Extended Abstract:
Motion Planners Learned from Geometric Hallucination

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Abstract—Learning motion planners to move robot from one point to another within an obstacle-occupied space in a collision-free manner requires either an extensive amount of data or high-quality demonstrations. This requirement is caused by the fact that among the variety of maneuvers the robot can perform, it is difficult to find the single optimal plan without many trial-and-error or an expert who is already capable of doing so. However, given a plan performed in obstacle-free space, it is relatively easy to find an obstacle geometry, where this plan is optimal. We consider this “dual” problem of classical motion planning and name this process of finding appropriate obstacle geometry as hallucination. In this work, we present two different approaches to hallucinate (1) the most constrained and (2) a minimal obstacle space where a given plan executed during an exploration phase in a completely safe obstacle-free environment remains optimal. We then train an end-to-end motion planner that can produce motions to move through realistic obstacles during deployment. Both methods are tested on a physical mobile robot in real-world cluttered environments.

I. INTRODUCTION

While classical motion planners, such as Dynamic Window Approach (DWA) [1], can reliably navigate the robot in cluttered spaces with properly tuned parameters, recent machine learning techniques have also been applied to the motion planning problem [2]. Those approaches either learn from a classical motion planner [2] or a human expert [3], or through an extensive amount of trial-and-error, such as Reinforcement Learning (RL) [4]. However, most learned motion planners still under-perform their classical counterparts. Despite the advantage of learning motion planners without hand-crafted rules [1] or in-situ adjustment [5] in a data-driven fashion, the performance is still bottlenecked by the requirement of good-quality training data [6].

Consider the “dual” problem of motion planning: instead of finding the optimal motion plan for a specific obstacle configuration, either using hand-crafted rules or training data, we seek to find the obstacle configuration(s) where a specific motion plan is guaranteed to be optimal. We name this process hallucination. Solving this problem gives us the freedom to allow random exploration in a completely safe obstacle-free space and collect an extensive amount of motion plans, whose optimally will be assured by a class of hallucination techniques. In this work, we introduce two of those techniques: to hallucinate (1) the (unique) most constrained and (2) a (not unique) minimal obstacle configuration.

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II. GEOMETRIC HALLUCINATION

Given a robot’s configuration space (C-space) partitioned by unreachable (obstacle) and reachable (free) configurations, \( C = C_{\text{obst}} \cup C_{\text{free}} \), we define the classical motion planning problem as to find a function \( f(\cdot) \) that can be used to produce optimal plans \( p = f(C_{\text{obst}} \mid c_e, c_g) \) that results in the robot moving from the robot’s current configuration \( c_e \) to a specified goal configuration \( c_g \) without intersecting the interior of \( C_{\text{obst}} \). Here, a plan \( p \in \mathcal{P} \) is a sequence of low-level actions \( \{u_i\}_{i \in \mathcal{U}} \), where \( u_i \in \mathcal{U} \). This work introduces two methods to approach the “dual” problem of finding optimal \( f(\cdot) \).

A. Hallucinating Most Constrained Obstacle Space [7]

Since different \( C_{\text{obst}} \) can lead to the same plan, the left inverse of \( f \), \( f^{-1} \), is not well defined (see Fig. 1 left). However, we can instead define a similar function \( g(\cdot) \) such that \( C_{\text{obst}} = g(p \mid c_e, c_g) \), where \( C_{\text{obst}}^* \) denotes the C-space’s most constrained unreachable set corresponding to \( p \).

Formally, given a plan \( p \) and the set of all unreachable sets \( \mathcal{E}_{\text{obst}} \), we say

\[
C_{\text{obst}} = g(p \mid c_e, c_g) \text{ iff } \forall C_{\text{obst}} \in \mathcal{E}_{\text{obst}}, \quad f(C_{\text{obst}} \mid c_e, c_g) = p \implies C_{\text{obst}} \subseteq C_{\text{obst}}^*. \tag{1}
\]

We denote the corresponding reachable set of \( C \) as \( C_{\text{free}}^* = C \setminus C_{\text{obst}}^* \). We call \( g(\cdot) \) the most constrained hallucination function and the output of \( g(\cdot) \) a most constrained hallucination. This hallucination can be projected onto the robot’s sensors. For example, for a LiDAR sensor, we perform ray casting from the sensor to the boundary between \( C_{\text{obst}}^* \) and \( C_{\text{free}}^* \) in order to project the hallucination onto the range readings (Fig. 1 right). Given the hallucination \( C_{\text{obst}}^* \) for \( p \), the only viable (and therefore optimal) plan is \( p = g^{-1}(C_{\text{obst}}^* \mid c_e, c_g) \). Note that \( g(\cdot) \) is bijective and its inverse \( g^{-1}(\cdot) \) is well defined. Leveraging machine learning, \( g^{-1}(\cdot) \) is represented using a function approximator \( g_{\theta}^{-1}(\cdot) \). Note that we aim to approximate \( g_{\theta}^{-1}(\cdot) \) instead of the original \( f(\cdot) \) due to the vastly different domain size: the most constrained \( (\mathcal{E}_{\text{obst}}^*) \) vs. all \( \mathcal{E}_{\text{obst}} \) unreachable sets.

During deployment, we use a smoothed coarse global path from a global planner to generate runtime hallucination so \( g_{\theta}^{-1}(\cdot) \) does not need to generalize to unseen scenarios. Other components, including a Turn in Place, Recovery Behavior, and Speed Modulation modules, are used in conjunction with \( g_{\theta}^{-1}(\cdot) \) to address inevitable out-of-distribution scenarios and adapt to the real C-space.

†Technically, \( c_g \) can be uniquely determined by \( p \) and \( c_e \), but we include it as an input to \( g(\cdot) \) for notational symmetry with \( f(\cdot) \).
mostly constant 0.4m/s linear velocity \(v \approx 0.4m/s\) and varying angular velocity \(\omega \in [-1.57, 1.57] \text{rad/s}\), the other with varying \(v \in [0, 1.0] m/s\) and \(\omega \in [-1.57, 1.57] \text{rad/s}\). If trained on the first dataset, the speed of the planner output is modulated by a Model Predictive Control based collision probability checker, achieving a max \(v = 0.6m/s\). Four neural network based planners are trained using the two datasets and two hallucination techniques. Simulated [9] and physical experiments are performed. While the minimal hallucination works well on both datasets and outperforms all other variants, and even a classical motion planner [1], the most constrained hallucination only performs well on the 0.4m/s dataset. This is because learning from varying speed while hallucinating only the most constrained space causes ambiguity for the learner.

III. CONCLUSIONS

We present a class of two geometric hallucination techniques that approach the classical motion planning problem from the opposite direction. Instead of seeking an optimal motion plan for an obstacle configuration, we find the obstacle configuration\(s\), where a motion plan is optimal. The first approach hallucinates the most constrained \(C\)-space, where the plan is the only feasible, and therefore optimal, plan. It largely reduces the learning complexity, since the learned motion planner \(g^{-1}_\theta(\cdot)\) only plans in the most constrained \(C\)-spaces, instead of any \(C\)-spaces. However, the downside of this approach is during deployment, runtime hallucination along with other extra components are necessary. The second approach finds a minimal obstacle set to make a plan optimal, augments this minimal set to generate a large body of training data, and therefore does not require any extra components during deployment.

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