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Iterative learning of grasp adaptation through human corrections

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ABSTRACT

In the context of object interaction and manipulation, one characteristic of a robust grasp is its ability to *comply with external perturbations* applied to the grasped object *while still maintaining the grasp*. In this work, we introduce an approach for grasp adaptation which learns a statistical model to adapt hand posture solely based on the perceived contact between the object and fingers. Using a multi-step learning procedure, the model dataset is built by first *demonstrating* an initial hand posture, which is then physically *corrected* by a human teacher pressing on the fingertips, exploiting compliance in the robot hand. The learner then *replays* the resulting sequence of hand postures, to generate a dataset of posture–contact pairs that are not influenced by the touch of the teacher. A key feature of this work is that the learned model may be further *refined* by repeating the correction–replay steps. Alternatively, the model may be *reused* in the development of new models, characterized by the contact signatures of a different object. Our approach is empirically validated on the *iCub* robot. We demonstrate grasp adaptation in response to changes in contact, and show successful model reuse and improved adaptation with additional rounds of model refinement.

1. Introduction

Object interaction and manipulation is a challenging topic within robotics research. When a detailed model of the object shape and surface properties is known, one can reason about grasp optimality. However, the prior knowledge requirement is extensive – object properties like the mass distribution or surface texture can be difficult to obtain, for example requiring force sensors or accurate tactile sensing – and how these properties change as the object is manipulated can be difficult to predict. When detailed information about the object shape and surface properties is not known, compromises like grasp sub-optimality and a strong reliance on accurate runtime sensing must be made. Object manipulation becomes even more challenging within the context of dynamic interactions, when the grasp on the object is not static.

In this work, the target behavior is *grasp adaptation*; that is, the ability to be intentionally responsive to external forces so as to comply smoothly with external perturbations, all while maintaining contact with the object (Fig. 1(a)). The use of force or impedance feedback controllers offer robust solutions to the goal of maintaining contact with an object; however, most works do not consider the additional goal of being intentionally *compliant* and to follow perturbations [1–4]. Smooth compliance in response to object perturbations when grasping necessitates a tight coordination between all fingers, else the grasped object might fall from the hand. Moreover, this coordination is typically ensured by a good knowledge of the hand kinematics and of the object shape [5–8]. To tackle this issue, rather than handcraft the coordination patterns across all fingers for each novel object, we adopt a learning approach based on human demonstration. The coordination patterns thus are extracted from a set of good example grasps. The use of demonstration learning is motivated further by the high-dimensionality of the task state-space, due to the number of degrees of freedom in the fingers and the sensory signals at play. Showing by example can simplify the specification of coordinated postures between all of the fingers. If the examples are shown kinesthetically, by physically touching the robot to move its fingers, demonstration also allows the teacher to provide the robot with an intuitive notion of force.

Our work takes the approach of learning a statistical model able to predict a desired hand posture and fingertip pressure from the current signature of the contact perceived at the robot's fingertips. The approach depends on tactile sensing at the fingertips and human demonstration to provide an example set

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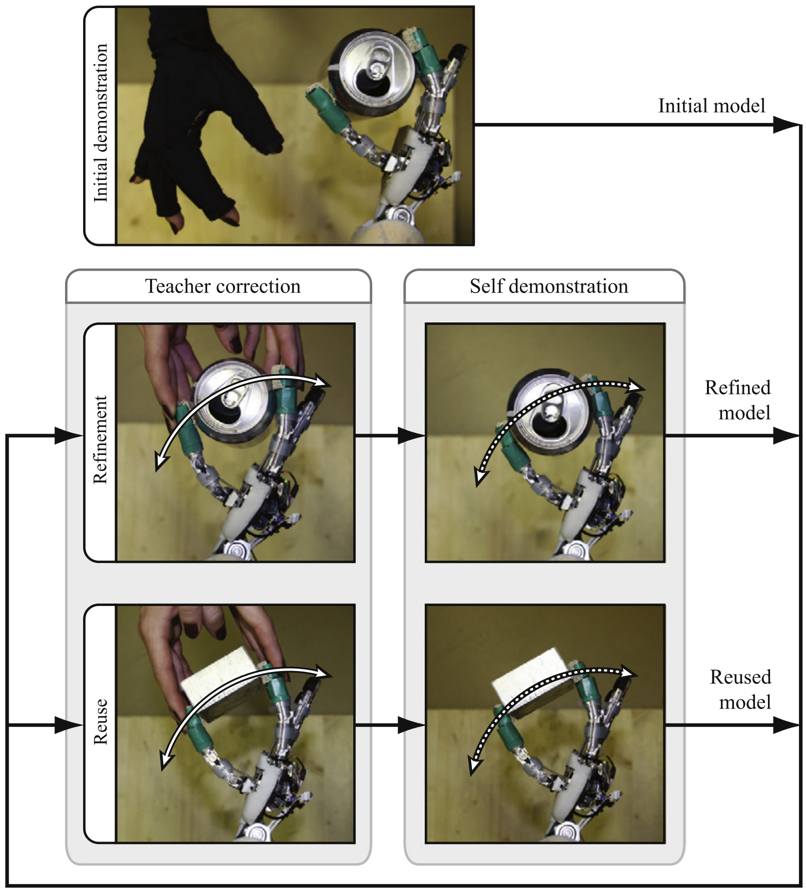
(a) Grasp adaptation to external perturbation.



(b) Policy development through refinement and reuse.

Fig. 1. (a) *Grasp adaptation:* When an external perturbation is applied on the object currently grasped by the robot, the robot dynamically adapts its grasp to comply with the perturbation. (b) *Overview of our approach for learning grasp adaptation skills:* An adaptive model for maintaining a grasp in response to changing contacts is built and updated (top→bottom) by having a teacher demonstrate a grasp and then refine the range of possible grasps for adaptation through corrective feedback (left column). Robot self-demonstration (right column) is necessary for acquiring sensory information that is not influenced by the touch of the teacher. Furthermore, the development of a new model that is responsive to a new object is also possible through model reuse.

of feasible grasps.[1] The approach does not require any kinematic nor dynamic model of the hand nor object, unlike model-based manipulation approaches. Such requirements of a detailed model and consequently, precise sensing capabilities, in practice can be an issue for many robotic platforms. Instead, the use of a probabilistic model allows for the encapsulation of the intrinsic non-linear mapping between the noisy tactile data and joint information, obtained directly from example grasps.

The dataset of examples is built both from human demonstration, and from self-demonstration by the robot after correction by a human teacher. In particular, our model derives from a multi-step learning procedure, that iteratively builds a training dataset from a combination of teacher *demonstration*, teacher *correction* and learner *replay* (Fig. 1(b)). Corrections are accomplished by having the teacher directly act on the fingers of the robot. In contrast to other demonstration mechanisms like vision systems or data gloves, we suggest that directly acting on the fingers allows the human to detect the forces applied to the grasped object, and thus to achieve a better demonstration of the applied forces. The dataset also is built *iteratively*, as the teacher interactively corrects the robot's executions and thus refines the learned behavior. A key distinction in our work when compared to other iterative demonstration learning approaches [9–13] is the focus on perturbations, that possibly take the execution far from what has been shown in the demonstration set. Our novel formulation for avoiding over-generalization also ensures that the robot's response is always valid with respect to the example dataset. Our corrections furthermore aim not only to improve upon a demonstrated behavior, but also to explicitly show additional flexibility and adaptation beyond an executed pose.

Our approach is empirically validated on the *iCub* robot [14], building contact models for multiple objects of different shapes

[1] We assume the training dataset consists of only valid grasps, such that the grasped object does not slip or fall from the hand, as ensured by the teacher's supervision.