Tuning-Free Contact-Implicit Trajectory Optimization

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The introduction of contacts into a trajectory optimization problem leads to non-smooth dynamics and precludes the use of gradient-based optimization methods in a variety of robot manipulation and locomotion tasks. Therefore, much work has focused on mitigating the discrete nature of contacts by developing appropriate models that enable the optimization to reason about contacts. In this method, contact-interaction trajectories emerge without explicit decisions about contact modes, and hence it is called contact-implicit trajectory optimization (CITO). There are two main approaches to CITO in the literature: (1) solving a nonlinear program with complementarity constraints using direct optimization and (2) using a smooth contact model and shooting optimization. The first approach can plan complex dynamic behaviors but the resulting motions need to be stabilized and nonlinear programming typically suffers from slow convergence. The second approach, on the other hand, was demonstrated to run as a receding horizon controller for planning and executing highly-dynamic motions on quadrupeds; however, it is tedious to tune the smooth contact model, and shooting optimization is sensitive to initial guess.

In our recent work [1], we have proposed a variable smooth contact model (VSCM) in which smooth virtual forces acting at a distance are injected into the dynamic model, in addition to the rigid-body contact mechanics. The virtual forces are exploited to discover contacts and minimized throughout the optimization. Moreover, in [2], we have shown that this problem can be solved with reliable convergence using a variant of successive convexification algorithm that was originally proposed in [3]. The use of the VSCM mitigates the burden of tuning by reducing the number of tuning parameters to one, namely a penalty on the relaxation (i.e., virtual forces). Nevertheless, it may be required to tune this penalty when the task or the robot is changed; and without extra tuning, abrupt changes may occur in the planned motions even with minor task modifications.

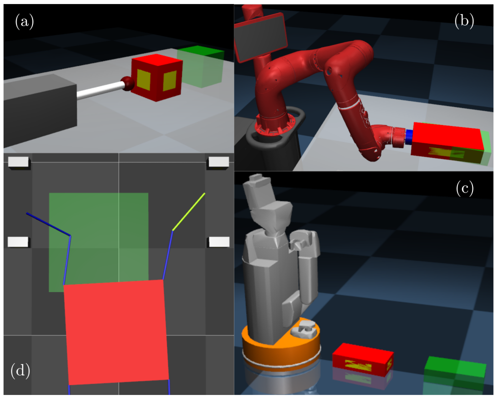

Fig. 1. Applications considered in this study: (a) 1-DOF pusher-slider system for a visual analysis of the problem, (b) a 7-DOF robot arm pushing a box, (c) a mobile robot pushing a box, and (d) locomotion in zero gravity.

In order to address these issues, we introduce a penalty-loop approach for CITO that is analogous to state-of-the-art trajectory optimization methods for collision avoidance, such as TrajOpt [4]. In these methods, the penalty on collision constraints is gradually increased so that the optimization can be initialized with an infeasible trajectory that is in collision, and the robot links are pulled out of obstacles by following the gradients. Since an infeasible initialization corresponds to a motion that completes the task using non-physical forces in the CITO case, we develop a method that increases the penalty on the relaxation until a motion that completes the task using only physical forces is found. Furthermore, in this case, it is possible to improve the previous solution by exploiting the contact information implied by the use of relaxation, i.e., the position, time, and magnitude of contact forces required to complete the task. To do so, we perform a computationally-cheap post process after each iteration.

We consider non-prehensile manipulation applications using a 1-DOF pusher, a 7-DOF arm, and a holonomic mobile robot and a planar locomotion application in zero gravity, see Fig. 1. We run simulation experiments for various goal positions to demonstrate the robustness of our framework. In all cases, the exact same configuration of the pipeline is used with a trivial seed, in which the robot stands still. The results demonstrate that our method provides an out-of-the-box solution with acceptable performance for a wide range of applications.

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