Improving grasp performance using in-hand proximity and contact sensing

Radhen Patel, Rebecca Cox, Branden Romero and Nikolaus Correll
University of Colorado Boulder, Boulder, CO 80309, USA

Abstract. We describe the grasping and manipulation strategy that we employed at the autonomous track of the Robotic Grasping and Manipulation Competition at IROS 2016. A salient feature of our architecture is the tight coupling between visual (Asus Xtion) and tactile perception (Robotic Materials), to reduce the uncertainty in sensing and actuation. We demonstrate the importance of tactile sensing and reactive control during the final stages of grasping using a Kinova Robotic arm. The set of tools and algorithms for object grasping presented here have been integrated into the open-source Robot Operating System (ROS).

1 Introduction

Grasping and manipulation tasks are system-level problems that require tight integration of mechanism design, perception, and planning. In a nutshell, a robot has to locate an object, plan and execute a grasp, and finally apply sufficient constraints to the object so that it remains in the robots hand. If the task goes beyond simple pick-and-place and requires further manipulation of the object, the robot also needs to consider the pose of the object. Choosing a perception system, a suitable end-effector, and a feasible plan is a co-design problem that has been dramatically facilitated with the emergence of standardized platforms such as the PR2 robot, Rethink Robotics Baxter, and open-source software such as ROS, OpenCV and MoveIt! [11]. Yet, only very few system-level grasping and manipulation studies exist, notably platforms presented at the Amazon Picking Challenge [13], the autonomous butler Herb [33], the PR2 [6], and other service robots that include manipulation for delivery, assembly or gardening tasks [8,23,12].

These studies are important, because the components of a grasping and manipulation system are difficult to benchmark in isolation. Specifically, it is often unclear exactly what assumptions have been made and how changes in these assumptions would affect the reliability and robustness of the system. At the task level, it is difficult to choose tasks that are representative for a wide range of real world manipulation tasks. For example, it is possible to score well in a pick-and-place competition by exclusively focusing on items that can be retrieved using suction.

The First Grasping and Manipulation competition at the International Conference on Intelligent Robots and Systems challenged the community to solve...
a wide variety of grasping and manipulation tasks that range from simple bin-picking tasks to performing complex sequences of pick-and-place tasks. The competition rules promote general solutions by only combining scores achieved with the same hand. In this spirit, we have developed a comprehensive autonomous grasping solution around a Kinova Jaco 7-DoF robotic arm, RGB-D sensor (Asus Xtion), and a three-fingered hand (Kinova) equipped with proximity and tactile sensors (Robotic Materials). The resulting system combines deliberate planning with reactive control using an intricate grasp state machine whose transitions are driven by 3D-perception and tactile events.

1.1 Related work

We provide a brief overview over related work in the sub fields that comprise grasping and manipulation.

What hand mechanism design is most suitable to address a large variety of tasks remains an open question. At one end of the spectrum there are anthropomorphic hands with multiple degrees of freedom [3, 24]; on the other end there are simple one degree-of-freedom prehensors [1] and underactuated devices [17] or soft robotic hands [19, 20], which are entirely made out of soft and compliant materials or structures rather than of rigid parts. Although intuition would suggest that a robotic end-effector’s versatility is related to its level of anthropomorphism, existing devices have been unable to accurately recreate the features of the human hand, making simple, easier to control designs competitive.

Planning for grasping and manipulation tasks has been traditionally studied using two distinct approaches: knowledge-based approaches and analytic approaches. The former is based on empirical studies of human grasping and manipulation [15], while the latter is based on physical models, that is the interactions between the hand and grasped object are modeled in terms of motions and forces, using the laws of physics [26]. However, each approach has its own disadvantages. As the mechanical and sensorial mechanisms of the human hand are difficult to reproduce and it is yet unclear how sensing and actuation interact, knowledge-based approaches are only of limited use [5]. Also, it is not clear how to generalize human-inspired grasps for novel objects.

Although the analytic approaches may allow a robot to reason about how to grasp a certain object by itself, the abstractions made in the analysis to make it tractable results in models that often are only applicable to simulations or carefully structured laboratory experiments [35]. Due to the limitations of the knowledge-based and empirical approaches, machine learning as a solution to these tasks has been on the rise. Methods vary from observing how humans grasp an object and reducing the configuration space of the robot to find pre-grasp postures [10], learning potential grasp points from 2D images [32], learning via reinforcement and imitation learning [24], to learning graspable and non-graspable objects via 2D and 3D features [23]. In our work, we ignore the problem of grasp generation and hard-code strategies that work well for the competition tasks and the mechanism/sensorial capabilities of our hand.
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Designing a perception system for grasping is strongly dependent on the end-effector choice, the variety of objects that need to be grasped, and on the environment the robot needs to operate in [36]. For example, whether objects will be grasped using suction or require careful alignment with a gripper impose very different requirements on perception. Similarly, methods that compute grasps based on the perceived geometry of an object might work very well for a large number of objects, but might fail with amorphous objects, for example a net of tennis balls [13]. Finally, whether the objects are placed nicely on a table, are cluttered, or occluded, will dramatically change the difficulty of the problem. Some approaches assume complete or partial knowledge of the object to synthesize a grasp hypothesis [13, 25], while others assume no prior knowledge of the object whatsoever [7]. Regardless of the underlying perception approach, grasping is unlikely to succeed when the resulting pose estimates from perception bear uncertainty. Only when execution is robust to uncertainties in sensing and actuation, can a grasp succeed with high probability. There are a number of approaches that use contact and tactile or visual feedback during grasp execution to adapt to unforeseen situations [21, 20]. These approaches increase robustness under uncertainty via some feedback mechanism. Such feedback can be obtained from visual, pressure, force-torque sensors, or proximity sensors [22]. In this work, we are building up on results from [28, 30, 27], which use proximity, distance, and dynamic tactile sensing information, to detect different grasp events and increase robustness of the overall process with respect to uncertainty in 3D perception.

2 Task specification

The autonomous track consisted of two stages: pick-and-place and manipulation. All sets of tasks were required to be performed fully autonomously, that is without human intervention. The pick-and-place stage required contestants to design a system that would pick and then place a set of objects into a designated area autonomously. The majority of the objects could be placed within their designated area without constraints on their orientation. A few objects had to be placed in a specific orientation, for example the hammer and the scissors as shown in Figure 1. The set of objects consisted of ten objects chosen from a set of twenty objects [9] that were disclosed before the competition. These objects were then randomly placed within a shopping basket (Figure 1), and the contestant were allotted 30 minutes to perform the task. Each successful placement was rewarded five points, leading to a maximum of fifty points.

The manipulation stage consisted of ten tasks (Figure 2) that varied in difficulty. The ten tasks were selected from a pool of 18 tasks and were divided into four levels based on difficulty. Contestants that designed a system that successfully completed one of four tasks in level one were rewarded ten points, twenty points for one of three tasks in level two, thirty points for one of two tasks in level three, and forty points for the one task in level four. As a result, a maximum of 200 points could be achieved.
3 Technical Approach

We developed a comprehensive autonomous grasping solution around a Kinova Jaco 7-DoF robotic arm, RGB-D sensor (Asus Xtion), and a Kinova three-fingered hand with proximity, contact and force sensors (Robotic Materials). The resulting system combines deliberate planning with reactive control using an intricate grasp state machine whose transitions are driven by 3D-perception and tactile events. In particular, we developed a general-purpose software pipeline composed of several independent nodes that perform specific tasks such as eye-to-hand calibration, object recognition and tracking, and kinematic control and planning of the arm (Figure 3) in the form of a Robot Operating System (ROS) package, which is available open-source.

3.1 Calibration

To initialize the system, the user needs to first calibrate the RGB-D camera. Our system allows the user to place the camera in a position suitable for their needs rather than rigidly attaching it to a single location. While this allows the system to quickly adapt to a variety of tasks that require different perspectives, mobility adds uncertainty to the model since the sensor’s location in space is unknown. In order to find the transformation between camera and robot frame, we rigidly mounted an augmented reality (AR) tag to the wrist joint of the Jaco arm (Figure 4, left). Once the AR tag is visible to the sensor, the system can estimate the transform between the sensor and the AR tag. Since the position of the wrist joint is known to our model, the system can then estimate the position of the sensor in space using forward kinematics. As a result, we are able to obtain a calibrated scene with an offset error of about 3 cm. The calibrated scene in RViz is shown in Figure 4, right.

1 https://github.com/correlllab/cu-perception-manipulation-stack
Fig. 2: Manipulation tasks from the competition. Clockwise, starting top left. LEVEL1 tasks (i) Scooping peas, (ii) Stirring, (iii) Salt shaking. LEVEL2 tasks (iv) Towel picking, (v) Plugging and unplugging USB lights, (vi) Hammering nails, (vii) Straw inserting. LEVEL3 tasks (viii) Nut fastening, (ix) Syringe pumping. LEVEL4 tasks (x) Paper cutting.

Fig. 3: A flow-chart depicting the various components of our system.

3.2 Perception

We developed a perception pipeline using the Point Cloud Library (PCL) to process the depth data received from the ASUS Xtion. In each task, the objects
lie on a table or flat surface that fills a large portion of the field of view of the 
depth sensor. We first segment out this tabletop using a simple non-deterministic 
outlier detection method (RANSAC). Filtering the tabletop out from the point 
cloud greatly reduces the points in our cloud and leaves gaps between remain-
ing objects that assist in segmentation. Using Euclidean distance, neighboring 
points are clustered together to form separate objects, assuming that they are 
sufficiently spaced apart. Objects too close together, such as a stack of blocks, 
are segmented using secondary features such as color. These segmented objects 
are then matched to already seen object templates present in the database using 
3D feature detectors and labeled accordingly (e.g., cup, plate, bowl).

Similar to 2D object recognition, 3D object recognition relies on finding char-
acteristic key points and matching them to a database. Features based on the 
normal of a surface are reliable since it has similar values when computed for the 
same surface of an object in different point clouds and at different orientations. 
The normal of each point is calculated by taking the nearest neighbors within a 
defined radius to find the tangent plane. The perpendicular vector of that plane 
pointing towards the camera is the normal. The vector not pointing towards the 
camera would not be visible to the sensor, so it can clearly be discarded. An 
example point cloud of a cup with computed normals and the corresponding 
feature histogram is shown in 5.

Next, we compare our detected features with our known database using the 
Signature of Histograms of Orientations (SHOT) descriptor [34]. Histograms are 
computed on the orientations of normals in a sphere or 3D volume and then 
grouped together using their intersection to form the local descriptor. Similar 
to the well known SIFT algorithm for 2D object recognition, SHOT is also 
robust to occlusion and rotation and can be used to determine orientation. One 
big advantage to using 3D object recognition over 2D is the ability to use the 
depth data provided from the camera for estimating the location. This additional 
location information is used to calculate grasping orientations and for avoiding 
collisions. Once the camera location is found relative to the robot arm, we are 
able to do a simple transformation to get the object’s pose relative to the robot 
for grasping and manipulation described later. All parameters of our processing 
pipeline are accessible in a user interface, allowing us to fine tune parameters to 
lighting conditions and changes in camera pose in the competition environment.

Fig. 4: Left: Position of camera relative to camera. Right: Model scene after 
calibration in RViz.
Fig. 5: 3D object Recognition of a cup. Clockwise, starting top left. (i) Point cloud of cup from the YCB Dataset, (ii) Green arrows display normals computed for a select few points in the cloud, (iii) Viewpoint Feature Histograms (VFH) showing the similarity of the model cup with the new cup.

Fig. 6: Left: Calibrated view of the experimental setup and the Jaco2 arm as seen in RViz. Right: Custom made fingers and integrated proximity and tactile sensors on Jaco2 arm.

3.3 Control

The control node of our system controls the arm through two modes, Cartesian control and velocity control. The mode chosen at a particular time step depends on the action being executed. In particular, we split up control into two distinctive actions, approach and search. The former deals with large scale movements that put the end-effector in the vicinity of the object of interest, while the latter uses the feedback from the finger sensor to place the end-effector at the optimal position for manipulation by searching for salient features of the object.

Tasks typically start with a Cartesian motion. First, the arm must approach the appropriate object specified by the task, so once the perception node gives the pose estimate of an object, the Cartesian control makes use of inverse kinematics to plan a trajectory and then the plan executes to appropriately position the arm. Note that the position is specified as offsets and rotations from an object centroid based-off manual experimentation. Once executed, the task goes into search mode to get in position to grasp the object properly and then closes the
hand. If the task requires further large scale movements, i.e., move a spoon to a bowl, then the Cartesian control mode will be activated again.

Limitations in the perception system, due to noise from the RGB-D sensor and miscalibration, lead to uncertainty in the object’s pose. Because of this uncertainty, exclusively relying on open-loop position control may lead to collisions or failed execution of the task, for example failing to grasp a spoon because it is not within reach. So to deal with this uncertainty in perception the Cartesian control positions the arm at a safe offset from the feature of interest, and then use velocity control to search for a task-relevant feature, for example the handle of a spoon. Once the feature is detected, which we will discuss in more detail below, the system will proceed with the appropriate action such as grasping the object or pushing the object. If the object is not found during the search, the sub task is restarted.

Sensor Feedback We use two distinct channels of information from the finger sensors (proximity and contact) within our feedback controller. Passing the non-linear sensor input through a high-pass filter with 20 Hz cut-off frequency [27] allows us to detect contact, which appears as extrema in the high-pass signal. The resulting signals are roughly equivalent to the SA-I and FA-I signals in the human hand, that is constant pressure and dynamic tactile events, respectively [27]. After calibrating the sensors by fixing the base value of non-linear and surface dependent sensory input moments before executing the grasp, values ranging above and below specific thresholds are considered object and contact detection events respectively (Figure 7). The pseudo code for both these event detection is provided in Algorithms 1 and 2.

Algorithm 1 Touch detection

| Line | Code |
|------|------|
| 1    | function DETECT_TOUCH(current_FA1_finger, y) |
| 2    | touch ← current_fingers_touch |
| 3    | FA1 ← [current_FA1_finger1, current_FA1_finger2, current_FA1_finger3] |
| 4    | for fingers ← 1 to 3 do |
| 5    | if FA1[fingers] < −threshold & current_finger_touch == False then |
| 6    | touch[fingers] ← True |
| 7    | if FA1[fingers] > threshold & current_finger_touch == True then |
| 8    | touch[fingers] ← False |

4 Results

In this section we describe how the finger sensors and perception pipeline facilitated grasping and manipulation using object recognition, contact point detection, and pose estimation for the ten competition tasks. Combining 3D perception with proximity information greatly increased the robustness of our manipulation approach by mitigating calibration error and sensor noise.
Fig. 7: Sensor values (analog reading) versus time for the SA-I (blue) and FA-I (pink) channel equivalents from the 1st finger on the Jaco arm. The gradual increase in the SA-I channel refers to an object detection event. The first peak in the FA-I channel refers to the contact event. A drop in the SA-I channel refers to the object separation event. The second down peak in the FA-I channel is the release event.

Algorithm 2 Object detection

1: function DETECT_OBJECT(current_SAI_finger,y)
2:    detected ← current_object_detect
3:    SAI ← [current_SAI_finger1, current_SAI_finger2, current_SAI_finger3]
4:    for fingers ← 1 to 3 do
5:        if SAI[fingers] < -threshold & current_object_detect == False then
6:            detected[fingers] ← True
7:        if FAI[fingers] > threshold & current_object_detect == True then
8:            detected[fingers] ← False
In task i and ii both required perceiving the thin and narrow spoon handle. Without using the finger sensors, failure modes include positioning the end-effector to far away from the spoon or running into the spoon and thereby changing its position. The proximity information from the sensors enabled us to position the end-effector correctly in a position to properly grasp the spoon using hard-coded search routines around the estimated position. Once the hand was in a position to grasp the spoon, it was moved to make contact with the spoon. If the robot continued to move after initial contact with the spoon, the spoon could get displaced leading to an empty grasp. The contact/release information from the sensors indicated when the fingers made contact with the spoon, and terminated the motion of the hand in a timely manner. The spoon was then securely grasped by closing the fingers in a controlled manner. The following tasks were then straightforward to execute via prerecorded motions; task i required simple motions to scoop peas and deposit them and task ii required stirring of the contents in a cup. With a proper orientation of the spoon after grasping, both tasks were easily completed.

Grasping a straw out of a cup (task vi) was similar to grasping the spoon. Using the proximity information from the sensors we could correctly locate the straw in space. The sensor’s high sensitivity allowed us to identify the touch event before the grasp started to displace the straw and successfully pick it up. It was difficult, however, to insert the straw into the plastic cup through the small opening in the lid due to the comparably large error in perception (3-5cm), and we did not use an additional step to use the sensors to properly locate the cup.

Unlike the aforementioned tasks, task iii, grasping and shaking a salt dispenser, was trivial in terms of perception and grasping. Dynamic manipulation, on the other hand, proved difficult for the Kinova robot. Sufficient jerk to release salt from the shaker could not be achieved within the limits of the arm. Here, using wrist rotation instead of moving the entire arm led to best results, but still dispensed the salt at a very slow rate that made the task take a long time to complete.

For task iv, the Kinova hand was able to create sufficient force closure with the USB light to pull it out of a USB connector in the socket. Plugging the connector back in was difficult due to lack of stiffness in the hand and the light itself, which was made from a flexible material. Solving this task successfully requires grasping the light as close as possible to its stiffest part and then use repeated trial and error or additional optical sensing.

Picking up a hammer and punching nails in a foam block (task v), was challenging due to the weight of the hammer and lack of stiffness in the Kinova hand. We note that since using in-hand sensors to make up for uncertainty, none of the tasks took advantage of the built-in compliance of the Kinova hand.

Inserting a screwdriver into a nut (task vii) again emphasized precision. Picking up the screwdriver was relatively simple, however correctly inserting the driver into the nut was not possible with our setup. Although trial and error based on an initial estimate on the nut’s pose is a viable strategy, the nut does
not have a large enough area that is suitable for self-alignment. In addition, the rotation of the screwdriver is crucial to catching the nut in order to apply a rotational force. The limited resolution in our perception pipeline does not provide us with enough information to align these items properly for manipulation.

Similar to removing the USB night light, charging and emptying a syringe with air (task ix) was a test to the robot hand’s ability to apply a pinch grasp strongly. Since a task like this requires two arms to perform, participants with a single robot arm were allowed to have a teammate hold the syringe with their hand while the robot pulled the syringe handle.

Picking up a towel and hanging it onto a hanger (task iv) was straightforward as it was supposed to simply picked and placed. Here, the challenge was picking up the towel very close to the table surface. Proximity information in the fingers allowed us to stop the arm above the table at a distance which was safe enough for the fingers not to brush against the table and reliable enough to grab the towel.

The final and most difficult task was taking a pair of scissors and cutting a paper along predefined lines (task viii). One had to first identify the lines on the paper which we did using a standard line-detection algorithm. Picking up the scissors was facilitated with the handle hanging over the table. The challenging part was orienting the scissors correctly to cut along the lines. The fingers of the Jaco arm did not have the ability to comply with the shape of the scissors when opening it (i.e., bending the fingers such that the hand does not lose grip of the scissors while repeatedly opening and closing the scissors). The scissors hence lose contact with the fingers when either opening or closing, making this task impractical with the gripper configuration used.

We have focused exclusively on the manipulation aspect of the competition as the bin-picking task would require a different perception strategy, focusing on object identification.

5 Discussion

A key insight in addressing a wide variety of tasks in a competitive environment was that 3D perception, mechanical compliance, and tactile sensing complement each other and deficiencies in one can be made up by the other to some extent. Indeed, many teams were able to solve a majority of the tasks without using any perception, but relied exclusively on mechanical compliance and hard coded positions of objects. Analogously, humans might be able to perform tasks without tactile sensing or being blind-folded, but it is the combination of the two that makes them most efficient.

Indeed, better 3D perception and calibration might have allowed us to forgo tactile sensing altogether. Likewise, some of the tasks could have been accomplished using exclusively in-hand proximity and contact sensing. It might be this redundancy, which lets the community mostly focus on thoroughly exploring single sensing modalities rather than exploring comprehensive solutions that combine 3D perception, tactile sensing and mechanical compliance.
We also learned valuable lessons in how to specify competition rules in order to push the community toward generalizable outcomes. Bin picking and tabletop manipulation are indeed sufficiently different problems that the system presented here was not able to solve tasks in bot categories, albeit mainly due to different requirements in perception. A loop-hole in this year’s competition rules was that augmenting the objects was not explicitly forbidden, allowing one team to mount foam cubes onto individual objects that could be grasped by the Baxter robot’s standard gripper with a large margin of error. This is an interesting solution, which uses compliance in a smart way and would lead to acceptable outcomes in some constraint scenarios, but only poorly generalizes to household manipulation tasks.

As in the Amazon Picking Challenge [13], proximity and tactile sensing were underrepresented in the competition. Albeit we greatly benefited from the availability of contact and touch information, all of the tasks could be solved relying on accurate pose estimation and compliance. The limitations of this approach are best illustrated in the towel manipulation tasks. Here, most teams let their robot’s hands run into the table in order to make sure they are close enough to the towel. While this worked for this task, the force exerted by compliant robots might lead to undesired outcomes in some environments, and excessive use of such strategies is unlikely in future real world applications.

Some of the tasks demonstrated the need for dynamic control strategies. Specifically, position and velocity-based controllers are not sufficient for tasks like emptying the salt shaker, which require accurate control of jerk. Similarly, undoing a plug leads to significant jerk, which leads to disturbance of the environment. The requirements on dynamic control are therefore two-fold: first, the ability to specify not only position and velocity, but also acceleration profiles. Second, high-bandwidth impedance control, usually available only in expensive industrial robot arms, is not a luxury, but safety critical for operations with quickly changing loading conditions.

The largest source of error resulted from errors in calibration. These include the intrinsic camera parameters, but also finding the transformation and rotation from the ASUS Xtion to the base of the arm. While there exist more powerful calibration strategies than chosen here and we could also permanently mount the camera to the robot’s arm frame, we note that different tasks require different camera perspectives. We therefore consider calibration an open problem, and are interested in exploring solutions that augment object localization and pose calibration using tactile sensing [14], as well as using the 3D model of the robot itself to add data points to the calibration process.

All of the tasks in this competition could be solved without using any motion planning. That is, all motions were executed by simply commanding the robot to a Cartesian pose, assuming that there exist a collision-free trajectory. As this cannot be assumed in a real-world application, we plan to integrate the solution presented here with the motion planning framework MoveIt! [11]. This task is less straightforward than it sounds as the discrete planning approach that
is customary in motion planning does not smoothly integrate with continuous feedback control, and how to do this properly is subject to further research.

6 Conclusion

We have presented a comprehensive perception and manipulation pipeline that combines 3D perception with proximity and tactile sensing using exclusively commercially available hardware. All software developed for this project is available open-source\textsuperscript{2} and continues to be expanded on.

We have shown that in-hand proximity and tactile sensing can dramatically improve the robustness of a large variety of grasping and manipulation tasks in face of uncertainty in sensing and actuation, and we argue that those sensing modalities are critical for performing robust manipulation in the real world.

Challenges that remain towards this end are: (1) increasing the accuracy of orientation estimation of objects and the efficiency of 3D perception for larger data sets of objects, (2) better integration of deliberative and reactive control strategies, and (3) improved mechanism design allowing for controlling compliance and stiffness to be able to manipulate heavy objects as well as those that require deformation of the hand.

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