What Is the Key to Dexterous Manipulation: Learning or Compliance?

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I. Introduction

This abstract aims to spark a discussion on the key building block for dexterous manipulation: is it learning or compliance? While those are not the only building blocks, both have driven significant progress and merit discussion. An essential factor in addressing this question is evaluating both the generality of a solution and the cost associated with achieving this generality. To compare the two, this abstract looks at one axis of generality: the ability to execute a manipulation skill in different wrist orientations. We show that a compliant hand can perform a cuboid rotation skill in varying wrist orientations at no additional cost. We explain that compliance enables self-stabilization [1], making it an ideal low-level building block for robust manipulation.

II. Learning

Deep reinforcement learning (RL) [2]–[8] is the dominant method in dexterous manipulation. It incurs significant computational costs when gathering up to hundreds of years of simulated experience [2], which can require weeks of wall time [6]. Difficult-to-interpret neural networks learn from this experience via feedback from complex reward functions [3]. RL controllers, often trained on privileged simulation data, mainly rely on accurate proprioceptive or tactile sensing [3] and cameras [2] to bridge the infamous sim-to-real gap.

III. Compliance

A. Comparing Results

Compliant systems drastically relax the assumptions on accurate sensing and control [9]. Compliant hands provide stable regions for finger gaiting [10] and make skills transfer unmodified to different objects, execution speeds, and object poses [11] – at no additional cost. We use the soft, pneumatically actuated RBO Hand 3 [12] with **no sensors** attached to compare against a learning-based approach.

Fig. 1A shows a looping cuboid rotation sequence. Fig. 1B demonstrates that this skill transfers unmodified to changing wrist orientations, highlighting the skill's robustness against changing gravity directions. Fig. 2 shows the number of rotations achieved by the same manipulation but in fixed wrist positions. We achieve up to 31.5 full rotations in the Thumb Up position, while Palm Down proves most challenging at 1.5 rotations. Fig. 2 also compares our simple approach to AnyRotate [3], a deep RL-based controller for object rotation around arbitrary axes. AnyRotate is a relevant baseline since, to our knowledge, no other learning-based framework explicitly tackles object manipulation across varying wrist orientations. We evaluate our skill on only one object, while AnyRotate averages performance over ten real-world objects. The results in Fig. 2 indicate that very capable dexterous manipulation is possible without learning.

The question is: what was the cost of this solution? AnyRotate relies on custom task-specific tactile sensors, multiple neural networks, and a complex training procedure. In contrast, our method requires no sensors. It merely executes the six-step open-loop manipulation sequence in Fig. 1A, defined by approximately three parameters per step (which finger groups move and where). Designing and tuning this sequence manually takes an expert only a few hours.

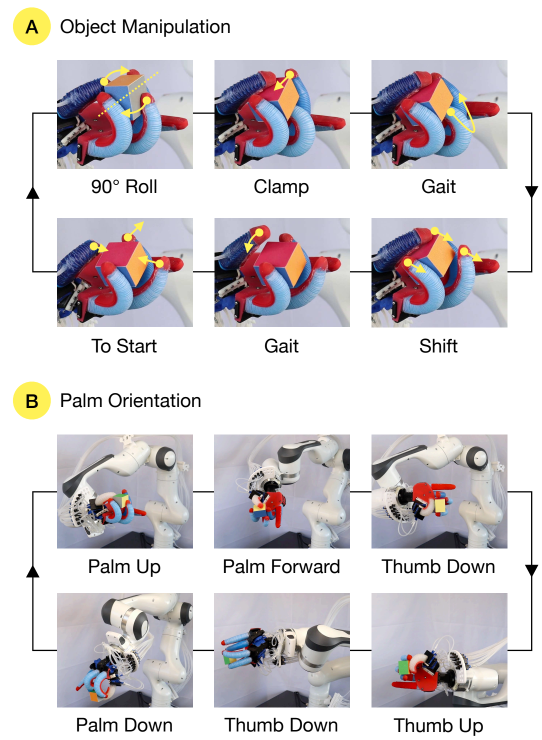

Fig. 1. We argue that compliance is key to dexterous manipulation because it enables robustness against external disturbances: the **open-loop** cube rotation sequence in (A) is programmed in the Palm Up position and transfers unmodified to continuously changing wrist orientations in (B). The hand controller is **not synchronized** to the arm movement. This demonstration runs for 6 minutes and 50 seconds without interventions and achieves five 360° cuboid rotations while the arm completes four full cycles.

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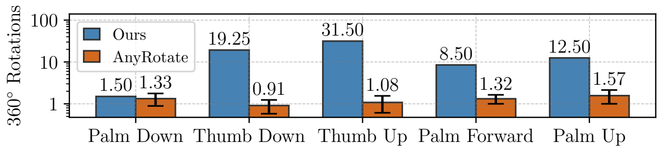

Fig. 2. Number of object rotations in different but fixed wrist poses in log scale. AnyRotate's results from Table 2 [3] also evaluate a single object rotation axis but report an average over ten objects while we rotate a single object. Their Base Up is our Palm Forward. Videos are accessible at `https://youtube.com/playlist?list=PLb-CNILz7vmtfNvvnbw58uElme1yGWYtL`.

B. Compliance Enables Self-Stabilization

How can our manipulation skill achieve such generality with no sensors and no learning? Fig. 3 shows that compliant grasps have a self-stabilizing property that aids in passively counteracting disturbances like gravity. First, a force-closure grasp is in equilibrium, meaning the resulting forces are balanced and the object is stationary. The valves remain shut, keeping the air mass inside the actuators fixed. Second, an external disturbance is applied, the hand deforms, and the object shifts (and rotates). When deformed, the compliant hand stores energy in the elastic deformation of the silicone and compression of air in the air chambers. Lastly, after removing the disturbance, the hand-object system returns to its minimum energy configuration corresponding approximately to the original configuration.

Metaphorically speaking, the soft hand creates funnel walls that passively stabilize the grasp in all directions and move the system back into a small, predictable region after deflection. To visualize this funnel, we abstract the hand-object system as a linear spring and calculate the stored potential energy via $E_p = \frac{1}{2}Fd$ where F is the force magnitude in the xy plane, and d is the deflection from the undisturbed object position. Fig. 4 shows a funnel resulting from 34 self-stabilizing trajectories starting in the equilibrium grasp from Fig. 3.1. A trajectory is self-stabilizing if the object returns to a position at most 5 mm from the trajectory's start position after removal of the disturbance. As shown in Fig. 4, the object travels back into a small return region with a spread of $\sigma_x = 1.4$ mm and $\sigma_y = 1.9$ mm. The important insight in Fig. 4 is that a soft force closure grasp can compensate any disturbance within the broad self-stabilizing region in gray as the object travels back into the predictable and small area in green upon removal of the force. Effectively, the funnel reduces object position uncertainty [13].

C. Leveraging Self-Stabilization for Manipulation

As shown in Fig. 4, the grasp's equilibrium without the disturbance is the system's attractor. We obtain robust object manipulation while maintaining self-stabilization by shifting this natural attractor of the grasp in space with a dexterous hand. This natural attractor is defined by the configuration of the fingers that would be attained if no external forces were acting on them, similar to the rest position of a spring. We control our soft actuators by changing the enclosed air-mass [14] in each actuator, uniquely defining this rest

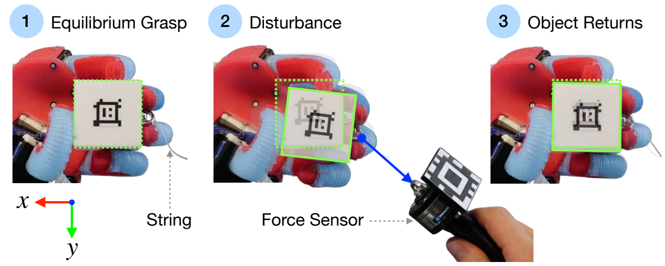

Fig. 3. Compliance enables self-stabilization on a soft hands. (1) To show the effect, an object is placed in a stable equilibrium grasp. A camera tracks the object's position via a marker. (2) An external disturbance is applied via a force sensor. The object is displaced from its equilibrium position. (3) After the disturbing force is removed, the object approximately returns to its original pose due to the purely passive self-stabilization.

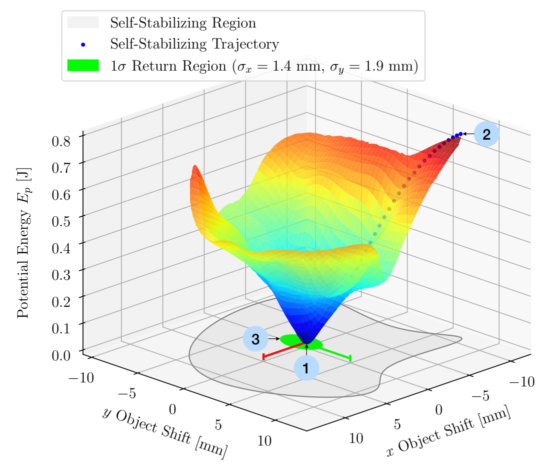

Fig. 4. Visualization of a self-stabilizing funnel to interpret the three stages from Fig. 3. (1) We start at an unperturbed grasp (zero object shift, zero energy change). (2) Analogously to a mechanical spring, the soft hand stores potential energy when a disturbing force deflects the object from the equilibrium grasp. Higher disturbances within the self-stabilizing region make the system travel further up the energy landscape. (3) After removing the force, the object travels back towards its minimum energy configuration, settling into the green return region, approximately corresponding to its original position.

position. Suppose we start from a self-stabilizing grasp and move the rest positions of all fingers as a bulk such that the relative finger positions are maintained and the contacts stick to the object. In that case, we preserve self-stabilization and obtain object motion that is approximately the movement of the rest positions. To realize this, we only require our soft hand's forward and inverse kinematics in unobstructed motion. In Fig. 1A, the *Roll* and *Shift* are realized through this insight. The *Gait* and *Clamp* are also generated by tracking rest position trajectories via inverse kinematics.

We conclude that compliance is an essential yet often overlooked building block for dexterous manipulation. Without leveraging compliance, one is making the problem unnecessarily hard. Thankfully, learning and compliance are not mutually exclusive. Compliance enables a great deal of generality for little cost, simplifies control, and is, therefore, an ideal building block for learning algorithms to build on.

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