Experience based Learning and Control of Robotic Grasping

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I. Introduction

One of the main challenges in the field of robotics is to make robots ubiquitous. To intelligently interact with the world, one of the key abilities that robots need to have is to manipulate objects. Typical environments in which robots will be deployed, such as a house or an office, are dynamic and it is very difficult to equip robots with an ultimate and general grasp planning capability. Planning a grasp is difficult due to the large search space resulting from all possible hand configurations, grasp types and object properties that occur in regular environments. Another important question is how to equip robots with capabilities of gathering and interpreting the necessary information for novel tasks through interaction with the environment in combination with minimal prior knowledge.

In relation to grasping, some recent approaches propose the use of prehensile postures where object features and experience is used to aid the selection of the pre-grasp posture and grasp controller(s). Such an approach significantly decreases the size of the search space. This paper presents a method for grasp generation for robotic hands where programming by demonstration, experience and shape primitives are used to provide a successful grasp. In other words, we integrate a top-down (experience) and a bottom-up methodology to develop a more natural grasp learning system. It is important to note that the bottom-up methodology can be seen as modeling of *corrective movements*. The proposed method is shown to work for choosing the grasp approach vector, but can also be used to choose other grasp control parameters, such as the fingers' relative closing speed, actions from tactile sensor inputs et cetera. The method is used in a Programming by Demonstration setting. The system recognizes the object and grasp type which are mapped to a suitable controller that can reach a successful grasp. In this work, the entire grasp sequence is thoroughly evaluated in a simulated environment, from learning a grasp to actually reaching it. We also discuss the necessary requirements for evaluating this approach in a real setting.

II. System Overview

In this section, we shortly present the building blocks of the currents system. More details about each of the steps will be given upon acceptance.

1) Object Recognition and Pose Estimation
   The system can identify *which* object and *where* it is [1], [2].
2) Grasp Recognition
   A glove with magnetic trackers provides hand postures to the grasp recognition system [3].
3) Grasp Mapping
   An off-line learned grasp mapping procedure translates the human grasps into robot grasps, Section III.
4) Grasp Planning
   The robot selects a grasp controller. The grasp will be approached from the direction that maximizes the probability of reaching a successful grasp, Section IV.
5) Grasp Execution
   A combination of velocity, position, and tactile force control is used to design of a semi autonomous grasp controller to reach the final grasp, Section V.

III. Grasp Mapping

It has been argued that grasp preshapes can be used to limit the large number of possible robot hand configurations. This is motivated by that when planning a grasp, humans unconsciously simplify this choice by selecting from only a few prehensile postures appropriate for the object and task [4]–[6]. Based on the above and previous work [3], the current grasp recognition system can recognize ten different grasp types. These grasp are mapped to appropriate robot grasps. The robot grasp types do not refer only to hand postures, but to grasping controllers. Fig. 1 illustrates the initial hand postures for each of the controllers.

IV. Grasp Planning

The planning is performed for different objects and two robot hands in the grasping simulator GraspIt! [8]. All results are stored in a *grasp experience* database. The work described in [8] and [9] concentrate on finding optimal fingertip positions, but leave out the problem of actually obtaining those positions. In our approach, the grasp controllers presented in Section V are then used to improve the final grasping. We extensively evaluate this approach in simulation to motivate its feasibility and future implementation on a real robot. It is important to note here that the planning is performed not only for each object and end-effector, but also for each grasp type. To decrease the search space, only a subset of grasp controller parameters are considered. For power grasps, three parameters (θ, ϕ, ψ) are varied describing the approach

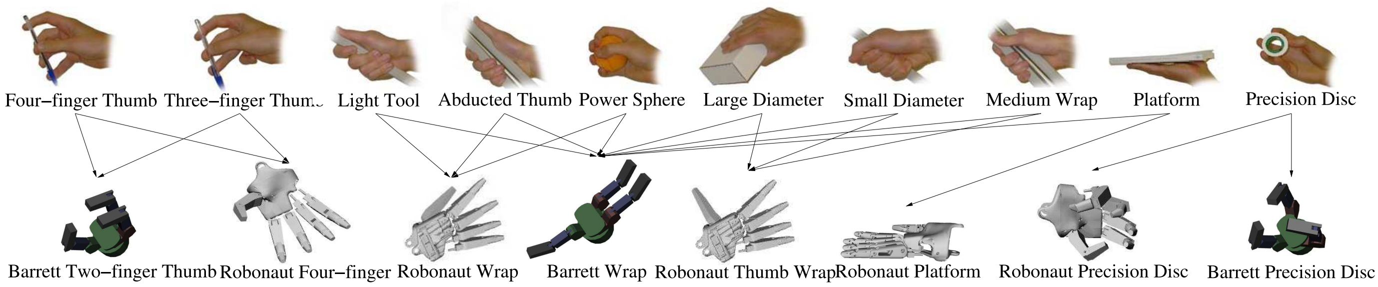

Fig. 1. Initial robot hand postures for different grasp types.

direction and hand rotation. For precision grasps, a fourth parameter d, that describes the retract distance when contact is detected, is added. In our experiments the search space size was (θ=8, ϕ=16, ψ=8, d=6) which required about an hour for training (6144 grasps in total).

A. Training on Object Primitives

A model of each object is necessary for training the grasp planner. It is not likely that the robot will be able to acquire very detailed models of objects that is supposed to manipulate, especially if the shape is very complex. However, it is realistic to assume that it will be possible to extract certain *features*, that are based both on the object's appearance and shape. In our system, the appearance is used for recognition and shape for grasp planning. Currently, it is assumed that a vision system can either generate a generic shape of the object (truncated cone, sphere, box, cylinder) or that this information is generated in advance through a training process.

V. Grasp Control

To enable more intuitive formulation, a control design is used that allows the controller to be specified in a direct and intuitive way [7]. In this example a Barrett hand is used. Each finger can be closed and the spread, the angle between the two fingers on the one side, can be controlled by setting the joint torque.

The basis for the controller is a linear transform T relating the original joint angles q to new control variables x, see Fig. 2. The transform is

$$x = Tq. \tag{1}$$

It is approximated that joint angle corresponds to finger position. The closing force is controlled using tactile force sensor data while joint encoder data is used to control the finger positions. Spread is not used for control here. Before contact, fingers are velocity controlled individually.

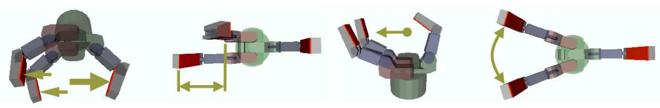

Fig. 2. Grasp controllers: total grasp force, stability, centering, and spread.

The four controllers from Fig. 2 gives the transform q (neglecting any scaling factors):

$$T = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1/2 & 1/2 & 1 \\ 0 & 1/2 & 1/2 & -1 \\ 0 & 1 & -1 & 0 \end{bmatrix}. \tag{2}$$

The control forces f are computed using a P-controller $f = De$ where D contains controller gains and e is an error vector with force and position errors. (Joint friction is simulated.) The joint torques F are computed as

$$F = T^T f = T^T De. \tag{3}$$

Fig. 3 shows an example grasp execution. However, given a certain controller, how can we be sure that it succeeds in reaching the final grasp in its semi-autonomous manner? In addition to controller parameters, the factors that affect the result are primarily object position with respect to the hand when the grasp is initiated and the object properties. Using the approach presented in the previous chapter, the boundaries for this space can be investigated, and the necessary requirements on object localization thus established.

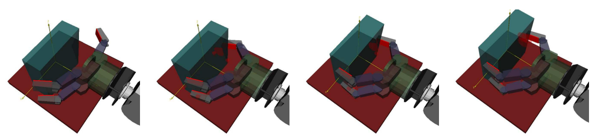

Fig. 3. Execution of a sample task using the controller described in Section V.

VI. Conclusion

The results of the experimental evaluation performed in a simulated environment suggest that the outlined approach and tools can be of great use in robotic grasping, from learning by demonstration to precise and robust object manipulation.

The grasp experience database contains not only a record of success rates for different grasp controllers but also the object-hand relations during an experiment. In this way, we can specify under what conditions the learned grasp strategy can be reproduced in new trials.

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