APPENDIX

A. Additional Details of the Dreame-SR Dataset

In Section V-A, we provide a brief introduction to our Dreame-SR dataset. In this section, we present more comprehensive information about the dataset. Additionally, we illustrate the complexity and diversity of our scenarios by showcasing nine distinct scenes in Fig. 6. For consistency, we adhere to the default world coordinate system of OpenCV (right-hand coordinate system), where the positive x, y, and z axes point to the right, forward, and upward, respectively.

To evaluate the robustness and stability of our system, we collect a diverse set of indoor scenes that pose significant challenges for purely vision-based systems. These scenes encompass various difficulties, such as dimly lit environments (*e.g.* LivingRoom02), spaces with extensive tiled reflective surfaces (*e.g.* Whole-Room00, BedRoom02, LivingRoom03), and areas characterized by repetitive and monotonous textures (*e.g.* BedRoom00, LivingRoom01). Each scene covers an area of approximately 15 to 30 square meters.

For data collection, we employ a camera with a 75-degree field of view to capture RGB images at a resolution of 672×504 pixels. Training RGB images are selected based on their angular velocity, ensuring that the chosen frames provide a rich set of statistical information. Further details, including frame counts and the number of SLAM points, are provided in Table IV.

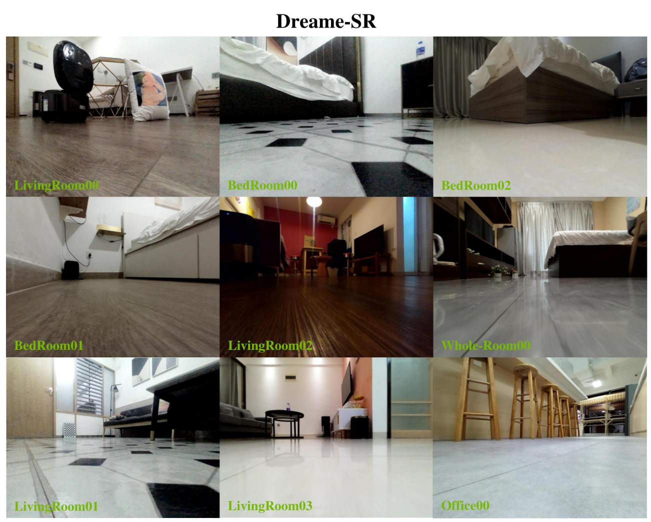


Fig. 6. Illustration of nine distinct indoor scenes from the Dreame-SR dataset.

B. Qualitative Results of the Dreame-SR Dataset

We present the qualitative results of our method alongside the radiance field baseline methods on the Dreame-SR dataset in Figs. 7 and 8. These results illustrate the effectiveness of our approach in comparison to existing techniques, highlighting the advantages of our method in various scenarios.

TABLE IV

STATISTICS ON THE NUMBER OF IMAGES, SLAM POINTS, AND LIDAR POINTS UTILIZED IN OUR DATASET.

Sequence	Frames	Poses	SLAM Points	LDS Points
LivingRoom00	1,631	✓	140K	✓
LivingRoom01	2,364	✓	190K	✓
LivingRoom02	3,498	✓	90K	✓
LivingRoom03	2,481	✓	66K	✓
BedRoom00	1,287	✓	70K	✓
BedRoom01	1,535	✓	67K	✓
BedRoom02	2,755	✓	44K	✓
Office00	3,008	✓	117K	✓
Whole-House00	4,965	✓	116k	✓
Whole-House01	2,309	✓	118K	✓
Whole-House02	2,772	✓	179K	✓

C. Additional Details and Results of the Ground Challenge Dataset

Setup. We evaluate our approach on the publicly available Ground Challenge dataset [29], which also includes low-altitude images. Each scene features only 50-150 seconds of data, with each trajectory consisting of 500-1500 image frames. The key differences between our Dreame-SR dataset and the Ground Challenge dataset are as follows:

- Our viewpoint is lower than that of the Ground Challenge data, resulting in frames that capture more ground area.
- Our camera operates at a frequency of 5 Hz, while the Ground Challenge dataset has a frequency of 15 Hz.
- We utilize single-line LiDAR, whereas the Ground Challenge dataset employs multi-line LiDAR.

These differences in equipment are illustrated in Fig. 9. Notably, our device is smaller and more flexible, making the image acquisition process more challenging.

Results. The quantitative results of the Ground Challenge dataset are shown in Table V, while Fig. 10 illustrates the qualitative outcomes. Given the different equipment settings, we focus our evaluation on the VEC Completion approach for this dataset. We selected five diverse scene trajectories: *Room1*, *Room2*, *Office2*, *Loop2_1*, and *Loop2_2*. As shown in the table, our method consistently outperforms other methods, including 3DGS and RAIN-GS, which yield comparable results. However, instant-NGP struggles with reconstruction, particularly due to motion blur present in the dataset, leading to its failure in reconstructing the *Loop2_1* scene. Visualizations clearly demonstrate the superior performance of our method, especially in terms of ground plane reconstruction, handling highly reflective surfaces, and preserving fine details.

Fig. 7. Qualitative results of SLAM-based reconstruction methods baseline on Dreame-SR datasets.

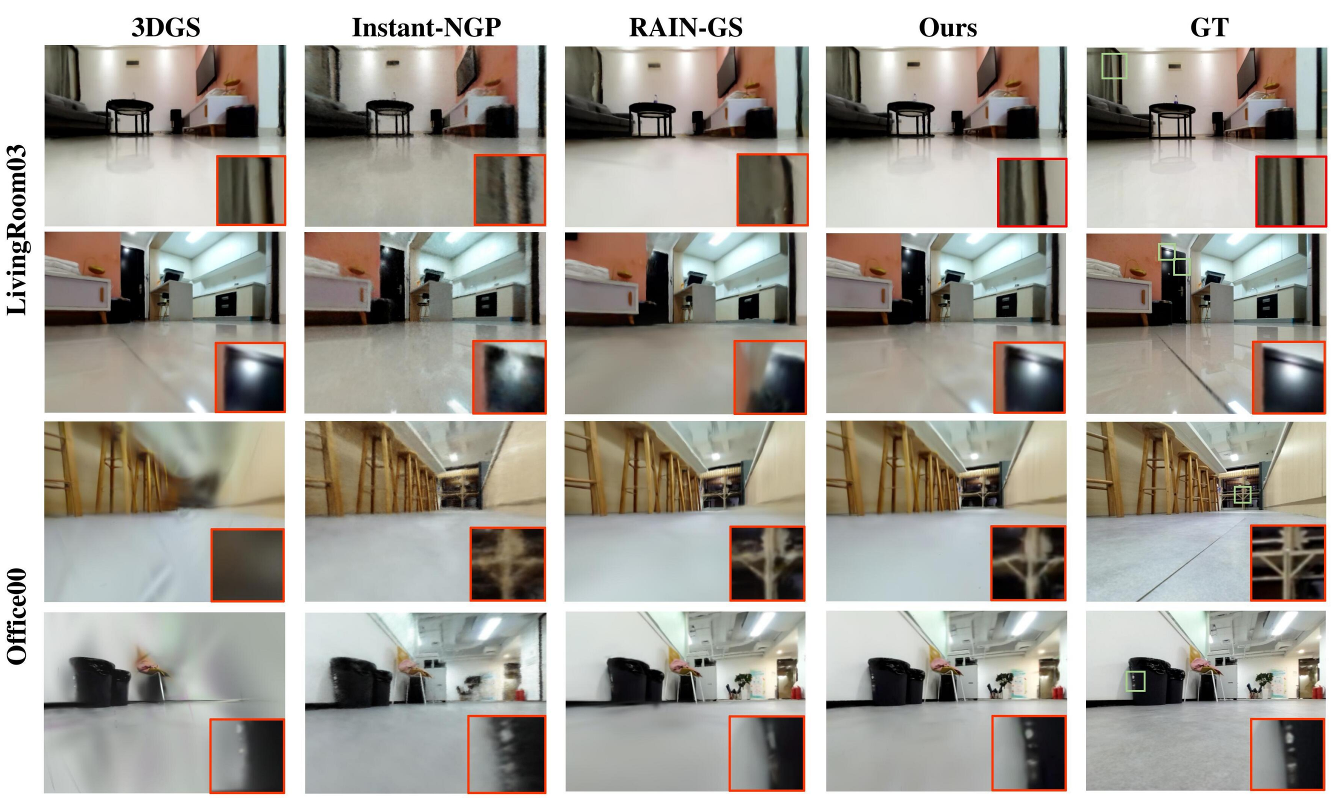
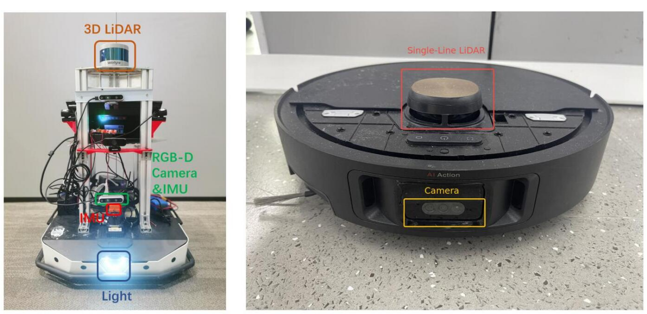


Fig. 8. Qualitative results of completion enhanced mapping methods baseline on Dreame-SR datasets.

TABLE V

QUANTITATIVE RESULTS OF COMPLETION ENHANCED MAPPING METHODS ON GROUND CHALLENGE DATASET. RED, ORANGE, AND YELLOW HIGHLIGHTS INDICATE THE 1ST, 2ND, AND 3RD BEST PERFORMING TECHNIQUE FOR EACH METRIC.

	3DGS [11]			Instant-NGP [13]			RAIN-GS [23]			ES-Gaussian (Ours)		
Sequence	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓
Room1	31.846	0.947	0.104	23.349	0.805	0.324	31.836	0.945	0.156	33.213	0.955	0.089
Room2	29.122	0.922	0.148	22.325	0.759	0.395	29.518	0.925	0.193	30.658	0.934	0.121
Office2	32.690	0.951	0.152	25.097	0.801	0.362	30.629	0.933	0.249	33.260	0.955	0.138
Loop2_1	31.819	0.949	0.139	13.708	0.442	0.627	32.162	0.946	0.251	33.810	0.959	0.126
Loop2_2	29.462	0.929	0.293	21.889	0.753	0.382	31.088	0.939	0.278	31.282	0.944	0.184
Average	30.988	0.944	0.149	21.273	0.712	0.418	31.047	0.938	0.225	32.445	0.949	0.132



Ground Challenge **Ours**

Fig. 9. Comparison of equipment used in the Ground Challenge dataset [29] versus that used in our sweeping robot system.

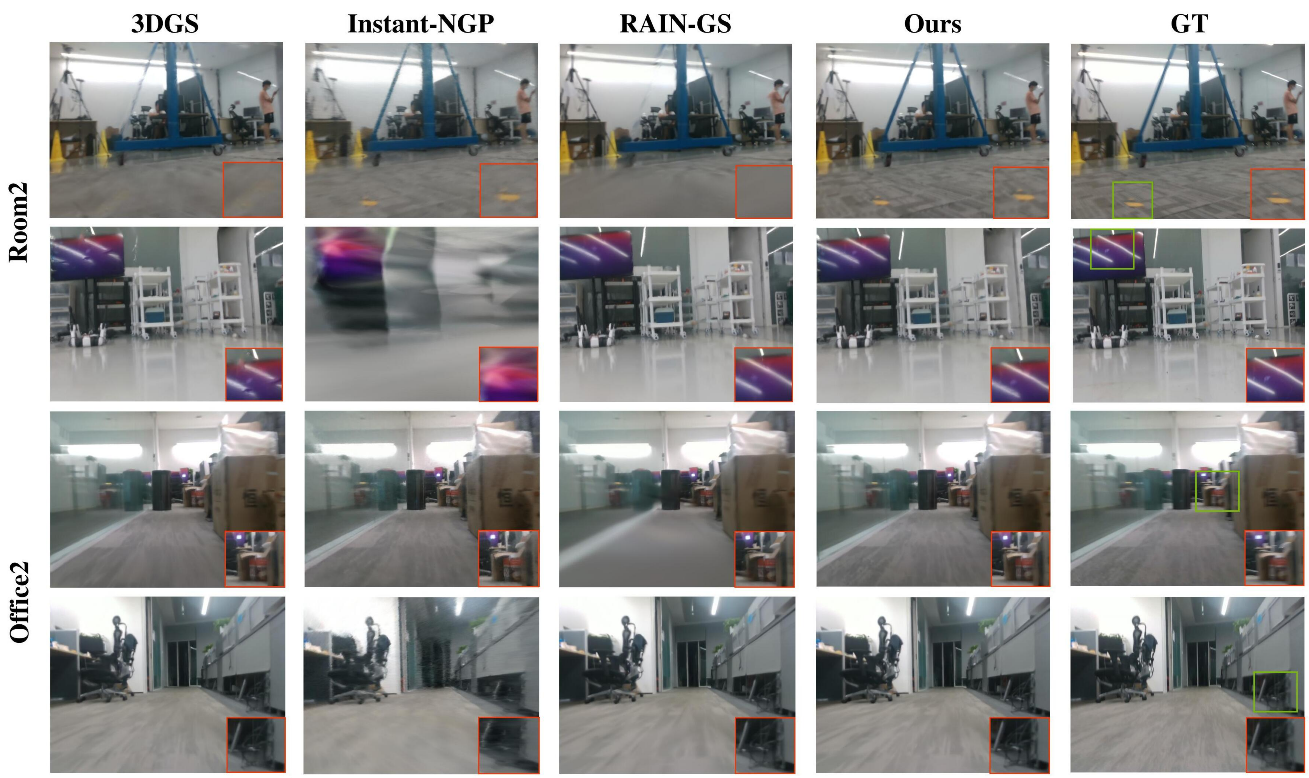


Fig. 10. Qualitative results of our method and the radiance fields baseline on Ground Challenge datasets.