

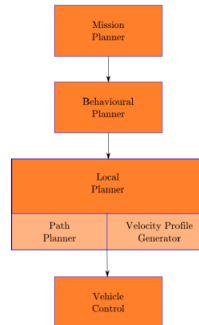
Motion Planning for Autonomous Driving

Philippe Weingertner, Minnie Ho

October 18, 2019

1 Problem definition

Within an Autonomous Driving pipeline we consider the planning problem. The behavioural planner defines a short term objective: it selects a maneuver to perform and defines an objective, where the ego vehicle wants to go, with associated constraints. The local planner will then compute a set of paths that are kinematically feasible and collision free with respect to static obstacles. For every candidate path, a velocity profile will be generated in order to avoid dynamic obstacles. This 2 steps decomposition of local planning is typical to make the problem simpler to solve in real time. Ultimately different trajectories are ranked and a preferred one is selected.



We focus on the local motion planning problem: we are given a path to follow and information about dynamic obstacles. We have to define a velocity profile such that the trajectory is collision free, comfortable (without too strong accelerations or decelerations) and efficient (as close as possible to the target velocity).

An autonomous vehicle has to deal with many sources of uncertainties. We consider sensor uncertainty and driving model uncertainty which translate to dynamics uncertainties.

2 Proposed Approach

From search to MDP search to AlphaZero.

2.1 Model

State Space is continuous, Action Space is Discrete

- Inputs: state description $[x, y, \dot{x}, \dot{y}]$ for all objects
- Output: longitudinal acceleration every 20 ms, discrete set of actions considered $\{-4, -2, -1, 0, 1, 2\} m.s^{-2}$

2.2 Inference

Without uncertainty, search problem: DP and UCS

With uncertainty, MDP problem: online MCTS tree search

2.3 Learning

We want to learn a useful heuristic to make the search more efficient. We will study the applicability of AlphaZero to Motion Planning: how we could combine planning and learning.

3 Experimental Setup and Status

Experiments: cf github

- Baseline: it is fast but bad
- Oracle: it is slow but good (assuming everything is known, no uncertainty)

4 Related work

References

- [1] Carl-Johan Hoel, Krister Wolff, and Leo Laine. “Automated Speed and Lane Change Decision Making using Deep Reinforcement Learning”. In: *CoRR* abs/1803.10056 (2018). arXiv: 1803.10056. URL: <http://arxiv.org/abs/1803.10056>.
- [2] Carl-Johan Hoel et al. “Combining Planning and Deep Reinforcement Learning in Tactical Decision Making for Autonomous Driving”. In: *CoRR* abs/1905.02680 (2019). arXiv: 1905.02680. URL: <http://arxiv.org/abs/1905.02680>.
- [3] Mykel J. Kochenderfer. *Decision Making Under Uncertainty: Theory and Application*. MIT Press, 2015.
- [4] David Silver et al. “Mastering Chess and Shogi by Self-Play with a General Reinforcement Learning Algorithm”. In: *CoRR* abs/1712.01815 (2017). arXiv: 1712.01815. URL: <http://arxiv.org/abs/1712.01815>.