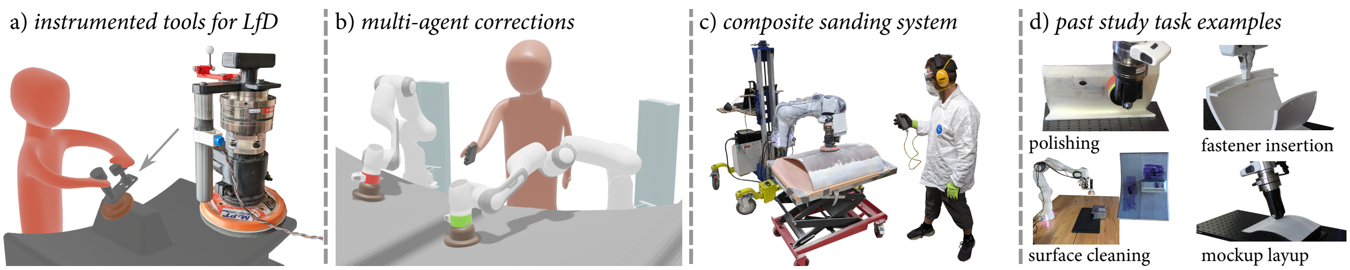

Figure 1: I develop tools and methods for skilled workers to interface with robot autonomy. Examples from past work include developing (a) Learning from Demonstration approaches to extract correctable robot behaviors, (b) methods to scale shared autonomy to multi-agent settings, (c) systems to evaluate approaches in realistic manufacturing settings, and (d) suites of representative manufacturing tasks for evaluation.

Area 1: Shared Autonomy Approaches to Handling Task Variability

My past work developed shared autonomy methods (i.e., arbitrating control between a user and robot) [4] for tasks involving prolonged environment contact, such as sanding or polishing. *My key contributions were to shift focus from learning rewards from corrections to inferring the task-relevant corrections an operator may wish to provide; to show how the resulting high level-of-autonomy systems enable multi-robot scaling opportunities; and to show how such technologies can embed in larger, practical human-robot teaming systems*.

Corrective Shared Autonomy – The types of task variability and resulting need for corrections vary depending on the given task. For example, the relevant corrections during sanding often involve modifications to the abrasiveness (e.g., *sand harder*), which is a combination of specific parameter augmentations to the applied force, pitch, and tangential velocity of the tool. To enable general robot corrections, I developed a method [5] to layer differential operator corrections to a robot's nominal policy using a joystick-like haptic input. The approach allows for corrections to any controllable state variable using a decoupled input and automatically proposes input mappings for low-dimensional operator corrections. The method is based on expert task demonstrations and uses principal component analysis and dynamical systems to automatically extract stable robot behaviors and operator interfaces for user's to address likely sources of task error. Through user studies, I showed how the resulting implementation achieved high usability ratings and enabled users to complete physical tasks (e.g., the layup, polishing, and fastener insertion tasks in Figure 1d) when the nominal policy lacked the robustness to complete the task.

Correcting Multiple Robots – Many tasks have small regions of variability that require intermittent operator intervention. 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. In traditional shared autonomy, such tasks would leave the operator mostly idle waiting to provide intervention. I proposed a solution that improves operator utilization and engagement by scaling and scheduling multiple executions around robot uncertainty (i.e., likely times of needed assistance). In collaboration with *Dylan Losey at Virginia Tech*, I developed a method to scale shared autonomy to the multi-agent setting where one operator provides corrections across multiple homogeneous robot executions (see Figure 1b) that are sequenced around probabilistic estimates of confidence [6]. Through a preliminary study with two robots completing a sanding task, we exemplified how the proposed method can increase worker efficiency *by more than 60 percent* without impacting task performance.

Systems and Deployment – Working with engineers at Boeing, I led a team of university researchers to create a collaborative sanding platform to assess the impact of different human-robot teaming paradigms, including corrective shared autonomy (see Figure 1c). The setup was motivated by composite sanding tasks in aviation manufacturing and combined tablet-based end-user programming [7], human-in-the-loop registration of task geometry [8], and real-time corrections using a custom haptic input [9]. We developed sanding case studies to assess different human-in-the-loop workflows and the system was demonstrated on-site at Boeing to project stakeholders and engineers.

Area 2: Acquisition and Parameterization of Robot Behaviors

My past work has focused on transferring human knowledge, specifically *environmental constraints* and *sequential task plans*, to robot behaviors. *My key contributions were to exploit human manipulation strategies in constrained manipulation (e.g., slip) and to demonstrate augmented-reality programming interfaces that enable the contextualized programming of multi-step multi-agent tasks.*

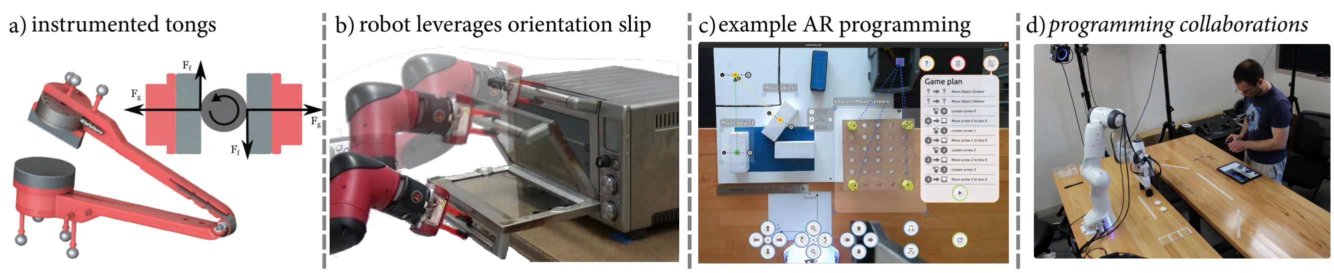

Figure 2: My work connects user input with underlying robot task structure. Examples from past work include using (a) instrumented tongs to identify manipulation strategies, (b) task affordances to improve robot execution in constrained tasks, and (c) augmented reality user interfaces to program high-level task specifications and (d) interdependent collaborative task behaviors.

Inferring Environmental Constraints – Ideally, experts teaching robots through demonstration can leverage a natural interface that does not impact the demonstration quality (e.g., an instrumented tool or video recording) [10]. To facilitate informed skill transfer, I collaborated with *Guru Subramani (now at Intuitive Surgical)* to develop methods that extract common geometric constraints (e.g., planar and revolute motions) from instrumented demonstrations (see Figure 2a) using formulations from multi-body dynamics and nonlinear optimization. I also showed how similar formulations can identify common human manipulation strategies, specifically slip [11] (see Figure 2b). In a user study, our constraint inference method achieved high-percentage recognition of geometric primitives and I showed how knowledge of the constraint (and knowledge of slip) can inform the robot control strategy during execution [12].

Interfaces for End-User Programming – For unstructured tasks, there is a need for methods that enable flexible programming by workers. In collaboration with *Emmanuel Senft (now at Idiap Research Institute in Switzerland)*, I explored end-user programming methods to task robots in remote and collaborative settings using tablet-based augmented reality (AR) interfaces (see Figure 2c/d). We showed that novice users can remotely or collaboratively task robots to perform complex multi-step tasks (such as sorting or assembly [7]), by leveraging abstractions (e.g., move all objects in a region), the visual grounding of a AR interface, and trigger-action programming [13].

Future Research Agenda: Interfaces for Flexible Human-Robot Teaming

My goal is to enable flexible human-robot teaming by connecting *human knowledge* and *robot autonomy*. My future research builds toward this vision by investigating how robots *acquire* and *execute* skills in collaboration with humans. Here I describe key research questions and areas where I plan to focus in future research.

Acquisition: Human-Centric Robot Skill Acquisition and Refinement

Tools to task robots lack the maturity required for deployment in complex environments with domain experts. Reducing this gap requires addressing technical and deployment (e.g., realistic assessments) challenges of robot behavior specification tools. My goal is to improve the effectiveness of robot skill acquisition through human-centered design and combinations of techniques from Learning from Demonstration (LfD) and end-user programming.

Human-centered approaches – There are many challenges in moving state-of-the-art LfD 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 [14]. In end-user programming, some challenges include levels of abstraction, prior knowledge, and the knowledge representation [15]. I will investigate *how new technical approaches co-developed with end users can address current challenges for learning new robot behaviors*. I will build on my expertise in developing natural interfaces and identifying/leveraging human strategy to create personalized interfaces for advanced tasks (e.g., precision tasks within manufacturing). I will develop guidelines that relate interface efficacy with task characteristics and learning approaches (e.g., imitation learning versus offline reinforcement learning) and assess proposed interfaces across a range of challenging tasks. By conducting this research, I aim to develop technical advances to behavior acquisition tools and consequently, raise the complexity of tasks that can be achieved through LfD and end-user programming approaches.

Combinations and Systems – I will also study *how combinations of tools can effectively define and refine robot behaviors for complex tasks*. In particular, I will study the impact of task and interface abstraction (e.g., task primitives, hierarchical models, reward-based models) [15] on policies for human-robot teaming. I will investigate how multiple modalities of input (e.g., natural demonstrations, AR programming, haptics) can be leveraged and combined to define, visualize, and refine a policy in a way that is intuitive for target end-users. As part of this research thread, I will develop tangible interfaces that combine previously-proposed tools for effective interaction (e.g., combining haptic corrective interfaces as part of tablet-based augmented reality programming) and study different technology allocations (i.e., relying more or less on the individual technologies in workflows). My aim is to showcase the value of combined tools and push toward the deployment of new behavior acquisition interfaces in industry.

Execution: Inter-Domain Formalisms for Human-Robot Teaming

Shared autonomy offers opportunities across a range of applications, yet many policies are designed for specific scenarios [16]. While inevitably systems will require context-specific decisions, there is an opportunity to better understand the relationship between task characteristics, operator characteristics, and the human-machine interface; which can lead to the development of more general guidelines for deploying teaming solutions.

Generalization Across Domains and Users – Many factors influence shared autonomy systems, including the level of operator skill, the criticality of the task, and environmental factors (e.g., collocated vs remote, visual context). I will explore *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 establish 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). As a starting point, I will investigate deploying differential shared autonomy methods across a range of domains to assess the impact of users and tasks on method efficacy. By assessing techniques across domains, I hope to develop new databases for data-driven shared autonomy approaches and to develop models for assessing task and user candidacy for shared autonomy approaches.

Multi-mechanism approaches – One design decision for shared assistance paradigms is the mechanism through which users provide input. Even within a single task, it may be most efficient to *leverage a range of levels and mechanisms of human input* (e.g., corrections, discrete input, strategic input). I will develop algorithms that reason about and effectively solicit assistance for effective human-robot teaming. For example, it may be possible to use the agent uncertainty (e.g., uncertainty in the action distribution of a robot policy) to inform the desired assistance. By developing such approaches, I aim to uncover methods that can minimize the effort required by experts when interacting with uncertain agents. I plan to investigate both single and multi-agent settings to develop intuitive and efficient collaboration mechanisms. My aim is to develop multi-mechanism assistance methods that lead to more effective (i.e., minimizing time and effort required by humans) and natural exchanges between humans and robots.

Concluding Statement

Going forward, I am excited to build a long-term research program in the area of human-robot teaming, continuing to develop new foundational paradigms that integrate skilled humans with robot autonomy, and leading the push toward deploying advanced human-robot teaming solutions in practice. In executing on my research vision, I will develop new methods, systems, and knowledge around how robots can acquire and execute skills with humans. Such solutions can change the nature of many types of work; making people more productive, engaged, and safe.

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