Dynamic Scene Decomposition Beyond Moving Objects for High-Fidelity 3D Reconstruction in Autonomous Driving

Supplementary Material

A. Experimental Setup Details

Dataset. For the KITTI [2] dataset, we select 0001, 0002 and 0006 sequences for evaluation with the left and right cameras. For 0001, we use frames 55 to 95 (inclusive). For 0002, we use frames 50 to 114 (inclusive). For 0006, we use frames 65 to 120 (inclusive). For the Waymo [6] dataset, we select seg102353, seg131865, seg132079, seg135064, seg104481, seg123746, seg176124, seg190611, seg209468, seg424653, seg537228 and seg839851 with the FRONT, FRONT_LEFT, and FRONT_RIGHT cameras. We follow the frame selection of [7] and [1].

B. Metric Definitions

NIQE (Natural Image Quality Evaluator): NIQE [5] is a blind image quality assessment (IQA) metric that quantifies the perceptual quality of an image without requiring a reference image. It operates by constructing a collection of perceptually relevant features from local patches of the image, modeled as a multivariate Gaussian distribution. The quality score is computed as the distance between the feature distribution of the test image and a pre-trained model derived from a corpus of natural images. Formally, for an image, NIQE [5] measures the deviation of its statistical properties from those expected in natural scenes.

BRISQUE (Blind/Referenceless Image Spatial Quality Evaluator): BRISQUE [4] is a no-reference IQA algorithm that operates in the spatial domain. It extracts locally normalized luminance coefficients and computes scene statistics of these coefficients to quantify naturalness. BRISQUE [4] utilizes a support vector regressor trained on human-rated distorted images to map these statistical features to quality scores. The metric specifically captures distortions arising from natural scene statistics violations, making it particularly effective for evaluating in-the-wild image degradations.

C. Additional Experiments

Results on nuScenes Dataset: To demonstrate the generalizability and robustness of DBM-GS, we conduct additional evaluations on the nuScenes dataset. We specifically target challenging scenarios, including sequences with missing LiDAR points(`scene-0040`), adverse weather conditions(`scene-0060`), and heavy traffic(`scene-0187`). For 0040 and 0187, we use frames 10 to 120 (inclusive). For 0060, we use frames 100 to 190 (inclusive). Our evaluation is conducted using only the front camera (`CAM_FRONT`).

Qualitative results are presented in Figure 1. Even under these demanding conditions, DBM-GS successfully maintains a clean static-dynamic decomposition and produces high-fidelity renderings, proving its effectiveness beyond standard benchmarks.

Results on nuScenes Dataset: Furthermore, we analyze the sensitivity of the hyperparameters in our geometry- and color-aware LiDAR loss on the nuScenes dataset. Specifically, we evaluate the impact of different values for α and the decay function $\beta(t)$. The quantitative results are summarized in the accompanying table.

Method	PSNR↑	SSIM↑	LPIPS↓	NIQE↓	BRISQUE↓
BézierGS [3]	31.57	0.927	0.112	5.65	48.95
Ours	31.73	0.929	0.108	5.54	47.31
Ours (α=1)	31.75	0.929	0.108	5.55	47.40
Ours (α=10)	31.76	0.929	0.108	5.56	47.57
Ours (β linear)	31.80	0.929	0.108	5.57	47.83
Ours (β log)	31.72	0.929	0.109	5.56	47.58

D. Limitations

Although DBM-GS achieves state-of-the-art performances in NIQE [5] and BRISQUE [4], it still has several limitations. First, DBM-GS relies on complete scene LiDAR point clouds to provide sufficient supervision signals, making reconstruction infeasible in regions without LiDAR data. Second, in some cases, DBM-GS fails to surpass the visual quality of state-of-the-art rendering models. Since these methods do not impose additional constraints on the background, their models can more easily fit the ground truth RGB images.

References

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Figure 1. Qualitative results on the nuScenes dataset. DBM-GS robustly handles challenging scenes involving missing LiDAR points, bad weather, and heavy traffic.

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