Programming-by-Demonstration of Reach to Grasp Tasks in Hand-State Space

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***Abstract*— This paper deals with programming-by-demonstration of robot manipulators, where a robot program is created automatically from human demonstrations despite morphological differences in the hand/arm structure.**

To find a correspondence between observed human motions and desired robot hand motions, we represent the task in hand state space. The hand state definition is perception-invariant and valid for both human and robot. The representation simplifies task reconstruction and preserves the essential part of the reaching motion associated with the grasp. We show how demonstrations of pick-and-place tasks can be interpreted and executed by a general-purpose robot manipulator equipped with a three-finger hand.

I. Introduction

Programming-by-Demonstration (PbD) of grasping and manipulation tasks offer a great benefit in that the programming effort is significantly reduced ([1], [4], [5]). In the proposed approach, robot executable code is directly produced from a human demonstration, using the hand state space representation. The representation serves as a link between man and machine that can be used for PbD. Interpretation of human demonstration is done on the basis of the following assumptions:

- The type of tasks and grasps that is *a priori* known by the robot. The *a priori* knowledge consists of the set of grasps and skills the robot can perform.
- The demonstration is performed so that the robot *should* be able to execute the task.
- The robot system can recognize the human grasps and these grasps can also be mapped to – and executed by – the robotic gripper.

Although the idea of copying human motion trajectories with the robot hand seems straightforward, it is not realistic for several reasons. One major problem is the different morphology between the human and the robot, known as the correspondence problem in imitation [3]. The difference in the location of the human demonstrator and the robot might force the robot into unreachable parts of the workspace or singular arm configurations even if the demonstration is perfectly feasible from human viewpoint.

II. Experiments

We recorded human demonstrations of a pick and place task with two different subjects, using the PhaseSpace Impulse motion capturing system. The data is collected at a sampling rate of 120 Hz, using 9 LEDs located a different point on the hand and one LED attached to the object. The experimental setup can be seen in Fig. 5. The robot used in the experiments is the industrial manipulator ABB IRB140. The anthropomorphic gripper is the KTHand, described in detail in [7].

A. Experiment 1 – Learning from demonstration

For this experiment 26 demonstrations of a pick and place task were performed with a soda can grasped with a spherical grasp. To make the scenario realistic the object is placed with respect to what is convenient for the human and what *seem* to be feasible for the robot. Of the 26 demonstrations 5 were discarded in the segmentation and modeling process for various reasons, while the remaining 21 were used for trajectory generation and to compute the variance. In this experiment only the reach to grasp phase is considered. The trajectory generator produced 21 reaching motions which are loaded to the robot controller and executed. In 8 attempts the execution succeeded while 13 attempts failed due to unreachable configurations in joint space. This could be prevented by placing the robot at a different location with better reachability. Moreover, providing the robot with more demonstrations with higher variations in the path will lead to looser constrains.

B. Experiment 2 – Gripper pose variation

To investige how end effector position – and hence the approach trajectory – affect grasp succes, we have dynamically simulated grasping an orange using different hand positions across a 3D-grid. A successful grasp can be either a precision disc grasp or a power grasp. A grasp is considered failed if no force closure grasp was reached during grasp formation. Fig. 2 shows the results from such simulations. Additional simulations and control details can be found in e.g. [6].

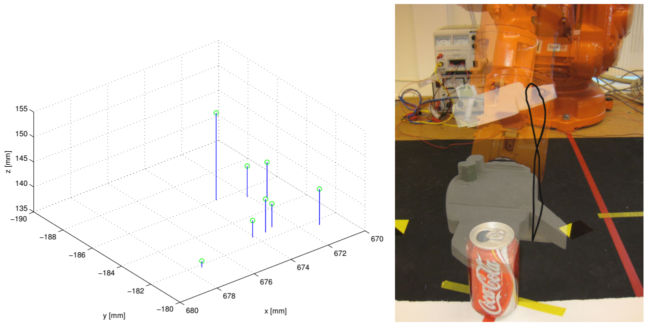

Fig. 1. **Left: The end effector position in the work space for 8 successfully executed trajectories.** Right: A trajectory generated when the initial position is the same as the desired final position, showing that the method generate trajectories as similar to the demonstration as possible based on the distance.

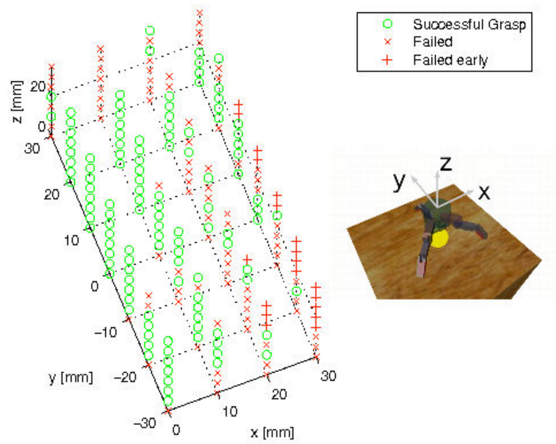

Fig. 2. Grasp results from dynamic simulations of different initial hand positions. Grid spacing is 10 mm in the xy-plane and 5 mm along the z-axis. Please note that the coordinate system orientation in this figure is different from that elsewhere in this paper.

The required accuracy in position of the end effector is in the centimeter range that can be compared to the variance in the robot trajectories, see Fig. 1, which are in the millimeter range. For fully autonomous execution of a grasp learnt using the suggested approach, we must also consider uncertainties with respect to object position, orientation, and in the object model itself.

C. *Experiment 3 – Generalizations in work space*

In this experiment the method is tested on how well it generalizes by examining if feasible trajectories will be generated when the object is placed at arbitrary locations and when the initial configuration of the manipulator is much different from the demonstration. This will determine how the trajectory planner handles the correspondence problem in terms of morphological differences.

First, trajectories are generated when the manipulator's end effector starts directly above the object at the desired final position with the desired orientation. The resulting trajectory is shown to the right in Fig. 1. Four additional case is also tested displacing the end effector by 50 mm in +x, -y, +y and +z direction, all with very similar results (from the robot's view: x is forward, y left and z up).

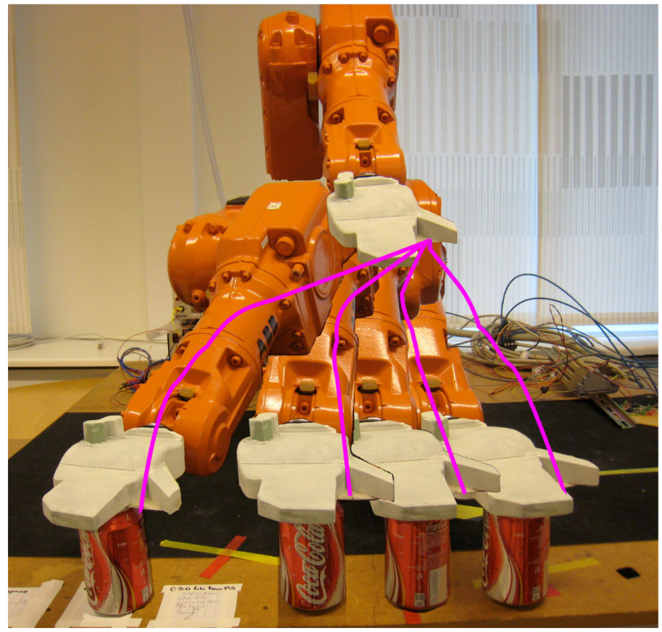

Fig. 3. The object is placed at four new locations within the workspace.

Second, reaching the object at a fixed position from a random initial configuration is tested. Fig. 4 shows the outcome from two random initial positions, where one trajectory is successfully followed and the other one fails.

Third, the object is placed at four different locations within the robot's workspace; displaced 100 mm along the x-axis, and -100 mm, +100 mm, +200 mm, and +300 mm along the y-axis, see Fig. 3. The initial pose of the manipulator is the same. The planner successfully produces 4 executable trajectories to the respective object position.

The conclusion from this experiment is that the method generalizes well in the tested scenarios, thus adequately addressing the correspondence problem.

D. *Experiment 4 – A complete task*

To test the approach on an integrated system, the KTHand is mounted on the ABB manipulator and a pick-and-place task is executed, guided by a demonstration showing pick-and-place task of a box (110x56x72 mm). The reach to grasp motion is executed as described in Sec. II-A and the grasp as described in Sec. II-B. The synchronization between the reach and grasp is performed manually. After the grasp is executed the motion to the placing point is performed by following the demonstrated trajectory. Since the robot grasp pose corresponds approximately to the human grasp pose it is possible for the planner to follow the human trajectory almost exactly. This *does not* mean that the robot actually can *execute* the trajectory. The retraction phase follows the same strategy as the reaching motion. Fig. 5 show the complete task learned from demonstration.

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Fig. 4. A trajectory generated from random initial positions reaching for the same object

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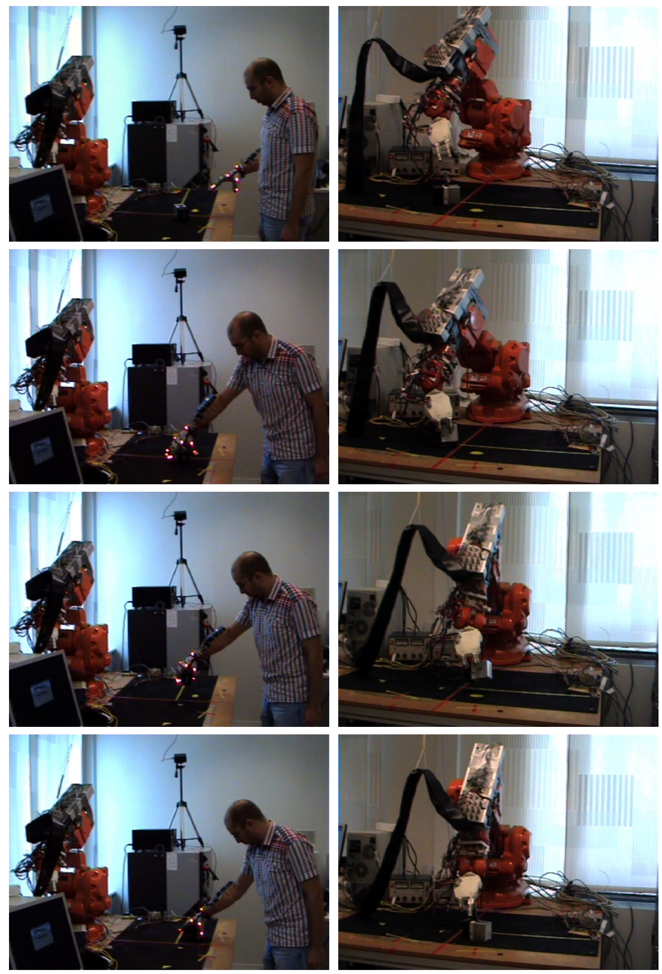

Fig. 5. Industrial manipulator programmed using a demonstration. A movie of the sequence is available at: http://www.aass.oru.se/∼asd/PbD.mov