Probabilistic Motion Planning in Uncertain and Dynamic Environments

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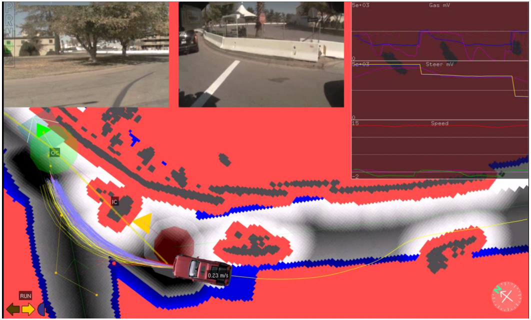
Content

Introduction

The MIT-Cornell Collision in DARPA Urban Challenge 2017



1. Sensor data association; 2. Failure to anticipate vehicle's intention; 3. Overemphasis on lane constraints [1].

[1] L. Fletcher, S. Teller, E. Olson, *et al.*, "The MIT - Cornell collision and why it happened", *Springer Tracts in Advanced Robotics*, vol. 56, pp. 509–548, 2009

Cooperative VS Non-cooperative

- Cooperative planning:
  All the agents mutually affect each other (interactions)
- Non-cooperative planning:
  The ego-vehicle takes all responsibility to avoid collision. → Freezing robot problem [2].

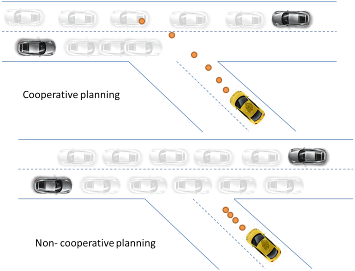


Figure : Cooperative planning and Non-cooperative planning

[2] P. Trautman and A. Krause, "Unfreezing the robot: Navigation in dense, interacting crowds", *IEEE/RSJ 2010 International Conference on Intelligent Robots and Systems, IROS 2010 - Conference Proceedings*, pp. 797–803, 2010

Problem Statement

Targeted problems

- How to model the interaction between the ego-vehicle and obstacles?
- How to incorporate the uncertainty of motion intentions into the trajectory planning?

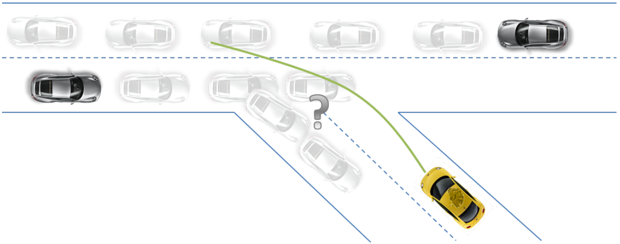


Figure : Where and How will the obstacle react?

Problem Statement

- States: $\mathbf{z}^R = [x, y, \theta, \delta, v]$, $\mathbf{z}^A = [x, y, \theta, v, g]$, $\mathbf{s} = [x, y]$, motion intention $g \in \mathcal{G} = \{\text{Going straight, Turning, Stopping}\}$
- Controlled actions: $\mathbf{u} = [u^\delta, u^a]$
- Trajectory of vehicle: $\pi_i(g_j) = \{\mathbf{s}_0^i, \mathbf{s}_1^i, ..., \mathbf{s}_m^i\}$
- Multipolicy under all motion intentions: $\Pi^i = \{\pi_i(g_1), \dots, \pi_i(g_l)\}$
- Likelihood of motion intentions: $\mathcal{W} = \{w_1, \dots, w_l\}$
- Optimization problem:

$$
\begin{aligned}
\mathbf{u}^*_{0:m-1} = \min_{u_{0:m-1}} & \sum_{k=0}^{m-1} J(\mathbf{z}_k, \mathbf{u}_k) + J(\mathbf{z}_m) \\
s.t. \quad & \mathbf{z}^R_{k+1} = f(\mathbf{z}^R_k, u_k), \qquad \forall k = \{0, \dots, m-1\} \\
& \mathbf{z}^R_{min} < \mathbf{z}^R_k < \mathbf{z}^R_{max}, \qquad \forall k = \{0, \dots, m\} \\
& \mathbf{u}_{min} < \mathbf{u}_k < \mathbf{u}_{max}, \qquad \forall k = \{0, \dots, m-1\} \\
& \text{Estimate } \Pi^i \text{ and } \mathcal{W}^i \text{ given } \pi^R, \quad \forall i = \{1, \dots, n\} \\
& \mathbf{s}^R_k \notin \mathbf{B}^i_k(\mathcal{W}^i, \Pi^i), \qquad \forall i = \{1, \dots, n\},
\end{aligned}
\tag{1}
$$

Joint Behavior Estimation and Planning

- Leverage the strengths of POMDP and MPC
- Chance constraint formulation for collision avoidance

Assumptions:

1. The obstacle vehicles follow a reference path for each motion intention.
2. The boundary of road is given.
3. The reference path of the vehicle is the central line of the road.

Joint Behavior Estimation & Planning - Overview

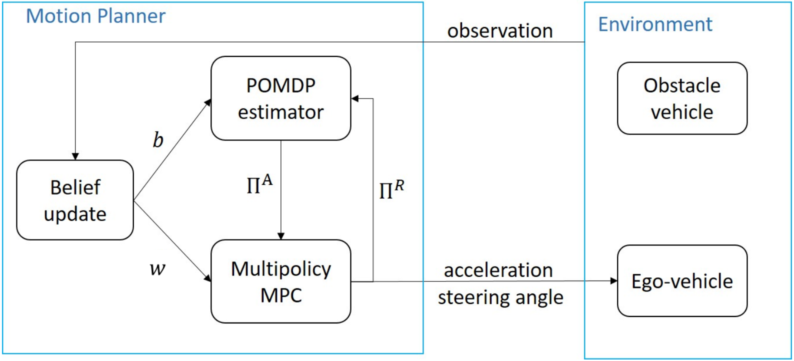


Figure : Scheme of joint behavior estimation and planning

Behavior Estimation

Aim:

Formulate a POMDP model to compute the optimal sequence of actions Π^A for obstacle vehicles under all motion intentions g.

Typical POMDP framework:

$$\{\mathbf{Z}, \mathbf{A}, \mathbf{O}, T(\mathbf{z}_{t+1}, a_t, \mathbf{z}_t), O(\mathbf{o}_t, \mathbf{z}_{t+1}, a_t), R(\mathbf{z}, a)\}$$

- State $\mathbf{Z}$: $\mathbf{z}^R = [x, y, \theta]$, $\mathbf{z}^A = [x, y, \theta, v, g]$
- Action $\mathbf{A}$: $\mathbf{A} = \{\text{Acceleration, Deceleration, Maintain}\}$
- Observation $\mathbf{O}$: $\mathbf{o}^R = [x, y, \theta]$, $\mathbf{o}^A = [x, y, \theta]$

Behavior Estimation

- Transition $T(\mathbf{z}_{t+1}, a_t, \mathbf{z}_t)$: The ego-vehicle follows the computed policy from MPC planner (initially assume the constant velocity model).

$$\begin{bmatrix} x_{t+1} \\ y_{t+1} \\ \theta_{t+1} \\ v_{t+1} \end{bmatrix} = \begin{bmatrix} x_t \\ y_t \\ \theta_t \\ v_t \end{bmatrix} + \begin{bmatrix} (v_t + a\Delta t)\Delta t \cos(\theta_t) \\ (v_t + a\Delta t)\Delta t \sin(\theta_t) \\ \Delta\theta \\ a\Delta t \end{bmatrix}$$

- Observation $O(\mathbf{o}_t, \mathbf{z}_{t+1}, a_t)$: The poses of the vehicle are directly observable.
- Reward $R(\mathbf{z}, a)$:

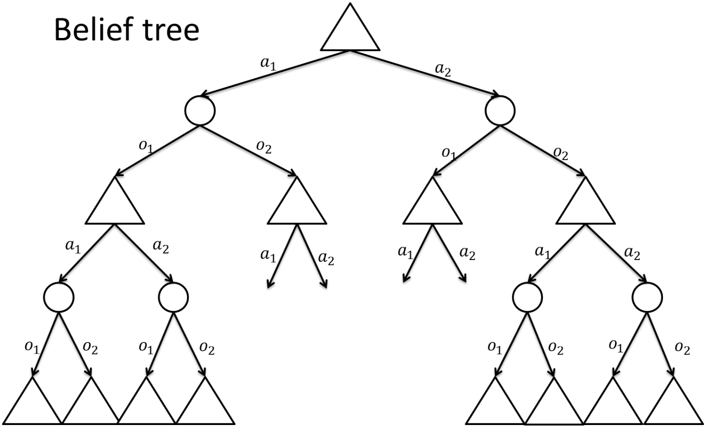
$$R(\mathbf{z}, a) = R_{progress}(\mathbf{z}, a) + R_{collision}(\mathbf{z}, a) + R_{action}(a)$$

$$R_{collision} = \begin{cases} -r_c, & \text{if } \mathbf{s}^0 \in \mathbf{E} \\ 0, & \text{others} \end{cases}, \quad R_{action} = \begin{cases} -r_a, & \text{if } a \in [Acc, Dec] \\ 0, & \text{others} \end{cases},$$

$$R_{progress} = \beta e^{-\frac{d}{2\sigma^2}}$$

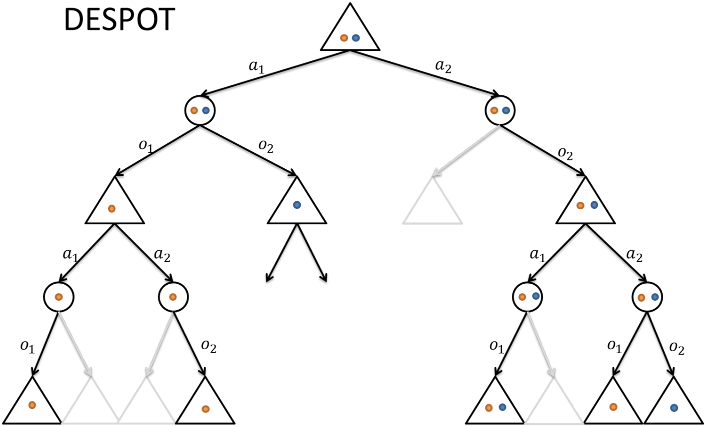
Behavior Estimation

POMDP Solver - DESPOT [3]

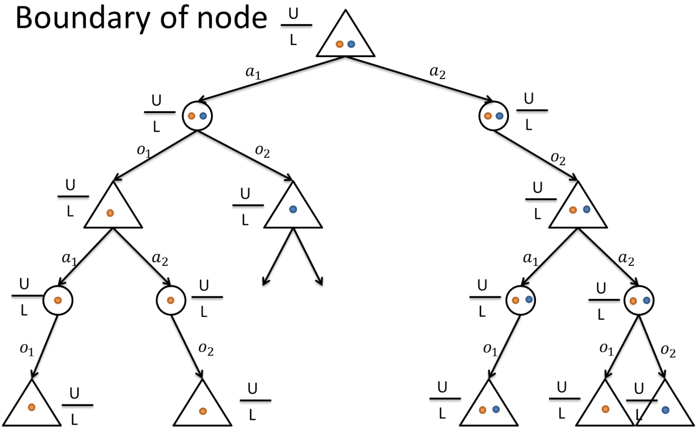


[3] A. Somani, N. Ye, D. Hsu, and W. S. Lee, "DESPOT : Online POMDP Planning with Regularization", *Advances in Neural Information Processing Systems*, pp. 1–9, 2013

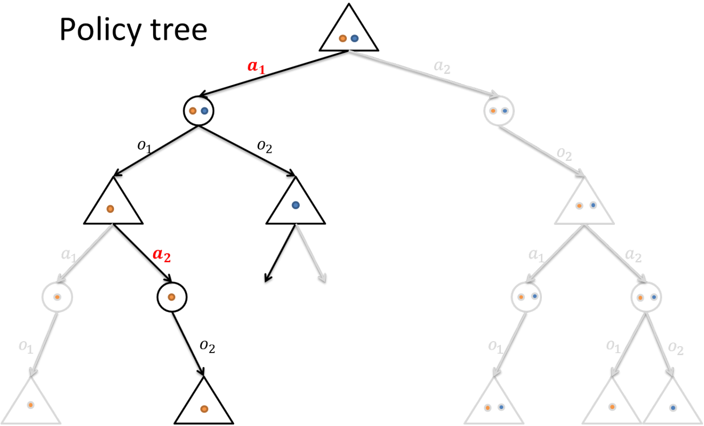
Behavior Estimation



Behavior Estimation



Behavior Estimation

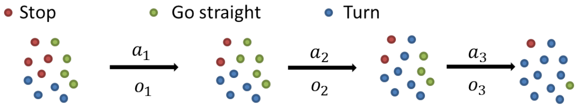


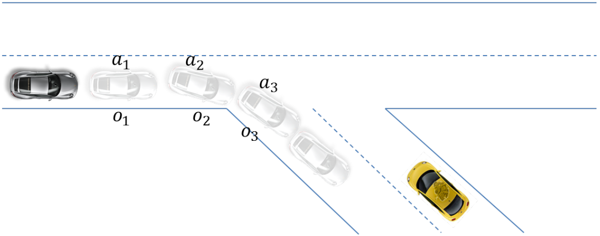
$$V(b) = \max_{a \in A} \{ \sum_{z \in Z} b(z) R(z,a) + \gamma \sum_{o \in O} p(o|b,a) V(\tau(b,a,o)) \}$$

Behavior Estimation

Belief update (Particle filter)

$$b_{t+1} = \eta O(\mathbf{o}_t, \mathbf{z}_{t+1}, a_t) \sum_{\mathbf{Z} \in \mathbf{z}} T(\mathbf{z}_{t+1}, a_t, \mathbf{z}_t) b_t$$





$$w_j = \frac{\text{number of particles with motion intention } g_j}{\text{overall number of particles}}$$

Receding Horizon Trajectory Planning

Aim:

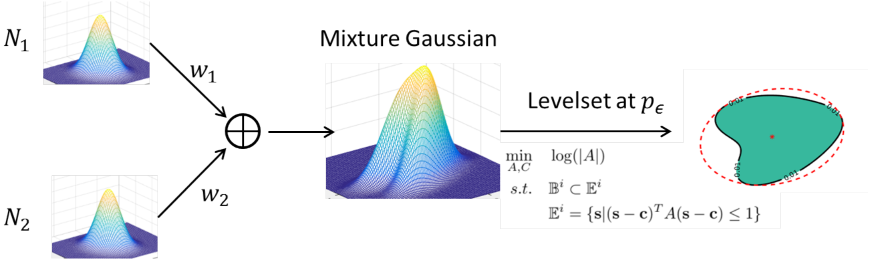
Compute the optimal trajectory $\mathbf{u}_{0:m-1}$ of the ego-vehicle using the obstacles' estimated trajectories Π^A and associated beliefs w_j of intentions

$$
\begin{aligned}
\min_{\mathbf{u}_{0:m-1}} \; & \sum_{k=0}^{m-1} J(\mathbf{z}_k^R, \mathbf{u}_k, \lambda_k)\Delta t_k + J(\mathbf{z}_m^R, \lambda_m)\Delta t_k \\
s.t. \quad & \mathbf{z}_{k+1}^R = f(\mathbf{z}_k^R, \mathbf{u}_k) \\
& \lambda_{k+1} = \lambda_k + v_k \Delta t_k \\
& \mathbf{z}_{min}^R < \mathbf{z}_k^R < \mathbf{z}_{max}^R \\
& \mathbf{u}_{min} < \mathbf{u}_k < \mathbf{u}_{max} \\
& b_l(\lambda_k) + w_{max} \leq d(\mathbf{z}_k, \lambda_k) \leq b_r(\lambda_k) - w_{max} \\
& \mathbf{s}_k^0 \notin \mathbf{E}_k^i(\mathcal{W}^i, \Pi^i) \qquad \forall i = \{1, ..., n\} \\
& \qquad\qquad\qquad\qquad\qquad \forall k = \{1, \ldots, m-1\}
\end{aligned}
$$

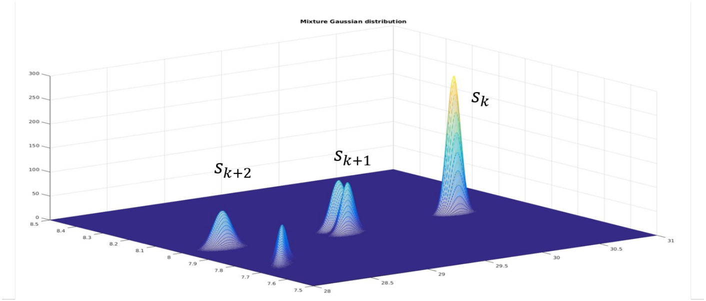
Receding Horizon Trajectory Planning

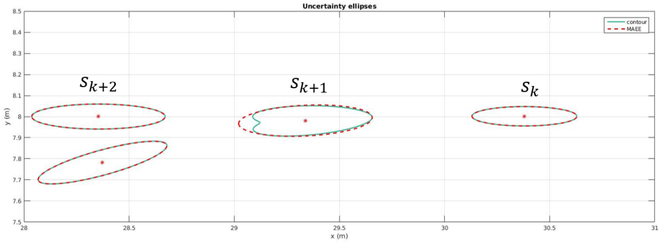
Probabilistic Collision Constraint:

Compute the uncertainty ellipses for each obstacle vehicle regarding under a certain collision probability p_ϵ regarding the multiple policies Π^A and associated weights $\mathcal{W}$



Receding Horizon Trajectory Planning

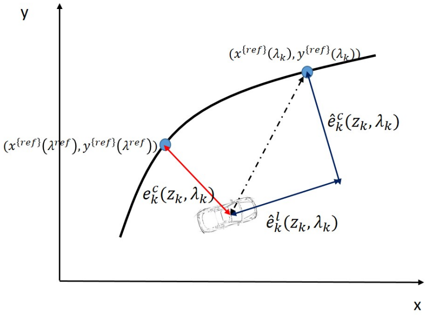




Receding Horizon Trajectory Planning

- Cost function:

$$J = \mathbf{p}^T \begin{bmatrix} \|\hat{e}^c_k(x_k, y_k, \lambda_k)\|^2 \\ \|\hat{e}^l_k(x_k, y_k, \lambda_k)\|^2 \\ v_k \Delta t_k \\ \|u^a_k\|^2 \\ \|u^\delta_k\|^2 \\ \|\dot{\theta}_k\|^2 \end{bmatrix}$$



- Dynamics:

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \\ \dot{\delta} \\ \dot{v} \end{bmatrix} = \begin{bmatrix} v\cos(\theta) \\ v\sin(\theta) \\ \frac{v}{L}\tan(\delta) \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} u^\delta \\ u^a \end{bmatrix}$$

Results

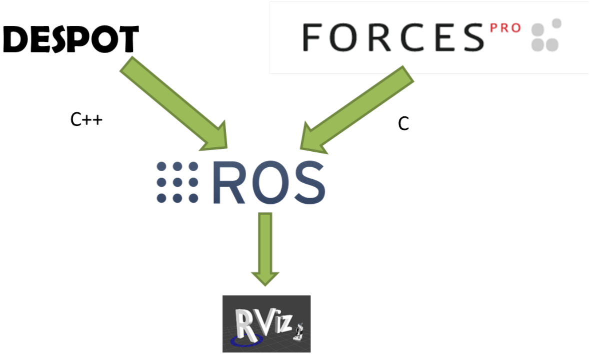


Figure : Simulation platform

Results

Negotiation with 4 obstacles in T-junction scenario

Simulation in T-junction Scenario

Task:
Navigate the ego-vehicle to safely merge to the traffic with the negotiation of 4 obstacle vehicles.

Results

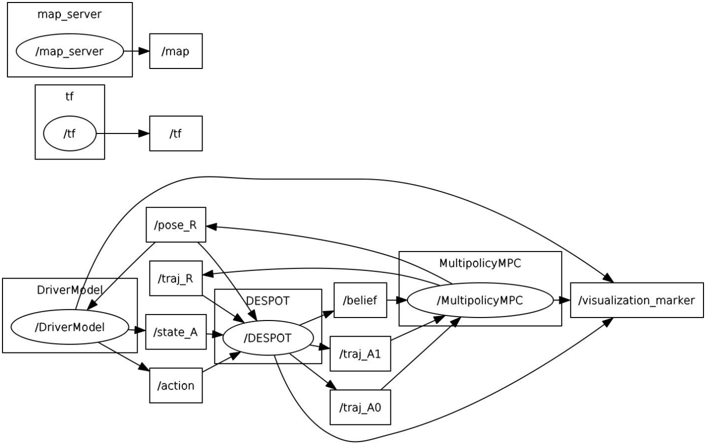
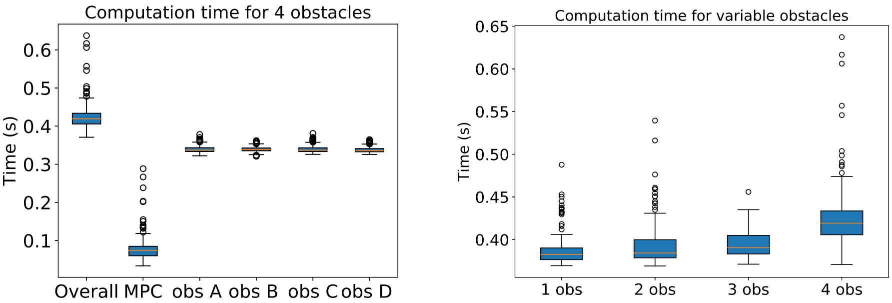


Figure : ROS graph of simulation

Results



(a) 4 obstacles (b) Variable obstacles

Figure : Computation time for our method

Conclusion

Table : Comparison with state-of-the-art

Approach	Real time	Scalability	Safety	Non-holonomic Model
Our approach	✓	✓ ✓	✓ ✓	✓ ✓
IGP [4]	✓ ✓	✓ ✓	✓	✓[1]
Multipolicy [5]	✓ ✓ ✓	✓	✓ ✓	✓ ✓[2]
Online POMDP [6]	✓	✓ ✓	✓ ✓	✓

1: Gaussian process as the dynamic model

2: Ego-vehicle's motion is restricted in the predefined policy sets

[4] P. Trautman, J. Ma, R. M. R. M. Murray, and A. Krause, "Robot Navigation in Dense Human Crowds: the Case for Cooperation", *Cds.Caltech.Edu*, pp. 2153–2160, 2013

[5] E. Galceran, A. G. Cunningham, R. M. Eustice, and E. Olson, "Multipolicy decision-making for autonomous driving via changepoint-based behavior prediction", in *Proceedings of Robotics: Science and Systems (RSS)*, Rome, Italy, 2015

[6] W. Liu, S. W. Kim, S. Pendleton, and M. H. Ang, "Situation-aware decision making for autonomous driving on urban road using online POMDP", , in *IEEE Intelligent Vehicles Symposium, Proceedings*, vol. 2015-August, 2015, pp. 1126–1133

Conclusion and Future Work

Contributions:

- A joint behavior estimation and trajectory planning method, utilizing the strengths of MPC and online POMDPs to achieve intention-aware navigation.
- A chance constrained formulation of MPC accounting for the uncertainty in the motion intentions of other traffic participants, over multiple motion policies.

Future work:

- The real time capability of the estimation needs to be improved.
- The uncertainty of the dynamics needs to be considered for the obstacle vehicle's model.
- It would be highly interesting to test it in a mobile robot.

Thanks! Q & A