CAREER: Robust Perception and Customization for Long-Term Autonomous Mobile Service Robots | Award # 2046955, April 1, 2021 - March 31, 2026 (Estimated)

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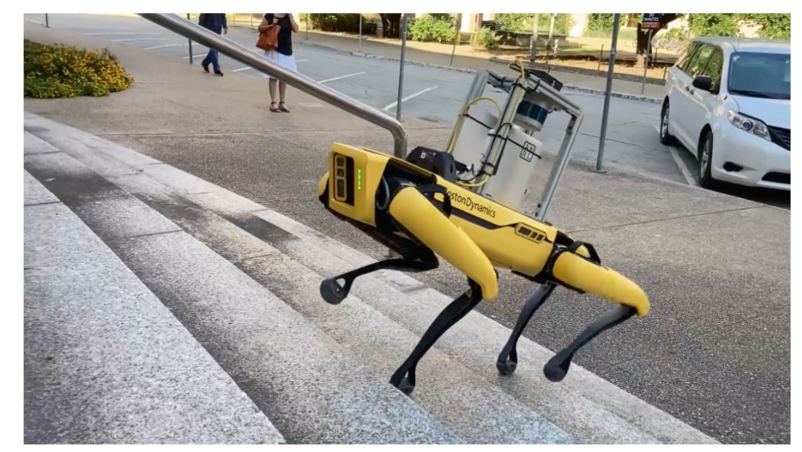
Challenges:

- Perception in the presence of constant changes
- Unexpected and unmodeled perceptual failures
- End-user customizability

Solution:

- ***Semantically meaningful*** long-term probabilistic object mapping
- ***Introspective perception*** for competence-aware autonomy
- ***Visual representation learning*** and ***neuro-symbolic program synthesis*** for customization

Veloso, M., Biswas, J., Coltin, B., & Rosenthal, S. (2015, June). CoBots: Robust symbiotic autonomous mobile service robots. In Twenty-Fourth International Joint Conference on Artificial Intelligence.



Biswas, J. (2019). The Quest For "Always-On" Autonomous Mobile Robots. In Twenty-Eighth International Joint Conference on Artificial Intelligence
Early Career Spotlight Talk

Scientific Impact:

- New probabilistic models for long-term perception
- Ability to autonomously reason about competence during deployments
- Novel learning paradigms for end-user customization

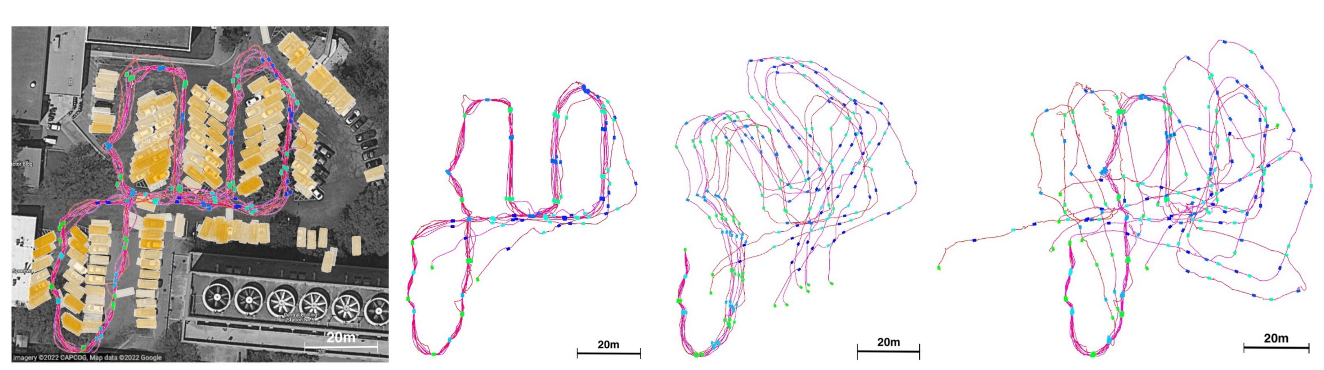
Broader Impact:

- Development of hands-on robotics courses: F1/10 Autonomous Driving, Autonomous Robots https://www.joydeepb.com/teaching.html
- Ability to deploy robots without expert supervision
- Broader deployments of autonomous mobile service robots in real human environments

Probabilistic Object Maps for Long-Term Robot Localization

Amanda Adkins, Taijing Chen, Joydeep Biswas (2021). Probabilistic Object Maps for Long-Term Robot Localization. arXiv Preprint arXiv:2110.00128

https://arxiv.org/abs/2110.00128



(a) POM-Localization with object detections (b) EnML (c) Cartographer (d) LeGO-LOAM

Fig. 5: Plots of trajectories through UT Austin Lot 53 as estimated by the approaches with highlighted blue/green waypoints. Performance of an approach is good when all estimates for a given waypoint are colocated. POM-Localization results are overlayed on a satellite view and shown with aggregated object poses from all trajectories.

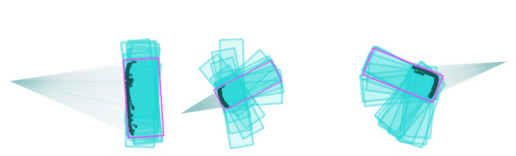
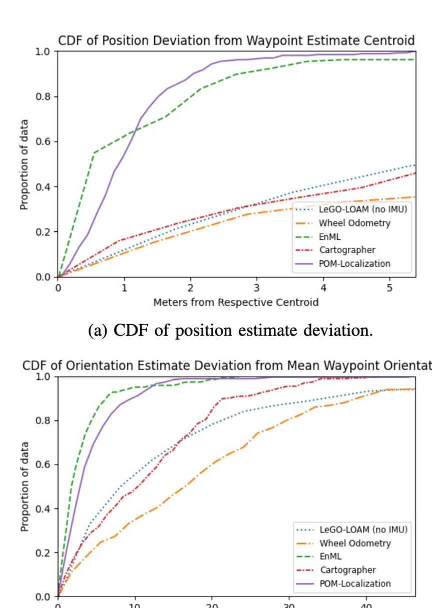


Fig. 2: Examples of observed point clusters and generated object pose samples. True object poses are shown in pink.



(a) CDF of position estimate deviation.

(b) CDF of orientation estimate deviation.

…g. 4: Position and orientation consistency across approaches. An optimal algorithm would quickly rise to 1.

	KITTI Sequence Number	00	02	03	04	05	06	07	08	09	10
	LeGO-LOAM	27.12	1630.55	3.51	4.11	7.97	1.19	0.76	113.44	6.48	1.76
Object Detections	POM-Localization (0-100)	29.46	1630.55	3.51	4.11	7.97	0.80	0.76	113.44	6.48	1.76
	POM-Localization (20-80)	22.93	1630.55	3.55	4.11	1.83	0.37	0.20	113.44	6.48	1.76
	POM-Localization (50-50)	1.73	**1322.19**	1.39	4.06	1.95	0.08	**0.03**	106.86	0.80	0.33
	POM-Localization (80-20)	**1.50**	1332.74	0.89	4.10	1.71	0.09	0.04	113.42	0.81	1.06
	POM-Localization (100^+-0)	1.59	1333.48	**0.82**	**4.04**	**0.18**	**0.04**	0.04	**97.58**	**0.23**	**0.17**
Semantic Segmentation	POM-Localization (0-100)	37.37	1553.24	3.52	4.11	5.43	1.63	0.79	111.50	9.78	3.23
	POM-Localization (20-80)	6.30	1570.66	3.22	4.09	**1.14**	0.28	0.22	97.24	1.08	1.97
	POM-Localization (50-50)	0.37	**1203.31**	2.00	**4.06**	2.27	0.24	0.06	91.43	0.80	0.96
	POM-Localization (80-20)	0.31	1408.15	0.88	4.09	1.60	0.17	0.07	69.33	0.60	0.79
	POM-Localization (100^+-0)	**0.28**	1417.72	**0.85**	**4.06**	1.30	**0.15**	**0.05**	**36.51**	**0.45**	**0.60**

Fig. 3: Absolute Trajectory Error (m) on KITTI dataset sequences for LeGO-LOAM and POM-Localization using observation models for object detections and semantic segmentation.

Competence-Aware Path Planning Via Introspective Perception

Sadegh Rabiee, Connor Basich, Kyle Hollins Wray, Shlomo Zilberstein, Joydeep Biswas (2022). Competence-Aware Path Planning via Introspective Perception. IEEE Robotics and Automation Letters

https://arxiv.org/abs/2109.13974

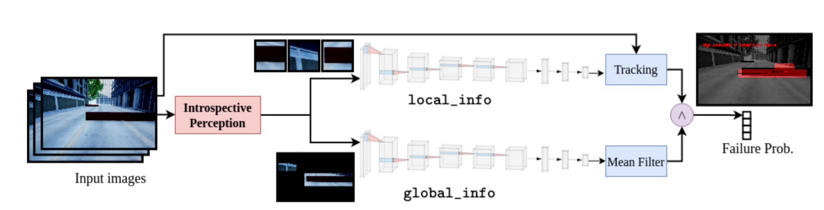
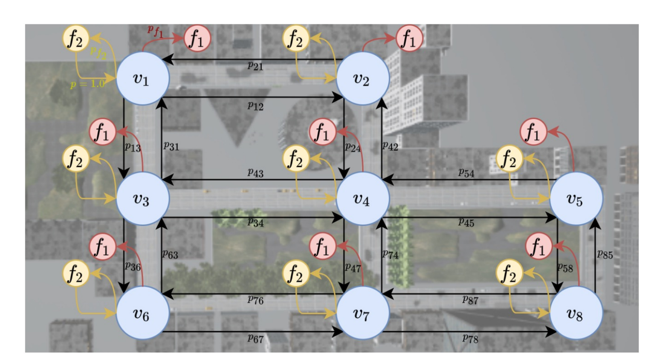


Fig. 2: Navigation competence predictor model architecture.



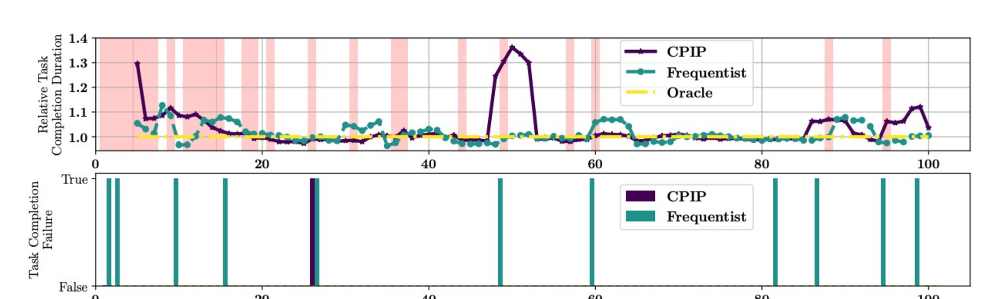
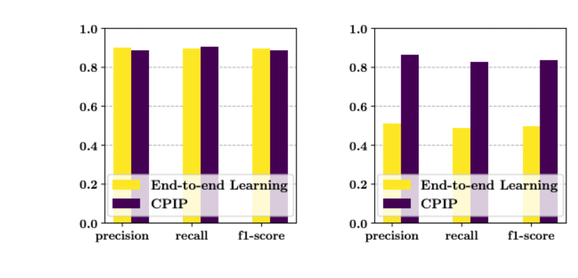
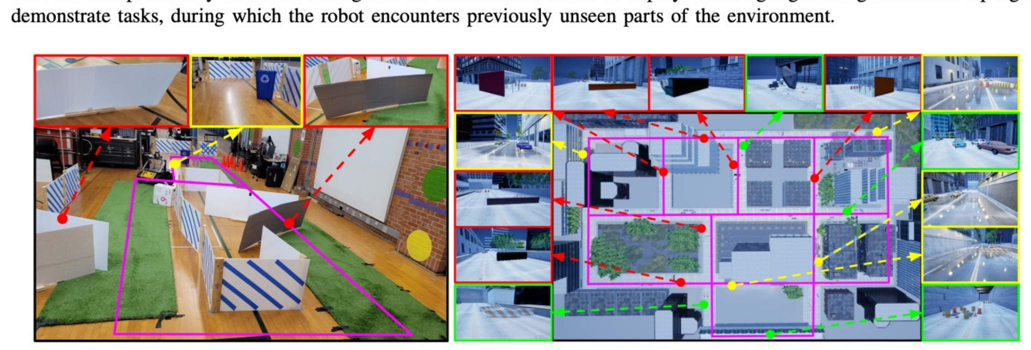


Fig. 6: Task completion failure instances and relative task completion duration w.r.t. an oracle planner that is provided with the true probability of failure throughout the environment ahead of deployment. Highlighted regions in the top figure demonstrate tasks, during which the robot encounters previously unseen parts of the environment.



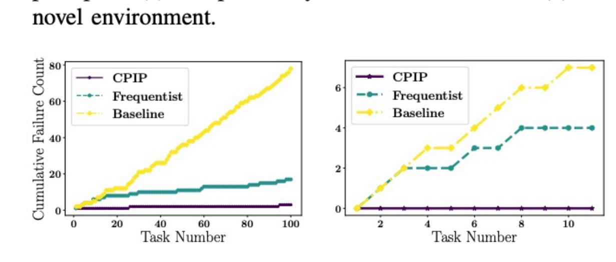
(a) (b)

Fig. 8: Results of the navigation failure prediction for CPIP vs. an end-to-end classifier that does not use introspective perception (a) in a previously seen environment and (b) in a novel environment.



(a) (b)

Fig. 7: Test environments in the real robot experiment (a) and the simulation experiment (b). Regions of the environments highlighted in red cause catastrophic failures, regions highlighted in yellow illustrate sources of non-catastrophic failures, and areas annotated with green, show areas where the robot can successfully operate autonomously.



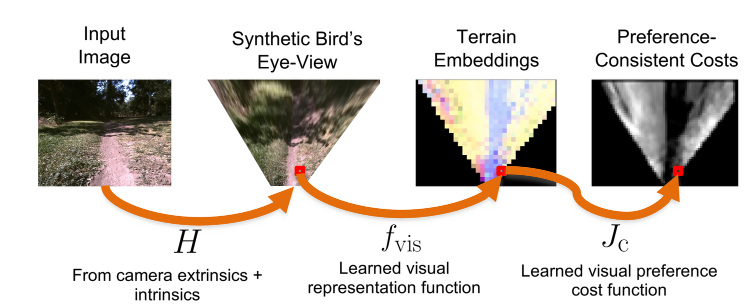
(a) (b)

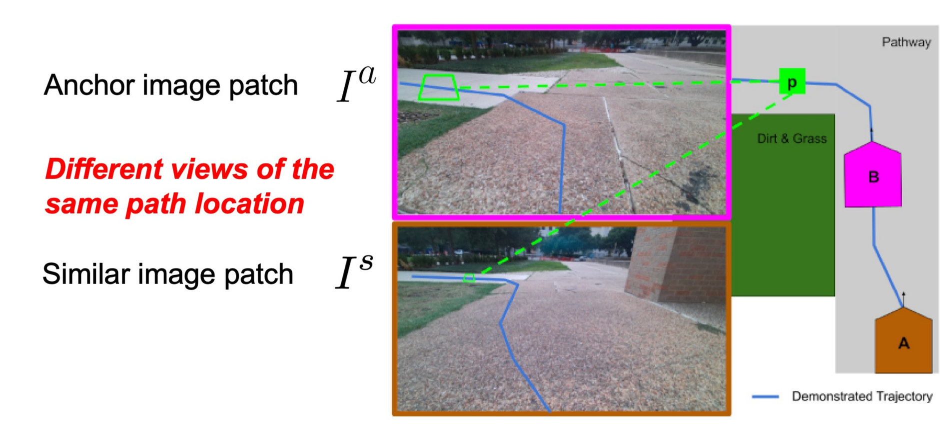
Fig. 5: Comparison of cumulative failure count (a) in the simulation experiment and (b) in the real robot experiment for this work (CPIP), SOTA (frequentist), and the baseline with no competence-aware planning.

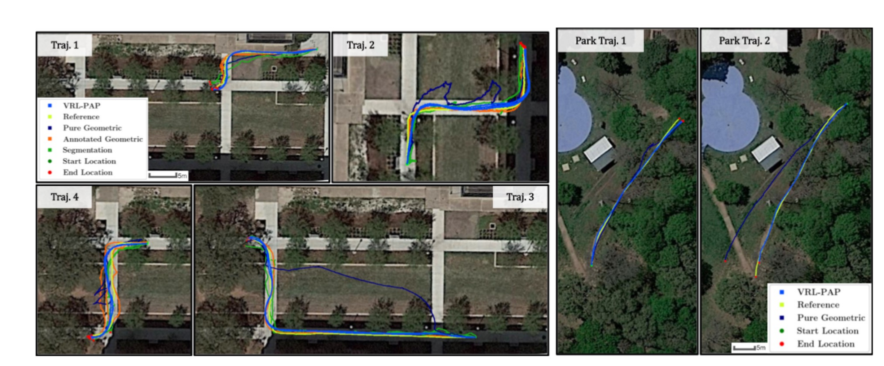
Visual Representation Learning For Preference-Aware Path Planning

Kavan Singh Sikand, Sadegh Rabiee, Adam Uccello, Xuesu Xiao, Garrett Warnell, Joydeep Biswas (2022). Visual Representation Learning for Preference-Aware Path Planning. In *Robotics and Automation (ICRA), IEEE International Conference on*

https://arxiv.org/abs/2109.08968





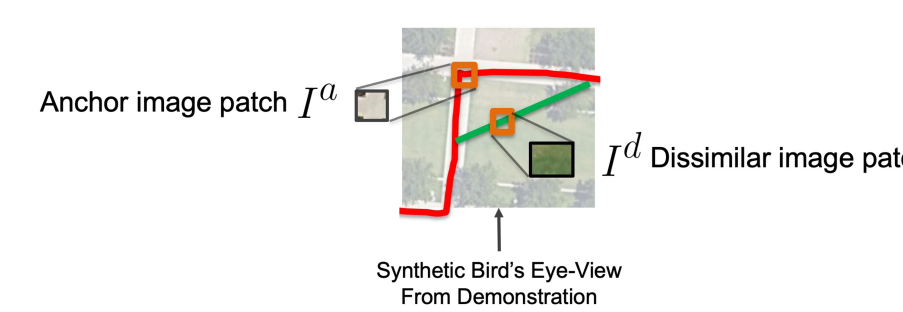


(a) Primary Evaluation Environment Trajectories (b) Secondary Evaluation Environment Trajectories

Fig. 2

Planner	Trajectory 1 Hausdorff Distance (m)	Trajectory 1 Off-Path Duration (s)	Trajectory 1 Intervention Count	Trajectory 2 Hausdorff Distance (m)	Trajectory 2 Off-Path Duration (s)	Trajectory 2 Intervention Count	Trajectory 3 Hausdorff Distance (m)	Trajectory 3 Off-Path Duration (s)	Trajectory 3 Intervention Count	Trajectory 4 Hausdorff Distance (m)	Trajectory 4 Off-Path Duration (s)	Trajectory 4 Intervention Count
Preference Learning	**0.95**	**0**	**0**	**0.93**	**0**	**0**	1.37	**0**	**0**	**1.49**	**0**	**0**
Segmentation	2.40	13	3.5	1.56	2.5	2	2.23	8.5	4	2.66	5.5	3
Annotated Geometric	1.05	1.25	1	1.15	0.25	0.5	**1.32**	**0**	1	2.17	4	**0**
Pure Geometric	$> 1.83^2$	24	4	$> 4.56^2$	18	5	$> 10.02^2$	62	7	$> 4.01^2$	15	5

TABLE I: Mean Metrics in Primary Evaluation Environment.



$$||f_{\text{vis}}(I^a), f_{\text{vis}}(I^d)|| > ||f_{\text{vis}}(I^a), f_{\text{vis}}(I^s)|| + \delta_v$$

*Terrain embeddings difference between **anchor** and **dissimilar** image patches must be at least δ_v greater than difference between **anchor** and **similar** image patches*