NRI: FND: Life-long Learning for Motion Planning in Human Populated Environments

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Overview

Scaling up belief-space planning for social navigation

Online Intention-Aware Planning for Social Navigation with POMDPs

Improving robots' notions of where they can go

Augmenting Motion Planning with Traversability Estimation



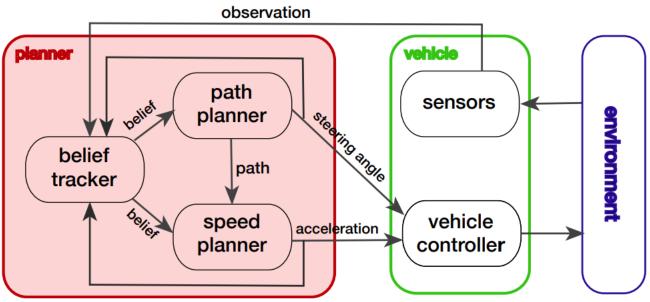






Planning for Social Navigation





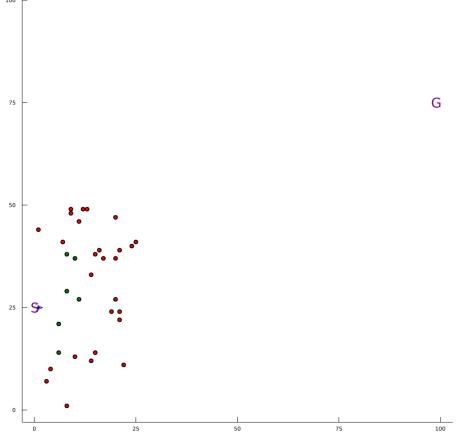
Intention-Aware Online POMDP Planning for Autonomous Driving in a Crowd. Bai et al. (2015)







Decoupling Path from Speed Raises Issues at High Densities



Path: Hybrid A* finds a collision-free path-to-goal

considering *n* identified pedestrians within a

sensing radius.

Speed: POMDP planner solves for speed along the path by

reasoning over pedestrian intentions.

Outcome: Frequent stopping behavior along the path, unable to perform small adjustments to avoid nearby pedestrians.

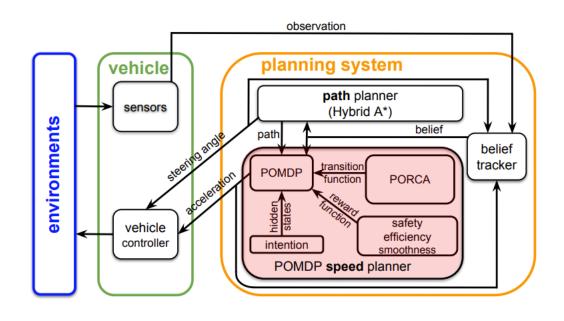






Planning for Social Navigation





PORCA: Modeling and Planning for Autonomous Driving among Many Pedestrians Luo et al. (2018)

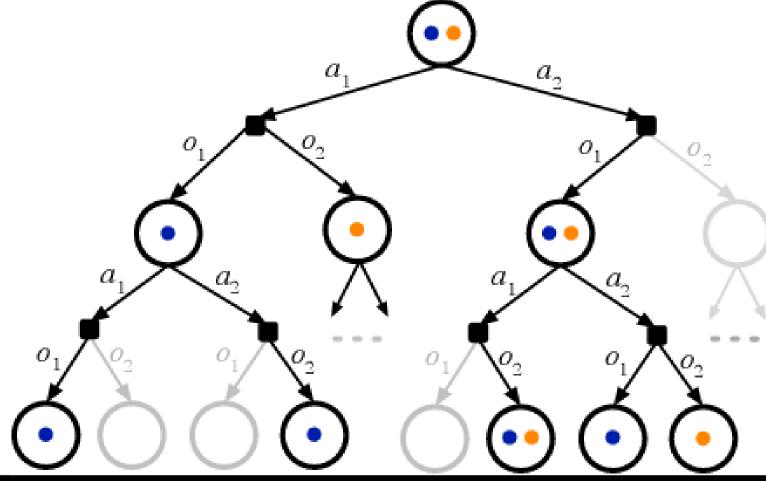






Combating Shallow Tree Depth with Better Priors

- Increased POMDP complexity decreases the effectiveness of the DESPOT solver
- To accommodate this tradeoff, we use a strong roll-out policy, informed by a multiquery planning algorithm (e.g., Probabilistic Road Mapping).
- This roll-out policy is used as a heuristic to guide the POMDP solution, but is not actually executed: the POMDP is solved rapidly enough to avoid executing beyond its search depth.









Extended-Space POMDP Planning

State Space: $[x_c, y_c, \theta_c, v_c, g_c]$ corresponding to

2D pose, speed, and goal of our vehicle.

 $[x_i, y_i, v_i, g_i]$ corresponding to

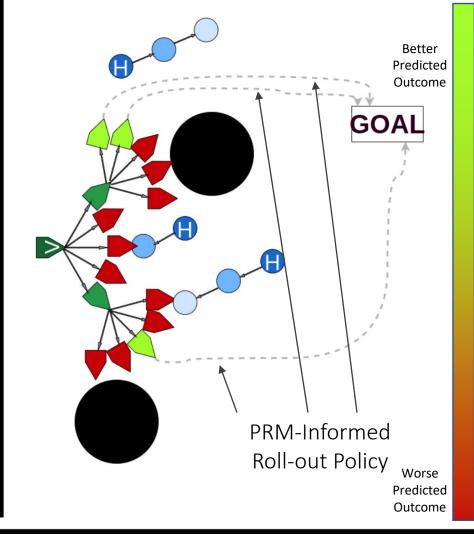
2D pose, speed, and goal of the

*i*th pedestrian.

Action Space: $[\delta_{\theta}, \delta_{v}]^{*}$ corresponding to changes in orientation and speed.

SB, or "Sudden Brake", which corresponds to a full-brake e-Stop

*Discretized to 11 different actions

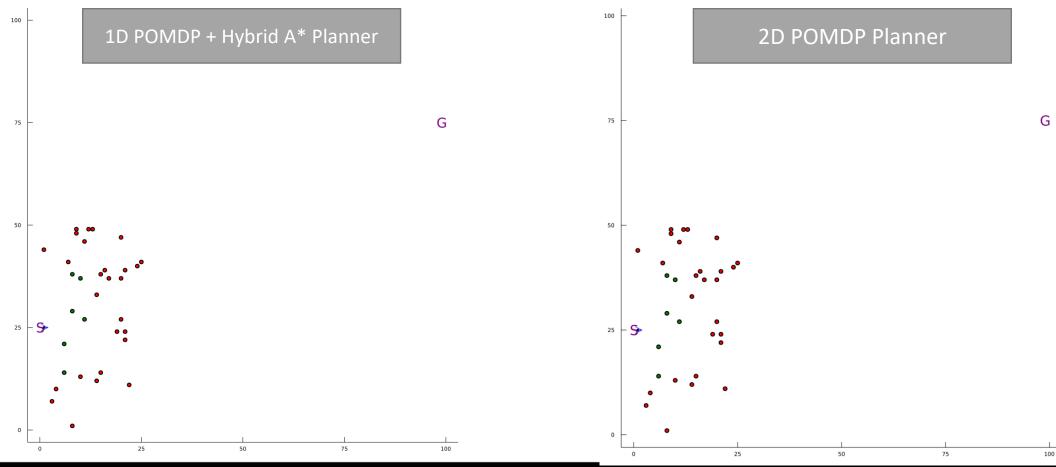








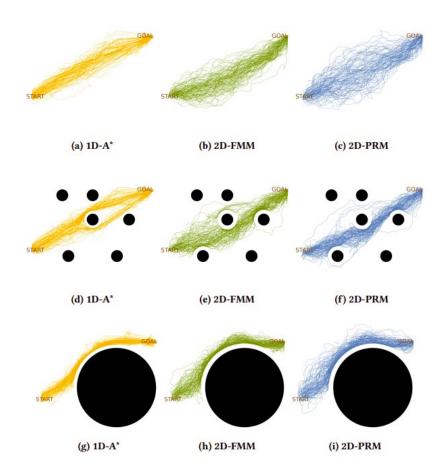
Result: Faster Navigation with Fewer Near-misses!











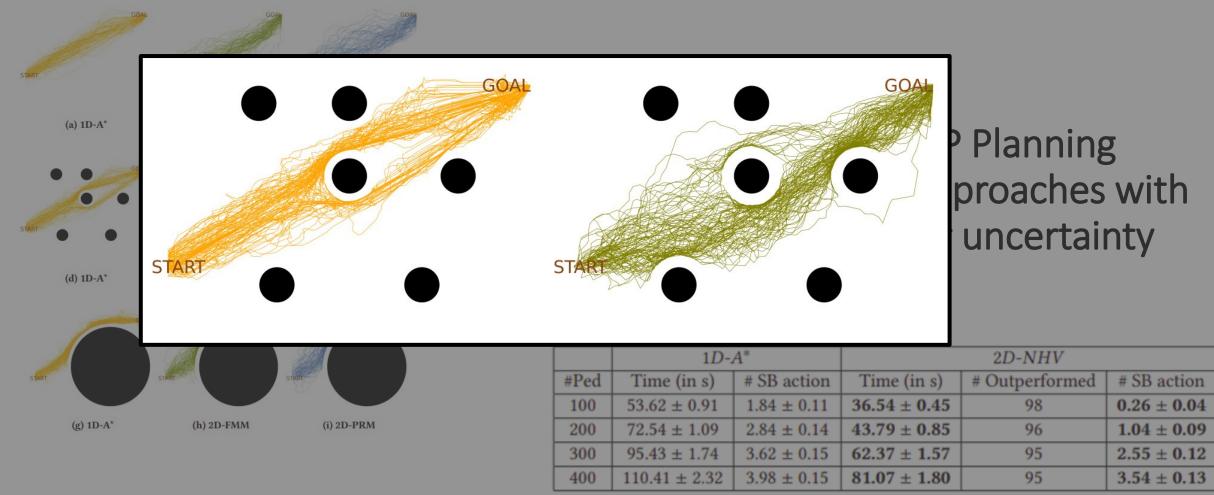
Extended Space POMDP Planning significantly outperforms approaches with decoupled reasoning over uncertainty

	1 <i>D-A</i> *		2D-NHV		
#Ped	Time (in s)	# SB action	Time (in s)	# Outperformed	# SB action
100	53.62 ± 0.91	1.84 ± 0.11	36.54 ± 0.45	98	0.26 ± 0.04
200	72.54 ± 1.09	2.84 ± 0.14	43.79 ± 0.85	96	1.04 ± 0.09
300	95.43 ± 1.74	3.62 ± 0.15	62.37 ± 1.57	95	2.55 ± 0.12
400	110.41 ± 2.32	3.98 ± 0.15	81.07 ± 1.80	95	3.54 ± 0.13















Talk Overview

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Obstacles in human populated spaces aren't always obvious









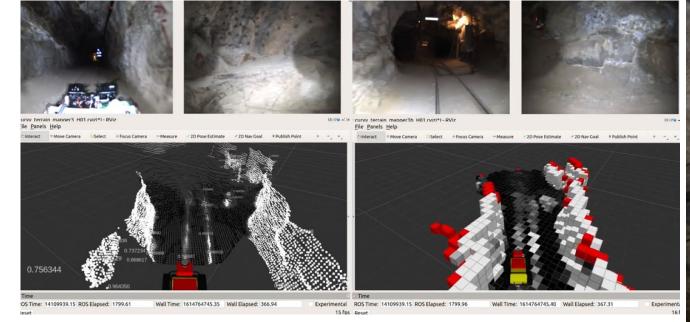
https://arxiv.org/abs/2110.04390

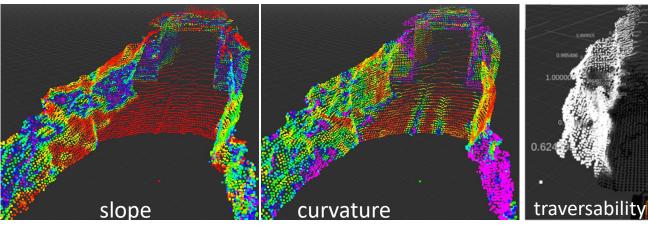






Traversability estimates are informed by both slope and surface curvature and are incorporated into the standard binary Bayes Filter occupancy grid formulation to determine voxel occupancy.





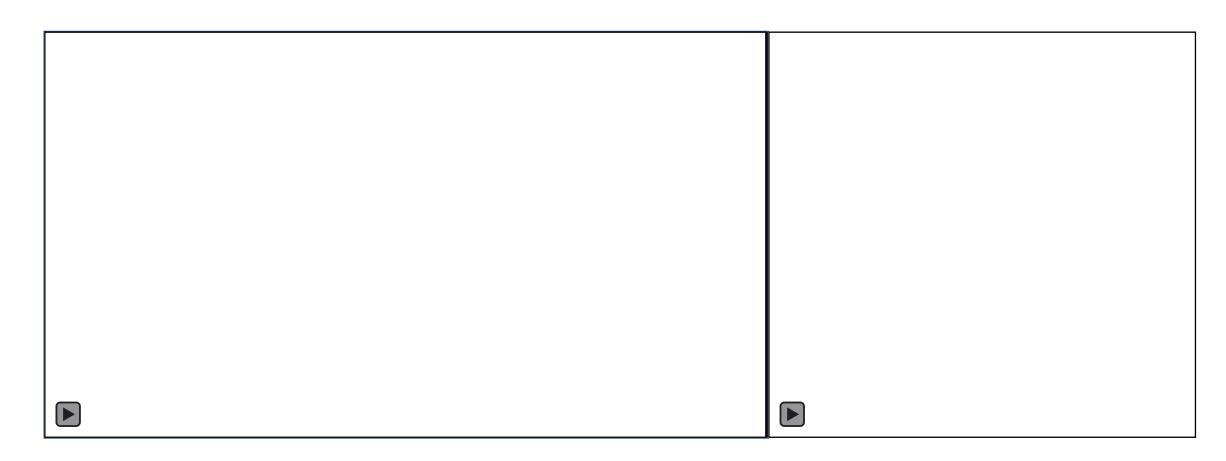








Traversability Estimation is Important!

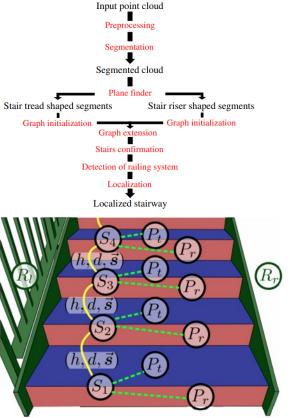


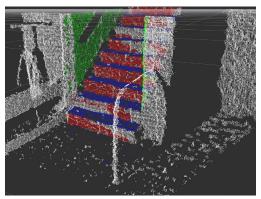


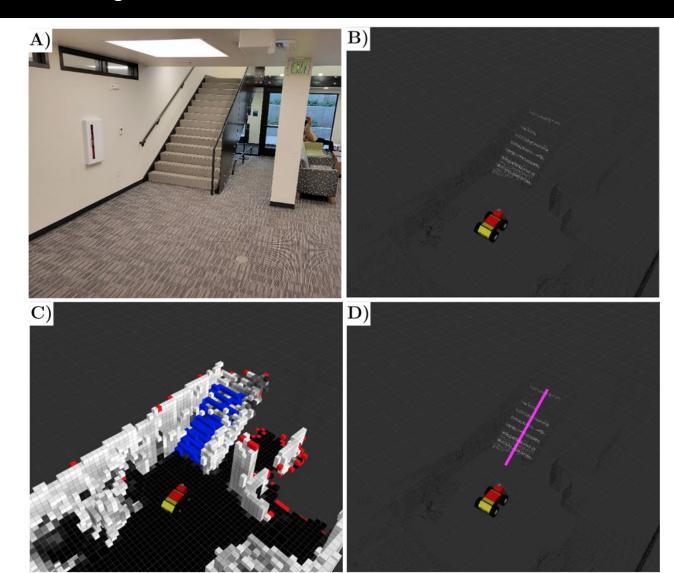




Special Cases (Stairs)







Westfechtel, Thomas, et al. "3D graph based stairway detection and localization for mobile robots." 2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). IEEE, 2016.















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