## Project Narrative

Over the past couple of decades robots have revolutionized technology. Robots have been particularly successful in manufacturing; with typical applications of welding, assembly, and pick-and-place tasks. Current industrial robots offer precise, repeatable actions with sub-millimeter accuracy making them an essential tool in factories and on assembly lines. From the success of the industrial robots, a natural next step is creating autonomous systems that function in less-controlled environments. Expanding the role of the robot and making them more accessible for a multitude of different applications, such as a robotic assistant in the home to a robot used in space exploration. A motivating factor in my research is to develop autonomous systems that can be used in space technology. For example, a dexterous robot could be designed to go where the risks are too great for people and complete tasks such as collecting samples, or repairing equipment.

In order to do this, we need to tackle a fundamental objective in robotics, which is to develop systems that are robust in uncertain environments. Recent advances in robotics have been successful in utilizing robotics in less controlled environments. For example, the Roomba is a robotic vacuum cleaner that can autonomously navigate through the unstructured environment of a home to clean the floors. Another example is the driverless car developed by Google, which has successfully completed hundred of thousands of accident-free autonomous driving miles[5]. Both of these technologies are great advances for robotics; however, these systems target navigation tasks rather than direct manipulation of objects in the environment, a key aspect of creating a robot for space exploration. Although there has been a great deal of research for robotic manipulation in structured controlled environments, manipulation under uncertainty is still a critical challenge and the focus of my research as a graduate student.

The term robotic manipulation encompasses any interaction the robot has that affects its environment, including grasping, pushing, pulling, and using tools to accomplish a more complex tax, such as painting. One of the simplest and most common types of robotic manipulation is grasping. Previous work on grasping has focused primarily on choosing locations for the fingers on the object to achieve stable grasps. However, this methodology in the presence of uncertainty can fail because unexpected contacts can disturb the object. There is no guarantee that we can reliably place the fingers at the intended location, due to failures in either perception or control. This can lead to a wide range of responses: the object could fall over, get pushed out of reach of the robot, or be subject to some other undesired influence resulting in a failed grasp. There have been efforts to account for uncertainty, for example using caging grasps[2]. This work has attempted to deal with uncertainty by giving up on knowing or predicting contacts at all. Although caging results in a grasp, it does not necessarily result in a known grasp that could be useful for future manipulation tasks, like using a spatula that has just been grasped to move a new object.

Although my proposed research focus is on various types of robotic manipulation, I first plan to work towards finding a better solution for grasping. Many solutions to these research problems that are developed in simulation in known and controlled environments won't work in reality since robots have limited and imperfect sensors; ultimately, this problem must be handled as a control problem in a partially observable domain. My work aims to deal with uncertainty in perception and control, guaranteeing with high probability that the robot ends up with a known grasp. Achieving this goal involves analyzing the process of the hand interacting with the object and modeling the behavior of the object as well as the hand. Robust strategies can be developed by anticipating and guarding against undesirable consequences of the robot touching the object incorrectly due to uncertainty. In addition, it is necessary to form a policy that reacts to the way the situation is unfolding, e.g.: if the object begins to slip out to the left, then the robot should react by repositioning its hand.

The first step in designing such a system is to model the interaction between the hand and the object. We can use decision-theoretic methods to formulate this problem. For example, A Markov Decision Process(MDP) is a framework for modeling decision making in situations where outcomes are stochastic and partly under control of a decision maker [3]. We can construct an MDP by describing the actions, transitions and reward functions. By using an MDP we can model the interactions between the robot's hand and the object. Then, we can solve the MDP and find a 'policy' for the robot. This policy can be used to determine the action the robot should take for any state of the robot and the object.

MDPs give a foundation for modeling the interaction between the object and the robot, but assume a completely observable environment. In general, robots do not have perfect state information due to uncertainty from limited perception and noisy, imperfect sensors. However, it is possible to do state estimation using probabilistic inference from sensor measurements to compute a distribution over possible states. Then, the uncertainty of the state distribution, or belief, can be incorporated into the planning process. Partially Observable Markov Decision Processes (POMDPs) are a commonly used model for formalizing decision problems under uncertainty[4]. Since there is uncertainty, the robot cannot directly observe the state of the world; however, using perception feedback and knowledge of our actions expected effect on objects in the world, the robot can maintain a 'belief space', a probability distribution over the set of possible states. A policy for a POMDP is much more complex than an MDP; in an MDP an action is specified for each state, for a POMDP an action is specified for every probability distribution of states in the space. Furthermore, exact solutions to POMDPs in this domain are intractable.

An approach to solving POMDPs is to plan in the "belief space". [1] suggests a method for belief space planning by defining nominal belief space dynamics by assuming future observations will obtain their maximum likelihood values. The dynamics model is then used with classic planning and control methods, such as Linear Quadratic Regulation(LQR) to calculate belief space policies based on a local linearization of the belief space dynamics. During the execution of these policies, the system tracks the true belief based on observations it obtains; if there is a large deviation from the expected observations, the system will begin replanning from the new belief state. Overall, this method is similar to the 'determinize and replan' approximation for MDPs, but it explicitly plans information gathering tasks. When there are surprising observations, the system replans, which makes it robust to unlikely outcomes. By using belief space planning assuming maximum likelihood observations, I hope to achieve known and robust grasps while tolerating uncertainty in perception and control.

This system could be built and tested in simulation, but eventually I would like to test this on a real robot. By participating in a visiting technologist experience, I could potentially have access to the actual hardware, which can help in creating better and more realistic models of the contact dynamics. Once a realistic simulation is created, I can then use the planning in belief space approaches to create a policy for a complex manipulation task that is robust under uncertainty. Furthermore, I could potentially test this policy on an actual robot to verify and refine my results.

A principal challenge for robotics is to perform tasks robustly in unstructured environments. Decision-theoretic methods offer an attractive way of formulating these problems, but the challenge of finding tractable approximate algorithms remain. I am beginning my research focus on using these methods for robotic grasping under uncertainty, however, I plan to use the results to generalize a framework for complex manipulation tasks under uncertainty. Progress in this area could lead to successful complex robot manipulation tasks in uncertain and uncontrolled domains, making it possible for a robot to do meaningful tasks for space exploration. In addition to furthering the field of autonomous technology for space research; robust manipulation tasks in uncontrolled environments have broad applicability in industry, search and rescue missions, assistive robotics, and other potential areas.

# References

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