Motion Planning for Automated Vehicles in Uncertain Environments

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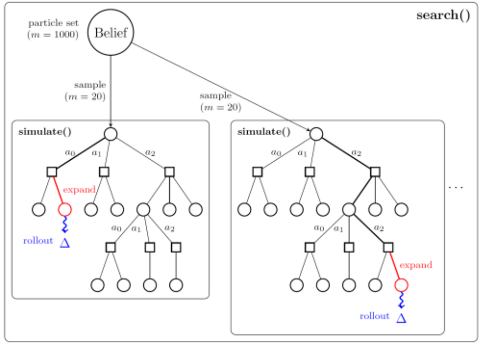

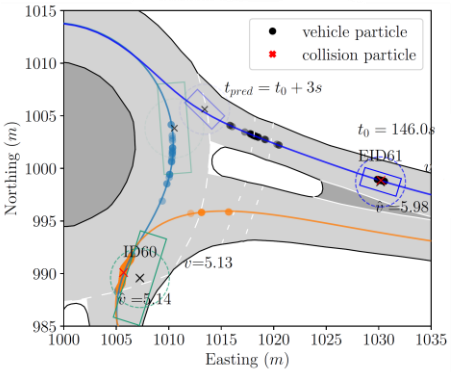

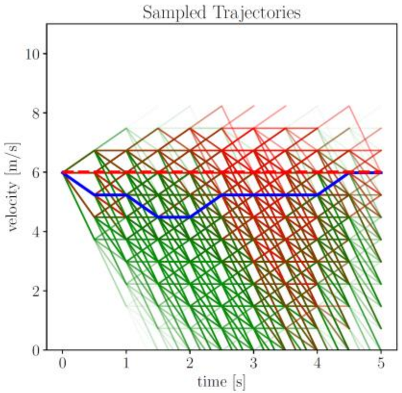

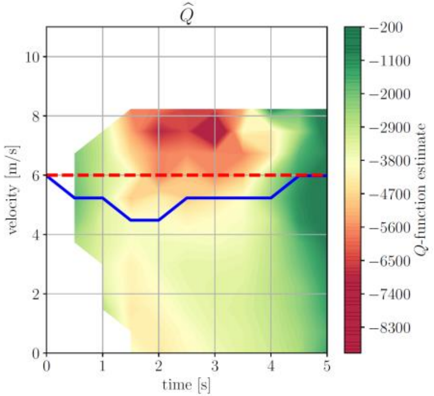

Outline

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  - POMDPs
- POMDPs in Automated Driving
  - State of the Art
  - POMDP Model in this work
- Particle Filter Tree (PFT) Algorithm
- Results
  - Driver Intent Estimation
  - POMDP Planner
- Conclusion & Future Work

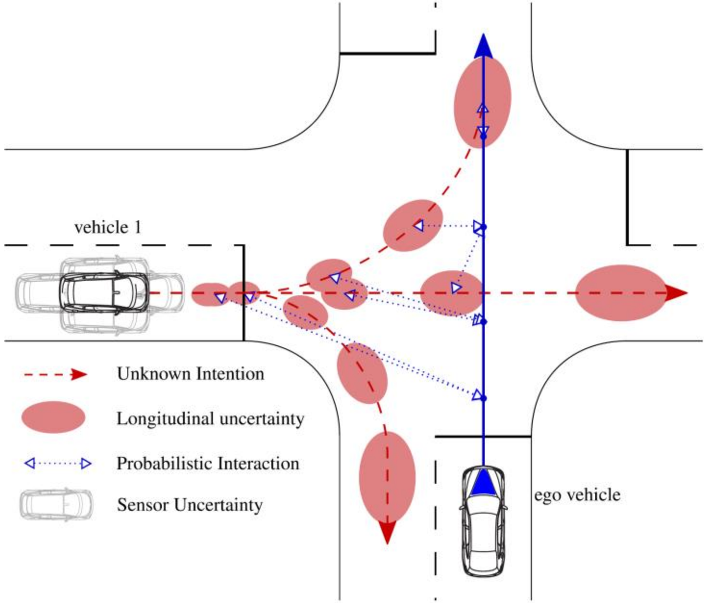
Motivation

Karlsruhe Institute of Technology

- Motivation for using POMDPs
  (Partially Observable Markov Decision Processes):
  - Plan with uncertain knowledge about environment
  - Combined prediction and planning

- Drawbacks:
  - Computational complex

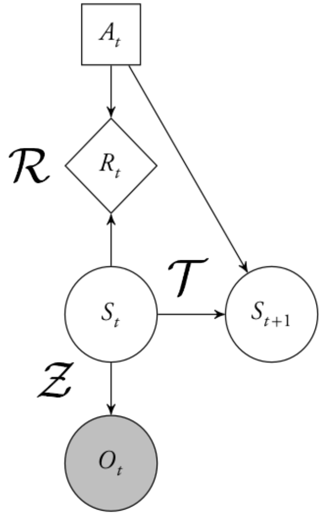
- Goal:
  - Find an optimal acceleration profile for the ego vehicle



C. Hubmann, et al., „Automated driving in uncertain environments: Planning with interaction and uncertain maneuver prediction", 2018.

POMDPs

- Defined by the 7-tuple $(\mathbb{S}, \mathcal{A}, \mathcal{T}, \mathcal{R}, \mathbb{O}, \mathcal{Z}, \gamma)$:
  - Action space $\mathcal{A}$, State space $\mathbb{S}$, Observation space $\mathbb{O}$,
  - Transition model $\mathcal{T}$,
  - Reward model $\mathcal{R}$,
  - Observation model $\mathcal{Z}$, and discount factor γ.
- Value function: $V^\pi(s) = \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t \mathcal{R}(s_t, a_t = \pi(s_t))\right]$
- Optimal policy: $\pi^* = \arg\max_\pi V^\pi(s)$
- Q-function: $Q(s_t, a_t) = \mathcal{R}(s_t, a_t) + \gamma \sum_{s_{t+1}} \mathcal{T}(s_{t+1}|s_t, a_t) V^*(s_{t+1})$, $V(s_t) = \max_{a_t} Q(s_t, a_t)$



Graphical model of a POMDP

POMDPs

- States are not fully observable
- Actions depend on belief state: $a_t = \pi(b_t)$

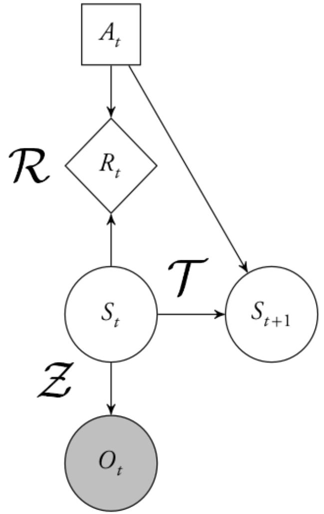
- Belief state depends on action-observation history:

$$b_t(s) = \Pr(s_t = s | h_t, b_0)$$
$$h_t = \{a_0, o_1, a_1, o_2, \ldots, a_{t-1}, o_t\}$$

- For sequential action selection, belief state must be updated:

$$b_t = \tau(b_{t-1}, a_{t-1}, o_t)$$

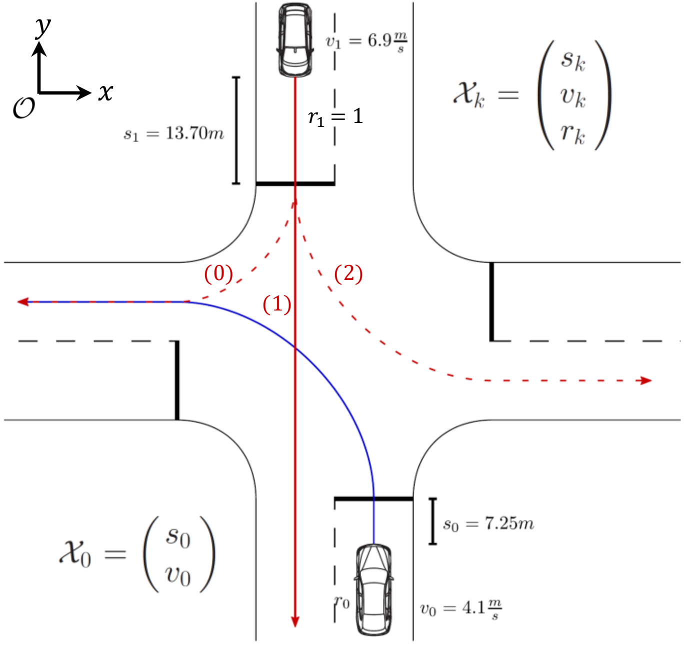
τ is implemented as Particle Filter



Graphical model of a POMDP

POMDPs in Automated Driving

- State of the Art (C. Hubmann, et al.):
  - Static routes are used
  - Vehicle heading is not used for intention estimation, but is a “strong” feature
  - Use of unweighted particle filter with simple rejection sampling
  - Use of Adaptive Belief Tree (ABT) algorithm
    - Simulates single particles
- Contribution:
  - Support changes in environment model
  - Weighted particle filtering



Visualization of the state space

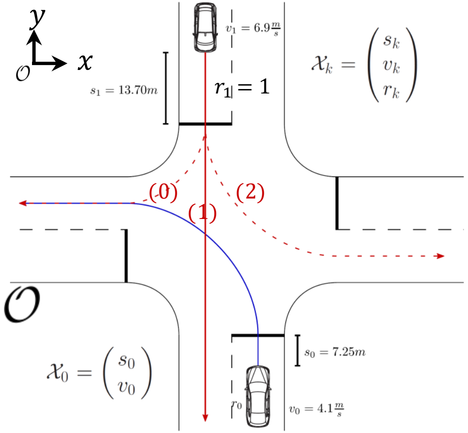
C. Hubmann, et al., „Automated driving in uncertain environments: Planning with interaction and uncertain maneuver prediction”, 2018.

Driving POMDP Formulation $(\mathbb{S}, \mathcal{A}, \mathcal{T}, \mathcal{R}, \mathbb{O}, \mathcal{Z}, \gamma)$

- State space includes all $N_{\mathcal{V}}$ vehicles from a scene:

$$s_t = (\mathbf{s}_{V_0,t}, \mathbf{s}_{V_1,t}, \ldots, \mathbf{s}_{V_{N_{\mathcal{V}}},t})^\top, \qquad \mathbf{s}_{V_0} = \begin{pmatrix} \mathbf{x}_0 \\ v_0 \end{pmatrix}, \qquad \mathbf{s}_{V_k} = \begin{pmatrix} \mathbf{x}_k \\ v_k \\ r_k \end{pmatrix},$$

  - $\mathbf{x}_k \in \mathbb{R}^2$ is the cartesian position in Cartesian coordinate system $\mathcal{O}$



Visualization of the state space

- Observation space:

$$o_t = (\mathbf{o}_{V_0,t}, \mathbf{o}_{V_1,t}, \ldots, \mathbf{o}_{V_{N_{\mathcal{V}}},t})^\top, \qquad \mathbf{o}_{V_0} = \begin{pmatrix} \mathbf{x}_0 \\ v_0 \end{pmatrix}, \qquad \mathbf{o}_{V_k} = \begin{pmatrix} \mathbf{x}_k \\ \theta_k \\ v_k \end{pmatrix},$$

- Action set:

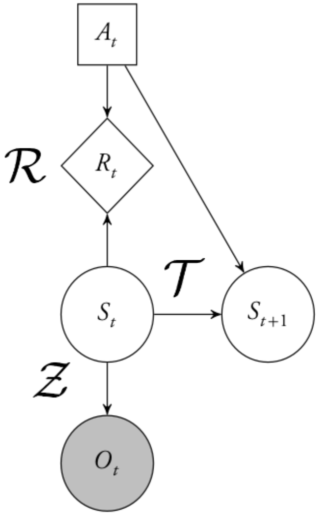
$$\mathcal{A} = \{-4.5, -3.0, -1.5, 0.0, 1.5\} \, \frac{m}{s^2}$$

Driving POMDP Formulation $(\mathbb{S}, \mathcal{A}, \mathcal{T}, \mathcal{R}, \mathbb{O}, \mathcal{Z}, \gamma)$

- Transition model $\mathcal{T}$:
  - 1D constant-acceleration model:

$$\begin{pmatrix} l_{t+1} \\ v_{t+1} \end{pmatrix} = \begin{pmatrix} 1 & \Delta t \\ 0 & 1 \end{pmatrix} \begin{pmatrix} l_t \\ v_t \end{pmatrix} + \begin{pmatrix} \frac{1}{2}(\Delta t)^2 \\ \Delta t \end{pmatrix} a_{t,V_k}$$

  - Intelligent Driver Model with additive noise for other vehicles
    - Interaction with the ego-vehicle is considered
    - Route of other vehicles does not change: $r_{t+1} = r_t$



Graphical model of a POMDP

- Reward model: $\mathcal{R}(s_t, a_t, s_{t+1}) = R_{\text{vel}}(\mathbf{s}_{V_0,t}) + R_{\text{acc}}(a_t) + R_{\text{coll}}(s_t, a_t, s_{t+1})$

Particle Filter Tree Algorithm

$$a^{t_0} = \pi(\hat{b}^{t_0}) = \arg\max_{a \in \mathcal{A}} \widehat{Q}(\hat{b}^{t_0}, a)$$

State Estimation

0 s

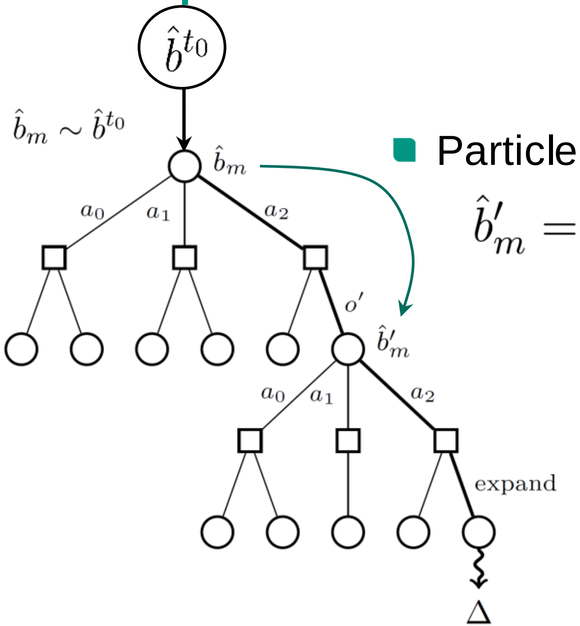
1 s

time

Tree Search

Planning horizon

$$\hat{b}^{t_1} = \tau(\hat{b}^{t_0}, a^{t_0}, o)$$



- Particle filter update in tree search:

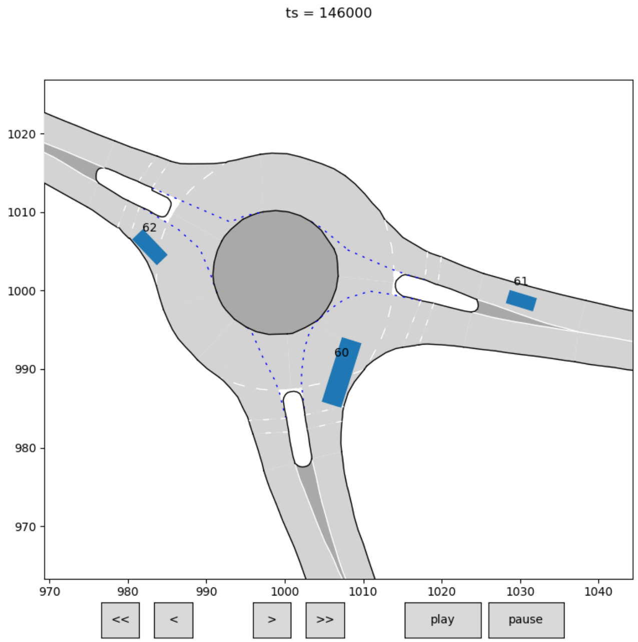
$$\hat{b}'_m = \tau(\hat{b}_m, a_2, o')$$

- Action selection with UCB
- Observation generation:

$$s \sim \hat{b}_m$$
$$s' \sim \mathcal{T}(\cdot|s, a)$$
$$o' \sim \mathcal{Z}(\cdot|s')$$

Results

- Scenarios from INTERACTION-Dataset
- Driver Intent Estimation (State Estimation)
  - Multiple time steps
- POMDP Planner (Tree Search)
  - Multiple time steps
  - Single time step
  - Influence of IDM parameter $v_{ref,k}$

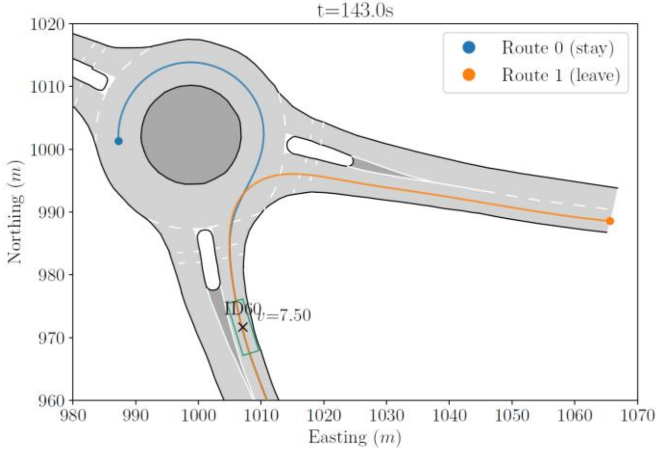


INTERACTION-Dataset Visualization

Zhan, Wei, et al. "Interaction dataset: An international, adversarial and cooperative motion dataset in interactive driving scenarios with semantic maps." 2019.

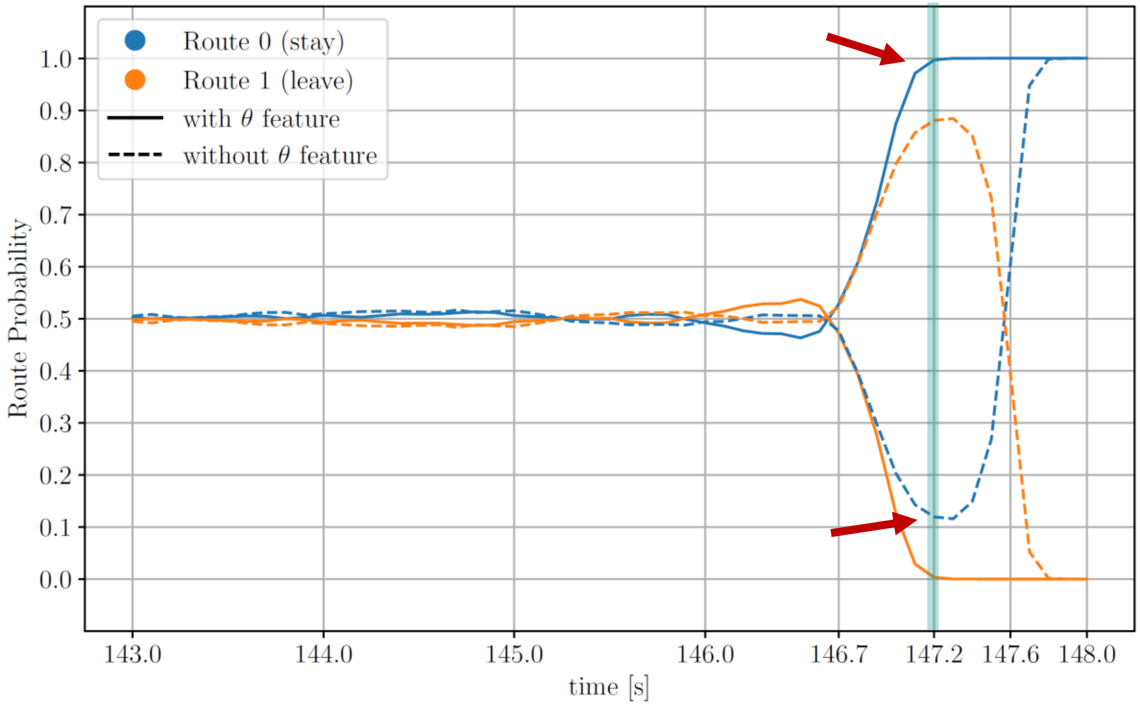
Driver Intent Estimation

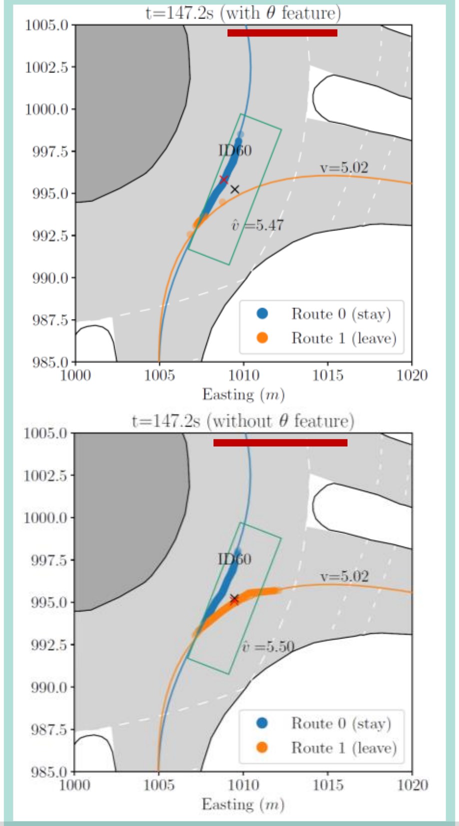
- Evaluation in roundabout scenario
- Different route options:
  - Left-turn (Route 0)
  - Right-turn (Route 1)
- Different feature combinations:
  - vehicle heading (yaw-angle θ) + lateral distance to route-centerline
  - only lateral distance to route-centerline



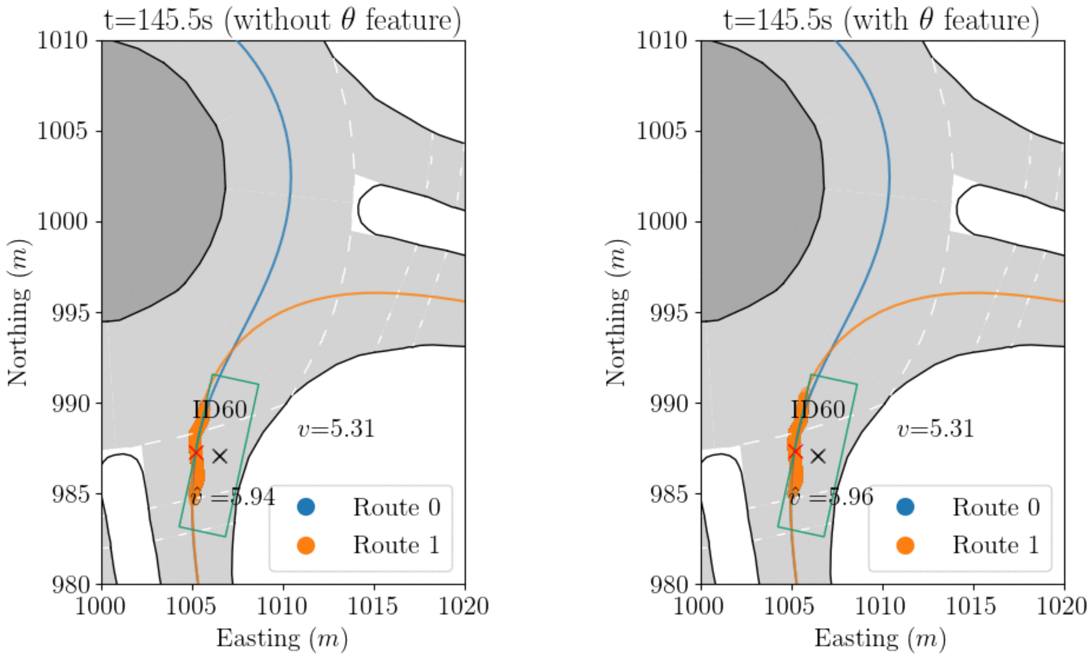
yaw-angle θ lateral distance

Driver Intent Estimation – Left-turn





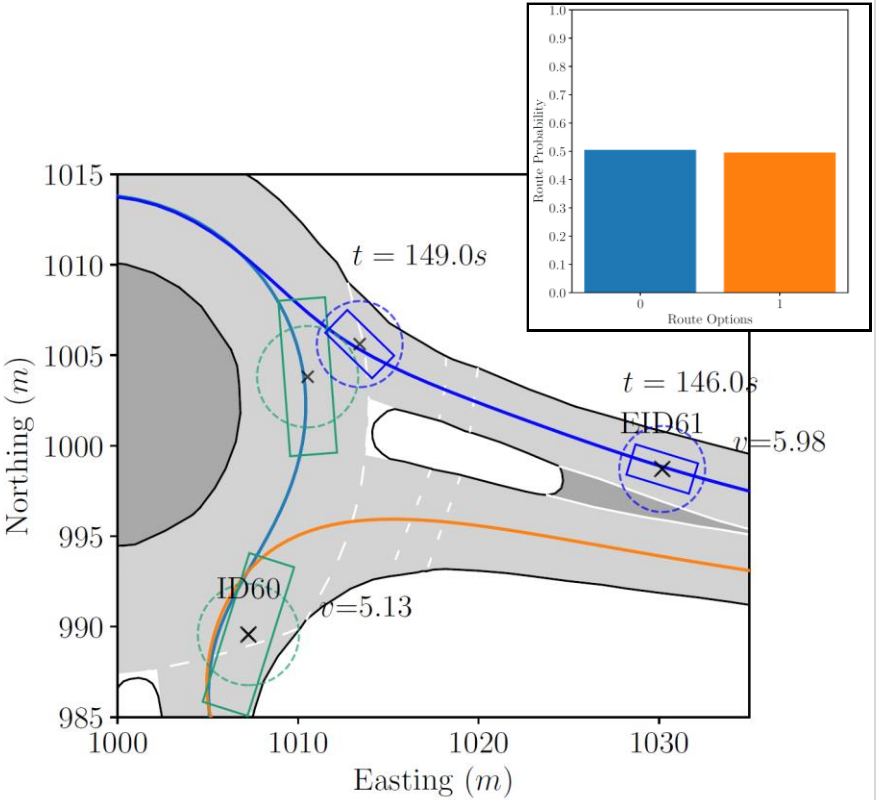
Driver Intent Estimation – Left-turn



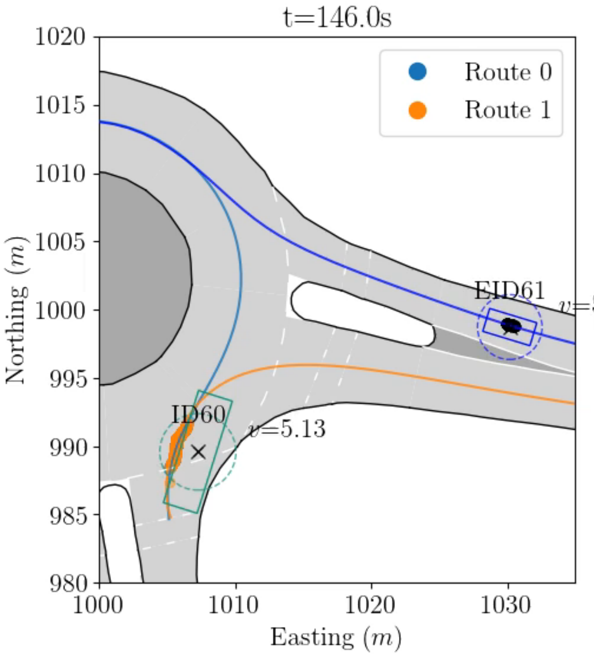
POMDP Planner – Scenario

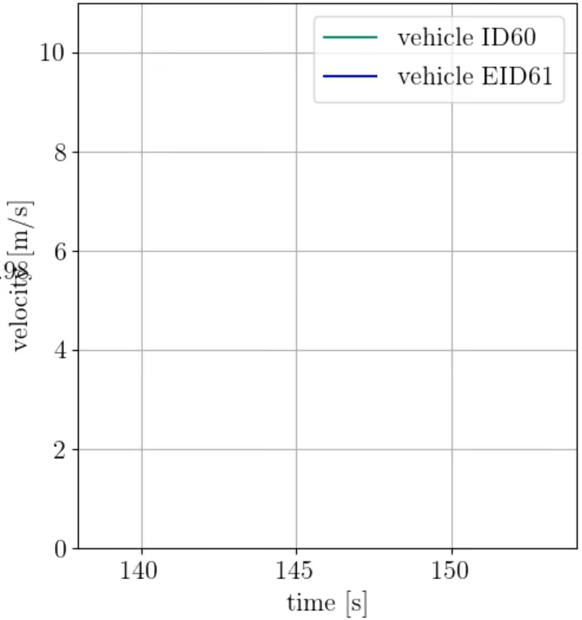
- Evaluation in roundabout scenario
- Initial velocities:
  - Ego Vehicle (blue): $v_0 = 6\frac{m}{s}$
  - Other Vehicle (green): $v_0 = 5\frac{m}{s}$
- Approx. time-to-collision: $3s$
- Route intention unclear

- Reference velocities:
  - Ego Vehicle (blue): $v_{ref} = 6\frac{m}{s}$
  - Other Vehicle (green): $v_{ref,k} = 4\frac{m}{s}$

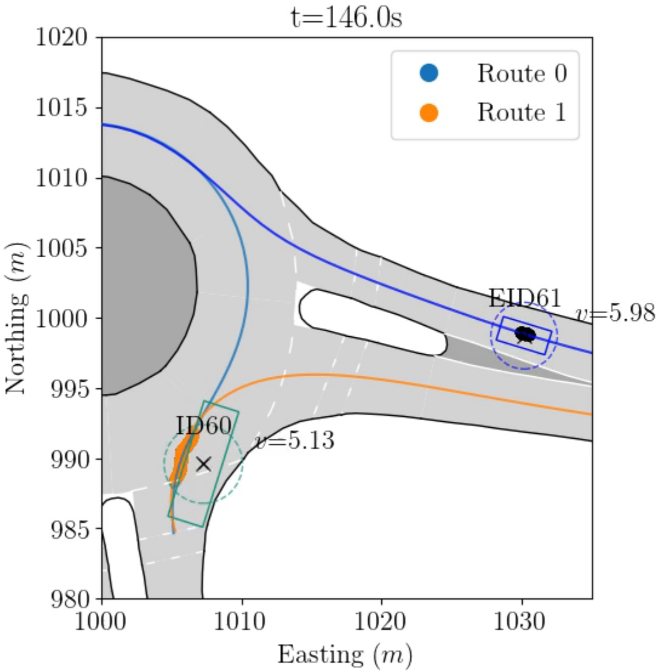


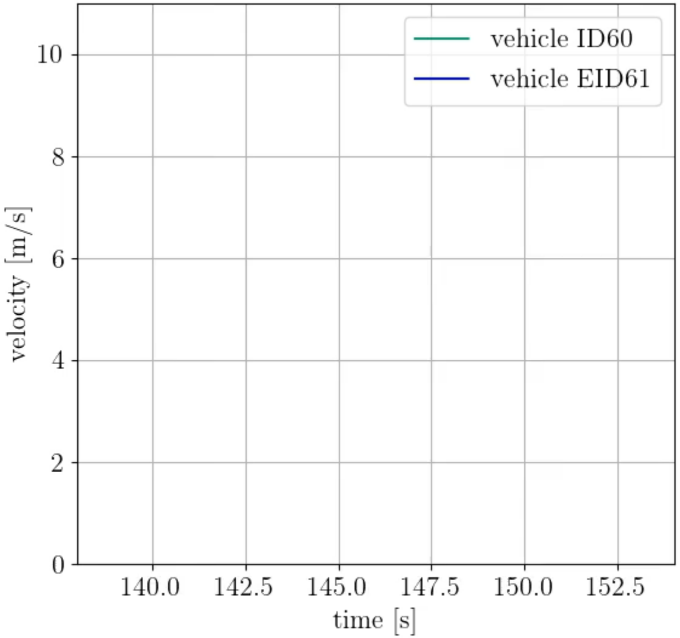
POMDP Planner – Scenario



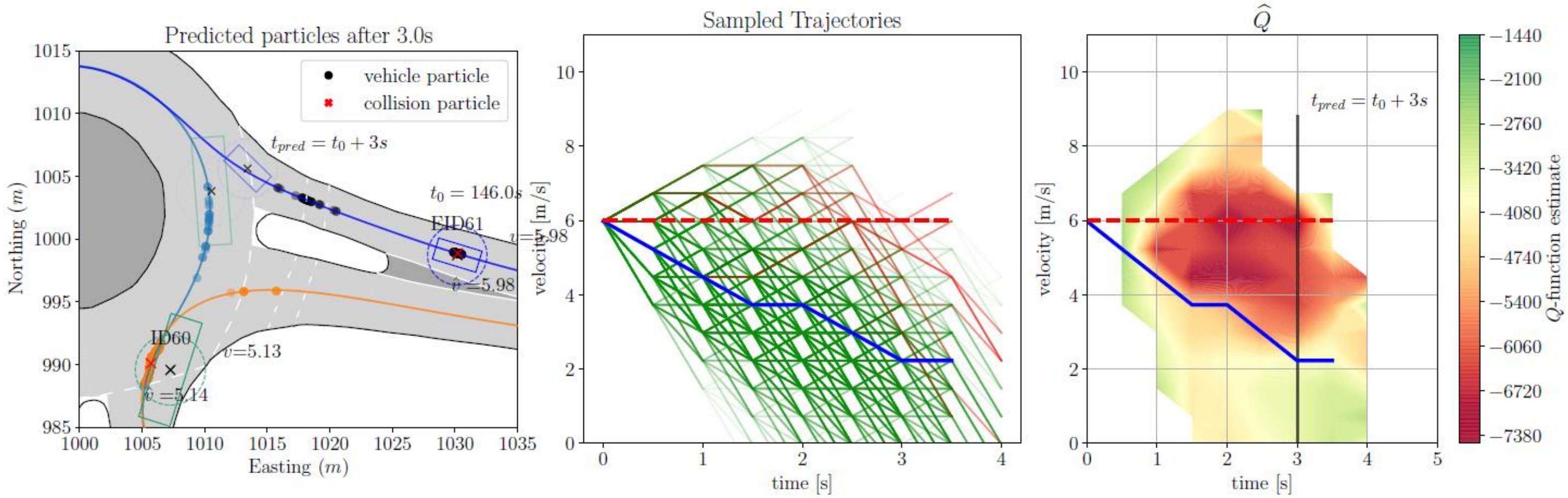


POMDP Planner Evaluation – Multiple Timesteps



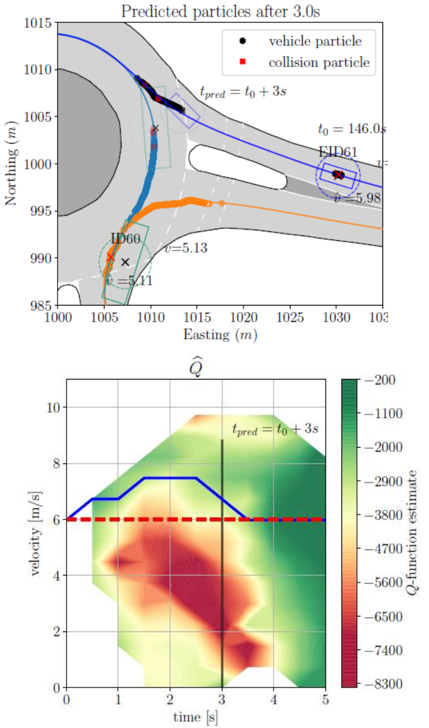


POMDP Planner – Single Timestep

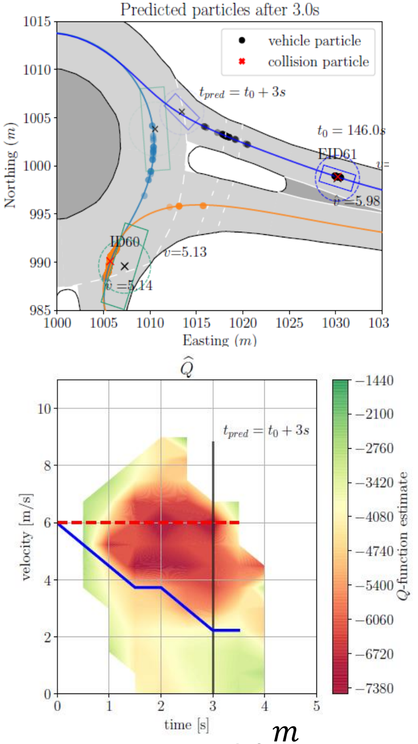


(b) Results for IDM reference velocity $v_{ref,k} = 4.0\frac{m}{s}$.

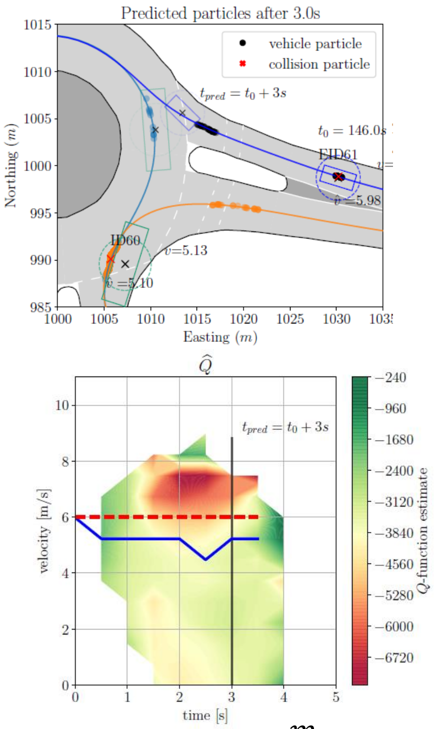
POMDP Planner – IDM parameter $v_{ref,k}$



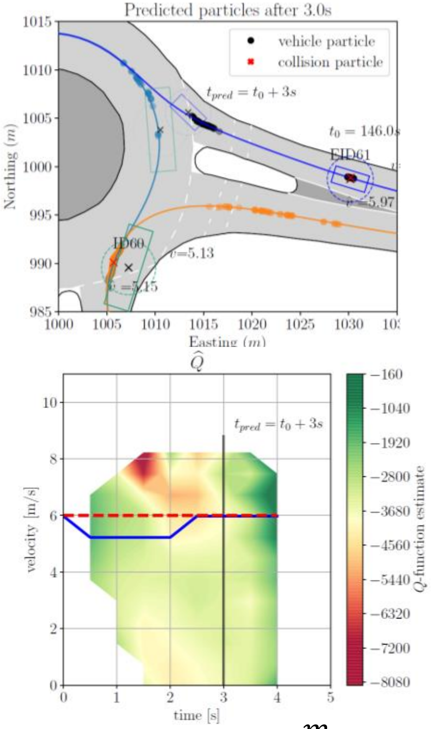
$v_{ref,k} = 3.5 \frac{m}{s}$



$v_{ref,k} = 4.0 \frac{m}{s}$



$v_{ref,k} = 7.0 \frac{m}{s}$

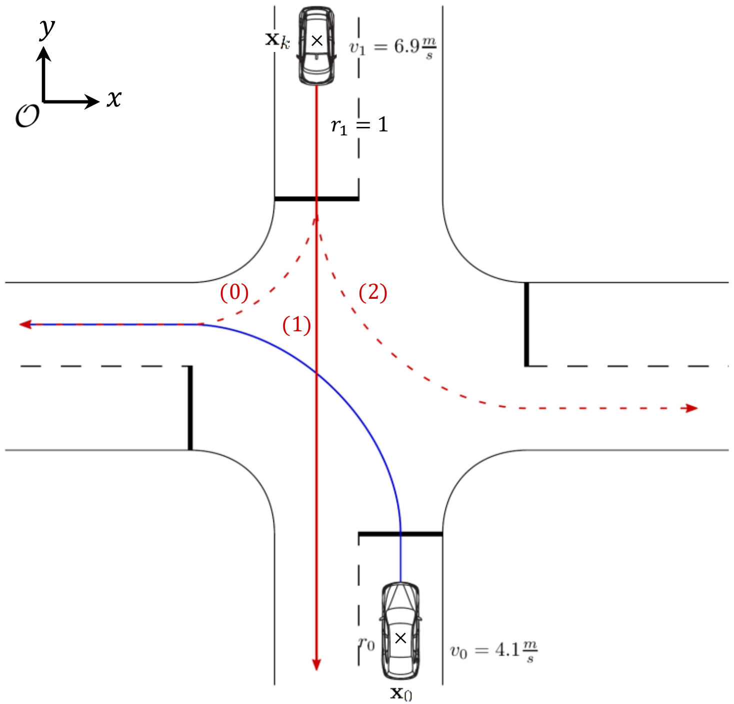


$v_{ref,k} = 10.0 \frac{m}{s}$

Conclusion & Future work

- Conclusion:
  - Weighted PF precisely estimates route intentions
  - POMDP Planner plans collision-free trajectories for long horizons in near real-time
  - Behavior model of other vehicles has big influence on trajectory

- Future work:
  - Estimate $v_{ref,k}$ as well
  - Use more sophisticated interaction and behavior models for other vehicles
  - Avoid replanning from scratch
  - Use learning to improve rollout and to reduce runtime



y
x
$\mathcal{O}$
$\mathbf{x}_k$
$v_1 = 6.9\frac{m}{s}$
$r_1 = 1$
(0)
(1)
(2)
r_0
$v_0 = 4.1\frac{m}{s}$
$\mathbf{x}_0$