

GaussianSpa: An “Optimizing-Sparsifying” Simplification Framework for Compact and High-Quality 3D Gaussian Splatting

Supplementary Material

7. Additional Results

7.1. Additional Quantitative Results

We summarize additional quantitative results on the Mip-NeRF 360, Tanks&Temples, and Deep Blending datasets in Table 3, Table 4, and Table 5, respectively. We plot additional PSNR-#Gaussians curves on diverse Scenes in Figure 14, in comparison with Mini-Splatting [17] and LightGaussian [16]. It can be observed that with the same number of Gaussians, our GaussianSpa shows superior rendering outcomes.

7.2. Additional Visual Quality Results

Figure 10 and Figure 11 provide additional rendered images comparing GaussianSpa with LightGaussian [16], Mini-Splatting [17], and original 3DGS on various scenes. Those additional results demonstrate our GaussianSpa achieves stronger representational power for background and detail-rich areas such as walls, carpets, and ladders, showcasing superior rendering qualities. Furthermore, Figure 12 and Figure 13 offer additional rendered Gaussian ellipsoids and point cloud views, respectively. These results further illustrate that GaussianSpa creates a high-quality sparse 3D representation that adaptively uses more Gaussians to represent high-frequency areas.

8. Additional Discussion

Convergence Analysis. We analyze the convergence behavior of GaussianSpa by examining the effects of hyperparameters such as δ , which controls the sparsity strength in Eq. 10, and the interval at which the “sparsifying” step is performed, as described in Section 3. Figure 9 shows loss curves for various δ and interval values, indicating similar convergence rates during our “optimizing-sparsifying”-integrated training process. After removing “zero” Gaussians at iteration 25K, the loss curve continues to converge consistently, confirming GaussianSpa’s feasibility.

Method	PSNR \uparrow	SSIM \uparrow	LPIPS \downarrow	Storage \downarrow
EfficientGS [28]	27.38	0.817	0.216	98 MB
LightGaussian [16]	27.28	0.805	0.243	42 MB
GaussianSpa	27.85	0.825	0.214	25 MB

Table 2. **Storage comparison evaluated on the Mip-NeRF 360 dataset.** GaussianSpa’s storage cost is reported based on the add-on compression methods (i.e., SH distillation and vector quantization) from LightGaussian [16].

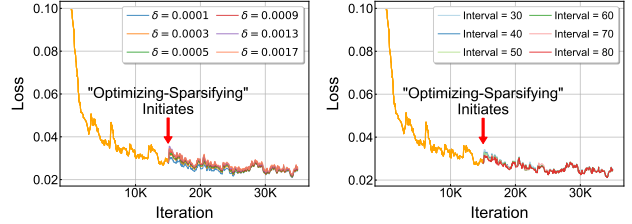


Figure 9. **Loss curves with multiple (left) δ and (right) interval settings.** The curves show that GaussianSpa exhibits a good convergence behavior in the “optimizing-sparsifying”-integrated training process.

Scene	Method	PSNR \uparrow	SSIM \uparrow	LPIPS \downarrow	# G (M) \downarrow
Bicycle	3DGS	25.13	0.750	0.240	5.310
	Mini-Splatting	25.21	0.760	0.247	0.646
	GaussianSpa	25.44	0.769	0.246	0.656
Bonsai	3DGS	32.19	0.950	0.180	1.250
	Mini-Splatting	31.73	0.945	0.180	0.360
	GaussianSpa	32.40	0.947	0.174	0.372
Counter	3DGS	29.11	0.910	0.180	1.170
	Mini-Splatting	28.53	0.911	0.184	0.408
	GaussianSpa	29.23	0.919	0.176	0.392
Flowers	3DGS	21.37	0.590	0.360	3.470
	Mini-Splatting	21.42	0.616	0.336	0.670
	GaussianSpa	21.75	0.610	0.329	0.674
Garden	3DGS	27.32	0.860	0.120	5.690
	Mini-Splatting	26.99	0.842	0.156	0.738
	GaussianSpa	27.26	0.848	0.151	0.728
Kitchen	3DGS	31.53	0.930	0.120	1.770
	Mini-Splatting	31.24	0.929	0.122	0.438
	GaussianSpa	32.03	0.934	0.117	0.423
Room	3DGS	31.59	0.920	0.200	1.500
	Mini-Splatting	31.44	0.929	0.193	0.394
	GaussianSpa	32.04	0.933	0.188	0.355
Stump	3DGS	26.73	0.770	0.240	4.420
	Mini-Splatting	27.35	0.803	0.219	0.717
	GaussianSpa	27.56	0.808	0.218	0.690
Treehill	3DGS	22.61	0.640	0.350	3.420
	Mini-Splatting	22.69	0.652	0.332	0.663
	GaussianSpa	22.94	0.660	0.329	0.637
Average	3DGS	27.45	0.810	0.220	3.110
	Mini-Splatting	27.40	0.821	0.219	0.559
	GaussianSpa	27.85	0.825	0.214	0.547

Table 3. MiP-NeRF360 per scene results. 3DGS results are reported from [19]. Mini-Splatting [17] results are replicated using official code.

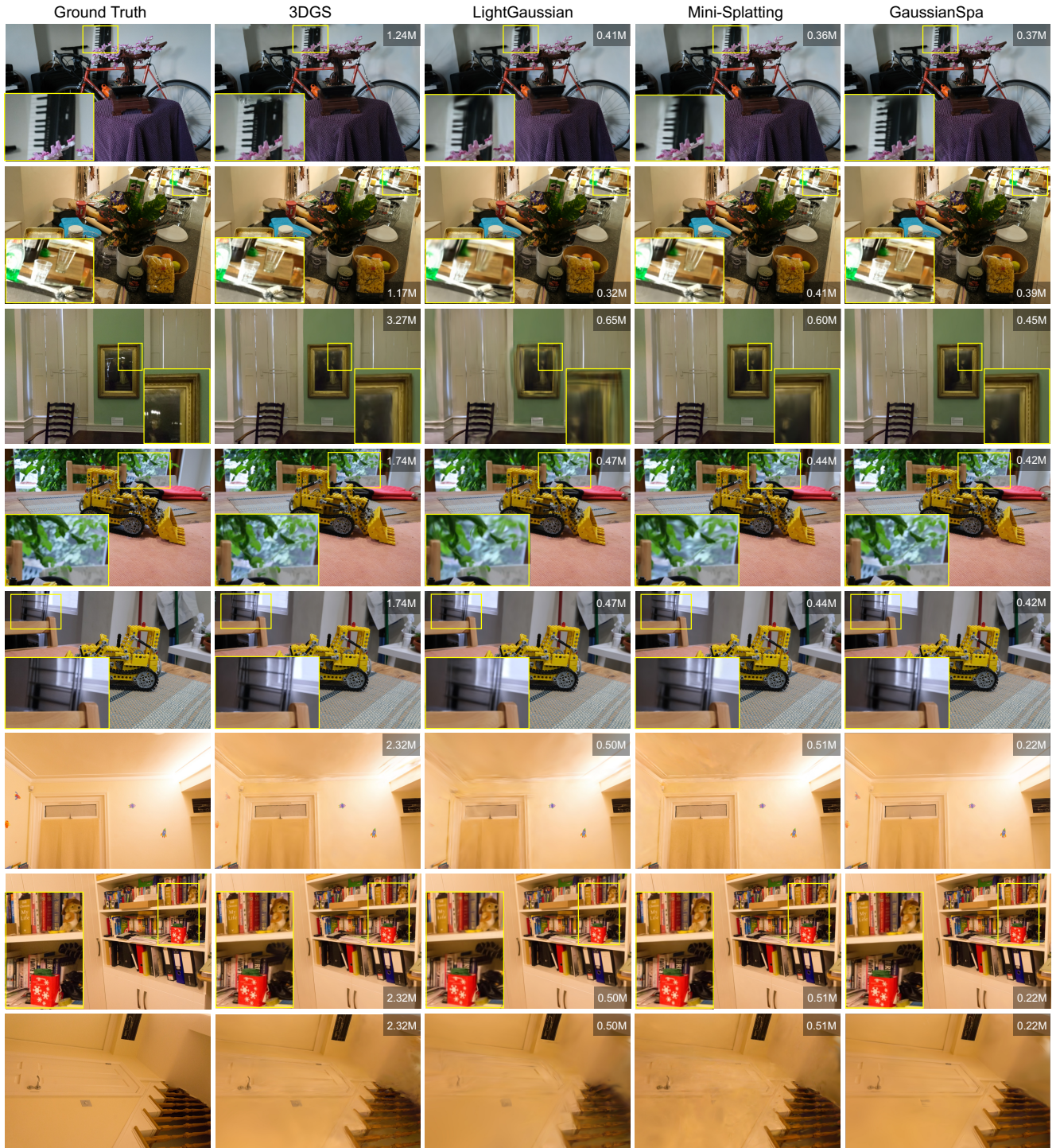


Figure 10. Additional visual comparison on more scenes. The numbers of remaining Gaussians in millions are displayed.



Figure 11. (Continue) Additional visual comparison on more scenes. The numbers of remaining Gaussians in millions are displayed.

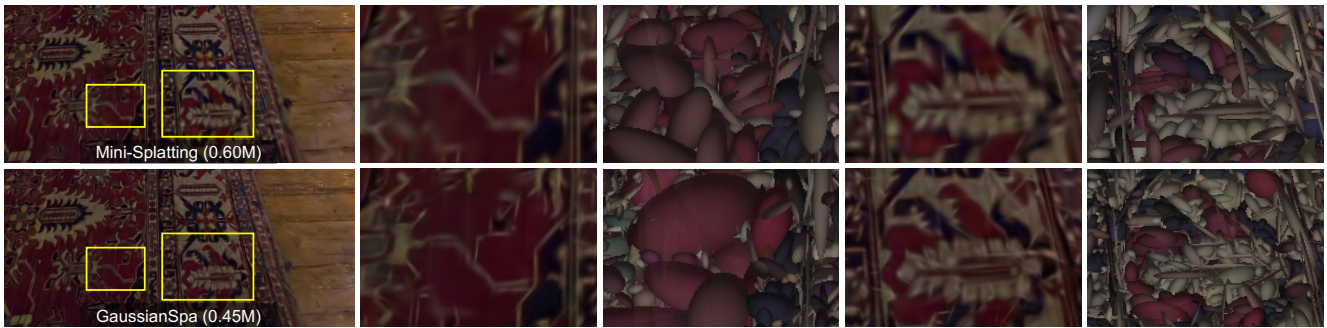


Figure 12. Additional visualized Gaussian ellipsoids. The numbers of remaining Gaussians in millions are displayed.

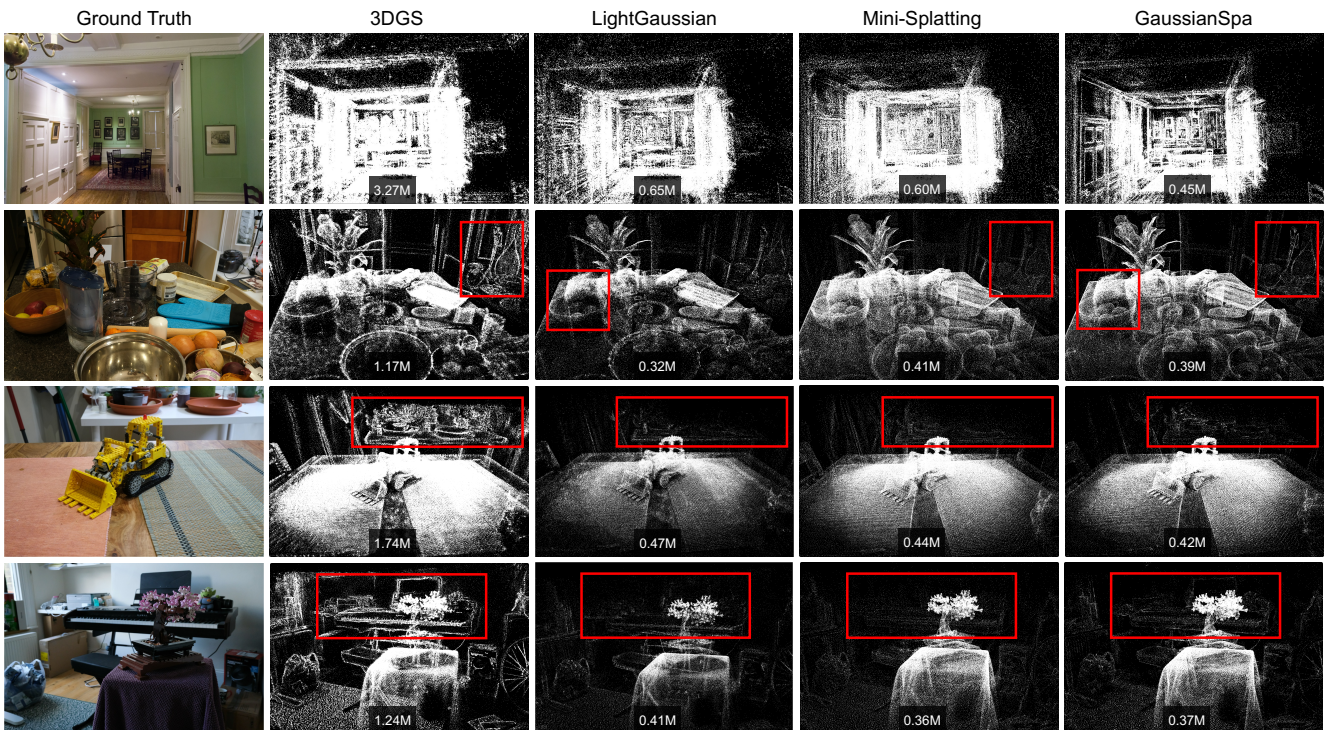


Figure 13. Additional visualized point clouds. The numbers of remaining Gaussians in millions are displayed.

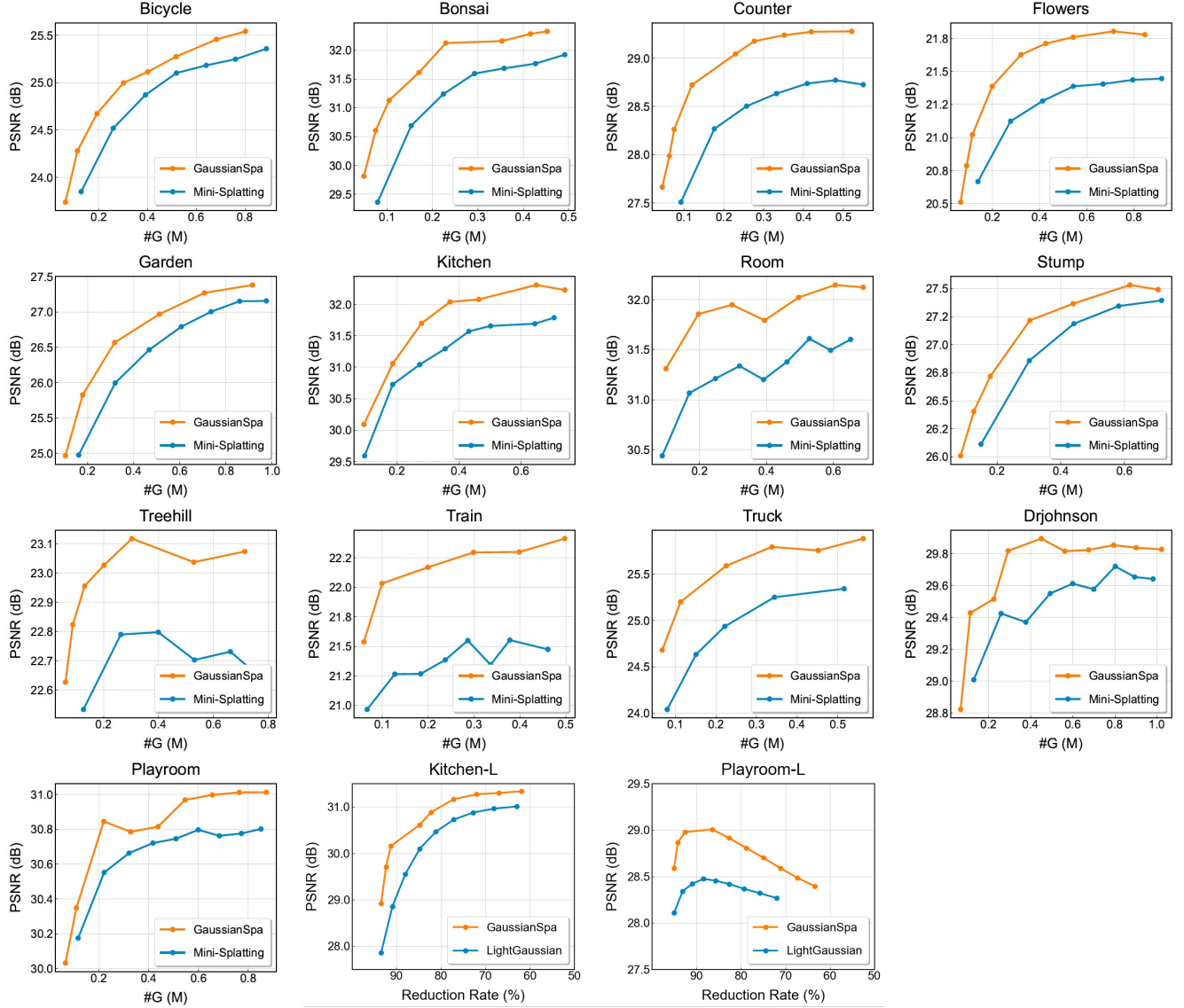


Figure 14. The first 13 sub-figures: Quality-#G (the number of Gaussians in millions) curves comparing GaussianSpa with Mini-Splatting [17] on multiple scenes. Our GaussianSpa consistently outperforms Mini-Splatting [17] with the same #G. The last two sub-figures: Quality-Reduction Rate curves comparing GaussianSpa with LightGaussian [16] on the Kitchen and Playroom scenes.

Scene	Method	PSNR↑	SSIM↑	LPIPS↓	# G (M)↓
Train	3DGS	21.94	0.810	0.200	1.110
	Mini-Splatting	21.78	0.805	0.231	0.287
	GaussianSpa	22.17	0.815	0.228	0.199
Truck	3DGS	25.31	0.880	0.150	2.540
	Mini-Splatting	25.13	0.878	0.141	0.352
	GaussianSpa	25.79	0.888	0.132	0.338
Average	3DGS	23.63	0.850	0.180	1.830
	Mini-Splatting	23.45	0.841	0.186	0.319
	GaussianSpa	23.98	0.852	0.180	0.269

Table 4. Tanks&Temples per scene results.

Scene	Method	PSNR↑	SSIM↑	LPIPS↓	# G (M)↓
Drjohnson	3DGS	28.77	0.900	0.250	3.260
	Mini-Splatting	29.37	0.904	0.261	0.377
	GaussianSpa	29.89	0.913	0.243	0.450
	GaussianSpa	29.82	0.909	0.254	0.293
Playroom	3DGS	30.07	0.900	0.250	2.290
	Mini-Splatting	30.72	0.914	0.248	0.417
	GaussianSpa	30.84	0.916	0.254	0.219
	GaussianSpa	30.84	0.916	0.254	0.219
Average	3DGS	29.42	0.900	0.250	2.780
	Mini-Splatting	30.05	0.909	0.254	0.397
	GaussianSpa	30.37	0.914	0.249	0.335
	GaussianSpa	30.33	0.912	0.254	0.256

Table 5. Deep Blending per scene results.