

# CogniPlan: Uncertainty-Guided Path Planning with Conditional Generative Layout Prediction – Supplementary Materials

Anonymous Author(s)

Affiliation

Address

email

## 1 Validation in Gazebo Simulation

2 **Environment Setup** We validate CogniPlan’s real-world performance in a high-fidelity Gazebo environment provided by Cao et al. [1, 2], using a four-wheel-drive mobile robot equipped with a  
3 16-line Velodyne LiDAR for odometry and mapping. The environment incorporates realistic motion constraints, while a local planner ensures safe execution of waypoints generated by the high-  
4 level planner. During validation, we adopt the graph rarefaction strategy from [3] to reduce graph complexity. Specifically, we preserve a dense graph structure in predicted regions while applying  
5 rarefaction in known areas, and remove nodes that are not connected via a valid path to the robot’s current node.

10 **Medium-Scale Environment.** We first evaluate CogniPlan in a  $54\text{m} \times 34\text{m}$  indoor environment crafted by Long et al. [4], which contains dense clutter and obstacles. They also introduced HPHS,  
11 a hierarchical planner that directly samples from LiDAR data. We compare CogniPlan against the baselines tested and reported in [4], including a frontier-based approach [5] and an improved RRT  
12 planner TDLE [6]. The results are shown in Table 1, where we observe that CogniPlan produces shorter paths with lower variance, indicating more consistent and stable trajectories due to effective  
13 layout/uncertainty prediction. The corresponding trajectory is visualized in Fig. 1.

Method	Frontier-based	TDLE	TARE	HPHS	CogniPlan
$D(\psi)$ (m)	270.6( $\pm 42.1$ )	290.5( $\pm 35.6$ )	190.3( $\pm 31.4$ )	176.9( $\pm 24.7$ )	<b>170.9(<math>\pm 18.1</math>)</b>
Efficiency ( $\text{m}^2/\text{m}$ )	3.14	2.93	4.31	4.78	<b>4.95</b>

Table 1: **Comparison over 10 runs in the medium-scale environment.** We report the mean and standard deviation of travel distance and path efficiency relative to the explored area.

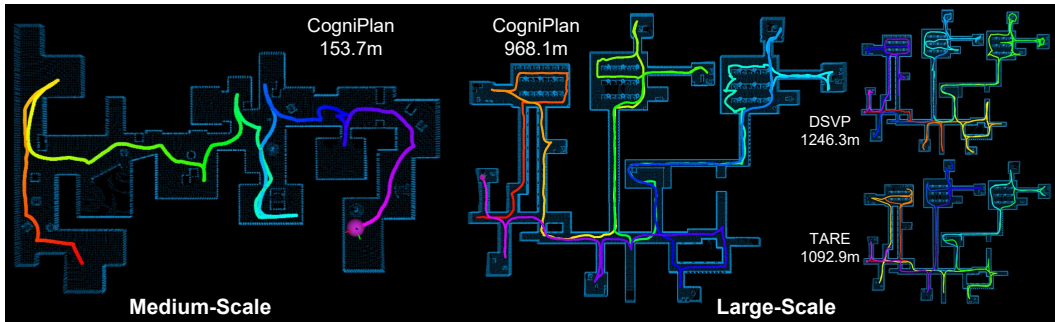


Figure 1: **Trajectories of CogniPlan and baseline planners in medium- and large-scale environment.** Colored lines represent the robot’s motion trajectories, with the red-to-purple spectrum indicating progression from start to end.

**Large-Scale Environment.** We further evaluate our method in a  $130\text{m} \times 100\text{m}$  indoor setting comprising long, narrow corridors interconnected with spacious lobby areas. We compare CogniPlan against DSV Planner [7] and TARE [1], both of which represent state-of-the-art conventional planner for large-scale environments. We run each method five times and present the exploration progress in Fig. 2 and trajectory example in Fig. 1. We notice that CogniPlan consistently outperforms TARE and DSV throughout the exploration process, with notably lower variance, highlighting that layout predictions can enhance both performance and robustness. Figure 3 visualizes the layout predictions during exploration. Despite the environment being significantly out-of-distribution from the training data of both the inpainting and planner models, the predicted layouts still effectively support planning and contribute to improved performance.

We believe this demonstrates the potential of the CogniPlan framework as a fully learning-based planning approach that enhances performance, path robustness, and explainability. It also opens up promising directions for future research in multi-agent planning and visual navigation.

Method	DSVP	TARE	CogniPlan
$D(\psi)$ (m)	1300.6( $\pm 58.7$ )	1144.9( $\pm 70.7$ )	<b>999.1(<math>\pm 17.1</math>)</b>
Efficiency ( $\text{m}^3/\text{m}$ )	4.03( $\pm 0.19$ )	4.58( $\pm 0.30$ )	<b>5.25(<math>\pm 0.09</math>)</b>

Table 2: **Comparison over 5 runs in the large-scale environment.** We report the mean and standard deviation of travel distance and path efficiency relative to the explored volume.

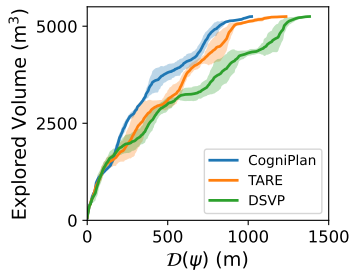


Figure 2: **Exploration progress in a large-scale environment.**

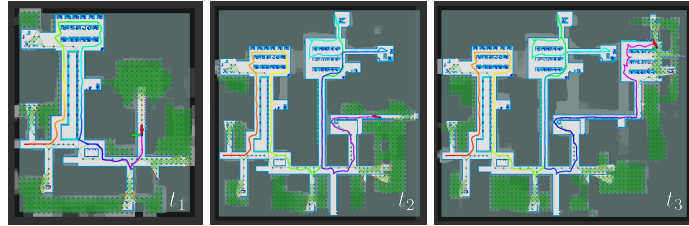


Figure 3: **Layout predictions at three different timesteps during exploration in a large-scale environment.** We also show the corresponding occupancy map (Octomap) and the rarefied graph (nodes and green edges).

## References

- [1] C. Cao, H. Zhu, H. Choset, and J. Zhang. Tare: A hierarchical framework for efficiently exploring complex 3d environments. In *Robotics: Science and Systems*, volume 5, page 2, 2021.
- [2] C. Cao, H. Zhu, Z. Ren, H. Choset, and J. Zhang. Representation granularity enables time-efficient autonomous exploration in large, complex worlds. *Science Robotics*, 8(80):eadf0970, 2023.
- [3] Y. Cao, R. Zhao, Y. Wang, B. Xiang, and G. Sartoretti. Deep reinforcement learning-based large-scale robot exploration. *IEEE Robotics and Automation Letters*, 2024.
- [4] S. Long, Y. Li, C. Wu, B. Xu, and W. Fan. Hphs: Hierarchical planning based on hybrid frontier sampling for unknown environments exploration. In *2024 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 12056–12063. IEEE, 2024.
- [5] J. Oršulić, D. Miklić, and Z. Kovačić. Efficient dense frontier detection for 2-d graph slam based on occupancy grid submaps. *IEEE Robotics and Automation Letters*, 4(4):3569–3576, 2019.
- [6] X. Zhao, C. Yu, E. Xu, and Y. Liu. Tdle: 2-d lidar exploration with hierarchical planning using regional division. In *2023 IEEE 19th International Conference on Automation Science and Engineering (CASE)*, pages 1–6. IEEE, 2023.

- 46 [7] H. Zhu, C. Cao, Y. Xia, S. Scherer, J. Zhang, and W. Wang. Dsvp: Dual-stage viewpoint planner  
47 for rapid exploration by dynamic expansion. In *2021 IEEE/RSJ international conference on*  
48 *intelligent robots and systems (IROS)*, pages 7623–7630. IEEE, 2021.