FRR: CAREER: Active Bayesian Inference for Collaborative Robot Mapping

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Research Plan:

- **Objective:** establish theory of active Bayesian inference and apply it to collaborative active mapping problems in robotics
- **Task A:** active Bayesian inference formulated as an optimal control problem for multi-robot sensing policy synthesis
- **Task B**: application of active Bayesian inference to collaborative active robot mapping

Education and Broader Impacts Plan:

- Demonstrate exploration and active mapping of unknown environments using a team of ground and aerial robots
- Develop **Robot Proving Grounds (RPG)**, a suite of open-source implementations, examples, and tutorials of core robotics algorithms for localization, mapping, motion planning, and control, unified in an easy-to-use simulation environment

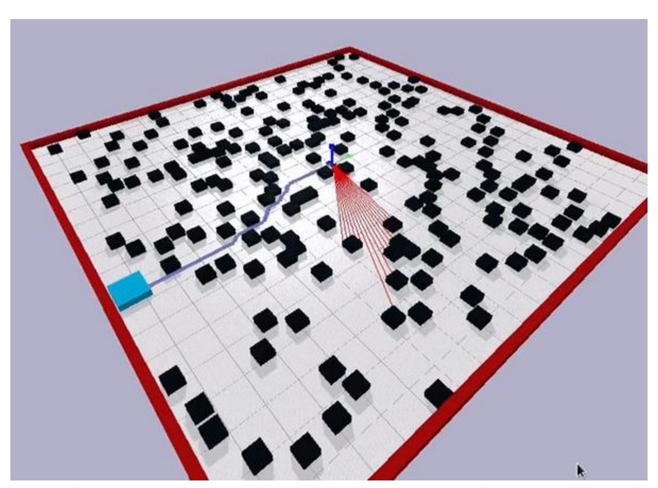
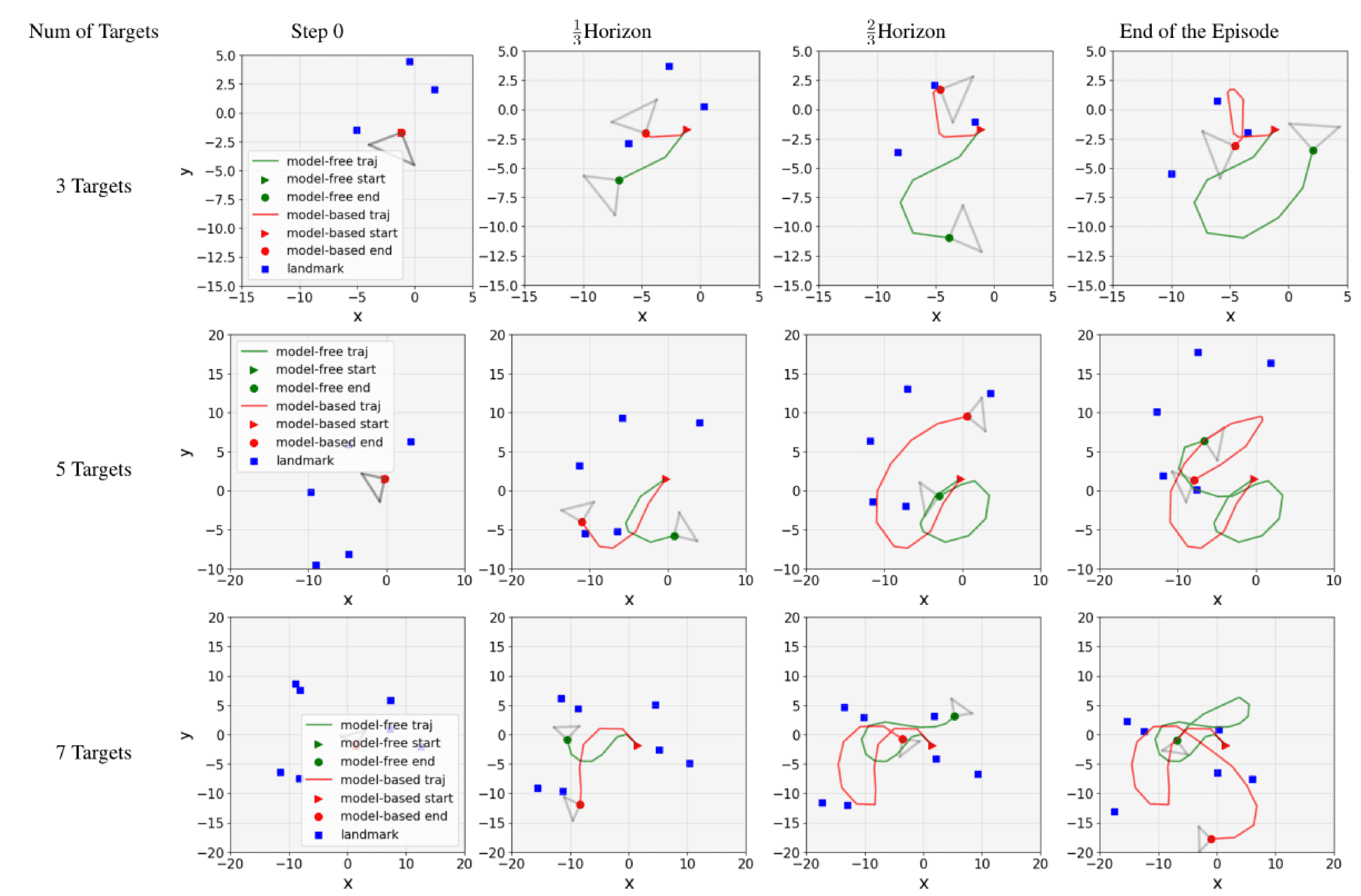


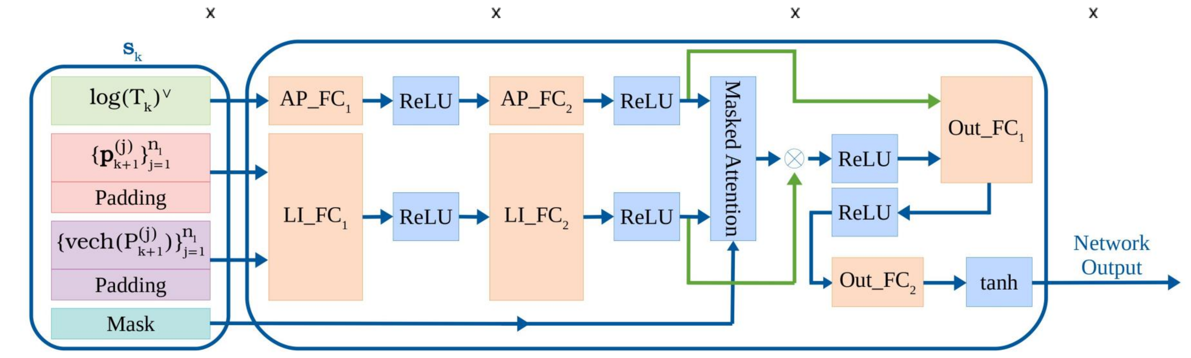
Figure: RPG pyBullet sim

- Outreach and research activities for K12 and undergraduate students using the RPG platform and additional support from UCSD outreach programs

Task A: Policy Learning for Active Target Tracking [1-3]

- Developed **differentiable field of view** (FoV) using signed distance function FOV representation and Gaussian CDF to model probability of detection
- Computed gradient of target state entropy with respect to sensor trajectory in **closed form** for linearized observation and motion models
- Used closed-form gradient to design **a model-based policy gradient optimization** algorithm to learn a sensing control policy for tracking variable numbers of targets
- **Neural network architecture with masked attention** to handle variable number of targets maps sensor pose and target means and covariances to sensor control inputs





Task B: Active Distributed Multi-Robot Mapping [4-6]

- Developed distributed algorithm for optimization over Riemannian manifolds subject to consensus constraints
- Application to distributed mapping and distributed trajectory optimization for map uncertainty reduction
- **Distributed mapping**: maximize expected range-category measurement log-likelihood over octree map distribution:

$$\max_{\{p_i\}} \sum_i \sum_t \int p_i(m) \log p(z_{it}|m)\, dm$$

subject to consensus constraints $\sum_j A_{ij} KL(p_i||p_j) = 0$ for all i

- **Distributed planning**: maximize mutual information between the octree map distribution $p_i(m)$ and future range-category measurements over the robot pose trajectories subject to pose trajectory consensus constraints

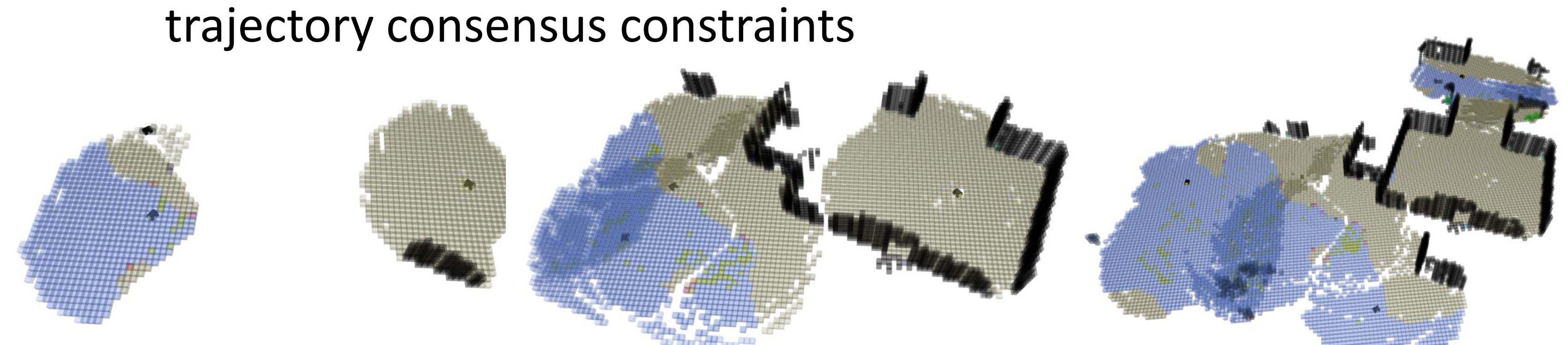


Figure: Time lapse of active distributed mapping

Task B: Learning Viewpoint-Aware Surface Models [7]

- **Signed directional distance function** (SDDF) $h: \mathbb{R}^n \times S^{n-1} \mapsto \mathbb{R}$ of set $\mathcal{O} \subset \mathbb{R}^n$ measures signed distance from point $\boldsymbol{p} \in \mathbb{R}^n$ to set boundary $\partial\mathcal{O}$ in direction $\boldsymbol{v} \in S^{n-1}$: $h(\boldsymbol{p}, \boldsymbol{v}; \mathcal{O}) \coloneqq \begin{cases} \min\{d > 0 \mid \boldsymbol{p} + d\boldsymbol{v} \in \partial\mathcal{O}\}, & \boldsymbol{p} \notin \mathcal{O}, \\ \max\{d \le 0 \mid \boldsymbol{p} + d\boldsymbol{v} \in \partial\mathcal{O}\}, & \boldsymbol{p} \in \mathcal{O}. \end{cases}$
- **SDDF gradient** with respect to $\boldsymbol{p}$ satisfies: $\nabla_{\boldsymbol{p}} h(\boldsymbol{p}, \boldsymbol{v})^\top \boldsymbol{v} = -1$
- A function h is a valid SDDF if and only if $h(\boldsymbol{p}, \boldsymbol{v}) = f(\boldsymbol{P}\boldsymbol{R}_{\boldsymbol{v}}\boldsymbol{p}, \boldsymbol{v}) - \boldsymbol{p}^\top \boldsymbol{v}$ for some $f: \mathbb{R}^{n-1} \times S^{n-1} \mapsto \mathbb{R}$, $\boldsymbol{P} = [\boldsymbol{I}\ \ \boldsymbol{0}]$, $\boldsymbol{R}_{\boldsymbol{v}} \in SO(3)$
- Developed neural network model that generates valid SDDFs by construction
- Current work is focused on **online SDDF estimation** to allow mapping complete scenes incrementally from streaming sensor data
- Developed techniques for octree decomposition of SDDF surface models, discontinuity approximation with parametric leaky ReLU, and SDDF prediction interpolation from incrementally constructed latent feature maps

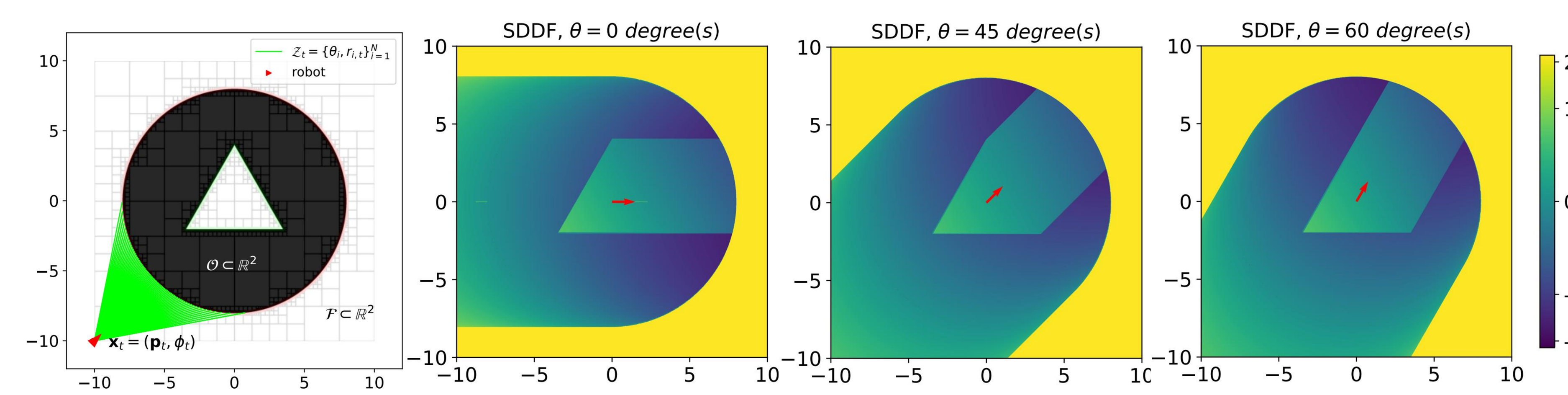


Figure: Signed directional distance function (right) associated with circular obstacle (left) at different viewing directions

References

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[2] P. Yang, Y. Liu, S. Koga, A. Asgharivaskasi, and N. Atanasov, "Learning Continuous Control Policies for Information-Theoretic Active Perception," IEEE International Conference on Robotics and Automation (ICRA), 2023

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[6] P. Paritosh, N. Atanasov, and S. Martinez, "Distributed Bayesian Estimation of Continuous Variables over Time-varying Directed Networks," IEEE Control Systems Letters (L-CSS), vol. 6, pp. 2545–2550, 2022

[7] E. Zobeidi and N. Atanasov, "A Deep Signed Directional Distance Function for Shape Representation and View Synthesis," arXiv: https://arxiv.org/abs/2107.11024 (under review)