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Towards the Use of Human Strategies to address Pose Uncertainty in Grasp Planning

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***Abstract*—In this paper we present a manipulation planner for grasping tasks that takes into account the uncertainty of the object pose to guide the hand aperture during the reach movement. Most classical grasp planning approaches focus on calculating the optimal contact configuration of the fingers, assuming that the target object pose is known accurately, which in many cases is only an ideal situation. The strategy we present is based on studies showing that humans vary their finger configuration depending on how certain they are of the object pose. We present the basic ideas behind this approach, the algorithm we have implemented in simulation and discuss our current and future work regarding the implementation in our physical robot as well as our proposed model for perceptual uncertainty.**

I. Introduction

Autonomous robots require manipulation capabilities in order to interact effectively with their environment. Research in *grasp planning* has developed till the point that currently there exist a number of approaches that allow a robotic system to plan and execute the grasping of an object [3]. Most of these planners guarantee success if certain conditions are met. One common assumption is that the environment is perceived with reasonably good accuracy or is known beforehand.

In reality, however, this is not the case. In [4], Kim et al. propose to consider the dynamics of the object and the pose uncertainty to evaluate more accurately grasp quality. Berenson et al. [2] approached the problem by considering *Task Space Regions* containing the possible object poses and planning on the intersection of these.

In this paper, we draw inspiration of human grasping to propose a sampling-based manipulation planner to address the pose uncertainty of the object in the arm trajectory planning and in the grasp selection. Studies with human subjects [5] show that, in the presence of bounded perceptual errors, humans achieve a high degree of success by using simple strategies, as we will explain in the following section.

II. Human Strategies for Perceptual Uncertainty

In [5], Schlicht and Schrater presented experimental results regarding human grasping in the presence of perceptual uncertainty. Namely, the participants had the task of grabbing a cylindrical rod while changing their visual focus (from having the rod in front of them till a peripheral viewing variation of $\pm 40°$). Two important observations from this study are:

- The hand aperture (distance between thumb and finger) increases linearly with respect to the measured perceptual uncertainty (peripheral viewing variation).
- During the reaching phase, the hand reaches its *maximum grip aperture*(MGA) at roughly 75-80% of the distance to the target object. It was observed that the time at which this maximum aperture occurs kept nearly invariant during the tests with different perceptual uncertainty.

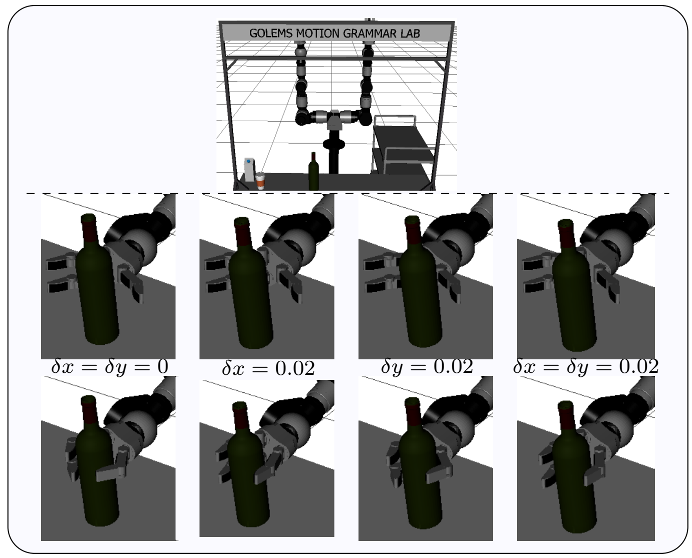

Fig. 1. Top: Initial scenario for a grasping task. Bottom figures: Different grasps (open and close configurations) executed with diverse simulated perceptual errors for x and y directions ($+x$ points at the hand approach direction, $+z$ goes up and y follows the right-hand-rule)

III. Algorithm

We consider the experimental results from Section II to address the pose uncertainty of a object to be grasped by a robot arm. Normally, a grasp planner follows the following workflow:

1) Generate (in simulation) a small set of candidate grasps for the target object:
   a) Set the fingers in a default (fixed) open configuration

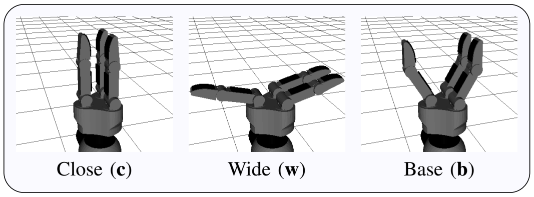

Fig. 2. Referential hand configurations used

b) Generate a large number of possible 6D poses for the free-floating hand model. If there is no collision, close the fingers until contact with the object is made. If the grasp is force-closure, add it to the final candidate set, otherwise prune it.

2) Sort the resulting grasp set based on a metric (i.e. ϵ).
3) Select a grasp and generate an arm trajectory that moves the hand from its starting pose to the grasp 6D pose, with the fingers in the default open configuration through the execution of the transit path. If no collisions are detected, close the fingers until contact is detected.

We propose to change steps 1.a) and 3) such that the open finger configuration of the hand is not fixed. Instead, we model the finger joints as a linear function depending on the uncertainty in the pose object. Consider the finger configurations in Figure 2. Depending on the amount of uncertainty perceived, the open finger configuration to grasp the object varies linearly between **c** and **w**. The linear function we use is shown in Figure 3. d is the normalized distance , which is calculated using Algorithm 1 and $u \in [0, 1]$ is a parameter that represents the uncertainty in the object pose.

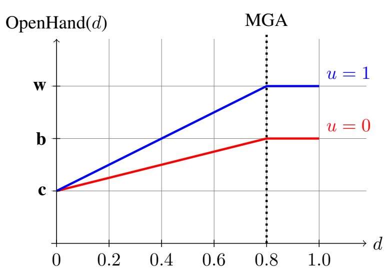

Fig. 3. Finger joint variation with respect to the normalized distance from the palm to T_{goal}

Algorithm 1: GetGoalDist(q)

return $\dfrac{\mathcal{D}(\texttt{ForwardKin}(q), T_{\text{goal}})}{\mathcal{D}(\texttt{ForwardKin}(q_{\text{start}}), T_{\text{goal}})}$

In order to address the finger open configuration variation through the reach movement, we have to modify the planning algorithm for the arm trajectory such that it considers the finger joint changes, in order to make sure that no collision is produced. For this, we modify the IKBiRRT algorithm [1], which we use to generate the arm trajectories. Specifically, we modify the `Extend` function, such that the finger configuration changes according to the uncertainty parameter u and the distance d. The modified function is shown in Alg.2

Algorithm 2: Extend($\mathcal{T}$, q_{near}, q_{target})

$q \leftarrow q_{\text{near}}$
while $q \neq q_{target}$ **do**
  `SetArmConfig`(q)
  $d \leftarrow$ `GetGoalDist`(q)
  `SetHandConfig`(`OpenHand`(d))
  if `NoCollision()` **then**
    $\mathcal{T}$.`addVertex`(q)
    $q \leftarrow$ `Step`(q, q_{target})
  else
    return *COLLISION*
return *REACHED*

Algorithm 3: OpenHand(d)

if $d \leq MGA$ **then**
  return $\mathbf{c} + \dfrac{d}{\text{MGA}}[(\mathbf{b} - \mathbf{c}) + (\mathbf{w} - \mathbf{c})u]$
else
  return $\mathbf{b} + (\mathbf{w} - \mathbf{b})u$

We performed experiments with a simulated environment replicating our physical robot, a bimanual fixed manipulator consisting of 2 Schunk 7-DOF arms, each with a 3-finger SDH hand. We varied the parameter u manually and tested plans generated with the approach explained above by disturbing the object pose. An example of these results is shown in Fig.1 with $u = 0.3$. We observed that for errors of up to 2cm (or higher in some directions), the reach arm trajectory and the grasp planned were able to perform valid grasps.

IV. Discussion and Future Work

In this paper we presented a simple strategy to address pose uncertainty for grasp planning problems. By using a linear function relating the fingers open joint configuration and the uncertainty measure u, we generate plans that, based on a human heuristic, have shown feasible resulting plans in the presence of simulated errors of up to 2cm. Currently, we are working on the implementation of this strategy on our physical robotic system. We are also investigating an effective way to parameterize the uncertainty measurement u. One alternative we are evaluating is to use a shape approximation of the perceived object pointcloud, such as superquadrics. As a metric, we are considering to use either one of the diameter of the fitted SQ or the fitting error of the pointcloud.

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