

# FSFSplatter: Geometrically Accurate Reconstruction with Free Sparse-view Images within 2 minutes

## Supplementary Material

### A.1. Details of framework and implementation

#### A.1.1. Implementation

The scene representation of FSFSplatter is based on 2DGS, and the rasterization pipeline is implemented based on AbsGS [12] and TrimGS [2]. Compared to basic 2DGS pipeline [4], the rasterization pipeline of FSFSplatter employs Abs accumulated gradient  $\bar{\Delta}_i^{\text{ACC}}$  when calculating the accumulated gradient  $\Delta_i^{\text{ACC}}$  (i.e., the gradient of the loss function  $\mathcal{L}$  with respect to the projected pixel coordinate  $u$ ). This approach mitigates gradient collision, thereby accurately addressing the blurring and loss of detail caused by over-reconstruction during Gaussian splitting, as shown in Eq. (A1). Here,  $m$  denotes the sequence of all affected pixels. Contribution-based pruning is implemented following TrimGS, with the key distinction being the extension from pruning designed for NVS in 3DGS to pruning designed for surface reconstruction in 2DGS, as formulated in ??.

$$\bar{\Delta}_i^{\text{ACC}} = \sum_{j=1}^m \left| \frac{\partial \mathcal{L}_j}{\partial u_i} \right|, \quad \Delta_i^{\text{ACC}} = \sum_{j=1}^m \frac{\partial \mathcal{L}_j}{\partial u_i} \quad (\text{A1})$$

#### A.1.2. Parameter Setting

For the contribution-based Gaussian pruning, we perform a pruning at the start of optimization and subsequently repeat it every 500 iterations, removing the 5% of Gaussian primitives with the lowest contribution. Experiments were performed with different pruning configurations. As presented in Tab. A1, fine-tuning the inter-pruning iteration intervals and pruning ratio to increase the total pruning quantity yielded improvements in optimization speed, while maintaining surface reconstruction accuracy and incurring a minor degradation in NVS.

Trim per Iter	Trim Percent	CD(mm)↓	LPLPS↓	PSNR↑	SSIM↑	Times↓
300	5%	36.42	0.119	35.13	0.962	104.2
300	10%	37.74	0.118	35.51	0.963	102.2
300	20%	35.21	0.121	35.35	0.962	99.2
500	5%	33.66	0.095	35.79	0.965	107.3
500	10%	39.91	0.118	35.57	0.963	104.1
500	20%	36.12	0.119	35.33	0.962	103.4

Table A1. Parameter tuning experiment of contribution-based pruning on Replica datasets.

For the loss function, the parameters  $m$ ,  $n_1$ , and  $n_2$  are set to  $1 \times 10^{-4}$ ,  $1 \times 10^{-2}$ , and  $1 \times 10^{-4}$ , respectively.

Furthermore, we evaluated the splitting parameter  $N$  (set as 2) for Gaussian self-splitting head. As shown in Tab. A2, since features before splitting are pixel-aligned and semi-dense, merely increasing the number of splits does not enhance the accuracy of the dense Gaussian scene. Instead, it significantly increases the time consumed during rasterization.

Split Number	Points Num	Rasterizer Times↓	PSNR↑	SSIM↑	LPIPS↓
1	473088	12.568	21.42	0.761	0.308
2	913408	13.436	23.70	0.786	0.248
4	1753088	27.387	23.89	0.799	0.231
8	3702784	53.139	23.47	0.787	0.280

Table A2. Parameter tuning experiment of self-splitting Gaussian head.

#### A.1.3. Evaluation Metrics

We employ PSNR, SSIM, and LPIPS to comprehensively evaluate the quality of NVS. For DTU datasets [1] and BlendedMVS datasets [11], where transparent masks are provided, we apply masks to all images prior to evaluation to ensure fair comparisons. To assess surface reconstruction quality, we utilize the Chamfer Distance (CD). Following previous works [1, 5], we adopt the L2 Chamfer Distance as our evaluation metric, as shown in Eq. (A2).

$$\text{CD}(\mathcal{M}, \mathcal{M}_{\text{gt}}) = \frac{1}{2|\mathcal{M}|} \sum_{x \in \mathcal{M}} \min_{y \in \mathcal{M}_{\text{gt}}} \|x - y\|_2 + \frac{1}{2|\mathcal{M}_{\text{gt}}|} \sum_{y \in \mathcal{M}_{\text{gt}}} \min_{x \in \mathcal{M}} \|x - y\|_2 \quad (\text{A2})$$

Since surface reconstruction from free RGB images is inherently scale-ambiguous, we perform surface registration to align reconstructed surfaces with ground truth surfaces for accurate evaluation. Following prior work [3], we first register and evaluate camera poses by sampling points from the camera optical centers and viewing directions and Iterative Closest Point (ICP) alignment. This step brings the surfaces into rough alignment. However, unlike previous methods that treat camera intrinsics as known priors, our approach predicts intrinsics via a neural network. As a result, direct camera pose alignment alone is insufficient due to errors in estimated intrinsics. To address this, we further refine the alignment by performing descriptor-based point cloud registration [8], ensuring accurate cor-

		CF-3DGS		FreeSplatter		Fast3R		Dust3r		VGGT		Ours	
		Rot	Trans	Rot	Trans	Rot	Trans	Rot	Trans	Rot	Trans	Rot	Trans
Replica	Office0	74.930	38.575	51.045	28.432	4.236	4.417	35.950	3.916	0.794	2.326	0.800	2.319
	Office1	43.651	31.719	62.805	42.110	11.592	4.145	60.846	3.468	0.778	3.625	0.740	3.426
	Office2	24.612	190.52	44.780	128.35	0.526	4.870	29.353	12.435	0.442	3.156	0.419	2.980
	Room0	44.478	173.42	32.990	229.53	0.497	2.343	38.550	13.274	0.889	8.321	0.893	8.308
	Room1	38.663	243.30	44.063	109.78	0.306	2.411	34.774	5.936	0.332	1.760	0.318	1.695
DTU	scan24	23.123	10.736	4.830	30.796	1.501	3.564	29.952	1.880	0.147	0.383	0.152	0.388
	scan37	56.389	95.731	10.628	8.832	5.295	18.280	47.159	15.749	0.461	1.446	0.441	1.458
	scan40	50.555	70.607	6.443	15.590	1.289	5.681	59.713	7.021	0.626	1.418	0.628	1.438
	scan55	30.339	69.516	4.707	15.411	1.325	11.293	49.758	4.359	0.203	1.209	0.216	1.221
	scan63	39.299	79.984	3.520	30.415	4.760	17.137	37.742	17.378	0.530	2.206	0.516	2.203
	scan65	11.181	94.896	6.210	39.433	2.124	16.450	25.381	12.917	0.230	1.241	0.276	1.125
	scan69	54.851	72.511	2.941	13.699	1.896	6.562	41.689	7.427	0.128	1.853	0.092	1.826
	scan83	42.331	86.062	1.877	12.644	6.083	36.981	77.169	26.918	0.325	2.530	0.487	2.181
	scan97	29.318	67.483	16.416	30.376	2.506	12.922	56.655	13.913	0.308	1.073	0.313	1.069
	scan105	54.325	67.535	3.267	26.114	3.190	26.857	34.217	8.835	0.219	2.054	0.210	2.108
	scan106	54.349	72.003	5.200	8.806	0.460	10.196	41.294	4.361	0.359	1.196	0.366	1.215
	scan110	40.470	61.468	10.383	13.227	1.909	7.209	42.506	8.192	0.296	0.810	0.301	0.761
	scan114	8.837	61.963	5.450	38.759	1.854	10.781	26.354	10.068	0.357	1.123	0.363	1.086
	scan118	43.873	81.839	2.640	3.735	2.032	15.600	35.484	10.656	0.081	0.576	0.089	0.502
	scan122	34.831	71.341	4.121	23.594	2.499	13.661	39.012	8.106	0.244	0.366	0.257	0.258

Table A3. Detailed pose estimation experiments, Rot( $^{\circ}$ ) $\downarrow$  and Trans(mm) $\downarrow$ , on Replica and DTU datasets.

	scan24	scan37	scan40	scan55	scan63	scan65	scan69	scan83	scan97	scan105	scan106	scan110	scan114	scan118	scan122	Mean
<b>Ours</b>	1.300	2.103	1.767	1.468	2.066	1.476	1.339	2.191	1.736	1.479	1.419	1.420	0.793	1.572	1.583	1.581
No $\mathcal{L}_{\text{rank}}$	2.012	4.942	2.639	2.130	3.900	3.800	2.856	3.472	3.095	2.450	2.041	2.453	1.338	4.244	2.200	2.905
No $\mathcal{L}_{\text{smooth}}$	2.395	4.096	2.046	1.922	3.240	2.716	3.353	3.445	4.266	2.119	2.799	1.489	1.360	2.651	1.895	2.653
No $\mathcal{L}_{\text{MVS}}$	2.348	3.639	3.192	2.992	5.926	2.855	3.014	3.304	3.013	2.853	2.709	3.991	1.886	3.218	2.008	3.130
No $T_k^{\text{cam}}$	2.638	3.270	3.046	2.581	5.687	3.366	3.319	2.624	4.203	1.715	1.529	2.115	1.326	3.625	1.783	2.855
<b>Ours(wo Opt.)</b>	1.592	2.580	2.040	1.878	2.950	1.743	1.572	6.820	2.167	1.534	1.689	2.052	0.921	1.895	1.692	2.208
No Trim	1.824	3.529	1.849	4.041	5.839	2.328	3.222	2.326	3.271	2.256	2.299	3.635	2.510	2.904	2.113	2.930
No $\mathbb{D}$	2.727	5.567	3.328	2.866	7.388	4.053	2.597	4.040	5.181	2.486	3.326	3.332	1.949	2.040	2.880	3.584

Table A4. Detailed ablation experiments, CD(mm) $\downarrow$ , on DTU datasets.

respondence between reconstructed and ground truth surfaces. CF-3DGS enables pose-free reconstruction of Gaussian splatting scenes, but it still requires camera intrinsics as input. In our experiments, we provide ground truth intrinsics to this method.

For methods that represent the scene as point clouds or depth maps (VGGT [6], DUST3R [7], and Fast3R [9]), default mesh generation pipelines are not provided. Therefore, we adopt an Open3D [13] Voxel-TSDF surface extraction strategy as the baseline to extract meshes for fair comparison.

For evaluating camera pose estimation quality, we use the RMSE. Since FSFSplatter is entirely based on RGB images, estimated poses differ from the ground truth by a scale factor. Following prior research [3], we perform rigid registration on the camera poses before evaluation and compute the absolute error in the ground truth scale. This approach eliminates inconsistencies in error evaluation caused by scale differences.

## A.2. Detailed experiments

### A.2.1. Detailed NVS quantization experiments

Tab. 2 presents the average quantitative evaluation results of NVS on DTU, Replica, and BlendedMVS datasets, while Tab. A6, Tab. A7, and Tab. A8 provide the detailed per-scene evaluation results for each dataset.

### A.2.2. Detailed ablation study

Tab. 6 presents the average CD of ablation study on DTU and Replica datasets, while Tab. A4 and Tab. A10 provide the detailed per-scene evaluation results.

### A.2.3. Detailed pose estimation experiments

Tab. 4 presents the average RMSE error on DTU and Replica datasets, while Tab. A3 provide the detailed per-scene evaluation results.

Scan		24	37	40	55	63	65	69	83	97	105	106	110	114	118	122	Mean
3DGS-GT	PSNR	31.128	29.295	25.873	36.033	34.249	32.639	32.441	37.970	31.912	36.649	37.903	34.387	34.111	40.040	40.704	34.356
	SSIM	0.841	0.887	0.865	0.970	0.949	0.964	0.935	0.963	0.937	0.933	0.951	0.945	0.931	0.959	0.969	0.933
	LPIPS	0.279	0.158	0.231	0.080	0.118	0.094	0.199	0.103	0.152	0.157	0.158	0.164	0.173	0.132	0.098	0.153
2DGS-GT	PSNR	20.265	22.157	23.860	28.613	26.711	25.606	26.693	30.251	25.402	28.982	31.817	27.723	30.078	36.417	35.506	28.006
	SSIM	0.609	0.782	0.745	0.907	0.927	0.937	0.882	0.941	0.869	0.895	0.923	0.903	0.886	0.940	0.953	0.873
	LPIPS	0.489	0.230	0.326	0.154	0.144	0.134	0.276	0.130	0.232	0.204	0.193	0.216	0.226	0.158	0.118	0.215
PGSR-GT	PSNR	27.518	26.766	25.185	35.262	28.352	27.879	29.146	30.967	27.968	30.423	30.004	32.456	34.668	40.089	38.549	31.016
	SSIM	0.841	0.905	0.906	0.978	0.944	0.963	0.911	0.950	0.922	0.937	0.954	0.937	0.957	0.973	0.976	0.937
	LPIPS	0.251	0.122	0.156	0.046	0.089	0.071	0.149	0.096	0.115	0.119	0.113	0.143	0.081	0.064	0.054	0.111
FatesGS-GT	PSNR	25.790	17.563	14.710	26.701	14.782	24.567	23.939	17.852	20.589	17.613	27.563	25.467	27.786	30.111	29.991	23.002
	SSIM	0.780	0.703	0.800	0.795	0.804	0.816	0.804	0.725	0.800	0.801	0.849	0.792	0.844	0.861	0.842	0.801
	LPIPS	0.343	0.281	0.280	0.315	0.240	0.374	0.333	0.438	0.323	0.375	0.351	0.400	0.296	0.332	0.358	0.336
3DGS	PSNR	20.938	23.568	25.674	28.973	29.863	28.280	27.256	34.471	26.401	32.361	30.170	28.248	30.539	36.792	37.067	29.373
	SSIM	0.618	0.787	0.730	0.906	0.933	0.943	0.894	0.954	0.878	0.901	0.928	0.909	0.889	0.941	0.955	0.878
	LPIPS	0.487	0.226	0.329	0.149	0.140	0.128	0.261	0.118	0.225	0.201	0.186	0.201	0.225	0.158	0.118	0.210
2DGS	PSNR	20.212	16.725	21.856	28.686	26.678	25.487	26.283	27.593	22.665	28.945	30.618	26.986	30.025	30.796	35.225	26.585
	SSIM	0.603	0.724	0.693	0.907	0.926	0.932	0.876	0.929	0.820	0.894	0.924	0.900	0.885	0.910	0.950	0.858
	LPIPS	0.495	0.267	0.355	0.154	0.145	0.140	0.290	0.143	0.292	0.205	0.192	0.219	0.228	0.197	0.124	0.230
PGSR	PSNR	21.146	17.712	21.858	29.532	26.743	24.684	26.983	27.803	22.494	28.793	30.880	28.184	31.726	32.199	36.279	27.134
	SSIM	0.636	0.716	0.733	0.941	0.929	0.934	0.876	0.926	0.811	0.912	0.944	0.908	0.928	0.922	0.965	0.872
	LPIPS	0.463	0.289	0.326	0.094	0.106	0.112	0.195	0.138	0.256	0.158	0.125	0.184	0.121	0.144	0.069	0.185
FatesGS	PSNR	16.564	16.781	20.542	23.955	29.153	20.238	23.836	24.370	20.296	22.916	25.261	24.491	26.948	31.785	29.240	23.758
	SSIM	0.506	0.729	0.662	0.828	0.947	0.889	0.798	0.894	0.783	0.833	0.876	0.867	0.844	0.911	0.916	0.819
	LPIPS	0.592	0.273	0.376	0.210	0.090	0.159	0.323	0.170	0.287	0.244	0.231	0.244	0.238	0.168	0.141	0.250
CF-3DGS	PSNR	19.495	17.156	21.760	24.198	24.421	27.438	27.590	29.752	23.873	26.474	28.559	28.852	27.106	30.780	32.207	25.977
	SSIM	0.650	0.754	0.715	0.839	0.918	0.933	0.868	0.949	0.845	0.883	0.884	0.917	0.859	0.904	0.927	0.856
	LPIPS	0.328	0.217	0.274	0.147	0.118	0.098	0.190	0.081	0.198	0.147	0.160	0.127	0.186	0.133	0.095	0.167
FreeSplatter	PSNR	15.427	8.386	16.189	15.365	22.240	7.930	21.433	25.158	14.965	21.129	24.063	19.481	10.203	25.891	26.146	18.267
	SSIM	0.381	0.566	0.399	0.577	0.822	0.658	0.652	0.851	0.586	0.732	0.739	0.718	0.548	0.776	0.827	0.655
	LPIPS	0.434	0.304	0.379	0.238	0.139	0.246	0.233	0.111	0.311	0.228	0.207	0.211	0.322	0.169	0.132	0.244
VGGT	PSNR	13.207	15.304	15.559	17.032	19.373	13.684	20.432	23.233	17.266	19.399	20.146	21.977	13.602	22.305	22.993	18.368
	SSIM	0.511	0.735	0.619	0.744	0.868	0.827	0.744	0.898	0.754	0.807	0.803	0.836	0.723	0.832	0.860	0.771
	LPIPS	0.404	0.204	0.282	0.170	0.130	0.173	0.206	0.100	0.214	0.176	0.194	0.164	0.238	0.146	0.107	0.194
Ours(wo Opt.)	PSNR	24.615	22.975	26.135	26.706	28.720	29.818	27.434	33.895	26.526	25.759	31.803	27.280	28.393	34.096	35.101	28.617
	SSIM	0.751	0.822	0.763	0.874	0.939	0.955	0.887	0.964	0.879	0.913	0.922	0.917	0.884	0.932	0.951	0.890
	LPIPS	0.312	0.153	0.201	0.119	0.082	0.065	0.141	0.060	0.153	0.128	0.143	0.122	0.144	0.091	0.068	0.132
Ours	PSNR	25.909	25.376	27.419	26.491	33.835	32.678	31.306	28.887	28.919	27.382	33.239	32.483	30.114	34.646	35.083	30.251
	SSIM	0.802	0.860	0.800	0.872	0.988	0.961	0.929	0.945	0.910	0.899	0.925	0.952	0.902	0.937	0.949	0.909
	LPIPS	0.231	0.133	0.173	0.104	0.015	0.060	0.100	0.090	0.121	0.149	0.117	0.080	0.124	0.082	0.067	0.110

Table A6. Detailed NVS experiments on DTU datasets.

Scan		Office0	Office1	Office2	Room0	Room1	Mean	Scan		5a48d4	5a618c	5a69c4	5b908d	59338e	Mean
3DGS-GT	PSNR	24.503	29.560	18.541	18.452	20.942	22.400	3DGS-GT	PSNR	18.990	16.663	17.389	18.280	17.341	17.733
	SSIM	0.848	0.883	0.749	0.786	0.755	0.804		SSIM	0.696	0.469	0.471	0.518	0.582	0.547
	LPIPS	0.417	0.348	0.456	0.428	0.393	0.409		LPIPS	0.411	0.516	0.516	0.572	0.480	0.499
2DGS-GT	PSNR	24.769	27.655	17.313	18.677	18.372	21.357	2DGS-GT	PSNR	17.751	17.420	16.283	17.722	17.027	17.241
	SSIM	0.852	0.877	0.740	0.788	0.742	0.800		SSIM	0.687	0.469	0.462	0.520	0.576	0.543
	LPIPS	0.416	0.353	0.469	0.425	0.417	0.416		LPIPS	0.418	0.512	0.522	0.570	0.483	0.501
PGSR-GT	PSNR	24.867	28.187	18.165	18.630	20.535	22.077	PGSR-GT	PSNR	18.755	17.003	16.273	19.026	17.098	17.631
	SSIM	0.793	0.880	0.701	0.739	0.753	0.773		SSIM	0.672	0.461	0.483	0.536	0.567	0.544
	LPIPS	0.450	0.293	0.494	0.457	0.398	0.418		LPIPS	0.382	0.529	0.508	0.545	0.486	0.490
FatesGS-GT	PSNR	25.736	28.701	17.818	18.287	20.870	22.282	FatesGS-GT	PSNR	16.678	16.324	16.423	19.991	13.396	16.563
	SSIM	0.863	0.875	0.747	0.783	0.761	0.806		SSIM	0.678	0.472	0.459	0.524	0.542	0.535
	LPIPS	0.400	0.337	0.461	0.426	0.388	0.402		LPIPS	0.416	0.511	0.523	0.558	0.521	0.506
3DGS	PSNR	25.428	27.012	17.730	18.772	21.346	22.058	3DGS	PSNR	24.075	16.587	18.005	18.310	16.788	18.753
	SSIM	0.861	0.861	0.745	0.785	0.758	0.802		SSIM	0.787	0.465	0.476	0.519	0.578	0.565
	LPIPS	0.411	0.357	0.464	0.434	0.391	0.411		LPIPS	0.326	0.517	0.510	0.574	0.486	0.483
2DGS	PSNR	23.905	26.530	17.560	18.530	19.844	21.274	2DGS	PSNR	20.773	17.093	16.617	18.195	16.371	17.810
	SSIM	0.850	0.871	0.742	0.783	0.749	0.799		SSIM	0.722	0.464	0.467	0.520	0.573	0.549
	LPIPS	0.415	0.354	0.462	0.433	0.398	0.412		LPIPS	0.386	0.513	0.519	0.569	0.489	0.495
PGSR	PSNR	24.280	25.815	17.366	18.774	20.973	21.441	PGSR	PSNR	22.861	16.725	17.330	19.215	16.742	18.655
	SSIM	0.780	0.871	0.691	0.743	0.750	0.767		SSIM	0.756	0.461	0.501	0.540	0.558	0.563
	LPIPS	0.465	0.301	0.509	0.463	0.404	0.428		LPIPS	0.309	0.528	0.497	0.548	0.492	0.475
FatesGS	PSNR	24.723	30.608	17.788	19.013	20.544	22.535	FatesGS	PSNR	20.626	14.752	18.949	19.419	17.816	18.312
	SSIM	0.856	0.900	0.744	0.789	0.748	0.808		SSIM	0.772	0.418	0.498	0.526	0.612	0.565
	LPIPS	0.408	0.325	0.461	0.422	0.395	0.402		LPIPS	0.333	0.537	0.496	0.552	0.466	0.477
CF-3DGS	PSNR	22.460	24.403	12.632	15.656	16.582	18.347								

Threshold	Office0			Office1			Office2			Room0			Room1			Average		
	1cm	5cm	10cm	1cm	5cm	10cm	1cm	5cm	10cm	1cm	5cm	10cm	1cm	5cm	10cm	1cm	5cm	10cm
3DGS	1.01%	4.79%	9.40%	1.06%	5.04%	10.46%	1.10%	5.52%	11.19%	0.57%	2.75%	5.41%	1.48%	7.22%	13.02%	1.04%	5.07%	9.90%
2DGS	0.65%	3.34%	6.72%	3.08%	15.72%	29.35%	0.83%	4.28%	8.49%	0.75%	3.71%	7.22%	1.85%	8.90%	16.32%	1.43%	7.19%	13.62%
PGSR	0.43%	2.14%	4.08%	2.44%	11.27%	20.80%	0.67%	3.32%	6.79%	0.35%	1.76%	3.59%	1.11%	6.45%	12.85%	1.00%	4.99%	9.62%
FatesGS	2.39%	11.33%	26.54%	5.29%	38.72%	72.16%	2.63%	12.00%	22.24%	4.62%	18.99%	34.34%	3.66%	29.20%	43.49%	3.72%	22.05%	39.75%
CF-3DGS	0.56%	2.91%	5.55%	0.66%	3.28%	6.46%	0.54%	2.82%	5.80%	0.51%	2.61%	5.13%	1.08%	5.42%	13.21%	0.67%	3.41%	7.23%
FreeSplatler	1.08%	5.42%	13.21%	2.19%	10.34%	19.84%	1.29%	5.20%	10.84%	0.95%	5.23%	10.57%	0.65%	3.25%	7.04%	1.23%	5.89%	12.30%
VGGT	13.35%	59.64%	82.39%	17.15%	66.20%	93.56%	5.57%	39.67%	62.52%	19.84%	59.35%	83.97%	21.65%	77.08%	87.19%	15.51%	60.39%	81.93%
<b>Ours(wo Opt.)</b>	<b>20.90%</b>	<b>78.87%</b>	<b>95.39%</b>	<b>16.18%</b>	<b>67.84%</b>	<b>93.84%</b>	<b>10.70%</b>	<b>57.48%</b>	<b>81.57%</b>	<b>28.38%</b>	<b>74.65%</b>	<b>95.84%</b>	<b>31.32%</b>	<b>92.42%</b>	<b>97.59%</b>	<b>21.50%</b>	<b>74.25%</b>	<b>92.85%</b>
<b>Ours</b>	<b>19.15%</b>	<b>79.01%</b>	<b>94.88%</b>	<b>16.66%</b>	<b>67.27%</b>	<b>95.31%</b>	<b>8.32%</b>	<b>51.51%</b>	<b>73.38%</b>	<b>26.05%</b>	<b>73.10%</b>	<b>93.58%</b>	<b>31.53%</b>	<b>89.88%</b>	<b>95.30%</b>	<b>20.34%</b>	<b>72.15%</b>	<b>90.49%</b>

Table A9. Depth accuracy $\uparrow$  under different thresholds on Replica datasets.

	Office0	Office1	Office2	Room0	Room1	Mean
<b>Ours</b>	30.96	33.91	51.49	28.08	23.87	33.66
No $\mathcal{L}_{rank}$	38.42	35.24	54.30	28.51	24.66	36.23
No $\mathcal{L}_{smooth}$	38.39	39.08	53.59	26.81	30.70	37.71
No $\mathcal{L}_{MVS}$	27.33	32.55	55.77	29.29	31.87	35.36
No $T_k^{cam}$	37.46	32.25	55.61	27.64	32.29	37.05
<b>Ours(wo Opt.)</b>	39.05	41.56	66.04	26.30	27.28	40.05
No Trim	40.75	43.89	66.04	25.48	27.29	40.69
No $\mathbb{D}$	59.48	38.02	112.69	44.77	44.21	59.83

Table A10. Detailed ablation experiments, CD(mm) $\downarrow$ , on Replica datasets.

#### A.2.4. Detailed optimization speed experiments

Tab. 5 presents the average time consumption of optimization based reconstruction algorithms on Replica datasets, while Tab. A11 provides the detailed per-scene evaluation results.

	3DGS	2DGS	FatesGS	PGSR	FSFSplatter
Office0	407.72	800.88	638.38	873.45	105.19
Office1	383.28	938.22	975.06	1102.7	103.22
Office2	438.57	825.10	811.89	1037.2	112.44
Room0	434.96	775.38	838.49	853.54	106.88
Room1	482.75	862.31	1315.8	1224.1	109.23
Average	429.45	840.37	915.93	1018.1	107.39

Table A11. Detailed optimization speed experiments(seconds) $\downarrow$  on Replica datasets.

#### A.2.5. Depth estimation experiments

	Office0	Office1	Office2	Room0	Room1	Average
3DGS	142.90	73.45	243.8	150.8	93.98	140.9
2DGS	66.55	30.96	86.62	109.1	82.09	75.08
PGSR	111.1	88.70	116.3	249.0	122.1	137.4
FatesGS	26.35	9.278	69.81	25.78	28.12	31.87
CF-3DGS	235.0	501.6	194.7	169.1	99.47	240.0
FreeSplatler	99.47	35.36	140.2	122.2	77.58	94.97
VGGT	7.713	4.488	27.80	6.450	5.444	10.38
<b>Ours(wo Opt.)</b>	<b>7.194</b>	<b>7.607</b>	<b>23.39</b>	<b>7.145</b>	<b>3.436</b>	<b>9.755</b>
<b>Ours</b>	<b>5.089</b>	<b>4.203</b>	<b>26.86</b>	<b>4.850</b>	<b>3.616</b>	<b>8.924</b>

Table A12. Depth mean distance(cm) $\downarrow$  on Replica datasets.

We have conducted detailed quantitative experiments on surface reconstruction on DTU and Replica datasets, as shown in Tab. 1 and Tab. 3. To further validate the geometric reconstruction accuracy of FSFSplatter, we evaluated performance on depth map synthesis using Replica datasets. As shown in Tab. A9 and Tab. A12, we assessed the mean depth error [10] and the accuracy under different thresholds. The results demonstrate that FSFSplatter exhibits excellent robustness and accuracy both with and without per-scene optimization.

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