Motion Planning for Autonomous Driving

Philippe Weingertner, Minnie Ho

November 5, 2019

1 Introduction

2 Related Work

There is a rich litterature related to Motion Planning and a very detailed survey of traditional methods is provided in [10]. Among the first 4 successful participants of DARPA Urban Challenge in 2007, the approaches vary. The winner, CMU Boss vehicle used variational techniques for local trajectory generation in a structured environment. This was done in a 2 steps path-velocity decomposition. A first step of path planning, using variational techniques, is performed and for every candidate path, a combination of different velocity profiles (constant, linear, linear ramp, trapezoidal) is applied : the combination of a path and velocity profile defines a trajectory. In unstructured environments (parking lots) or in error recovery situations a lattice graph in 4-dimensional configuration space (position, orientation and velocity) is searched with Anytime D* algorithm to find a collision-free path. More details are provided in [4, 1, 9]. The vehicle from Stanford used a search strategy coined Hybrid A* that constructs a tree of motion primitives by recursively applying a finite set of maneuvers. The search was guided by a carefully designed heuristic. The vehicle arriving 3rd, Victor Tango from Virginia Tech, constructs a graph discretization of possible maneuvers and searches the graph with the A* algorithm. The vehicle arriving 4th, developed by MIT used a variant of RRT algorithm with biased sampling. While all these techniques differ, they fundamentally rely on a graph search where nodes correspond to a configuration state and edges correspond to elementary motion primitives. Although they provide solutions, the runtime and state space can grow exponentially large. In this context, the use of heuristic to guide the search is important.

---

3 Approach

4 Experimental Setup and Status

The source code is available here: CS221 Project

- Baseline: the decision is fast, immediate, but we find a collision free velocity profile only in 35% of the cases.
- Oracle: the search space is big. With a time step of 250 ms, looking for a collision free velocity profile over the next 100 meters we find in 100% of the cases a collision free solution; but in 47.2 seconds with UCS and in 190.7 seconds with DP running on an iCore9. We explored the graph with a depth of 24. UCS has a complexity of $\mathcal{O}(n \log n)$ with $n = |\text{states}|$. It potentially explores fewer states than DP.
- Planning with MCTS tree search
- Q-learning
- Combining Planning and Learning (with an efficient learned heuristic)

References

[1] David Bissell et al. "Autonomous automobilities: The social impacts of driverless vehicles". In: *Current Sociology* (Dec. 2018), p. 001139211881674. DOI: 10.1177/0011392118816743.

[2] Panpan Cai et al. "LeTS-Drive: Driving in a Crowd by Learning from Tree Search". In: *CoRR* abs/1905.12197 (2019). arXiv: 1905.12197. URL: http://arxiv.org/abs/1905.12197.

[3] Michael Everett, Yu Fan Chen, and Jonathan P. How. "Motion Planning Among Dynamic, Decision-Making Agents with Deep Reinforcement Learning". In: *CoRR* abs/1805.01956 (2018). arXiv: 1805.01956. URL: http://arxiv.org/abs/1805.01956.

[4] Dave Ferguson, Thomas M. Howard, and Maxim Likhachev. "Motion Planning in Urban Environments". In: *The DARPA Urban Challenge*. 2009.

[5] Andreas Folkers, Matthias Rick, and Christof BÃŒskens. "Controlling an Autonomous Vehicle with Deep Reinforcement Learning". In: June 2019. DOI: 10.1109/IVS.2019.8814124.

[6] 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.

[7] 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.

[8] Mykel J. Kochenderfer. *Decision Making Under Uncertainty: Theory and Application*. MIT Press, 2015.

[9] M. McNaughton et al. "Motion planning for autonomous driving with a conformal spatiotemporal lattice". In: *2011 IEEE International Conference on Robotics and Automation*. May 2011, pp. 4889–4895. DOI: 10.1109/ICRA.2011.5980223.

[10] B. Paden et al. "A Survey of Motion Planning and Control Techniques for Self-Driving Urban Vehicles". In: *IEEE Transactions on Intelligent Vehicles* 1.1 (Mar. 2016), pp. 33–55. DOI: 10.1109/TIV.2016.2578706.

[11] F. Pusse and M. Klusch. "Hybrid Online POMDP Planning and Deep Reinforcement Learning for Safer Self-Driving Cars". In: *2019 IEEE Intelligent Vehicles Symposium (IV)*. June 2019, pp. 1013–1020. DOI: 10.1109/IVS.2019.8814125.

[12] Markus Schratter et al. "Pedestrian Collision Avoidance System for Scenarios with Occlusions". In: *CoRR* abs/1904.11566 (2019). arXiv: 1904.11566. URL: http://arxiv.org/abs/1904.11566.

[13] 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.

[14] David Silver et al. "Mastering the game of Go without human knowledge". In: *Nature* 550 (2017), pp. 354–359.