Inertially-safe Grasping of Novel Objects

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I. INTRODUCTION

We address the problem of grasping novel objects in a way that minimizes the torques that the hand is required to produce. The problem of grasping new objects has received a lot of attention in the past few years [1], [2], [3], [4], most of which has focus on finding grasps for which the shape of the gripper locally matches the shape of the object. While selecting a grip that makes it difficult for the object to escape is clearly important, it also seems natural that the inertial parameters of objects need to be taken into account.

In this paper, we present a planner that suggests grasps that respect both of these criteria. Our planner searches for grasping points where the gripper nicely fits to the object, with a strong preference for grasps that are near the center of mass of the object. In other words, our planner finds grasping solutions that fulfill constraints imposed by both local shape *and* forces acted by the object. Our planner allows the robot to avoid situations that can be potentially dangerous for the robot itself, for example trying to grasp a large object by one of its extremities and risk damaging the robot's hand.

The main challenges of planning grasps for novel objects is that we only have an incomplete model of the object available. If we assume that we take a single snapshot of the object from a 3D sensor, it then is an involved task to find suitable finger placements of the robotic hand on the unknown backside surface of the object. It is also equally hard to infer the position of the object's center of mass when only one side of the object is visible.

We overcome the finger placement problem by using a part-based grasp planner, by which previously-learned prototypical parts [2] are fitted to the incomplete object snapshot, yielding a gripper pose that aligns the fingers to the object's surface.

We then infer the object's center of mass from vision. The object's center of mass is set at the center of gravity of the visible side. While this approach is simple, it already allows us to produce useful behaviors, as shown in the next section. In future work, we envision *learning* the mapping between a partial view and the object's mass and center of mass. We believe that important clues for predicting the mass of an object can be obtained from vision. The object's color, texture and reflective diffusiveness have the potential to discriminate between materials such as wood, metal, plastic or glass.

In the rest of this paper, we present a proof of concept for planning grasps that optimize both the object-gripper shape alignment and inertial parameters.

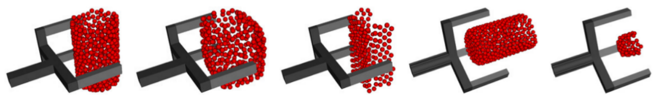

Fig. 1: Prototypes used for grasp planning.

II. EXPERIMENT

In this section we discuss how our grasp planner works and we show planning results for three objects. We can divide our grasp planner into two parts. One part is responsible for the alignment of the gripper with a part of the object that fits the gripper's shape, whereas the second part weights possible object-relative gripper poses by the torque produced at the grasping point.

A. Criterion 1: Object-gripper Shape Matching

We address the shape-alignment problem with a part-based planner [2]. The robot learns the shape of parts by which objects are often grasped, from a set of examples provided by a teacher. This process provides the robot with a set of grasping *prototypes* (Fig. 1), that each associate a point cloud to a gripper pose. The point cloud of a prototype represent the shape of an object part such as a handle, or a short section of a cylinder. The gripper parameters associated to a prototype are its position, orientation, and preshape of the manipulator. In this work we use five prototypes that have been previously learned from real world grasp examples [2]. They are shown in Fig. 1.

The part-based planner allows the robot to suggest a grasp for a novel object by fitting all the prototypes to the partial view of the object, and selecting the grasp associated to the prototype that best fits the data. We denote a prototype's point cloud by P as well as the point cloud of the object's partial view by S, with $P = \{p_i\}_{i\in[1,N]}$ and $S = \{s_i\}_{i\in[1,M]}$, where the p_i and s_i are points in $\mathbb{R}^3$.

To rank different alignment hypothesis we define a similarity measure between two point clouds by a cross-correlation function

$$s^*(P,Q) = \int_{\mathbb{R}^3} \phi_P(x)\phi_Q(x)dx, \tag{1}$$

where $\phi_P(x)$ and $\phi_Q(x)$ are probability density functions computed from P and Q via kernel density estimation.

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B. Criterion 2: Finding A Low-force Grasp

The previous section defined a criterion for defining how well a given gripper pose fits the object's shape (Eq. 1). This section discusses a criterion finding a low-torque grasp. In this paper, we do not have a way of estimating the object's mass. As a result, this section defines a *relative* torque criterion, i.e., one that allows the robot to compare two grasps on the same object and compute which of these two grasps requires the least force.

This criterion relies on the definition of a weighting function, that models the torque that the hand needs to produce at the grasping point. We define the grasping point as the mean of all the contact points between the prototype and the fingers of the robotic hand and we approximate this point to be about in the center of the robotic hand. The torque at the grasping point can be computed by

$$\tau_t = (t - r_{com}) \times f_{ext}, \tag{2}$$

where t is the grasping point, r_{com} is the center of mass of the object and f_{ext} is proportional to $g \cdot e_z$, i.e., the gravitational acceleration of the object. With our conventions of coordinate frames the force is acting along the Z-axis. Finding the exact position of the center of mass given a partial 3D snapshot of the object is not an easy task. Therefore we approximate r_{com} with the centroid of the object snapshot S. This approximation assumes a tabletop scenario where the table is segmented off the perceived point cloud via dominant plane removal. We define the torque-weighting function as

$$W_t = 1 + \max(0, b - c|\tau_t|), \tag{3}$$

where t corresponds to the position of the gripper (i.e., the grasping point) in the world reference frame. The constants b and c are chosen manually, such that the W_t outputs a number between 1 and $1 + b$ for a suitable range of torques.

C. Finding The Optimal Gripper Pose

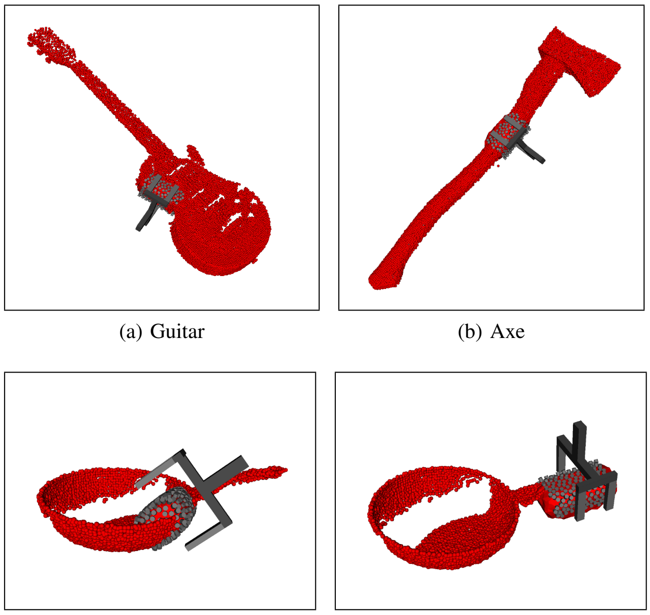
With our grasp planner we can compute new grasps by maximizing both the similarity measure (1) and the torque-weighting function (3) with respect to the gripper pose (t, r)

$$\arg\max_{(t,r)}\{s^*(T_{t,r}(P), S) \cdot W_t \cdot R_{t,r}\}. \tag{4}$$

Here, $T_{(t,r)}(\cdot)$ the transformation of its argument by t, r, and $R_{t,r}$ is the reachability function, which equals to 1 if the grasp for the current pose guess can be planned without collision and an existing solution from inverse kinematics, or 0 otherwise.

D. Results

Figure 2 shows the output of our grasp planner for three common household objects. In all grasps, the robot prefers poses near the center of mass of the object. For instance, the torque of the grasp of Fig. 2(b) is six time lower than the torque of the grasp that is suggested if W_t is ignored in Eq. 4. In the leftmost image of Fig. 2(c), we would have preferred a grasp slightly closer to the disk of the pan. This experiment illustrates that striking the right balance between low torque and good shape alignment is not easy. In the case of this frying pan, the point cloud at the leftmost end of the handle is more noisy than the rightmost end, which prevents our planner from placing the gripper at the leftmost pose.



(a) Guitar

(b) Axe

(c) Frying pan

Fig. 2: Grasps for three different objects computed with our grasp planner with torque weighting parameters $b = 0.4$ and $c = 0.1$. (c) Here, we can see the grasps planned for a frying pan with torque weighting (left) and without torque weighting (right).

III. CONCLUSION

We presented a method for planning grasps that account for both the shape of the object at the grasping point, and the torque that the object applies on the gripper. By approximating the center of mass of the object from a partial point cloud, our method allows a robot to avoid dangerous grasps, and prefer grasps closer to the actual center of mass of the object. In future work, we plan to let the robot learn the mapping from various 2D and 3D features to an object's mass and center of mass, to refine the torques inferred by our model.

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