Real Robot Challenge 2021 - Stage 1 Report

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Abstract

We extend heuristic grasping and motion planning used in RRC 2020 [5] with impedance control to reach the best performance of -33410 [1]. In the future work, we plan to explore data-driven grasp configuration selection mechanisms.

1 Background: Grasp and Motion Planning

in RRC 2020, Funk et.al. [2] used heuristic grasping and motion planning to bring a rigid object to the target position $\mathbf{x}_t \in \mathbb{R}^3$ in a workspace $W \subseteq \mathbb{R}^3$, using TriFinger robot. It consists of four components with overall algorithm given below:

1. `BringToCenter`: bring the object to the workspace surface centre, using dynamic motion primitives.
2. `GetGrasp`: obtain one of the heuristics grasp configurations for the robot or a randomly sampled grasp configuration, respecting feasibility constraints (no collisions and force closure).
3. `Plan`: evaluation of grasp to reach $\hat{\mathbf{x}}$ using RRT motion planner [3].
4. `Execute`: plan execution using PD controller; in case of failure (e.g., dropped object), execution stops.

Algorithm 1 Grasp and Motion Planning

Require: o - object, $\mathbf{x}_t$ - target position, ϵ - tolerance, P - plan (initially empty).

repeat
    `BringToCenter`(o) ▷ use dynamic motion primitives
    while `Empty`(P) **do**
        $g \leftarrow$ `GetGrasp`(o)
        $P \leftarrow$ `Plan`$(g, \hat{\mathbf{x}})$ ▷ If no plan found, empty plan returned
    `Execute`(P) ▷ plan execution with PD controller
until $\|\texttt{Position}(o) - \hat{\mathbf{x}})\|_2 \leq \epsilon$

By using this approach, we achieved -38983 reward on the manipulation testsuite provided.

2 Methodology: Impedance Control

When experimenting with TriFinger, we concluded that the performance gains can be achieved with an improved control strategy. In particular, the PD controller used before had no force/tactile feedback and achieved gripping by using points inside the object as the target positions. To deal with this, we decided to use impedance control (as described in [4, 1]). Using it, the control law is as follows:

$$\tau = \mathbf{J}^\top [K_P(\mathbf{x}_t - \mathbf{x}) + K_D(\dot{\mathbf{x}}_t - \dot{\mathbf{x}}) + \mathbf{f}] + \mathbf{g}$$

[1] Video for robot execution can be found here.

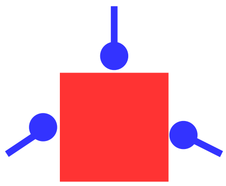
where $\tau \in \mathbb{R}^9$ are desired joint angles, K_P, K_D: hand-tuned gains, $\mathbf{f}$ are contact forces of each finger tip, $\mathbf{J}$ is the Jacobian, and $\mathbf{x}$, $\dot{\mathbf{x}}$ are current position and velocity for fingertips. By integrating impedance control, we have achieved -33410 reward on the manipulation testsuite provided.

3 Discussion and Future Work

After improving current improvements, we plan to spend more time on designing a mechanism to select suitable heuristic grasp configurations. Currently, the object is grasped with one of the three heuristic grasp configurations (see Figure 1) or sampled grasp, but there is no mechanism to determine the suitability of the grasp configuration without performing computationally expensive motion planning. We plan to continue working on this problem and learn a mechanism to evaluate grasp suitability for particular manipulation without motion planning. By doing so we not only aim to improve the time required to find a good grasp but to avoid a need to execute `BringToCenter` to have further gains.

(a) 2F2: 2 face using 2 fingers

(b) 2F3: 2 face using 3 fingers



(c) 3F3: 3 face using 3 fingers

Figure 1: Different heuristic grasping strategies for manipulating a rigid block with TriFinger robot.

References

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[5] Takuma Yoneda, Charles B. Schaff, Takahiro Maeda, and Matthew R. Walter. Grasp and motion planning for dexterous manipulation for the real robot challenge. *CoRR*, abs/2101.02842, 2021.