I. RELAXED-RIGIDITY CONSTRAINTS RESULTS

A. Overview

Using the proposed framework, we compare five different in-hand manipulation solutions using Level I tasks:

- The *relaxed-rigidity, relaxed-position, & relaxed-position-orientation* in-hand manipulation methods by Sundaralingam and Hermans [1]; these methods enable a robotic system to repose a grasped object without breaking/making new contacts on the object.
- The *IK-rigid* method, in which a rigid contact model between the object and the fingertips is assumed.
- The *point-contact* method, which assumes a point contact with friction model for the fingertips. That is, the contact position is assumed fixed, while the relative orientation can change. This is a simplification of the model formulated in [2].

The desired grasp is given by a desired palm pose P_d with respect to the object.



Fig. 1: Objects from the YCB dataset used in the experiments with corresponding labels and measured weights below them.

B. Setup Details

The methods are first compared within a trajectory optimization framework offline. Then, they are executed on the Allegro hand-a multi-fingered hand attached to a box frame. For the evaluation, we used ten objects from the YCB dataset shown in Fig. 1. The object and hand were tracked using ARUCO markers [3] using an ASUS XTION camera. A human initialized the object in the initial hand pose. Each generated trajectory was executed five times. We used two different initial grasps and five different desired grasps per object. Five trials were run for each generated trajectory, accounting for 50 executions per object. In total, 500 trajectories were executed on the robot. The goal positions range from 0.8cm to 8.33cm, with a mean of 4.87cm, from their respective initial positions. The goal orientations range from 1.53% to 30.7%, with a mean of 11.96%, from their respective initial positions. The generated grasp sets are available at https://robot-learning. cs.utah.edu/project/in_hand_manipulation.



Fig. 2: Comparison of time taken to generate the trajectory across five different methods: *IK-rigid, point-contact, relaxed-position, relaxed-position-orientation* and *relaxedrigidity.*



Fig. 3: Comparison of planned hand pose across four different methods: *IK-rigid, relaxed-position, relaxed-positionorientation* and *relaxed-rigidity*. Results show the position error between the desired final hand pose and the final hand pose obtained by the trajectory optimization.

C. Results

For every trajectory that is run on the robot, the position error and orientation error was recorded. We additionally report the planning time in Fig. 2. Since all trajectories are run without replanning, the execution time is fixed at 1.67s. As suggested in our benchmarking framework, the errors are plotted as a box plot (showing first quartile, median error, third quartile) with whiskers indicating the extremes of the inliers within 1.5 times the interquartile range. In all plots results correspond to objects grasped with three fingers. We will first report the error between the planned hand pose and the desired hand pose, followed by results on executing the generated trajectories on the real robot.

1) Convergence of Optimization to Desired Hand Pose: We report the error between the planned hand pose and the desired hand pose across these methods: *IK-rigid*, *relaxedposition*, *relaxed-position-orientation* and *relaxed-rigidity*. We do not show offline results for the *point-contact* method



Fig. 4: A comparison of the different methods on real-world executions. Top: Position error Middle: Position error% Bottom: Orientation error%. The median position error decreases for all objects with the *relaxed-rigidity* method. Except for *banana* and *gelatin box*, the orientation error% improves for the *relaxed-rigidity* method for all objects.

as computing the object pose from the solution is not possible since the optimization does not internally simulate the object's pose. However, we will report the results of *pointcontact* method in the real-robot experiments. The errors are plotted in Fig. 3. It is evident that IK-rigid has difficulty reaching the desired object position, a result of the problem being over-constrained, as such we do not report experimental results for this method on the real robot.

2) Real Robot Execution Results: The position error and orientation error for all trials across all objects are shown in Fig. 4. The *relaxed-rigidity* method has the lowest median position error across all objects. Its maximum error across all objects is also much smaller than the *point-contact* method. Additionally, one can see that the *relaxed-rigidity* method has

TABLE I: Summary of results with the best value in bold text. The errors are the median of all trials.

Method	drops%	(cm)	r _{pos}	$err_{or}\%$
point-contact	5	1.69	36.81	9.74
relaxed-position	9	1.64	30.95	10.43
relaxed-position-orientation	7	1.54	29.19	9.84
relaxed-rigidity	0	1.32	28.67	9.86

a lower variance in final position than the competing methods across nearly all objects. We report the median errors and the percentage of object drops in Table I. The *relaxed-rigidity* method never dropped any object across the 500 trials that were executed while all other methods dropped the object significantly. The contact points based metrics, G_{euc} and G_{geo} , are not reported because these methods perform Level I tasks, i.e. only concerned with the hand's pose.

REFERENCES

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