How to Think about Designing and Controlling Robotic Hands

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***Abstract*—Designing and evaluating versatility in robot grasping is a long-standing challenge. Grasp success is affected by many factors such as object shape, pose, occlusions, and robot accuracy, and formalizing the variations is important for designing effective compensation systems. Rather than trying to design a universal grasp for all objects, we start with the point-solution of an ideal grasp on a simple object, make it locally robust, and then use a set of these template grasps to span a large functional space. We focus on using analysis of *variation budget*—the amount of variation a grasp can tolerate—as a way to evaluate and compare the design tradeoffs between and within systems.**

I. Addressing Variation

Researchers have proposed many strategies in attempt to build a versatile grasping system. However, it is difficult to evaluate and compare different systems when the strategies are so diverse. We posit that analyzing the sources of variations (object geometry and pose, robot and vision inaccuracy, etc.) and relating them to the behavior of specific grasping strategies can provide a cohesive framework to explain system tradeoffs. This can enable prediction of performance on novel objects or under novel conditions.

For analysis, we break a typical grasping system into four subsystems (Figure 1):

The *Task Interface* is used to engage the robot's general capabilities to perform a specific task. The more variation compensations done automatically by the robot, the more user-friendly and autonomous the system is.

The *Perception System* collects data from the real world and creates an internal model of the object and environment. Perceptual inaccuracies introduce variation, whereas more accurate perception reduces variability at the expense of system complexity.

The *Planning-Reasoning System* plans low-level actions such as where to place fingers on an object to overcome variation in shape or pose.

The *Low-Level Control System* is the interface to interactions with the external world, such as closed-loop controllers for joints and passive or compliant mechanisms to automatically adapt to small ranges of external variations.

Existing systems can be analyzed by how they use these subsystems to compensate for variation:

Traditional *industrial manipulators* use careful structuring of the environment and precise hardware design to eliminate variation in the object and the robot. Any variation from task to task is addressed in the task interface, and requires significant reconfiguration to work effectively.

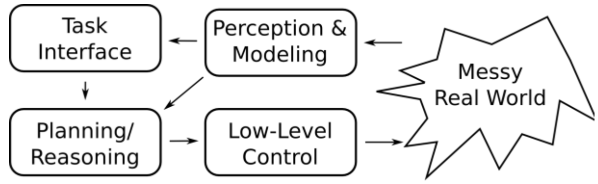

Figure 1: System breakdown of a typical grasping robot.

Underactuated grippers [1] compensate for variations in object pose, geometry, perception errors, and arm positioning errors by mechanical design. Compliance in the fingers allows them to passively adapt to the details of the object geometry, and thereby reduces the load on both the perception and planning systems.

Simulation-based planners such as *GraspIt* [2] use simulation and grasp quality metrics to determine where to place the fingers to overcome variation in object shape and pose. This requires a precise object model from the perception system (usually using *a priori* objects to fit noisy data). Classical versions of these systems do not account for variation in perception or low-level control.

Grasp site strategies [3] compensate for variations in object shape by planning where to put the fingers based on matching grasp sites to templates. The premise is that there is less variation in the grasp site than in the object geometry. They do not compensate for arm accuracy variation.

The *JPL grasping system* uses rigorous sensor fusion to compensate for variations in object pose, perception, and robot registration. This was successful at overcoming many variations across different robots in testing [4].

The *Dynamic Motion Primitive* approach from USC team instead focuses on the use of a carefully-parameterized active compliance in the low-level control system to improve the system's ability to handle positioning and registration errors [5].

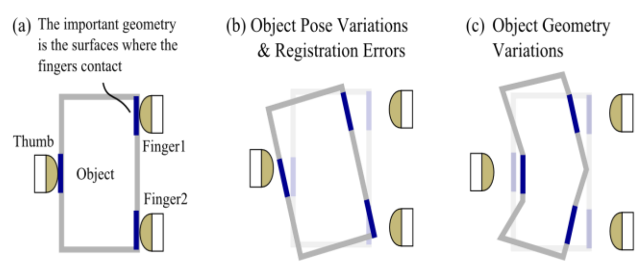

Figure 2: Variations in object geometry from object pose, geometry, registration errors, and perceptual uncertainty

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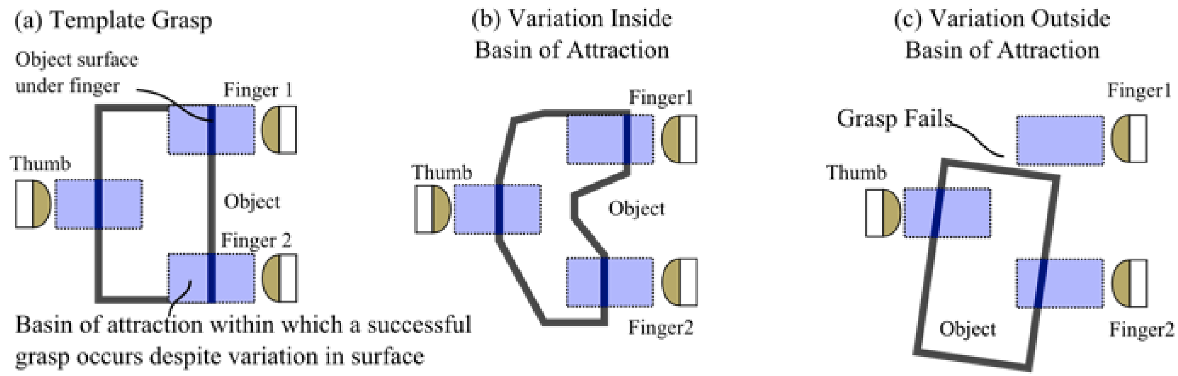

Figure 3: Analysis of all sources of variation generates a "basin of attraction" for variation from the original template grasp. If object surfaces fall within this range under the current variations in geometry, pose, arm inaccuracies, etc., the gasp will succeed.

II. Template Grasps and Variation Budget

Designing a universal hand is an ill-defined problem. Instead, we invert the usual order: rather than starting with an object and determining how to grasp it, we start with a template grasp—an ideal grasp on a simple object, and then create a "variation budget" around it. A variation budget is the range of variation that the system can tolerate for a given template. It is the combination of perception uncertainty, robot inaccuracy, registration error, etc. Its size can be extended using targeted mechanical design, sensor suites, and software strategies. The principle advantage is that within such a specific context, the effects of local variations can be better understood, as well as quantified and therefore compared across disparate systems. To extend system capabilities to a greater range of objects and variations, additional template grasps can be added.

For example, compensating for geometric variations is the focus for much research in grasping. But when put in perspective of a template grasp, all geometric variations (from object, robot, and sensing) can be condensed into one variable: local variation in the surface where fingers contact the object (Figure 2). The impact of surface normal and extent on a grasp's success can then be locally evaluated as basins of attraction (Figure 3). The same evaluation process can be applied to analyze objects and systems.

Generically, a template grasp is a specific method for an ideal grasp on a standard object, like cylindrical power grasp on a bottle or pinch grasp of a pen. It should be designed to leverage mechanical design, sensor suite, and control software to maximize the variation budget of the system. We present here a surface grasp using the iHY hand [1] as an example of this approach. Surface grasp is a three-fingertip grasp of a symmetric object resting on a support surface.

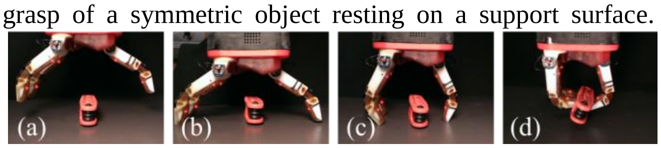

Figure 4: Surface grasp: a) approach surface b) stop - *guarded move* c) scrape surface with fingers - *contact relative motion* d.) tighten grasp – *contact relative motion*

Variations in the height of the surface are compensated by using a guarded approach (tactile threshold) from above, and the impact of varied object size is minimized by sliding the compliant fingers along the supporting surface until contact. The basin of attraction size is set by the range of finger position that result in a force closure grasp. The required performance of the hand and arm, vision, and control software systems can then be related to the size of the basin.

III. Conclusion

We present a framework to understand versatility in robot grasping centered on the idea of template grasps and variation budget. This encapsulates many types of common variations and suggests a methodology for designing better capabilities using discrete skills. It also provides a way to evaluate the versatility of different grasping systems more tractably and understand the tradeoffs between different approaches. This is an important step to move from *ad hoc* approaches towards more rigorous system design and analysis.

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