Learning Driving Corridor Cost Functions Using Inverse Reinforcement Learning

Background

There are many classical approaches for motion planning in autonomous driving [1, 2, 3], of which many are dependent on cost functions. On the other hand, machine learning approaches bring high-level reasoning capabilities to the table but often lack the safety and explainability necessary for real-world applications. Hybrid approaches aim at combining the best of both worlds be integrating the high-level reasoning of machine learning into explainable motion planning algorithms. In recent years, Inverse Reinforcement Learning (IRL) [4, 5, 6] has been proposed for learning cost functions or the weights of cost terms adaptively to a scenario [7, 8].

Description

Our chair is known for its motion planning [9], especially an approach based on driving corridors derived from reachability analysis, where each driving corridor represents one high-level maneuver [10]. Recently, we extended our approach to rule-compliant driving corridors [11, 12], however, the execution time on certain scenario types is not real-time capable. We are currently investigating graph-search approaches to accelerate it but deciding which node to compute next depends greatly on the heuristic and its weights.

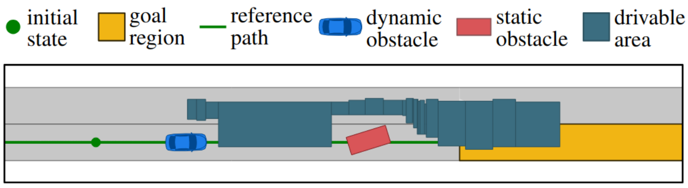

Figure 1: Motion planning with driving corridors.

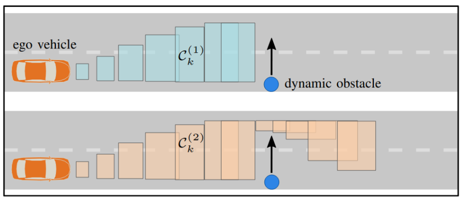

Figure 2: Two exemplary driving corridors, one representing a braking maneuver (blue) and one a more dangerous evasive maneuver (orange).

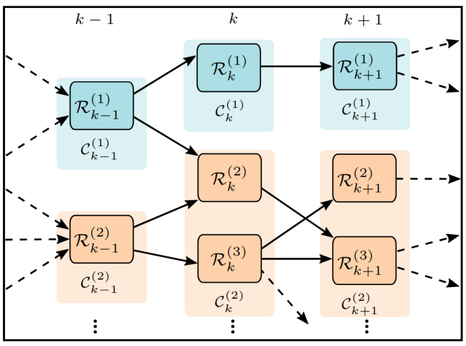

Figure 3: Connected components in one situation with two corridors (blue and orange).

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The aim of this thesis is to apply Inverse Reinforcement Learning to learn the weights of proposed heuristic terms (e.g. in [10, 12, 11]) to accelerate the driving corridor computation. If possible, the agent should be able to adapt the weights online.

Outline

We have already developed a Python/C++ tool and a depth-first search approach to select the most promising connected component (= part of a driving corridor [10]) first. Based on this tool and its output, this thesis should develop a representation of both the driving corridor and the scenario for the IRL agent and a selection strategy for the best component. Then, the agent should be trained and compared to our hand-tuned heuristics.

Tasks

- Familiarization with our Reachbility-based corridor approach and the tool
- Literature deep dive on suitable ideas for a representation of the corridor for the agent and the scenario, as well as a selection strategy for the connected components
- Implementation of the derived ideas and training of the agent
- Evaluation against the hand-tuned heuristic
- Development of a strategy for adapting the learned weights and costs online given a changing scenario

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