How to Think about Grasping Systems - Basis Grasps and Variation Budgets

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Abstract In unstructured environments, grasping systems should cope with a wide range of object and environment variations, across size, shape and pose, friction and mass, visual occlusions and shadows, robot control inaccuracy, and many other factors. This paper proposes a framework for analyzing the sources of variations in grasping tasks as a way to understand grasping system performance. The concomitant design approach starts with a collection of *basis grasps*, each a specific arrangement of the fingers on a specific object. Next, we use motion sequences, sensing, and passive mechanics to make these grasps robust to variations in objects, sensing, and control. We then analyze each grasp's robustness to local variation to determine the *basin of attraction*, the range of variation it can tolerate while still achieving a good grasp. Finally, we treat this basin of attraction as a *variation budget* that can be distributed across subsystems to inform system tradeoffs between object variation, perception errors, and robot inaccuracies. The principle advantage is that within the context of specific grasps, the effects of local variations can be understood and quantified, and therefore compared across disparate approaches.

1 Grasping Systems & Variation

Creating versatile grasping capabilities is a longstanding challenge in robotics. Although robots grasp effectively in structured factories, they need to be more versatile

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to handle objects in unstructured environments where many factors affect grasp success, including a wide range of object shapes and sizes, incomplete and frequently inaccurate perception, uncertainties in surface friction and mass, and robot positioning errors. The high-dimensionality of the problem makes it difficult to understand the capabilities and limitations of grasping systems. Analytical methods (such as grasp simulation and manipulability analysis) are limited because real environments contain too many objects described by too many parameters for tractable evaluation. Standardized object sets enable experimental comparison of the performance of different systems, but it is not straightforward to extrapolate from such experiments to predict performance on novel objects. Thus there is a lack of effective system-level metrics, and this poses a major barrier to progress because understanding the capabilities and limitations of grasping systems is essential for comparing the benefits of different approaches, and for evaluating design tradeoffs within and between robot subsystems. As a result, robotics researchers must currently direct their efforts based on intuitive analysis of prior results.

The goal of this paper is to develop a framework for understanding grasping system performance and for designing capable systems. In the first half of this paper, we cast the grasping problem as *overcoming variation* and project it onto a traditional robot subsystem decomposition. This forces explicit examination of which sources of variation matter, and provides a way to understand the tradeoffs between alternate ways to address the variation, which is particularly useful to compare the performance of disparate systems.

In the second half of this paper, we use this approach to build a methodology for designing grasping capabilities. First, we start with a *basis grasp*: a specific finger configuration on a specific object. Second, we design a combination of motion sequences, sensing, and passive mechanics to make grasp acquisition robust to variations in object shape and pose, perception, and robot control. Third, we analyze the basis grasp's robustness to local variation to determine the *basin of attraction*, the range of variation it can tolerate while still achieving a good grasp. Finally, we treat this basin of attraction as a *variation budget* that can be distributed across subsystems to inform system tradeoffs between perception errors, robot inaccuracies, and object variation. To extend system capabilities to a greater range of objects and variations, additional basis grasps can be added. The principle advantage of this approach is that within such a specific context, the effects of local variations can be understood, as well as quantified and therefore compared across disparate systems.

2 Posing the Grasping Problem as Overcoming Variation

The ultimate goal is to build grasping systems that work everywhere, on everything. The challenge is overcoming variation, which comes from a wide range of sources, including object diversity in shape, friction, mass, and pose; perceptual variability due to limited camera resolution, segmentation errors, and occlusion; robot arm and finger positioning errors; noise and sensitivity limits in force sensors; and many

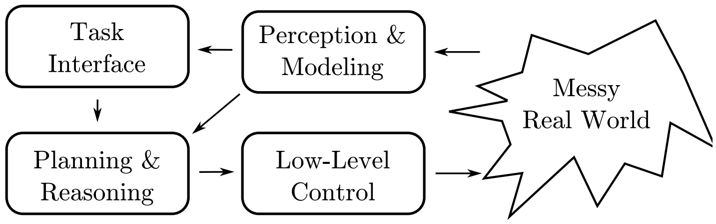

Fig. 1 A typical system breakdown for a grasping robot. The task interface is used to direct the robot's general capabilities to a specific task, setting the required parameters. The perception & modeling system takes raw sensor data from the real world and uses it to synthesize an internal model. The planning & reasoning system uses this model to map the task parameters to the sequence of commands executed by the low-level control, and (if necessary) change the plan based on new feedback from the perception/modeling system.

others. In this section, we present an overview of how the subsystems of a robot grasping system work together to deal with variability. This provides a consistent way to understand the relative advantages of different approaches and to understand the tradeoffs within subsystems, enabling incremental progress in the development of grasping systems.

2.1 System Breakdown

As a foundation for analysis, it is helpful to break out the typical subsystems of a robotic grasping system as described in Fig. 1. This, of course, shows only the major interactions (real systems have more complex information flow), roughly following the classical "sense - think - act" structure.

The *Task Interface* presents the robot's general capabilities to a user so they can engage it to perform a specific task. This can be very simple – how to move individual robot joints – or more complicated – what objects are perceived by the robot, how to grasp them, etc. Robots do not need to autonomously compensate for all sources of variation to be useful, but the more they can overcome automatically, the simpler the task interface is and the better they can function outside static environments.

The *Perception System* gathers and interprets data from the messy real world to create an internal model of the object to be grasped and the surrounding environment. This can both remove variation by creating an accurate internal model, and introduce variation through perceptual inaccuracies. The more detailed the model, however, the more difficult or time-consuming it is to create: a simple 2D view of the facing side of an object is easier to obtain than a precise 3D geometric model that includes the object's far side.

The *Planning-Reasoning System* plans low-level actions such as where to place fingers on an object to overcome variation in shape or pose, and how to sequence corrective actions. It bases these plans on the model created by the perception system, information from the task interface, and any *a priori* knowledge.

The *Low-Level Control* system is the interface to interactions with the external world, such as arm and hand hardware and closed-loop controllers for joints, and passive or compliant mechanisms that automatically adapt to limited ranges of external variations. Choosing the appropriate basis for this control has a large impact on the level of variation tolerated from the rest of the system – stiff position-controlled actuators exert large forces in response to positioning errors from the perception system, whereas force-control loops may require more nuanced reasoning about how to use environmental affordances to maintain stability.

2.2 Robot Grasping Results Viewed in Terms of Variation

Using this framework, prior research in grasping, albeit on diverse and seemingly unrelated topics, can all be seen as working towards coping with variation.

Traditional industrial applications of robots use careful structuring of the environment and heavy, stiff robots to eliminate variation in the object and in robot motion. This severe restriction on object and environment variation allows industrial application to use simple perception, planning, and control systems. Any variation from one object to another, such as switching the production line to a new product, must be addressed through the task interface. Typically, this requires a highly-trained technician to use low-level programing or a teach pendant to reconfigure the system for each new object.

Simulation-based planners such as GraspIt [22] and OpenRave [5] compensate for variations in object geometry and pose by finding the right locations to place fingers to achieve a good grasp. Many different hand poses are sampled, and their quality is evaluated using grasp metrics such as as *epsilon quality* [10] and reachability. These planning systems place a large burden on the perception system because they require a precise, complete model of the object geometry, so, for example, the perception system must fill in raw sensor data by fitting object models from *a priori* object libraries to clusters of points. Most simulation-based planning approaches do not compensate for variations due to inaccuracies in the perception or robot control systems, though recent work by Weitz et al. [29] incorporates this into the grasp quality metric.

Grasp site strategies compensate for variations in object pose and geometry by searching for consistent grasp sites on varied objects. This simplifies the perception system because it removes the need for detailed or *a priori* object models. Instead, this approach attempts to find acceptable grasp sites directly in raw perception data. Saxena et al. search for grasp sites directly in 2D image data [27]. By manually labeling the grasp points for a parallel gripper on a set of objects in simulation, they create visual classifiers for grasp sites by simulating scenes under a wide range of poses and lighting conditions. These classifiers perform well on novel objects outside of simulation. Working with laser range data, Klingbeil et al. use a template to search for regions that match the shape of a parallel-jaw gripper [17]. Herzog et al. present a more generalized approach in a similar vein [12] based on a general grasp site template searched across orientations. This allows the re-use of more complicated grasps from human demonstrations, and results are presented using both a parallel-jaw gripper and a Barrett Hand in two different preshapes. The existing literature does not show how much variation is tolerated in the identified grasp sites, but the overall performance of such systems is strong.

Heuristic grasp planners use empirical rules to determine where to place a hand to compensate for varied geometry and pose. For example, Hsiao et al. create a set of candidate grasps around stereotyped poses and score them based on factors such as the quality of perception data at the grasp site, their likelihood to cause the object to be knocked over, and their proximity to the current position of the gripper [13]. This approach also reduces demands on the perception system, as detailed object models are not required. Understanding the capabilities and limitations of these systems is challenging because it is difficult to connect the collection of heuristics to the range of variation in object shape and pose where they are successful; most papers only characterize system performance against *ad hoc* collections of objects.

Anthropomorphic hands are perhaps the most complex examples of the low-level control system in Fig. 1. These hands attempt to mimic human functionality with three to five highly-dexterous fingers that can exert contact forces in any direction [23, 4, 20]. In principle, the many degrees of freedom in these hands can be used to cope with a wide range of object variation. Unfortunately, understanding how to use this complexity in unstructured grasping has proved elusive. A number of factors contribute to the challenges. The needed interactions with planning and perception systems have not been successfully defined or implemented. There is a considerable body of theoretical work that seeks to compensate for variations in object geometry and task constraints by controlling contact forces; a good review is presented by Shimoga [28]. However, although this provides an elegant way to understand the role of geometric variation, low-level control of these complex machines has been limited by factors such as friction, tendon dynamics, and poor contact sensing. Anthropomorphic hands have rarely been used outside of controlled research settings.

Underactuated hands compensate for variations in object pose, object geometry, perception errors, and arm positioning errors by mechanical design [18, 8, 1, 2]. 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. [7]. Recent work such as the coin-flip primitive presented by Odhner et al. in [19] has extended this approach beyond grasping into manipulation.

The final examples examined here come from three teams in the DARPA Autonomous Robot Manipulation competition that developed systems to perform a set of pre-specified tasks with a known set of objects and tools [11]. These are among the best-integrated and autonomous grasping systems presented to date, so their approach to dealing with variability is of particular interest.

The system created by Hudson et al. [14] primarily used the perception system to overcoming variations in robot arm positioning and camera registration. They modeled the difference between the arm's actual pose and expected pose using an unscented Kalman filter, and made extensive use of *a priori* object models to compensate for occluded camera views. This effectively compensated for variations from both the low-level control system (which introduced positioning errors up to several cm) and from the perception system, and the team achieved top scores in the competition. It provided only a limited solution to object variation; the grasp planner used a full 3D model of each object to create a library of grasp candidates by simulating which hand placements maximize contact surface, and the resulting grasp candidates were manually pruned for each object.

The system created by Schaal et al. [26] primarily used the low-level control system to overcome variation in the arm positioning and object geometry and pose. In their approach, grasping is reformulated from the position domain to the force domain using "Dynamic Motion Primitives" (DMPs). Because the DMP only requires a few parameters, this formulation also enables the effective use of machine learning to optimize the grasping plans. The plans themselves are created from demonstration. Because force-domain execution requires less information about the object than position-domain execution, this approach is more readily adapted to unknown objects. Although *a priori* object models are used in [26] in a manner similar to Hudson et al.'s approach (using iterative-closest-point matching to align model and sensor data), the team was subsequently able to extend it to a model-free approach [12]. An extensive calibration routine is required to compensate for variations in the response of the strain gauges used to measure force.

Bagnell et al. [3] overcame variation by detecting errors and sequencing corrections using behavior trees implemented in a framework called the "Behavior Architecture for Robotic Tasks" (BART). This approach relied on creating a good task interface to sequence and combine primitives in the planning-reasoning system.

Thus these three teams focused on different subsystems in their solutions, with the first focusing on the perception system, the second on the low-level control subsystem, and the third on the task interface and planning-reasoning subsystems. By considering the mechanisms for coping with variability, we can understand why these teams achieved roughly comparable performance despite the use of radically different approaches.

3 Basis Grasps and Variation Budgets

We can also apply the framework prospectively to design and analyze new robot grasping capabilities, again defining grasping capability in terms of the ability to successfully execute a grasp across variation (in object geometry, perceptual noise, etc.). Under this definition, the key challenge to creating broader functionality is to understand what variation matters for achieving a successful grasp, and to design systems that compensate for it. To do so, we invert the usual order: rather than starting with an object and determining how to grasp it, we start with a *basis grasp*, a specific finger configuration, and determine the range of object variation where it

Fig. 2 The i-HY hand.

will work. Second, we enlist the entire robot (perception, planning, low-level control systems) to make this grasp tolerate local variation and still achieve a successful grasp. Third, we analyze the bounds of this variation to determine the *basin of attraction* around the template configuration. This is both a measure of grasping capability, and a metric for where the grasp can be successfully applied. To extend the range of object variation that can be grasped, we can create a collection of basis grasps with different basins of attraction.

The principle advantage is that variation is easier to understand when examined locally as deviation from a basis grasp. This means it is faster to establish which sources of variation are dominant in determining a grasp's success. It is also easier to see how to cope with variations using a robot's full capabilities, and it is more tractable to establish bounds for the system's ability to grasp related objects. In the following section, several examples are presented to illustrate the framework.

3.1 Overhead Three-fingertip Grasp

In the first example, we study the i-HY hand [25] (Fig. 2) in an overhead fingertip grasp on a box-shaped object sitting on a table (Fig. 3). This hand has three compliant, underactuated fingers, each controlled by a separate actuator, along with a fourth actuator that controls the orientation of the two fingers. Tactile sensors are located on the fingers, and the proximal joints are equipped with magnetic encoders; the deflection of the distal joints can be determined from the excursion of the tendon measured at the proximal joints and at the spools on the actuators. In this basis grasp, the fingers are placed on antipodal surfaces of the object.

Determining the object variation range. Now, we analyze the dominant types of variation that limit successful grasps. The point of this analysis is not to demon-

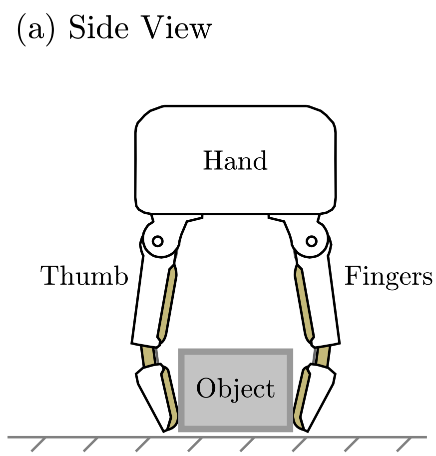

Fig. 3 An example basis grasp: the overhead fingertip grasp on a rectangular prism (a) side view (b) overhead view.

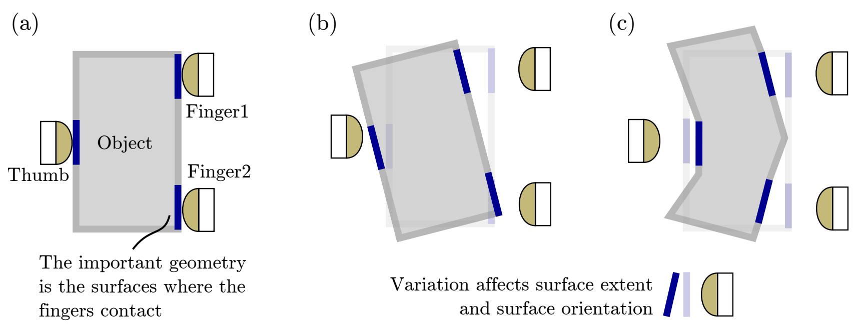

Fig. 4 (a) The important part of an object's geometry is the place where fingers contact the object. This can be used to parameterize variations due to (b) object pose and robot registration and (c) object geometry and imperfect visual segmentation.

strate a method that overcomes any arbitrary source of variation, but to show how such analysis can be used to easily understand the capabilities and limits of a given grasping system. In this grasp (as in many), the dominant factor is object geometry and object pose. The basis grasp is defined with the fingers well-aligned with the hand (Fig. 4a), but if the object pose is rotated due to inaccuracies in the perception or control systems, finger contact locations will be displaced and rotated (Fig. 4b). Simple analysis of finger motions and surface normals can then reveal the range of pose variation where this grasp will succeed.

Similarly, if the object shape is not a rectilinear box, the grasp may still succeed. The key observation is that the only part of the object geometry that affects grasping

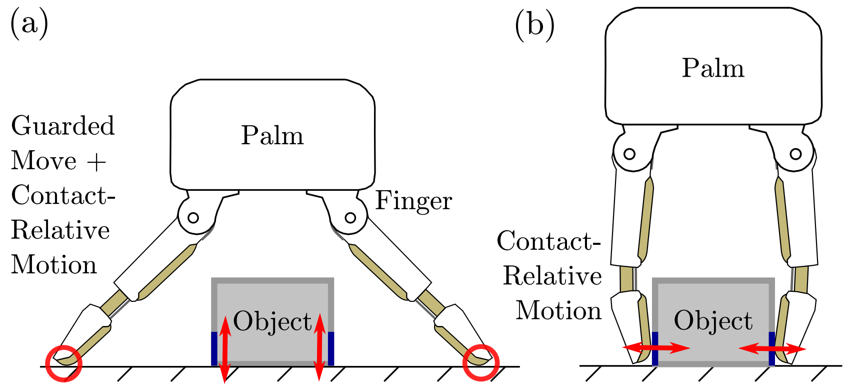

Fig. 5 Sensing, control, and targeted mechanical design can be used expand the basin of attraction. For the surface grasp, (a) a guarded move against the supporting surface is used to compensate for variation in the contact surface height, and (b) contact-relative motion around the object surface is used to compensate for variation in the contact surface extent.

is the contact surface patches where the fingers make contact (Fig. 4c). Thus when the grasp is used as the reference frame (rather than the object, as in traditional grasp analysis), all geometric variations from object, robot control, and sensing can be condensed into one quantity: the local variation in the surface patches where fingers contact the object. Once again, analysis of finger motions and surface normals will specify the range of shape variation (and combination of shape and pose variation) where this basis grasp will succeed.

Extending the grasp variation range. To make this grasp more robust to local variation, we then enlist the other subsystems of the robot, particularly the low-level control system. One variation that is important to take into account is vertical position of the object, due to errors in the perception system, mis-calibration of the robot arm with respect to the vision system, robot control errors, etc. We can compensate for vertical variation by referencing the finger pose to the table supporting the object (Fig. 5). This is done by with a guarded move from above (i.e. approach-until-contact), using tactile sensors in the finger tips to determine when contact occurs. This eliminates the need for precise estimation of the height of the object from the perception system. We also slide the fingers along the table surface as they close – this approach uses the compliance of the fingers to compensate for any minor variation in vertical position that might allow thinner objects to slip underneath the fingertips as they close.

We can extend the basis grasp's tolerance to variation in the width of the object (i.e. the contact surface patches) by again using a guarded move. After the fingers contact the table surface, the hand is lifted incrementally while maintaining fingertip contact. When the tactile sensors in the distal link signal contact with the side of the object, the controller can shift from closing the fingers to increasing grasp

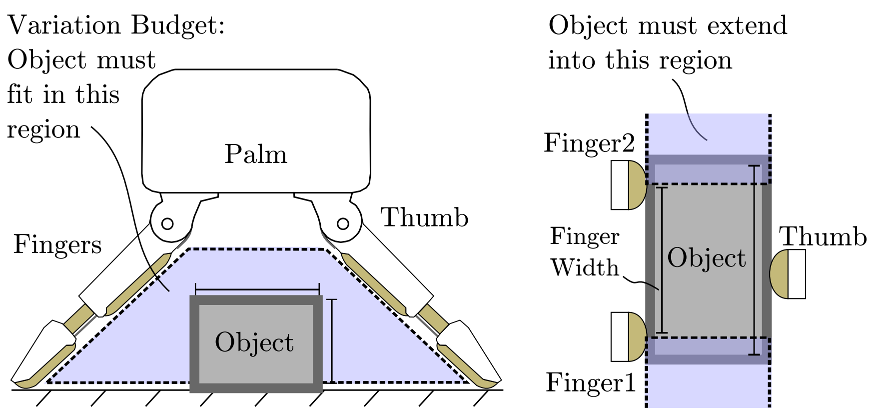

Fig. 6 The basin of attraction for the overhead fingertip grasp when the object is centered in the grasp.

force. Alternatively (or in addition), the joint position signals can indicate that the fingertips have stopped closing. Note that these strategies for dealing with variation in both vertical height and width are based in strategic use of low-level control – neither guarded moves or compliant contact require detailed information from the world model created by the perception system.

Having defined the basis grasp in terms of finger configuration as well as low-level control behavior, we can establish quantitative bounds on how much variation can be tolerated for each important parameter of variation. The fingers must contact the object as they close, which means the object width must fit inside the fingers in order for the acquisition strategy to succeed (Fig. 6-left), and the object must extend laterally past the two adjacent fingers (Fig. 6-right). This forms a performance bound on how much variation in object size the grasp can tolerate, as shown in the shaded region in Fig. 6. Similar analysis can be applied to variation in object orientation, friction, mass, etc. – where selection of factors to include is a function of the dominant balance in a given grasp. We propose the term *basin of attraction* to describe the range of variation the grasp tolerates.

A simple experiment was performed to illustrate this approach, as shown in Fig. 7. A small object (an allen key set, approximately 25 x 25 x 75 mm) was placed on a table and the hand executed the overhead fingertip basis grasp. This process was repeated as the hand was shifted in each direction. Fig. 7-left shows the results for shifting in the width direction, and Fig. 7-right shows the results for shifting laterally. In each plot, the height of the red line above the displacement axis indicates the region of grasp success, which closely corresponds to the simple analysis predicting grasp success.

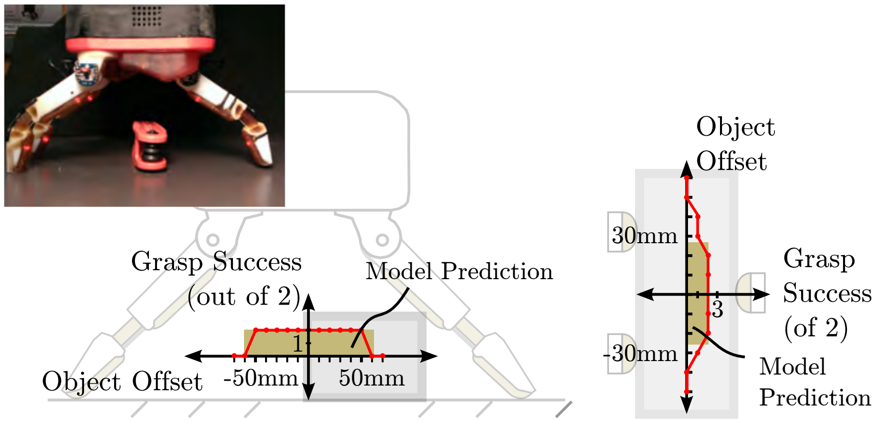

Fig. 7 Experimental validation of the basin of attraction closely matches predicted results. A small object (allen key set) was grasped under a variety of positioning offsets to determine the bounds on the basin of attraction.

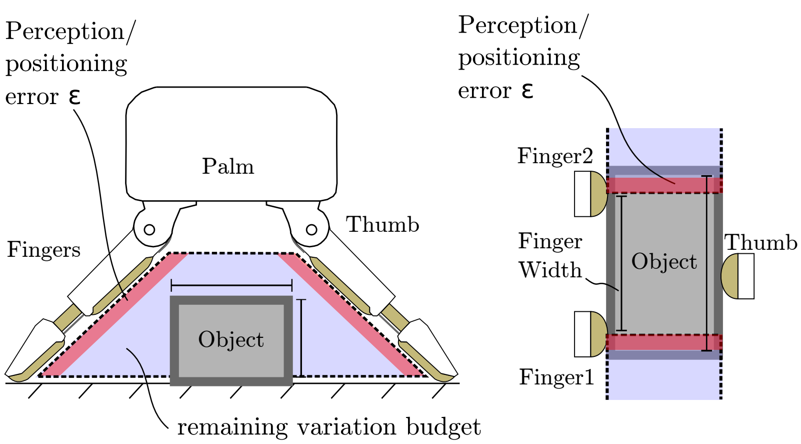

Fig. 8 The basin of attraction serves as a variation budget that can be spent on different subsystems. Here uncertainties due to perception and robot control are represented as the red regions that shrink the shaded region that is available to deal with object variations.

Variation budgets. Now that the limits to variation have been determined, this basin of attraction can be treated as a *variation budget* that can be allocated to the diverse sources of variation for a particular application (Fig.8). For example, the uncertainties due to limitations in the visual perception and robot control subsystems can be determined, and subtracted from the total basin of attraction. The remaining region then defines the range of object variation that the system will be able to deal with effectively - i.e., the overall system's variation performance. This approach makes it possible to evaluate quantitative tradeoffs between different sub-

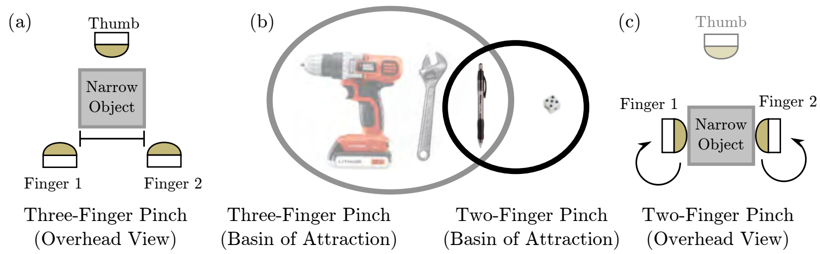

Fig. 9 Building a collection of basis grasps. (a) The Overhead Three-fingertip Grasp does not cover sufficient object variation to grasp narrow objects. (c) A robot's skills can be augmented by adding additional basis grasps, such as the two-fingered pinch. (b) The central panel shows the basin of attraction (circles) for each of the two grasps; the region of intersection includes objects that can be successfully grasped with either basis grasp.

systems and determine, for example, the impact of low-precision arm control or high-resolution RGB-D imaging on the range of objects that can be grasped. It can also be used to compare different grasping strategies and grasping systems.

3.2 *Other Basis Grasps*

A single basis grasp spans only a limited (but defined) range of objects; a collection of them can be used to provide wider capabilities. For example, the Overhead Three-fingertip Grasp cannot grasp objects smaller than the spacing between the adjacent fingers (Fig. 9a). However, another primitive can be constructed based around the pinch configuration, with the two fingers rotated so that they meet in the center (the thumb is not used), as shown in Fig 9c. This extends the hands capability for grasping small objects. The same approaches can be used to generate tolerance of local variation (guarded moves, compliance), but note that there is a different dominant balance for which variation is important for this grasp. Two opposing fingers are less able to resist moments caused by offset center of mass, so the object's mass and alignment with the center of mass matter more than with the three-fingered grasp.

4 Discussion

The goal of this paper is to present a way to reason about dominant effects in the messy problem of robot grasping. Despite a significant effort to find a unified theoretical framework for grasping, none has achieved widespread success. This is perhaps not surprising given the complexity of the physical phenomena involved in robotic grasping – it involves incomplete perceptual data, complex interaction mechanics (varied surface friction, compliance, closed-loop kinematic chains), varied boundary conditions (clutter, affordances), and an arbitrary range of object geometries. The key to creating effective functionality in the near term is understanding where the problem can be condensed, and how to quantify the condensed functionality.

The success of a number of specific grasp primitives in the literature reflects this observation. Although they do not lay out the implications for overall system design, they have achieved some of the most consistent functionality to date. The widespread use of guarded moves can be seen as an example of using local context to narrow the scope of variation so it can be effectively overcome, including work with parallel-jaw grippers [13], compliant hands [24, 21], and more traditional rigid hands [9]. The overhead pinch grasp used by Jain and Kemp [15] is another example, where the stereotyped action provides the ability to use ”low-dimensional task-relevant features” for control. Another example is the push-grasp primitive presented by Dogar and Srinvasa [6]. In this case, sliding frictional contact is used to align a tall object in a power grasp. In this case, the specific context of the grasp primitive makes it possible to analyze the impact of friction on the motion of the object to calculate the translational displacement necessary to align the object in the hand. Kazemi et al. present a force-compliant grasping skill designed to lift small objects from flat supporting surfaces into a power grasp [16] – the context of the surface makes it easy to understand where to use compliance to correct interaction forces, and the basic idea was used by most teams in the DARPA Autonomous Robotic Manipulation Challenge [26, 14].

In all these cases, what is missing has been a good way to compare these different primitives, and a framework to understand how to create more comprehensive capabilities. It is important to note that in many cases, establishing an inner bound for variation tolerance may be sufficient–such an approximation may underestimate system performance, but will not lead to failed grasps.

In conclusion, we present a framework that uses variation as a lens to understand generality in robot grasping. First, we demonstrate that system’s ability to overcome variation provides a way to compare and evaluate the capabilities of different grasping systems and apply it to a collection of leading examples. Second, we present a methodology for designing grasping systems based on the observation that *it is easier to design around local variation than to create effective parameterizations of global variation*. Analyzing variation around specific grasp configurations provides a local context that makes it tractable to create a set of *basis grasps* that span a quantifiable range of object variation. This is an important step to move from *ad hoc* approaches towards more rigorous system design and analysis.

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