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Holistic Large-Scale Scene Reconstruction via Mixed Gaussian Splatting

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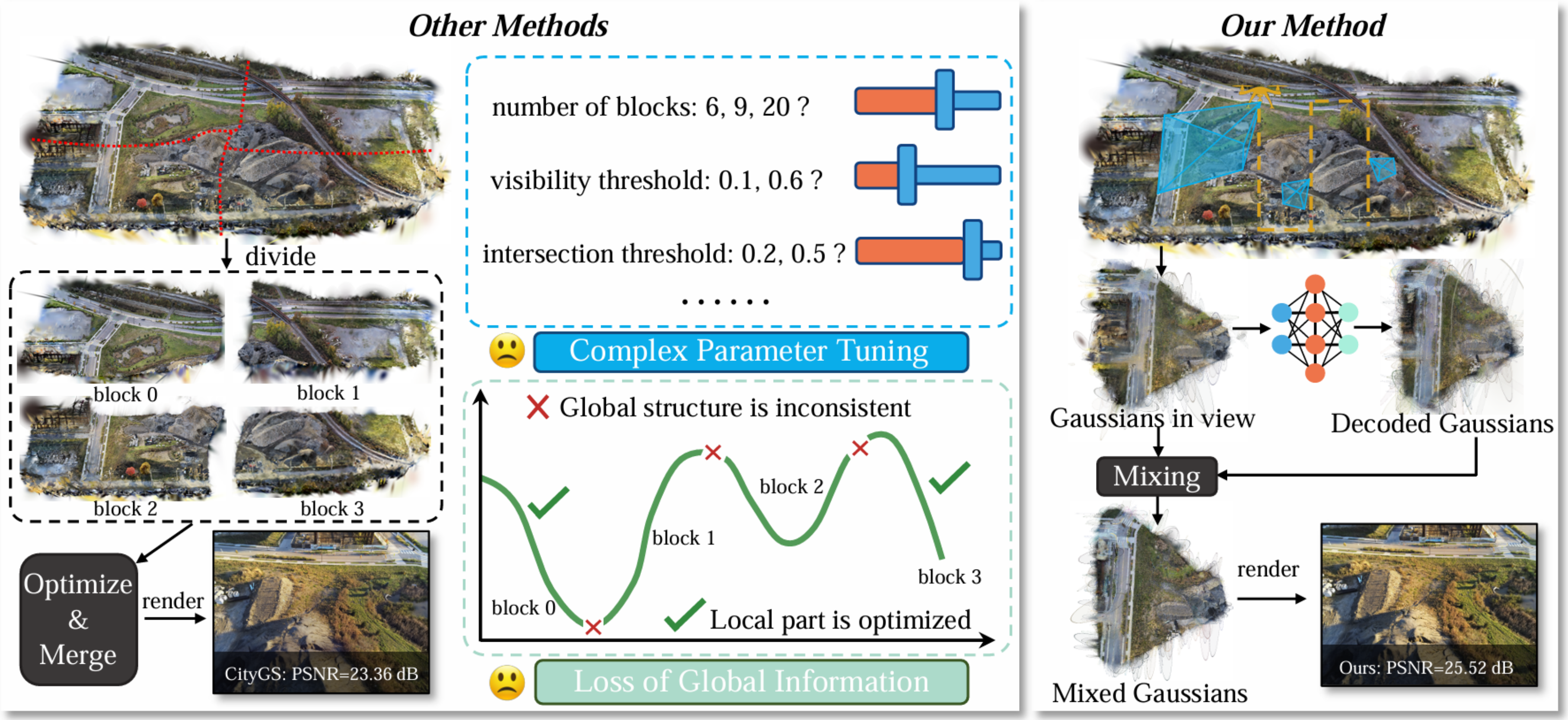
https://mixgs.github.io/

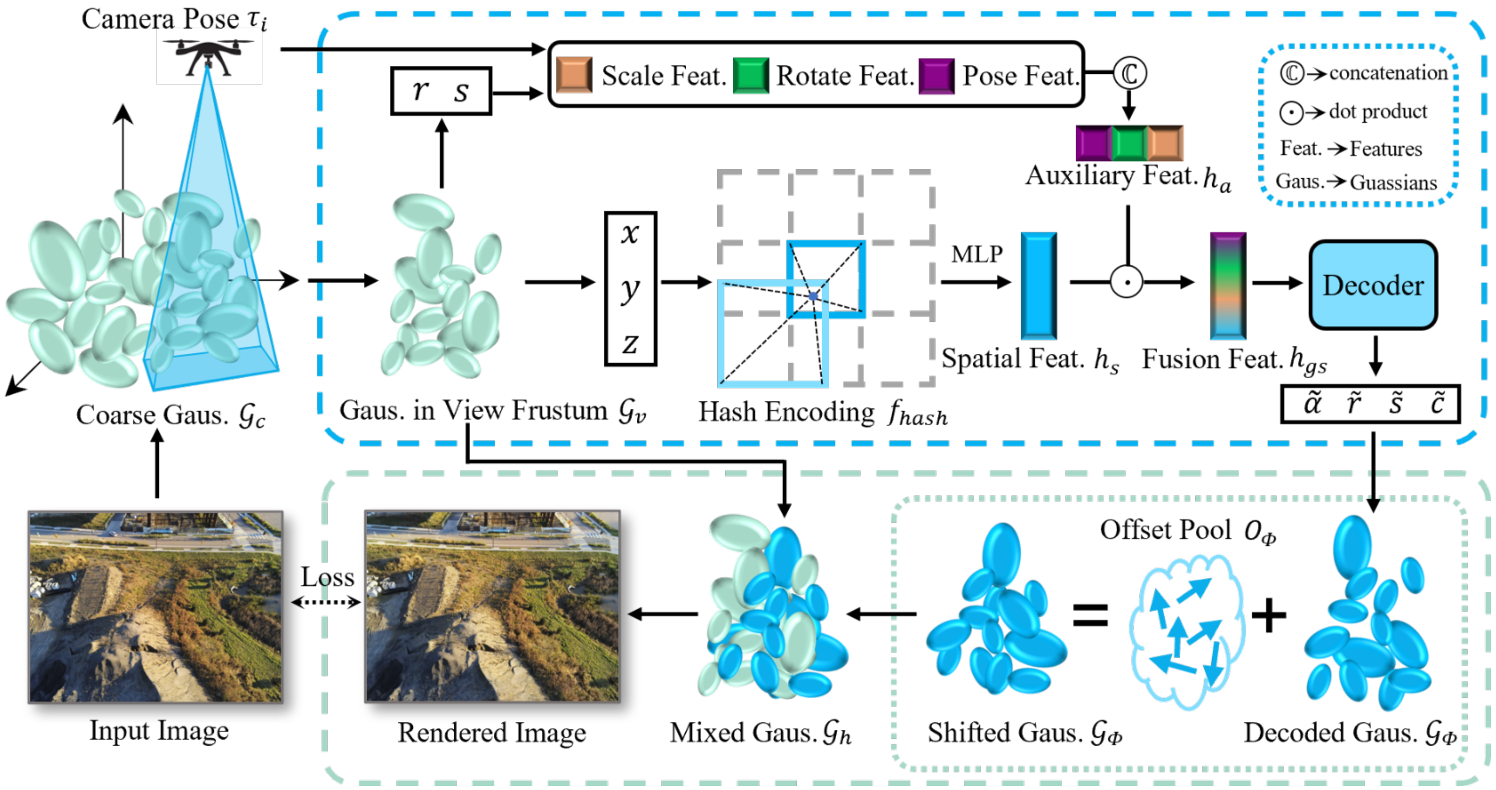
Introduction



- Limitation 1: Scene partitioning heavily relies on prior knowledge and manual parameter tuning.
- Limitation 2: independently optimizing each block can lead to locally optimal but globally suboptimal solutions.

Our MixGS framework treats the entire scene and the Gaussian Representation network as a holistic optimization problem.

Methodology



Divide-and-conquer schema:

$$\mathcal{G}_{bj}^{*} = \min_{\mathcal{G}_{bj}} \sum_{i=1}^{M_{bj}} \mathcal{L}\left(\xi(\mathcal{G}_{bj}, \tau_i), I_{i,bj}^{\mathrm{gt}}\right), \quad \forall bj \in \{b1, \ldots, bn\},$$

Our MixGS schema:

$$\mathcal{G}_c^{*}, \Phi^{*} = \min_{\mathcal{G}_c, \Phi} \sum_{i=1}^{M} \mathcal{L}\left(\xi(\mathcal{G}_c \cup \mathcal{G}_\Phi, \tau_i), I_i^{\mathrm{gt}}\right).$$

- We develop a mixed Gaussians rasterization pipeline that simultaneously captures global and local scene
- Training with one GPU with 24GB VRAM

Experimental Results

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Results on the Mill19dataset and UrbanScene3D dataset

Scenes	Building			Rubble			Residence			Sci-Art		
Metrics	PSNR ↑	SSIM ↑	LPIPS ↓	PSNR ↑	SSIM ↑	LPIPS ↓	PSNR ↑	SSIM ↑	LPIPS ↓	PSNR ↑	SSIM ↑	LPIPS ↓
Mega-NeRF [52]	20.92	0.547	0.454	24.06	0.553	0.508	22.08	0.628	0.401	25.60	0.770	0.312
Switch-NeRF [73]	21.54	0.579	0.397	24.31	0.562	0.478	22.57	0.654	0.352	26.51	0.795	0.271
GP-NeRF [62]	21.03	0.566	0.486	24.06	0.565	0.496	22.31	0.661	0.448	25.37	0.783	0.373
3DGS [22]	20.46	0.720	0.305	25.47	0.777	0.277	21.44	0.791	0.236	21.05	0.830	0.242
VastGaussian† [29]	21.80	0.728	0.225	25.20	0.742	0.264	21.01	0.699	0.261	22.64	0.761	0.261
Hierarchy-GS [23]	21.52	0.723	0.297	24.64	0.755	0.284	–	–	–	–	–	–
DOGS [10]	22.73	0.759	0.204	25.78	0.765	0.257	21.94	0.740	0.244	24.42	0.804	0.219
CityGaussian [33]	21.67	0.764	0.262	24.90	0.785	0.256	21.90	0.805	0.217	21.34	0.833	0.232
MixGS (Ours)	23.03	0.771	0.261	26.66	0.792	0.267	23.39	0.815	0.219	24.20	0.856	0.220

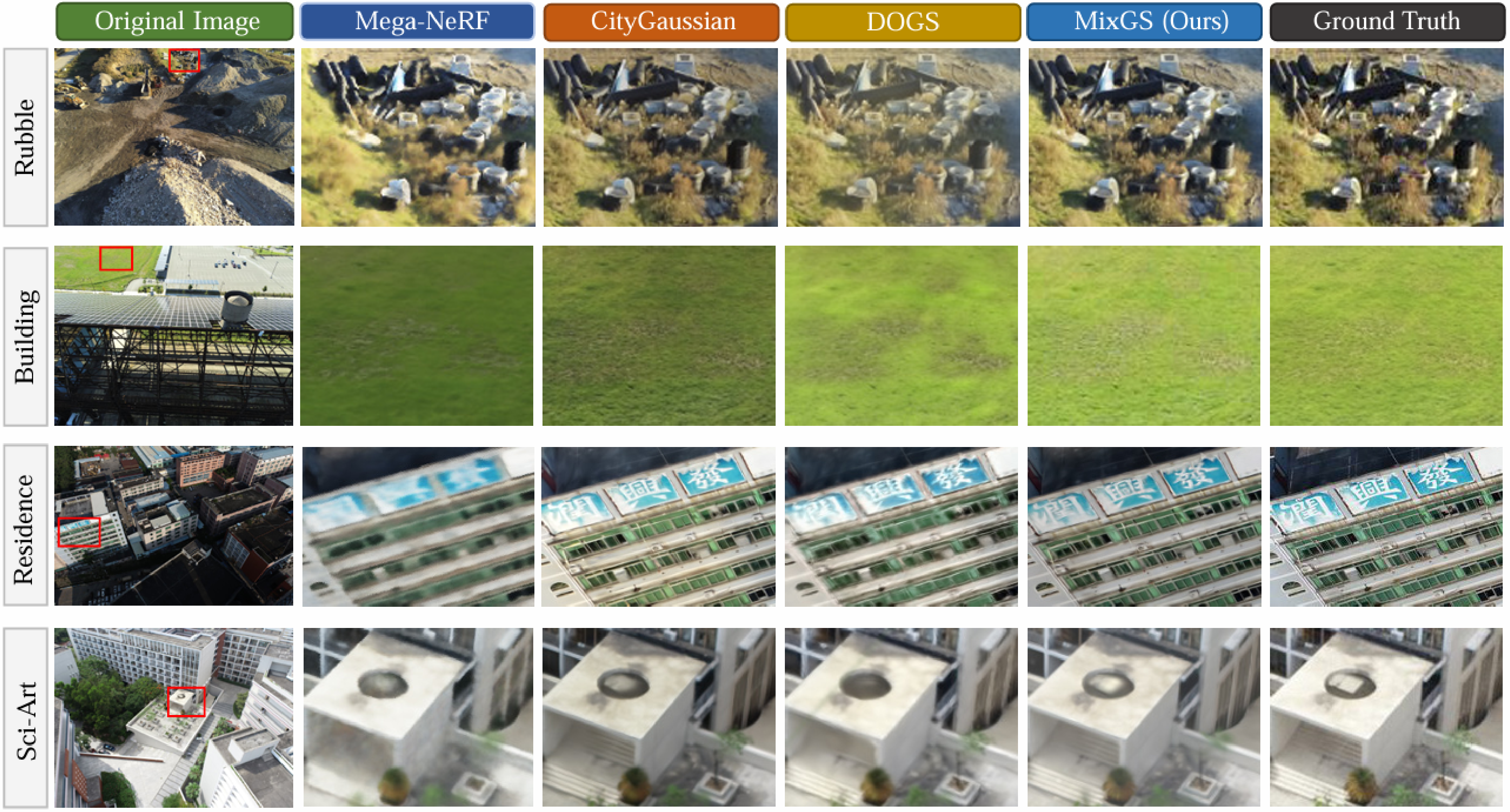
Experimental Results

Rendering speed comparison：

Methods	GPU Type	Building	Rubble	Residence	Sci-Art
Mega-NeRF [52]	A100 40G	<0.1	<0.1	<0.1	<0.1
Switch-NeRF [73]	A100 40G	<0.1	<0.1	<0.1	<0.1
GP-NeRF [62]	A100 40G	0.42	0.40	0.31	0.34
3DGS [22]	A100 40G	45.0	47.8	62.1	72.2
CityGaussian (w/ LoD) [33]	A100 40G	37.4	52.6	41.6	64.6
CityGaussian (w/o LoD) [33]	A100 40G	24.3	43.9	32.7	56.1
MixGS (Ours)	3090 24G	33.5	42.5	36.6	53.9

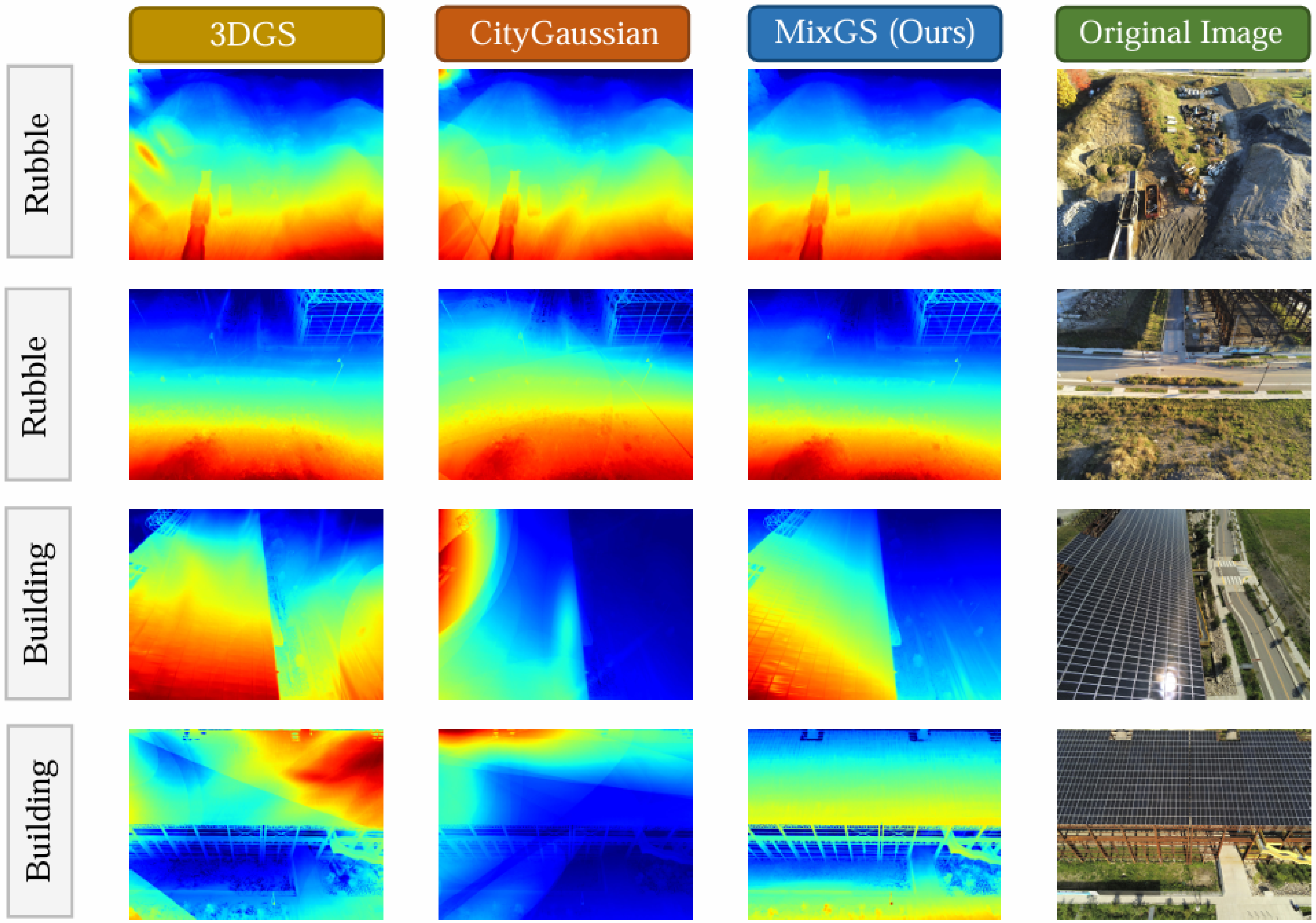
Experimental Results

Qualitative comparison：



Experimental Results

Qualitative comparison：



Conclusion

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- We introduce MixGS, a novel **holistic optimization** method designed to overcome the limitations of existing approaches that rely on divide-and-conquer strategies for large-scale scene reconstruction.

- We develop a **mixed Gaussians rasterization** pipeline that simultaneously captures global and local scene information through view-aware Representation modeling for implicit feature learning.

- Extensive experimentation demonstrate that MixGS achieves state-of-the-art results while maintaining comparable rendering speed on established benchmarks for large-scale scene reconstruction.

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Thanks!

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