Generalization of Dexterous Robot Manipulation Skills Learned from Human Demonstration

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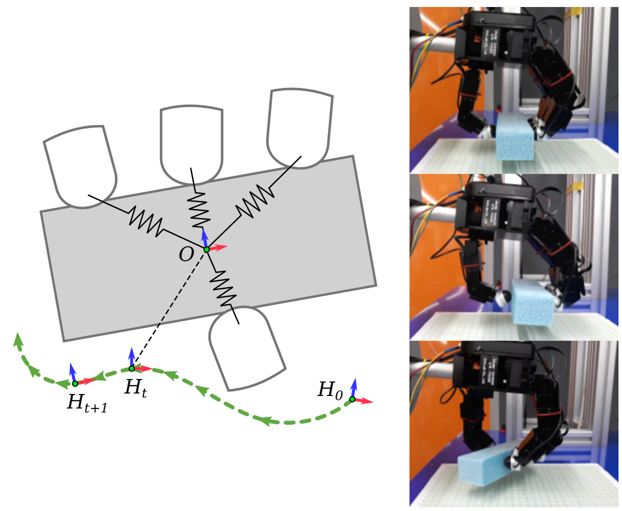
Dexterous hand manipulation tasks are challenging due to the complexities of encoding the task, coordinating the fingers, and tracking the object. Since some daily tasks require the manipulated object to follow tricky trajectories as in writing and sewing, it is not viable to design the motion manually. When the desired motion is known, the controller has to deal with both the task execution and the object grasping simultaneously. Due to the hand-object occlusions visual object tracking is limited and tactile sensing is necessary. We propose a combination of the dynamical movement primitives (DMP), the virtual spring framework (VSF) and a force-feedback based online grasp adaptation method to overcome these challenges. The DMP is used to learn the complex trajectories from demonstration, the VSF is used to coordinate the fingers to keep the object in grasp during manipulation, and the force-feedback is used to continuously adjust the grasping forces to increase the contact stability.

The VSF is an impedace-based, object-agnostic grasping method that assumes virtual springs that connect the finger-tips to a virtual object frame (Fig. 1.a). The virtual frame is approximated using only the fingertip positions without knowing the exact model or pose of the object. Stiffness parameters of the springs are determined heuristically or learned from demonstration as in [4]. It also adds compliance to the system which is helpful against uncertainties [2]. The VSF allows designing simple object-centric dexterous manipulation actions such as translation and rotation as presented by [7] and [4]. However, some tasks depend not only on the final state but also on the specific trajectory as discussed above.

Learning policies to achieve complex trajectories is possible using reinforcement learning [1], learning from demonstration [3] or both [5]. We follow the demonstration approach since it requires less resources. The DMP makes it possible to learn complex trajectories from a single demonstration.

The DMP is a framework that represents the motion as a dynamical system [3]. The dynamical system is designed to ensure convergence to a goal state. Custom trajectories are learned as an additive term that perturbs the system. It is possible to change the initial and goal conditions of a task without losing the trajectory shape. The dynamical system also provides an attractor landscape which drives the system towards goal in case of perturbations.



(a) (b)

Fig. 1. (a) Virtual spring framework and object trajectory control. Robot fingertips are connected to the object frame O with virtual springs. Object pose is controlled in order to minimize the error between O and the reference frame H_t. The reference frame follows a trajectory that is learned from demonstration. (b) The experiment setup. The initial state (top image), the final state after translation (middle image) and the final state after rotation (bottom image).

We use the DMP to learn object-centric trajectories for the virtual object frame of the VSF. Thus, the trajectory is unaware of the finger positions and kinematics. The DMP defines the motion of the object, and the fingers follow the object passively with the influence of virtual springs. Desired finger motion is transformed to desired joint motion using inverse kinematics and the joints torques are calculated using PID control. This provides a base controller to both achieve the task and keep the object in hand. However, grasping an unknown object is prone to occasional contact losses.

We use the feedback from fingertip force sensors to prevent contact losses. This method adjusts the stiffness of virtual springs during the manipulation in order to keep the forces around a desired value. This is done by a loose proportional controller that allows a reasonable steady-state error to enable the manipulation by responding only to larger errors.

We evaluate the method with experiments on a real robot hand [6]. The robot learns the rotation and translation tasks (Fig. 1.b) from a single example, demonstrated kinesthetically by a human (Fig. 2.a). It then reproduces the actions

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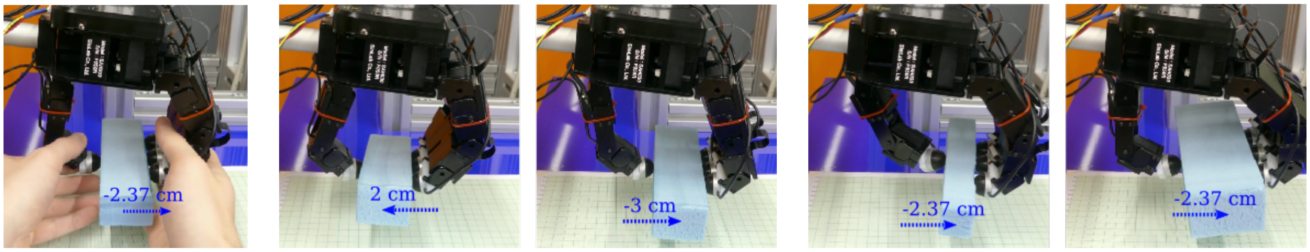

(a) (b) (c)

Fig. 2. (a) Kinesthetic demonstration of the translation action. (b) Reproduction with different initial and goal positions. (c) Reproduction with different object sizes. Blue arrows show desired translation amounts.

autonomously with different initial state, final state, object size conditions as shown in Figure 2. We also observe that the force-feedback improves the grasp stability during manipulation.

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