

Hierarchical Task and Motion Planning using Logic-Geometric Programming (HLGP)

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Abstract—In this work, we present a hierarchical approach to task and motion planning (TAMP) within an optimization-based framework. Recent work on formulating TAMP as a logic enhanced nonlinear program has shown remarkable capabilities. However, scaling this approach to domains with many discrete decisions or longer horizons implies a computational bottleneck. To overcome this, we introduce hierarchies within this framework, where on coarser levels a problem with less discrete decisions is solved. Formally, the hierarchies are defined in a way that the resulting nonlinear programs on coarser hierarchy levels are lower bounds on the finer hierarchies. We demonstrate the generality of the approach for both a bi-manual manipulation task and a mobile manipulation scenario which includes a “worm” like walking robot.

I. INTRODUCTION

In joint Task and Motion Planning (TAMP), it is common to introduce discrete abstractions for the purpose of reasoning over high level decisions. Given such a discrete decision sequence, a geometric planner must figure out the continuous motions of a robot to fulfill the planned tasks. Logic-Geometric Programming (LGP) is one variant to formalize the relation between discrete decision variables and a continuous nonlinear mathematical program (NLP) that represents the underlying continuous world problem [2]. The purpose of the discrete decisions in LGP is to simplify the underlying mathematical problem – ideally by enumerating sub-problems that can be handled efficiently by a continuous NLP solver. One core property of LGP is that the resulting NLP optimizes for a globally consistent continuous motion sequence conditioned on the discrete decisions. This is important, since, for example, the way an object is grasped greatly influences how it can be placed or used as a tool.

However, when scaling this approach to longer horizons or situations in which there are many possible discrete decisions such as for grasping, the computational demand for solving many NLPs during the search greatly increases. To overcome this, we propose to introduce a hierarchy of LGPs at the discrete decision level for the purpose of providing efficient lower bounds of the underlying LGP problem.

In our approach, a coarse level LGP is solved first that contains less constraints in the underlying NLP. The discrete decisions of this solution conditions a fine level LGP in two respects: Within the coarse LGP they imply an NLP which checks geometric and kinematic feasibility of these coarse decisions, potentially making simplifying assumptions about the kinematics. On the fine level LGP, the decisions of the

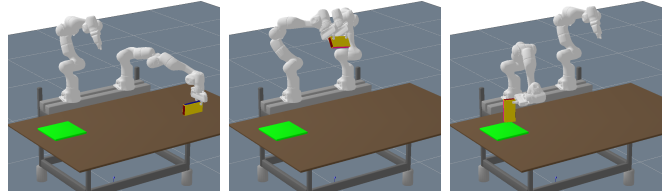


Fig. 1. Box re-orientation task that requires both arms for the solution

coarse level imply constraints on the allowed sequences of decisions of the real manipulation problem. The associated NLP of the fine LGP then solves for a globally consistent motion plan, which is in contrast to previous notions of abstractions in hierarchical TAMP [1], since in LGP feasible abstract decisions are not guaranteed to be refinable.

In Sec. III-A, we demonstrate the method and its computational benefit on a bi-manual manipulation task that involves grasping, re-orientation, handover, and placing. The planning on the fine level plans a motion that includes the detailed grasping geometry of a box shaped object. In Sec. III-B, we consider a novel domain where a “worm” robot can use its two end-effectors to walk, climb and pick-and-place objects, showing interesting sequential manipulation capabilities.

II. HIERARCHICAL LOGIC GEOMETRIC PROGRAMMING

We start by restating the LGP framework of [2] in a form that will allow us to introduce a hierarchy. The goal is to find a global path x in the configuration space as the solution of a logic enhanced NLP, which solves a given TAMP problem, while fulfilling plausibility constraints. The path itself consists of K subpaths $x_k : [T_{k-1}, T_k] \rightarrow \mathcal{X}_k$, $x_k \in C^2$. These K different phases are referred to as kinematic modes, in which the resulting path is smooth. The set $\mathcal{X}_k \subset \mathbb{R}^{l_k} \times SE(3)^{o_k}$, $\dim(\mathcal{X}_k) = n_k$ denotes the n_k -dimensional configuration space of all objects and articulated structures in mode k . The central mathematical object to define the objectives and constraints are so-called feature maps $\phi : \mathcal{X} \times \mathbb{R}^{n_k} \times \mathbb{R}^{n_k} \rightarrow \mathbb{R}^{d_k}$, $\phi \in C^1$, which map the world configuration (and their derivatives) to a d_k -dimensional space like positions of robot links, distances between objects, object poses, etc. The sets $\mathcal{T}_{\text{sos,ineq,eq}}(s_k)$ of active objectives and constraints at a certain phase k of the motion are determined by a discrete decision variable s_k . The possible transitions $s_k \in \text{succ}(s_{k-1})$ between such discrete states from s_{k-1} to s_k is defined by a first order

