

Planning under uncertainty with sensor occlusions in urban driving scenarios

Offline and online planning approaches for solving the occluded crosswalk problem

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Motivation

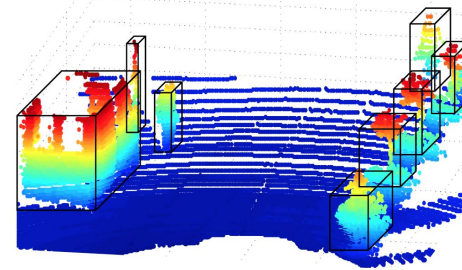
Need safe and efficient planning for autonomous vehicles in urban scenarios

Even with perfect sensors, **sensor occlusions** lead to **planning uncertainty**

- Static occlusions (buildings, signs, trees)
- Dynamic occlusions (other traffic participants)

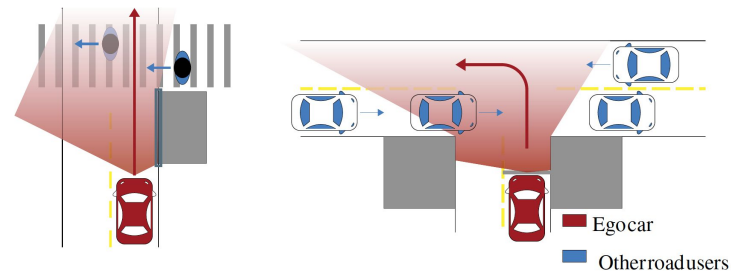
Common occlusion scenarios

- *Occluded crosswalk*
- Occluded unsignalized T-intersection
- Occluded overtaking (rural!)



Ideal detection result from LIDAR

S. D. Pendleton *et al.*, “Perception, planning, control, and coordination for autonomous vehicles,” *Machines*, vol. 5, no. 1, pp. 1–54, 2017.



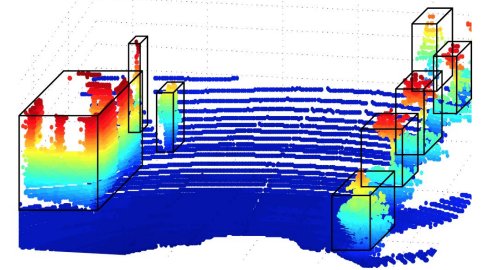
Common occlusion scenarios

M. Bouton, A. Nakhaei, K. Fujimura, and M. J. Kochenderfer, “Scalable Decision Making with Sensor Occlusions for Autonomous Driving,” *2018 IEEE Int. Conf. Robot. Autom.*, pp. 2076–2081, 2018.

Motivation

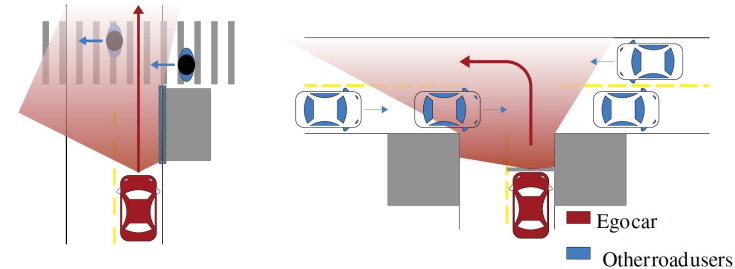
To achieve safe and efficient planning, other traffic participants need to be reasoned about and **sensor uncertainty and sensor occlusions** need to be accounted for

Occluded crosswalk is a good initial problem



Ideal detection result from LIDAR

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Common occlusion scenarios

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Related Work

Pedestrian avoidance

(Kapania, 2019); (Pusse, 2019)

Sensor occlusions

Crosswalk, static & dynamic occlusion (Bouton, 2018); (Schratte, 2019)

Crosswalk, dynamic occlusion (Thornton, 2018)

Risk quantification (Yu, 2018)

Field-of-view propagation (Hubmann, 2019)

Intention-aware planning

Pedestrians (Bai, 2015); (Luo, 2018); (Cai, 2019)

Drivers (Sunberg, 2017)

Problem Setting

Occluded crosswalk POMDP

Ego vehicle (\cdot_{ego}) and pedestrian (\cdot_{ped})

s: position

v: velocity

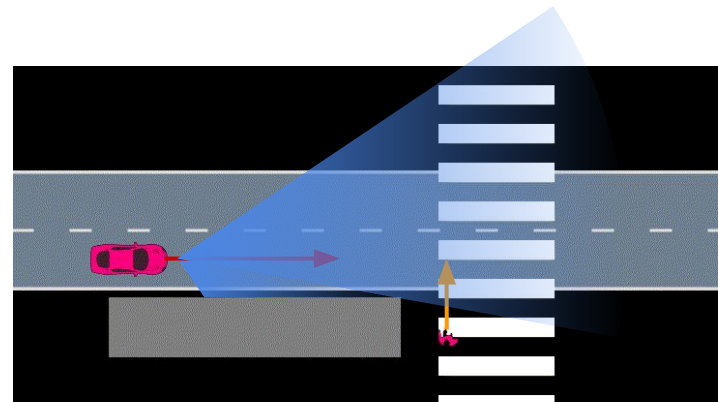
a: acceleration

2D continuous reduced spaces

$$S: (s_{\text{ego}}, v_{\text{ego}}) \times (s_{\text{ped}}, v_{\text{ped}}) \cdots \times_i (s_{\text{ped}}, v_{\text{ped}})_i$$

$$A: a_{\text{ego}}$$

$$O: (s_{\text{ego}}, v_{\text{ego}}) \times (s_{\text{ped}}, v_{\text{ped}}) \cdots \times_i (s_{\text{ped}}, v_{\text{ped}})_i$$



Occluded crosswalk scenario with ego vehicle and one pedestrian

Options to discretize spaces, extend number of traffic participants

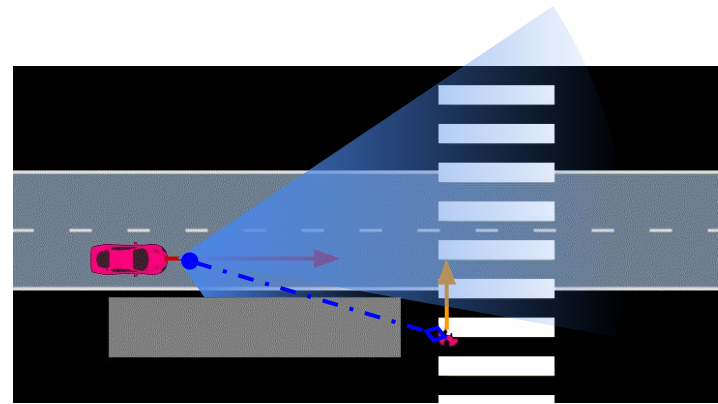
Problem Setting

Occluded crosswalk POMDP

Transition, reward, and observation models

- T: linearized vehicle dynamics w/noise
linearized pedestrian dynamics w/noise
- R: -1 for collision with pedestrian,
+1 for reaching roadway end
- O: fully-observable ego vehicle
partially-observable pedestrian

Reach end of roadway without collision as quickly as possible using finite-horizon discounting



Occluded crosswalk scenario with ego vehicle and one pedestrian

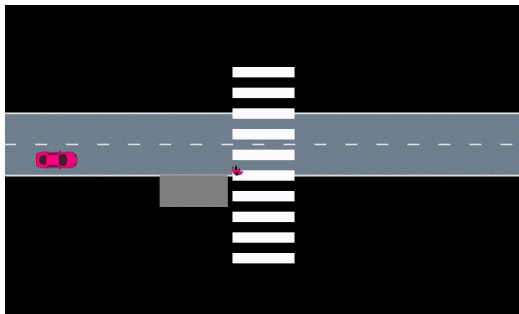
Obstacle prevents even partial observability of pedestrian

Progress & Future Work

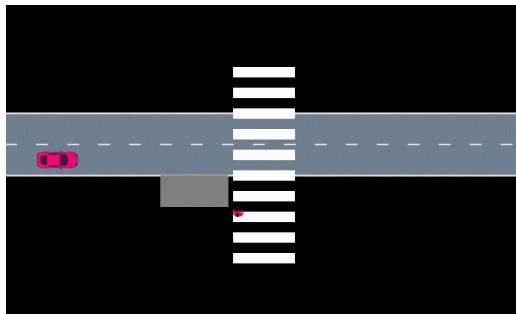
POMDPs.jl & AutomotivePOMDPs.jl

- | | | |
|------------------|--------------------|--|
| 1. SingleOCPOMDP | crosswalk | ego, one pedestrian |
| 2. OCPOMDP | crosswalk | ego, multiple pedestrians |
| 3. UrbanPOMDP | urban intersection | ego, multiple pedestrians, multiple cars |

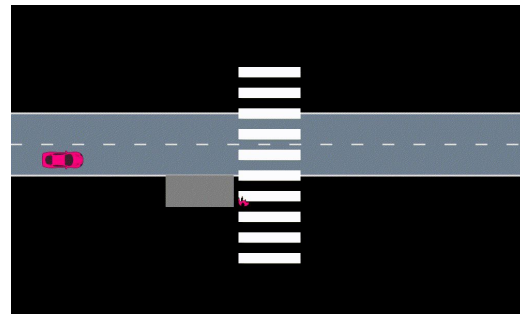
Examine performance of offline solvers



Random policy simulation



QMDP policy simulation



SARSOP policy simulation

Progress & Future Work

Examine effects of:

- discretization (continuous v. discrete, discrete resolution)
- sensor types (Gaussian sensor, LIDAR sensor)

Metrics & results

- Success rate
- Crossing time (\approx reward)
- Computation time & bound convergence
- Policy & history visualizations

Offline approaches will likely become intractable in more complex scenarios, so **explore online approaches in the OCPOMDP scenario**

```
Loading the model ...
Input file   : model.pomdp
Loading time : 261.95s

SARSOP initializing ...
Initialization time : 297.29s

-----
Time  |#Trial|#Backup|LBound  |UBound  |Precision|#Alphas|#Beliefs
-----
297.29 0      0      -8.33525e-05 0.238063  0.238147  4      1
343.25 3      50     0.107623  0.234757  0.127134  52     26
392.92 8      103    0.140963  0.230195  0.0892325 100    49
441.26 11     155    0.146635  0.22927  0.0826354 148    64
482.68 15     200    0.161548  0.229001  0.0674531 183    78
528.84 18     250    0.162559  0.227923  0.0653644 227    92
573.68 22     300    0.172311  0.225924  0.0536128 273    110
619.98 26     350    0.172311  0.222978  0.0506668 311    125
-----

SARSOP finishing ...
Preset timeout reached
Timeout      : 600.000000s
Actual Time  : 619.980000s

-----
Time  |#Trial|#Backup|LBound  |UBound  |Precision|#Alphas|#Beliefs
-----
619.98 26     350    0.172311  0.222978  0.0506668 311    125
-----

Writing out policy ...
Output file  : policy.out
```