Supplementary Material for
Sparse2DGS: Geometry-Prioritized Gaussian Splatting for Surface Reconstruction from Sparse Views

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A. Ablation Study on MVS Feature Splatting

We leverage MVS feature splatting for geometry-enhanced supervision (Sec. 3.2). As the adopted CLMVSNet [8] extracts feature maps at 3 different scales through an FPN, we analyze the impact of each feature scale on reconstruction quality. As shown in Tab. 1, high-resolution feature maps provide finer-grained geometric constraints, leading to better performance (row **a** to row **c**). Moreover, we set the feature vector of each Gaussian primitive as learnable parameters. As shown in Tab. 1 (row **d**), the coupled learning of feature and geometry degraded the final performance, validating the necessity of fixing feature values for geometric optimization.

	Feature Res.	Fixed	Accuracy↓	Completion↓	Average↓
(a)	$H/4 \times W/4$	✓	0.853	1.645	1.248
(b)	$H/2 \times W/2$	✓	0.835	1.651	1.243
(c)	$H \times W$	✓	**0.816**	**1.632**	**1.224**
(d)	$H \times W$	✗	0.830	1.648	1.239

Table 1. **Ablation study on feature splatting.**

B. Comparison of Different Gaussian Primitive Update Strategies

In addition to the generic density control strategy used in 3D Gaussian Splatting [5], GaussianPro [2] employs traditional MVS to optimize rendered depth maps and projects geometrically consistent depths into a point cloud, which is used to expand the Gaussian primitives. As shown in Tab. 2, we compared this strategy with our proposed Selective Gaussian Update strategy (Sec. 3.4). The traditional MVS optimization strategy of GaussianPro does not show significant advantages with the MVS-initialized point cloud. Our Selective Gaussian Update strategy leverages rendered geometry to refine Gaussian primitives, achieving better results.

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Methods	Accuracy↓	Compleness↓	Average↓
Baseline	0.790	1.612	1.201
GaussianPro [2]	0.791	1.598	1.194
Selective Gaussian Update	**0.760**	**1.544**	**1.152**

Table 2. **Quantitative results of different Gaussian primitive update strategies.**

C. Comparison of Surface Reconstruction and Novel View Synthesis

We compare the surface reconstruction and novel view synthesis results of different methods on the DTU dataset. We follow the dataset split strategy of SparseNeuS [7], selecting views 23, 24, and 33 for training. The recent Gaussian-based state-of-the-art NVS method, DNGaussian [6], employs monocular depth for regularization. Although it achieves reliable novel view synthesis under sparse views, the reconstructed surface exhibits noise and missing regions (Fig 1). As shown in Table 3, our method achieves the best LPIPS and SSIM scores for novel view synthesis. Moreover, it demonstrates superior surface reconstruction accuracy and completeness compared to all other methods.

	Settings	Accuracy↓	Completion↓	Average↓
(a)	CLMVSNet [8]	0.82	1.70	1.26
(b)	CLMVSNet [8] + Ours	0.74	1.52	1.13
(c)	TransMVSNet [3]	**0.61**	1.60	1.11
(d)	TransMVSNet [3] + Ours	0.63	**1.43**	**1.03**

Table 4. **Improvement upon different MVS methods.**

D. Experiment on Different MVS Methods

As shown in Tab. 4, we compare the reconstruction performance of different MVS methods combined with Sparse2DGS. TransMVSNet [3] (row **c**) is trained on the DTU dataset using ground truth depth, achieving superior reconstruction performance compared to the unsupervised CLMVSNet [8] (row **a**). By initializing the Gaussians with CLMVSNet and performing test-time fine-tuning, we achieve performance comparable to that of TransMVSNet

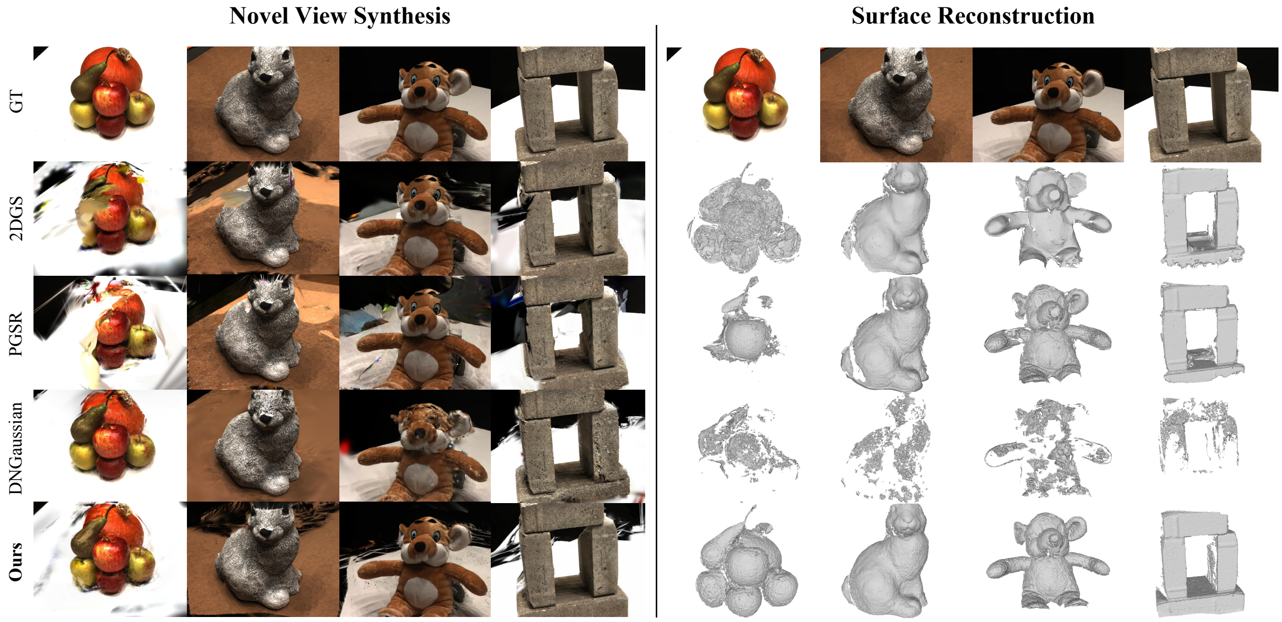

Figure 1. **Visualization of surface reconstruction and novel view synthesis results.**

Methods	PSNR ↑	SSIM ↑	LPIPS ↓	Accuracy↓	Completion↓	Average↓
2DGS [4]	16.55	0.601	0.385	2.17	3.45	2.81
GOF [9]	16.67	0.575	0.388	3.09	2.55	2.82
PGSR [1]	15.30	0.536	0.409	1.64	2.52	2.08
DNGaussian [6]	**19.09**	0.664	0.390	4.22	7.15	5.68
Ours	17.49	**0.726**	**0.275**	**0.74**	**1.52**	**1.13**

Table 3. **Quantitative comparison of surface reconstruction and novel view synthesis from sparse views.**

(row **b**). Additionally, initializing with the point cloud from TransMVSNet leads to improved performance, further demonstrating the effectiveness of our method (row **d**).

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