Learning Purely Tactile In-Hand Manipulation with a Torque-Controlled Hand

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Abstract— **We show that a purely tactile dextrous in-hand manipulation task with continuous regrasping, requiring permanent force closure, can be learned from scratch and executed robustly on a torque-controlled humanoid robotic hand. The task is rotating a cube without dropping it, but in contrast to OpenAI's seminal cube manipulation task [1], the palm faces downwards and no cameras but only the hand's position and torque sensing are used. Although the task seems simple, it combines for the first time all the challenges in execution as well as learning that are important for using in-hand manipulation in real-world applications. We efficiently train in a precisely modeled and identified rigid body simulation with off-policy deep reinforcement learning, significantly sped up by a domain adapted curriculum, leading to a moderate 600 CPU hours of training time. The resulting policy is robustly transferred to the real humanoid DLR Hand-II, e.g., reaching more than 46 full 2π rotations of the cube in a single run and allowing for disturbances like different cube sizes, hand orientation, or pulling a finger.**

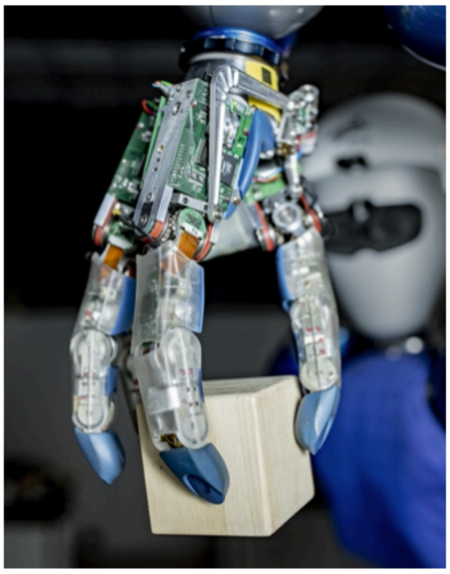

Fig. 1. DLR's humanoid robot Agile Justin [10] performing an in-hand manipulation task with the torque-controlled DLR Hand-II [11]: rotate the cube without dropping it. Only the built-in joint angle and torque sensors of the hand are used but no cameras.

I. Introduction

Dextrous in-hand manipulation, i.e., moving and reorienting an object inside the hand without dropping it (see Fig. 1), is a challenging task demanding for complex multi-finger strategies with intricate multi-contacts. This is even more so when the task has to be performed robustly with permanent force closure, e.g., to withstand gravity in an upside-down setting. Often the task has to be executed blindly, e.g., because of occlusions by the hand itself, only based on tactile feedback. Humans achieve all of this with ease, using in-hand manipulation all the time in everyday live.

A. Related Work

For simulated environments, there is a large body of work investigating in-hand manipulation for challenging and dynamic tasks, some of which are using advanced humanoid hands. The methods applied range from classical control and planning methods [2, 3] up to learning from scratch applying modern deep reinforcement learning algorithms [4, 5, 6]. In these works, the full dynamic state of the manipulated object is taken for granted which is easy to achieve when working in simulation.

To use the full object state also on a real robotic system, an additional visual tracking system has to be added. In their seminal work, OpenAI [1] used visual tracking not only for the object state but also for the finger tips. This way and in addition with domain randomization they could achieve robust sim2real transfer of a complex manipulation strategy, which was learned in simulation, to a real five-finger hand (Shadow Hand). The task was to rotate a cube to given orientations in the hand with the palm facing up, hence, without the need for force closure. Using on-policy deep reinforcement learning, the task was learned from scratch but needed a huge compute budget of about 300k CPU hours (about 30 CPU years). Using the same robotic and learning setup, in a follow-up paper [7] they even learned to solve a (sensor-equipped) Rubik's cube single-handedly, but again without permanent force closure and needing an extremely high compute budget of 10k CPU years.

Haarnoja et al. [8] and Nagabandi et al. [9] are also using visual object tracking, but directly learn on the real robotic system. The former solves the task of rotating a valve with their off-policy sample efficient Soft Actor Critic (SAC) algorithm and the latter uses dynamic learning and model predictive control to manipulate two Baoding balls. Both tasks are not force closure.

Other work uses no explicit object state but only tactile information (via tactile sensing or via torque controlled joints), e.g., in a model-based control setup [12] or with (reinforcement) learning directly on the robotic system [13, 14, 15, 16]. All these in-hand manipulation tasks naturally use force closure but are all rather simple, i.e., small movements of the object without regrasping.

Recently, Bhatt et al. [17] presented an approach for

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