Project Page

Embracing Dynamics:
Dynamics-aware 4D Gaussian Splatting SLAM
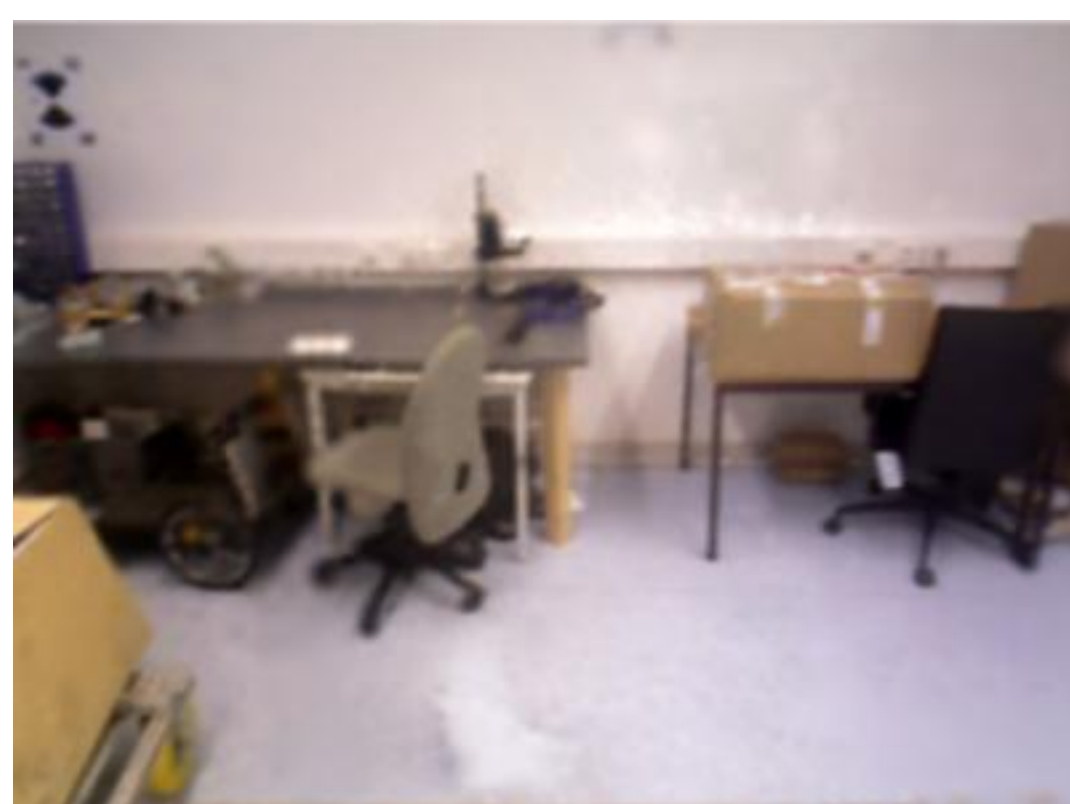
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Motivation

- 3D Gaussian Splatting (3DGS): **Static** map representation

- **Limitations** of 3DGS-based SLAM:
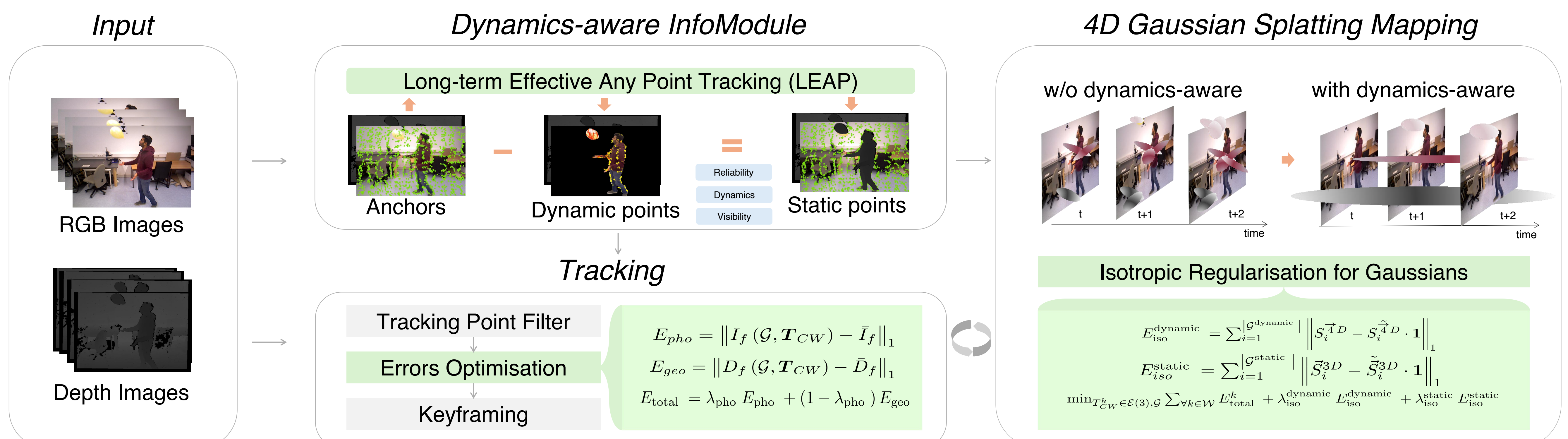

a) Incomplete map   b) Map with Artifacts

(Source: Xu, Y., Jiang, H., Xiao, Z., Feng, J., & Zhang, L. (2024). DG-SLAM: Robust Dynamic Gaussian Splatting SLAM with Hybrid Pose Optimization. NeurIPS 2024)

Contributions

- Proposed *D4DGS-SLAM*, the 4DGS-based SLAM system for dynamic environments

- Enhanced the SLAM system with dynamics-aware InfoModule

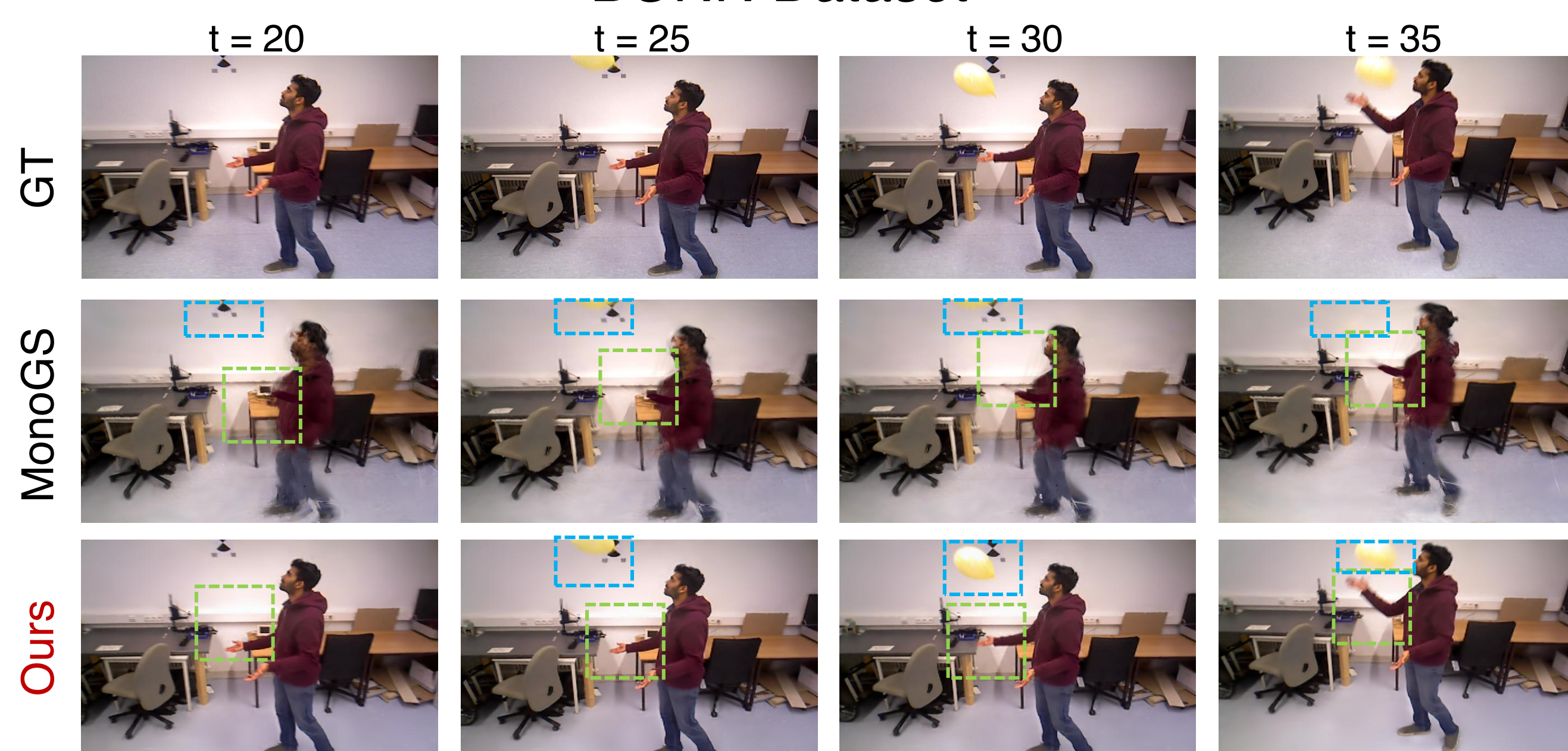- SOTA tracking and mapping performance on multiple dynamic SLAM benchmarks

Pipeline

Input

RGB Images

Depth Images

Dynamics-aware InfoModule

Long-term Effective Any Point Tracking (LEAP)

Anchors − Dynamic points = Static points

Reliability / Dynamics / Visibility

Tracking

Tracking Point Filter → Errors Optimisation → Keyframing

$$E_{pho} = \left\| I_f(\mathcal{G}, \boldsymbol{T}_{CW}) - \bar{I}_f \right\|_1$$
$$E_{geo} = \left\| D_f(\mathcal{G}, \boldsymbol{T}_{CW}) - \bar{D}_f \right\|_1$$
$$E_{total} = \lambda_{pho} E_{pho} + (1 - \lambda_{pho}) E_{geo}$$

4D Gaussian Splatting Mapping

w/o dynamics-aware   with dynamics-aware

Isotropic Regularisation for Gaussians

$$E_{iso}^{dynamic} = \sum_{i=1}^{\left|\mathcal{G}^{dynamic}\right|} \left\| S_i^{\vec{4}D} - S_i^{\vec{4}D} \cdot \mathbf{1} \right\|_1$$
$$E_{iso}^{static} = \sum_{i=1}^{\left|\mathcal{G}^{static}\right|} \left\| \bar{S}_i^{3D} - \bar{\bar{S}}_i^{3D} \cdot \mathbf{1} \right\|_1$$
$$\min_{T_{CW}^k \in \mathcal{E}(3), \mathcal{G}} \sum_{\forall k \in \mathcal{W}} E_{total}^k + \lambda_{iso}^{dynamic} E_{iso}^{dynamic} + \lambda_{iso}^{static} E_{iso}^{static}$$

Results

BONN Dataset

t = 20   t = 25   t = 30   t = 35

Results of metric ATE RMSE on several dynamic scene sequences in BONN dataset.

"*" denotes the version reproduced by NICE-SLAM. "-" denotes the tracking failures. The metric unit is [cm].

Method	ball	ball2	ps.tk	ps.tk2	ball.tk	Avg.
ORB-SLAM3 [2]	5.8	17.7	70.7	77.9	3.1	29.8
ReFusion [12]	17.5	25.4	28.9	46.3	30.2	27.7
DROID-VO[19]	5.4	4.6	21.4	46.0	8.9	15.4
iMAP*[17]	14.9		28.3	52.8	24.8	36.1
NICE-SLAM[30]	16.6	68.8	54.9	45.3	21.2	44.1
Vox-Fusion[25]	65.7	82.1	128.6	162.2	43.9	88.4
Co-SLAM[20]	28.8	20.6	61.0	59.1	38.3	46.3
ESLAM[5]	22.6	36.2	48.0	51.4	12.4	31.4
Rodyn-SLAM[4]	7.9	11.5	14.5	13.8	13.3	12.3
SplaTAM[6]	35.5	36.1	149.7	91.2	12.5	57.4
GS-SLAM[24]	37.5	26.8	46.8	50.4	31.9	33.1
DG-SLAM [22]	3.7	4.1	4.5	6.9	10.0	5.5
Ours	**3.6**	**3.9**	**4.5**	**5.2**	**8.5**	**5.1**

Ablation study on the Ball Scene in Bonn Dataset.

D-Aware Means The Dynamics-Aware Infomodule

	ATE RMSE↓	PSNR↑	SSIM↑	LPIPS↓
w/o D-aware	27.9	20.23	0.790	0.371
w/o 4DGS	7.2	18.23	0.645	0.327
Ours	**3.6**	**27.89**	**0.857**	**0.236**

Tartanair-Shibuya Dataset

t = 10   t = 11   t = 12   t = 13

Camera tracking and mapping quality on several dynamic sequences in Tartanair-Shibuya dataset.

		sh01			rc03				rc06				rc07			Avg.		
	ATE↓	PSNR↑	SSIM↑	LPIPS↓	ATE↓	PSNR↑	SSIM↑	LPIPS↓	ATE↓	PSNR↑	SSIM↑	LPIPS↓	ATE↓	PSNR↑	SSIM↑	LPIPS↓	ATE↓	PSNR↑	SSIM↑	LPIPS↓
SplaTAM [6]	64.0	12.02	0.310	0.457	52.6	11.11	0.234	0.621	82.8	13.33	0.513	0.358	93.4	13.25	0.477	0.509	73.2	12.43	0.384	0.486
MonoGS [9]	53.0	13.91	0.303	0.576	58.8	13.21	0.241	0.638	82.8	16.63	0.516	0.404	85.6	14.74	0.489	0.534	70.1	14.62	0.387	0.538
Ours	**3.2**	**23.48**	**0.673**	**0.368**	**4.1**	**24.38**	**0.686**	**0.267**	**2.1**	**21.39**	**0.793**	**0.243**	**5.1**	**21.73**	**0.669**	**0.387**	**3.6**	**22.75**	**0.705**	**0.291**

Map quality on several dynamic sequences in BONN dataset.

	ball			ball12			ps.tk			ps.tk2			ball.tk			Avg.		
	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓
SplaTAM [6]	17.59	0.766	0.244	16.81	0.650	0.332	18.90	0.655	0.270	17.25	0.721	0.263	15.55	0.633	0.413	17.22	0.685	0.304
MonoGS [9]	17.72	0.712	0.478	19.44	0.747	0.367	18.8	0.776	0.399	20.01	0.755	0.375	18.89	0.623	0.272	18.97	0.715	0.338
Ours	**27.89**	**0.857**	**0.236**	**29.65**	**0.839**	**0.272**	**27.66**	**0.832**	**0.265**	**31.18**	**0.876**	**0.259**	**27.19**	**0.865**	**0.264**	**28.71**	**0.854**	**0.259**