MSCD-GS: Motion-Separated Cooperative Deblurring Dynamic Reconstruction via Gaussian Splatting

Supplementary Material

In the supplementary material, we present the quantitative comparison results for each scene to verify the effectiveness of the proposed method, as shown in Tables 1, 2, and 3. Additional qualitative results are attached to ours project page (https://liaoyongjian1.github.io/MSCD-GS/).

1. Static Gaussians Deblurring

To compensate for the motion blur introduced by camera movement during exposure, we model the static Gaussian trajectory using a learnable continuous $SE(3)$ motion field. Instead of assuming a fixed camera pose per frame, we represent the exposure-time motion using two trainable $SE(3)$ control points:

$$\Theta = \{\xi_0, \xi_1\}, \quad \xi_i \in \mathbb{R}^6, \tag{1}$$

where each ξ_i encodes a minimal $SE(3)$ perturbation. These control points parameterize the start and end of the exposure interval and are optimized jointly with the Gaussian field. Given these two control points, the static Gaussian transformation at any normalized time within the exposure is obtained through geodesic interpolation on $SE(3)$. Therefore, we obtain a set of physically consistent deblurring warps $\{\Delta R, \Delta T\}$ that compensate for the motion-induced distortion in static Gaussians.

2. Dynamic Gaussians Deblurring

The motion blur of dynamic Gaussians arises not only from camera motion but also from the intrinsic movement of objects during exposure. To address this challenge, we propose a neural motion-field predictor, which estimates multi-moment $SE(3)$ corrections and per-frame geometric offsets for all dynamic Gaussian primitives. Unlike the static-Gaussian module that models camera-induced blur using two $SE(3)$ control points, predictor captures object-level, nonlinear, and high-frequency motions through a learned continuous motion representation.

To effectively capture local geometric variations motion patterns, we encode both the 3D Gaussian centers $\boldsymbol{\mu_D} \in \mathbb{R}^3$ using a Fourier feature embedder:

$$\gamma(\boldsymbol{\mu_D}) = \left[\boldsymbol{\mu_D}, \sin(2^k \boldsymbol{\mu_D}), \cos(2^k \boldsymbol{\mu_D})\right]_{k=0}^{K_{\mu_D}}. \tag{2}$$

In addition to position and view embeddings, we encode each dynamic Gaussian's current geometric state feature:

$$\gamma(S, R_D) = [S, q], \tag{3}$$

where $q \in \mathbb{H}$ is the quaternion representing Gaussian's rotation R_D (normalized with $\|\mathbf{q}\| = 1$). The fused feature $\Upsilon = [\gamma(\boldsymbol{\mu_D}), \gamma(S, R_D)]$ is processed by a residual fully-connected backbone. Ultimately, predictor outputs motion parameters for multiple temporal moments: $\Delta\boldsymbol{\mu_D}, \Delta R_D, \Delta S$.

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Types	Methods	man			seesaw			skating		
		PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓
Static Deblurring Reconstruction	Deblurring-3DGS (ECCV'24) [3]	24.32	0.769	0.188	18.71	0.617	0.329	19.83	0.495	0.375
	BAD-GS (ECCV'24) [10]	23.85	0.642	0.287	23.57	0.678	0.293	22.93	0.645	0.289
Dynamic Reconstruction	4D Gaussians (CVPR'24) [8]	25.15	0.837	0.273	27.38	0.849	0.303	27.26	0.872	0.269
	E-D3DGS (ECCV'24) [1]	25.81	0.855	0.210	29.02	0.892	0.195	29.41	0.898	0.197
	SoM (ICCV'25) [7]	25.89	0.909	0.232	26.45	0.931	0.193	31.22	0.963	0.165
	SplineGS (CVPR'25) [5]	26.59	0.885	0.238	27.76	0.921	0.191	30.05	0.951	0.174
Dynamic Reconstruction + Deblurring Network	E-D3DGS + NAFNet [2]	27.82	0.928	0.104	30.03	0.965	0.096	30.43	0.951	0.097
	SoM + NAFNet [2]	27.90	0.926	0.107	30.05	0.963	0.099	30.45	0.968	0.100
Dynamic Deblurring Reconstruction	DyBluRF (CVPR'24) [6]	27.81	0.920	0.111	29.93	0.950	0.094	30.47	0.966	0.099
	BARD-GS (CVPR'25) [4]	28.44	0.922	0.084	30.49	0.958	0.105	31.90	0.943	0.102
	Deblur4DGS (arXiv'25) [9]	30.20	0.953	0.056	29.67	0.957	0.091	33.03	0.969	0.077
	MSCD-GS (Ours)	31.72	0.930	0.052	33.33	0.969	0.040	37.00	0.975	0.026

Methods	street			third			women		
	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓
Deblurring-3DGS (ECCV'24) [3]	19.72	0.498	0.317	15.83	0.476	0.562	22.77	0.726	0.224
BAD-GS (ECCV'24) [10]	20.12	0.661	0.341	21.76	0.639	0.305	25.41	0.671	0.301
4D Gaussians (CVPR'24) [8]	27.12	0.785	0.302	28.81	0.834	0.268	25.48	0.738	0.303
E-D3DGS (ECCV'24) [1]	27.19	0.767	0.215	30.37	0.927	0.193	24.28	0.774	0.202
SoM (ICCV'25) [7]	28.71	0.948	0.135	29.82	0.944	0.171	24.68	0.897	0.244
SplineGS (CVPR'25) [5]	25.85	0.931	0.145	30.69	0.958	0.154	24.71	0.844	0.274
E-D3DGS + NAFNet [2]	28.17	0.929	0.106	30.39	0.950	0.094	26.69	0.924	0.095
SoM + NAFNet [2]	28.20	0.956	0.108	30.50	0.956	0.097	26.94	0.930	0.096
DyBluRF (CVPR'24) [6]	28.20	0.946	0.100	30.54	0.959	0.092	25.11	0.869	0.109
BARD-GS (CVPR'25) [4]	30.58	0.960	0.101	31.50	0.958	0.091	28.43	0.926	0.093
Deblur4DGS (arXiv'25) [9]	30.37	0.961	0.098	31.11	0.957	0.089	27.51	0.901	0.104
MSCD-GS (Ours)	32.95	0.964	0.039	32.59	0.960	0.058	31.69	0.946	0.046

Table 1. Quantitative comparison of **Deblurring 4D Reconstruction** on the Stereo Blur dataset. Colors indicate the best, second best, and third best results respectively. Our method can reconstruct high-quality 4D scenes compared to similar methods under conditions involving images with motion-blur inputs.

Types	Methods	man			seesaw			skating		
		PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓
Static Deblurring Reconstruction	Deblurring-3DGS (ECCV'24) [3]	21.53	0.665	0.280	15.45	0.489	0.440	21.20	0.582	0.321
	BAD-GS (ECCV'24) [10]	22.19	0.756	0.141	22.13	0.905	0.138	22.41	0.829	0.130
Dynamic Reconstruction	4D Gaussians (CVPR'24) [8]	23.62	0.852	0.210	23.84	0.886	0.190	23.75	0.880	0.203
	E-D3DGS (ECCV'24) [1]	23.71	0.853	0.208	24.32	0.891	0.183	25.09	0.897	0.186
	SoM (ICCV'25) [7]	24.84	0.889	0.238	25.57	0.913	0.200	30.11	0.946	0.169
	SplineGS (CVPR'25) [5]	24.76	0.875	0.240	26.04	0.922	0.173	28.30	0.938	0.170
Dynamic Reconstruction + Deblurring Network	E-D3DGS + NAFNet [2]	26.18	0.937	0.157	25.42	0.933	0.149	25.89	0.912	0.152
	SoM + NAFNet [2]	25.12	0.876	0.172	25.93	0.911	0.158	30.47	0.953	0.163
Dynamic Deblurring Reconstruction	DyBluRF (CVPR'24) [6]	24.30	0.919	0.151	26.56	0.930	0.128	29.14	0.915	0.134
	BARD-GS (CVPR'25) [4]	25.84	0.920	0.101	25.89	0.935	0.125	29.30	0.930	0.122
	Deblur4DGS (arXiv'25) [9]	28.05	0.948	0.064	27.52	0.942	0.107	30.77	0.956	0.093
	MSCD-GS (Ours)	29.64	0.949	0.054	29.76	0.945	0.051	31.84	0.960	0.054

Methods	street			third			women		
	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓
Deblurring-3DGS (ECCV'24) [3]	19.29	0.431	0.317	19.46	0.694	0.325	20.95	0.688	0.279
BAD-GS (ECCV'24) [10]	19.85	0.632	0.177	20.13	0.678	0.193	21.83	0.718	0.151
4D Gaussians (CVPR'24) [8]	17.99	0.740	0.344	26.99	0.930	0.168	17.16	0.752	0.286
E-D3DGS (ECCV'24) [1]	18.04	0.764	0.353	27.37	0.927	0.181	18.43	0.771	0.276
SoM (ICCV'25) [7]	27.87	0.929	0.139	28.92	0.947	0.156	23.88	0.853	0.248
SplineGS (CVPR'25) [5]	25.27	0.919	0.146	28.79	0.946	0.155	23.06	0.843	0.268
E-D3DGS + NAFNet [2]	25.75	0.896	0.178	27.94	0.925	0.146	20.22	0.803	0.180
SoM + NAFNet [2]	28.15	0.935	0.167	29.26	0.941	0.182	27.63	0.844	0.158
DyBluRF (CVPR'24) [6]	26.01	0.928	0.135	27.17	0.928	0.124	22.23	0.851	0.153
BARD-GS (CVPR'25) [4]	27.98	0.942	0.122	28.90	0.948	0.112	24.20	0.890	0.113
Deblur4DGS (arXiv'25) [9]	28.22	0.944	0.093	28.96	0.955	0.104	23.50	0.865	0.114
MSCD-GS (Ours)	26.02	0.907	0.090	31.42	0.964	0.079	28.28	0.918	0.064

Table 2. Quantitative comparison of **Novel View Synthesis** on the Stereo Blur dataset. Since our method can reconstruct high-quality 4D scenes, it also achieves state-of-the-art performance in Novel View Synthesis.

Types	Methods	card PSNR↑	card SSIM↑	card LPIPS↓	kitchen PSNR↑	kitchen SSIM↑	kitchen LPIPS↓	poster PSNR↑	poster SSIM↑	poster LPIPS↓
Dynamic Reconstruction	4D Gaussians (CVPR'24) [8]	24.39	0.880	0.146	21.05	0.857	0.255	24.44	0.866	0.193
	E-D3DGS (ECCV'24) [1]	24.65	0.895	0.141	22.52	0.886	0.209	24.53	0.899	0.195
	SoM (ICCV'25) [7]	24.96	0.893	0.156	21.22	0.883	0.209	24.58	0.899	0.192
	SplineGS (CVPR'25) [5]	24.84	0.882	0.170	22.58	0.898	0.266	25.57	0.900	0.190
Dynamic Reconstruction + Deblured Network	E-D3DGS + NAFNet [2]	25.68	0.891	0.138	23.26	0.894	0.196	26.11	0.901	0.191
	SoM + NAFNet [2]	25.78	0.902	0.131	23.12	0.891	0.198	26.18	0.905	0.190
Dynamic Deblurring Reconstruction	DyBluRF (CVPR'24) [6]	24.73	0.872	0.128	21.74	0.843	0.251	25.50	0.903	0.191
	BARD-GS (CVPR'25) [4]	25.76	0.833	0.170	23.47	0.833	0.167	26.96	0.836	0.189
	Deblur4DGS (arXiv'25) [9]	25.62	0.901	0.109	21.91	0.860	0.171	26.54	0.849	0.188
	MSCD-GS (Ours)	29.75	0.913	0.113	30.91	0.919	0.066	29.52	0.912	0.185

Methods	shark-spin PSNR↑	shark-spin SSIM↑	shark-spin LPIPS↓	walk PSNR↑	walk SSIM↑	walk LPIPS↓	windmill PSNR↑	windmill SSIM↑	windmill LPIPS↓	toycar PSNR↑	toycar SSIM↑	toycar LPIPS↓
4D Gaussians (CVPR'24) [8]	22.50	0.897	0.201	18.10	0.848	0.195	24.00	0.866	0.203	21.55	0.883	0.207
E-D3DGS (ECCV'24) [1]	24.07	0.905	0.229	19.20	0.896	0.166	24.06	0.897	0.205	21.70	0.895	0.203
SoM (ICCV'25) [7]	23.73	0.904	0.206	18.35	0.899	0.162	23.91	0.901	0.243	21.50	0.902	0.221
SplineGS (CVPR'25) [5]	24.28	0.908	0.182	18.39	0.859	0.176	23.82	0.899	0.179	21.67	0.891	0.186
E-D3DGS + NAFNet [2]	24.87	0.916	0.184	20.35	0.905	0.159	25.46	0.900	0.159	22.11	0.908	0.190
SoM + NAFNet [2]	24.33	0.913	0.181	20.49	0.901	0.151	25.91	0.903	0.144	22.32	0.889	0.159
DyBluRF (CVPR'24) [6]	23.87	0.899	0.204	19.83	0.865	0.192	24.46	0.895	0.180	20.80	0.874	0.249
BARD-GS (CVPR'25) [4]	25.43	0.856	0.158	23.31	0.827	0.144	27.52	0.906	0.128	23.47	0.868	0.142
Deblur4DGS (arXiv'25) [9]	25.09	0.915	0.162	20.80	0.864	0.212	26.60	0.916	0.162	25.55	0.916	0.141
MSCD-GS (Ours)	27.48	0.919	0.087	23.62	0.870	0.141	28.14	0.915	0.065	27.48	0.919	0.087

Table 3. Quantitative comparison of **Novel View Synthesis** on the real-world blurry dataset. The results demonstrate that our method can achieve state-of-the-art performance in Novel View Synthesis.