Lack of Understanding of Objects as a Cause of Manipulation Failures

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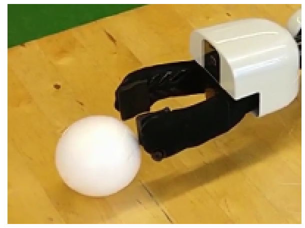
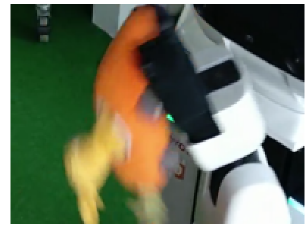
***Abstract*— Failures in manipulation are an inevitable aspect of robot operation, particularly in open-ended, human-centered environments, where robots need to be able to handle different types of objects. There are various causes of such failures, but one common problem is the lack of understanding of the differences between physical object properties, due to which manipulation strategies that are useful in one scenario become unsuitable in another. This problem could be alleviated by tighter integration with object ontologies and by equipping robots with an ability to learn the properties of previously unseen objects through self-guided experimentation.**



(a) Pushed ball while grasping



(b) Toy slip after grasping

Fig. 1: Failures due to lack of adaptivity to object properties

A. Problem: Failures Due to Insufficient Object Knowledge

In everyday environments, robots need to manipulate a variety of objects, such that objects from different categories generally require specific treatments. For instance, cutlery is slim and may slip, an egg can break if pushed too hard, while a bag is soft and may deform while being handled. Failures will thus inevitably occur if a robot is unable to adapt its manipulation strategy to the specific object at hand.

Our robots have often experienced failures that were essentially caused by the lack of adaptivity to unique object properties. In Fig. 1, we illustrate two such failures.[1] In the first case, our robot estimates the pose of a ball on a table and then reaches for it, but inadvertently pushes the ball away before grasping, which results in an unsuccessful grasp. In the second case, the robot grasps a toy on the table successfully at first, but the toy slips out of the gripper while the arm is being retracted. In both cases, the specific properties of the manipulated objects were not taken into account, namely the lightness of the ball and its ability to roll away in the former case, and the softness of the toy in the latter case. According to our evaluation in [1], the grasping strategy that failed in these two cases is reasonably reliable in general, but lacks the ability to adapt to different object properties (other than size), thus resulting in failures.

B. Potential Solutions: Utilising Object Ontologies and Learning Object Properties

To avoid failures of this kind, robots first of all need to be equipped with semantic knowledge about objects, for instance encoded in an object ontology such as in [2] or [3], and such knowledge should be utilised during execution. One recent work that somewhat goes in this direction is [4], although without the explicit use of an ontology.

An ontology is unlikely to capture the details about all relevant objects in an environment, so it is also important that robots have the ability to experiment with objects, such as in [5], in order to learn their properties. Such experimentation should ideally be performed in a constrained manner, as objects may potentially be damaged otherwise. In this context, learning constraints on the executions parameters, as we have done in [6], may contribute to a more guided learning process.

Finally, combining information from various sensory modalities, as in [7] and [8], is necessary during online execution as well, since the complementarity of different sources can contribute to an increased execution robustness.

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[1]A video illustrating these two failures, as well as a few others, can be found at `https://youtu.be/461RVBWBeNo`

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