Statement of Research — Mike Hagenow

My goal is to **create flexible shared autonomy robotic systems for tasks that are physically demanding, injury-prone, and difficult to fully automate**. Specifically, I have developed a novel approach called Corrective Shared Autonomy (CSA) where skilled operators provide real-time corrections to an otherwise autonomous robot policy. Operators provide corrections through a decoupled input to any robot state variable (e.g., kinematics, applied force, tool speed) required to address uncertainty in the task model (e.g., defects during sanding). I have developed algorithms to automatically extract robot behaviors and admissible types of operator corrections, including coordinations of state variables, and demonstrated the efficacy of the algorithms through user studies with realistic tasks. By creating flexible shared autonomy methods, I hope to facilitate the adoption of human-robot teaming and to ultimately prevent worker injuries in physically straining tasks.

Background

One challenge in deploying robotic solutions for complex tasks, particularly those involving physical interaction, is guaranteeing reliability in the presence of uncertainty. Consider developing a platform for the sanding task shown in Figure 1a. For a robot to autonomously sand, it needs to understand the geometry of the surface, determine the tool path, adaptively set the applied force and compliance, and react appropriately to defects in the surface. Fully autonomous solutions to such processes are either infeasible or require a prohibitively large amount of tuning, which makes them both non-flexible and costly. As a result, many physical tasks are still completed manually in practice. Unfortunately, the tasks that are hardest to automate, such as grinding, sanding, and polishing, often tend to be the most physically demanding, imparting high force and vibration loads on workers [9]. Consequently, repetitive exposure to these tasks leads to many serious musculosketal injuries. One promising solution is to combine a robot and skilled operator as part of a shared autonomy system. In this paradigm, the worker can continue to input expert process knowledge while the physical burden of the task is offloaded to the robot. Ideally, these systems would also minimize the operator's workload as much as possible. One way to minimize workload is to structure operator input as corrections to an otherwise autonomous system. While previous work has developed shared autonomy approaches leveraging corrections as an input modality [11][13][12][3][10][1], there has been little work on complex tasks involving physical interaction.

Research to Date and Future Directions

The premise of Corrective Shared Autonomy (CSA) is that an operator provides the subset of input that is required to address task variability through a decoupled input (similar to a joystick) while the robot handles the remainder of the execution. For example, while a robot performs passes over a surface during sanding, the operator may provide corrections to simultaneously augment the applied force, tool speed, tool angle, and tangential velocity to address intermittent defects. In preliminary work [4], I showed through a user study that CSA allows operators to address variability in tasks such as fastener insertion, polishing, and layup (see Figure 1 B.) and lowers perceived physical demand and effort [8] compared to a common shared control approach and completing the task manually. In follow-up work [5], I showed how instrumented expert demonstrations can automatically inform the nominal robot behavior, admissible corrections, and decoupled input mapping using techniques from Learning from Demonstration (LfD) [14] and demonstrated high system usability [2] in a user study.

In the future, I will continue research at the intersection of controls, human-robot interaction, and LfD to determine how shared autonomy systems can assist workers in a range of physical and complex tasks. To continue to refine the CSA method, I plan to explore advanced task models (e.g., hierarchical models, model conditioning) and the corresponding impact on operator corrections. I also plan to investigate ways to improve operator utilization such as scaling one operator to multiple robot setups by scheduling and adapting their executions around known regions of task uncertainty. Finally, I plan to further study representative tasks (e.g., composite sanding in Figure 1 d.) and explore applications of similar shared autonomy approaches in other domains (e.g., continuing to develop human-in-the-loop systems for space operations [6][7]).

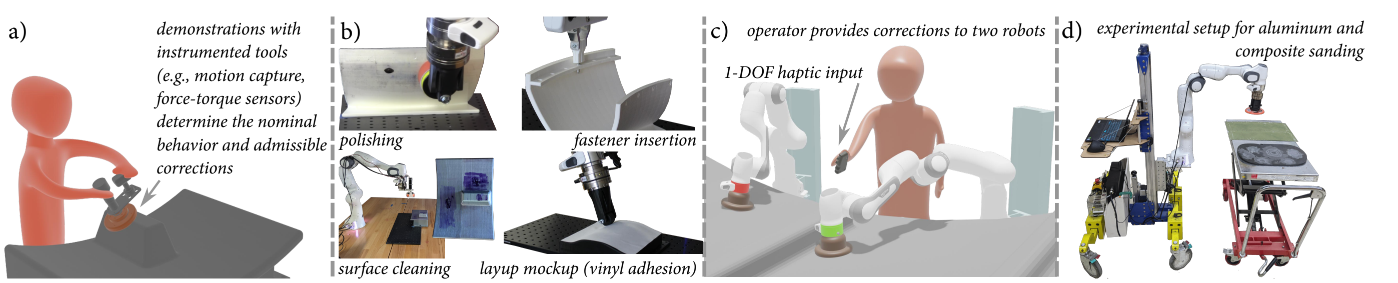

Figure 1: Selections from past and planned work. (a) Learning from Demonstration approach to extract nominal behavior and corrections using instrumented tools. (b) Example tasks assessed using corrective shared autonomy. (c) Future work where an operator provides corrections to two robots with staggered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

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