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AD-GS: Alternating Densification for Sparse-Input 3D Gaussian Splatting

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Issues with Sparse-Views

- Sparse supervision ⇒ floaters, inaccurate geometry.
- Due to overfitting.

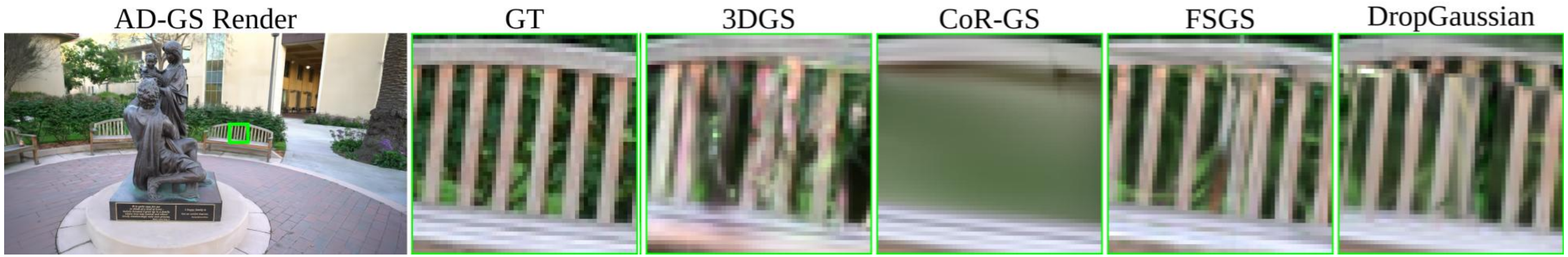
Train Renders (3 views)

Novel views

Novel View Video

Related work: Sparse-input 3DGS

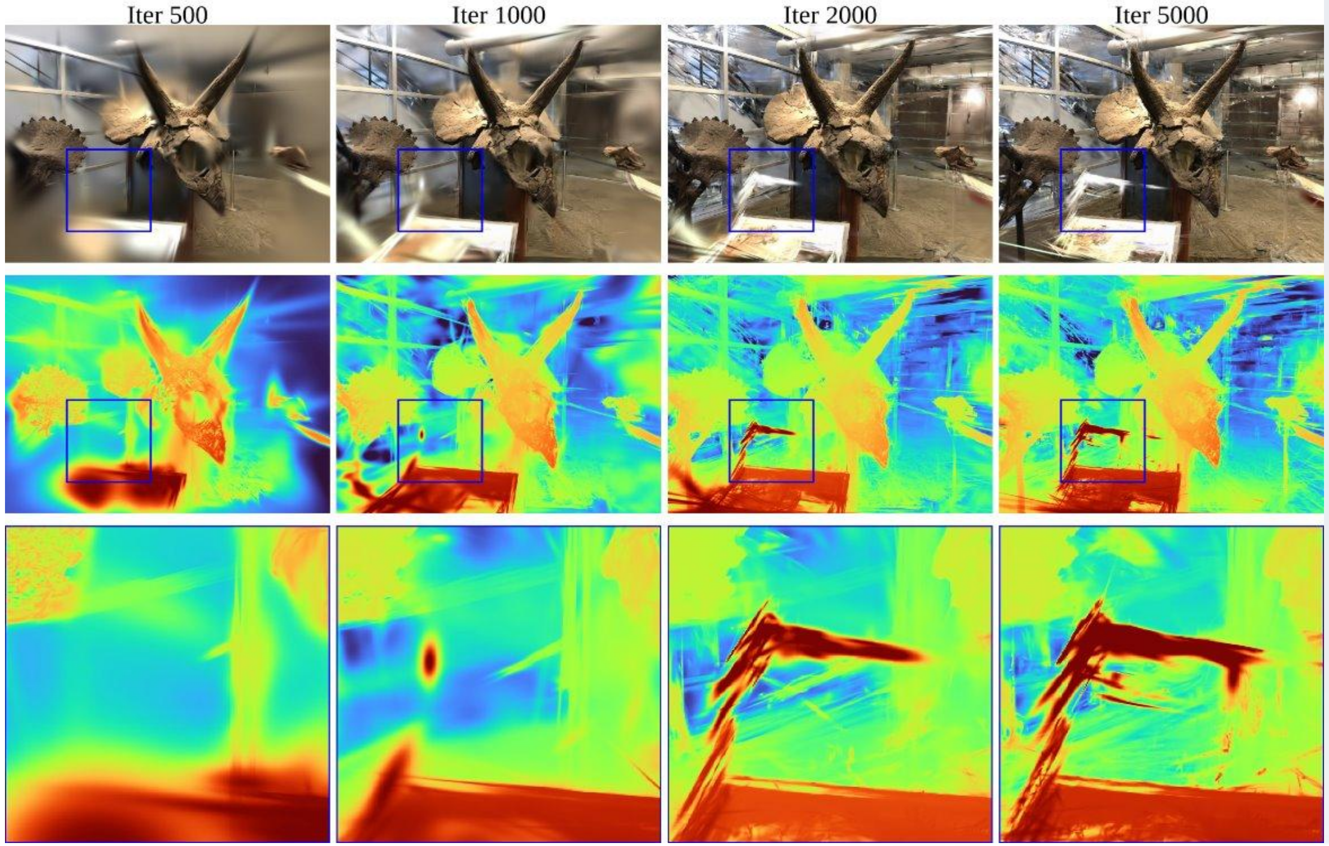
- FSGS – uses priors from deep depth prediction networks, but such priors may not generalize (Zhu et al., ECCV 2024)
- CoR-GS – enforces consistency between paired 3DGS models, but this smooths reconstructions (Zhang et al., ECCV 2024)
- DropGaussian – randomly drops Gaussians during training, but this can hurt fine details (Park et al., CVPR 2025)



Role of densification in the sparse input case has hardly been explored.

Issue with Densification in Sparse setting

- Splitting/Cloning at implausible positions → floaters
- Misplaced Gaussians can trigger further unnecessary densification
- Lack of constraints



Technical Challenge

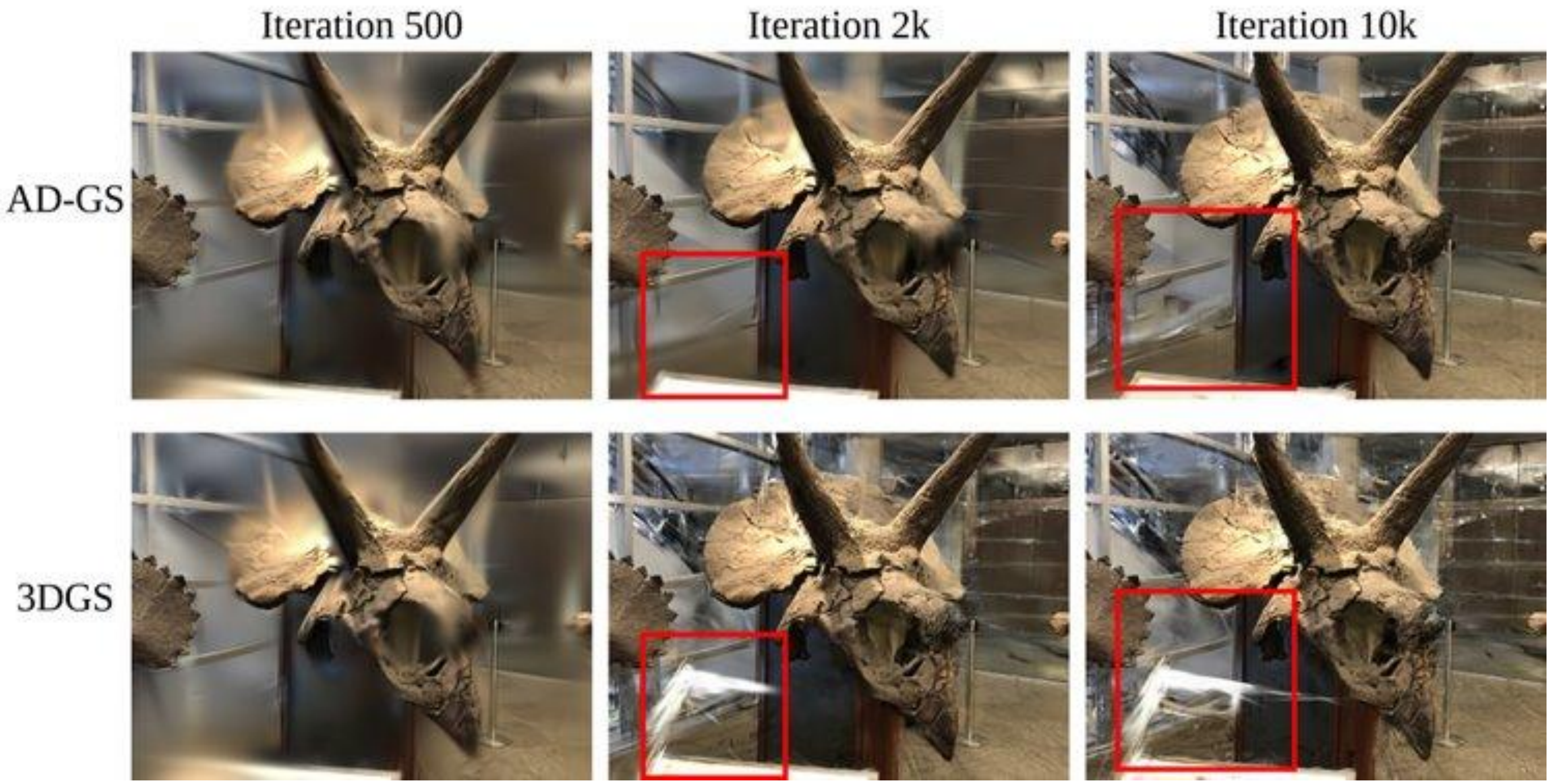
- Floaters can be removed by smoothness constraints, but smoothness causes loss of details.
- Details can be recovered through aggressive densification, but end-up causing more floaters.
- Need a careful mix of smoothness and densification.

Our Idea and Contributions

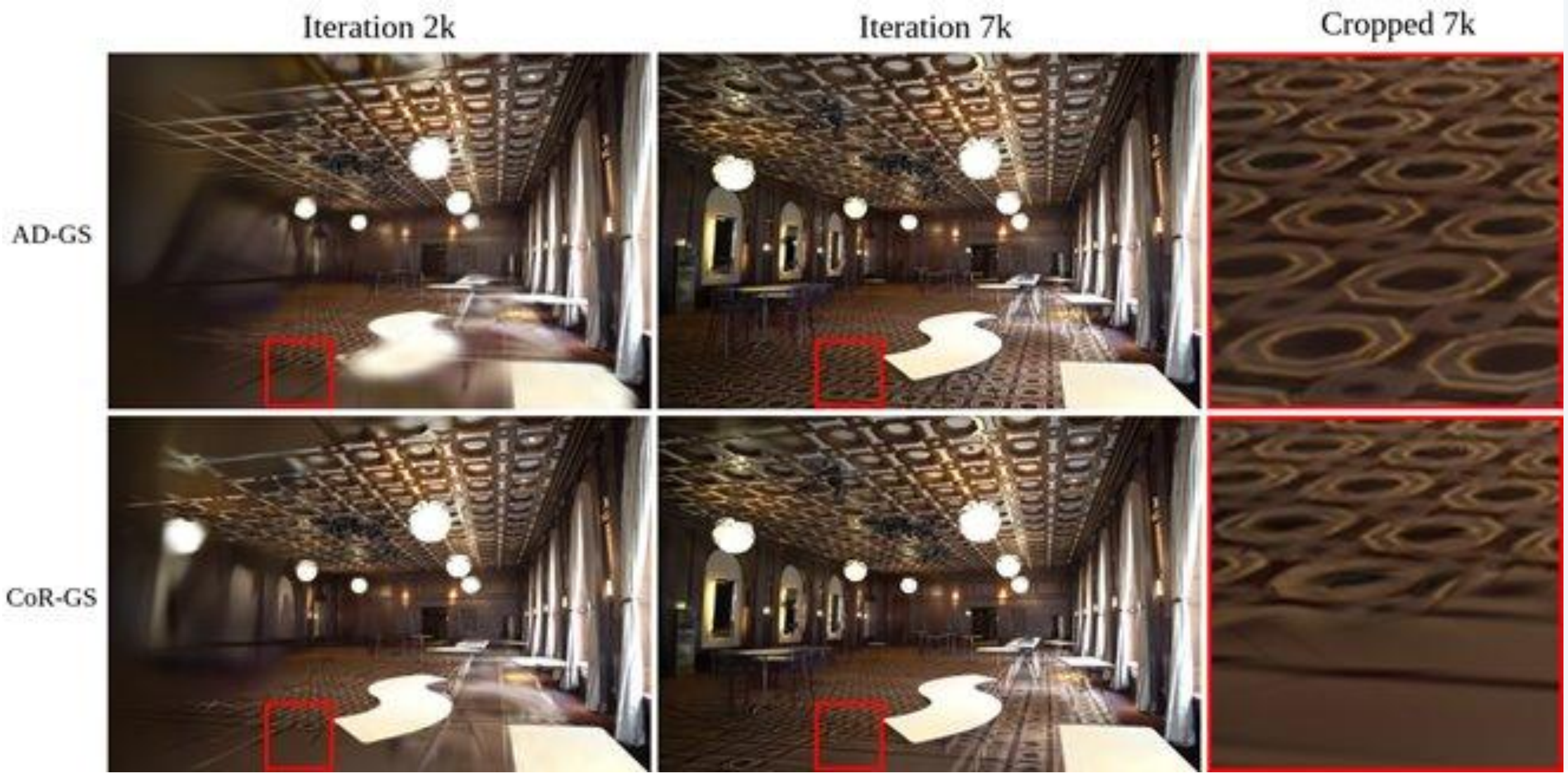
- Idea: Alternate between
  - High Densification (aggressive growth, photometric loss-only) and
  - Low Densification (pruning + geometry losses)
    - Geometric Losses
      1. Edge-Aware Depth Smoothness Loss
      2. Pseudo-View Consistency Loss
  - Different densification threshold and pruning threshold in each stage

- Alternating Densification for 3D Gaussian Splatting (AD-GS) leads to high-quality reconstructions in sparse input settings.

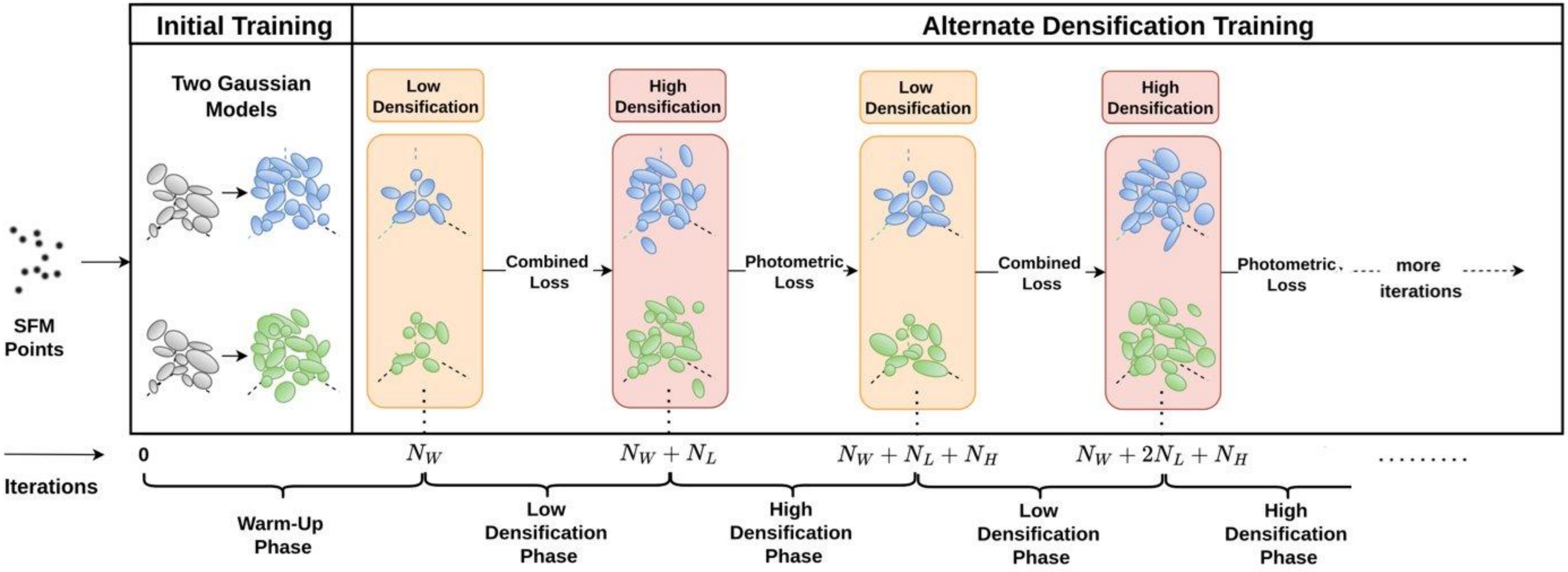
Example (Floater Removal)



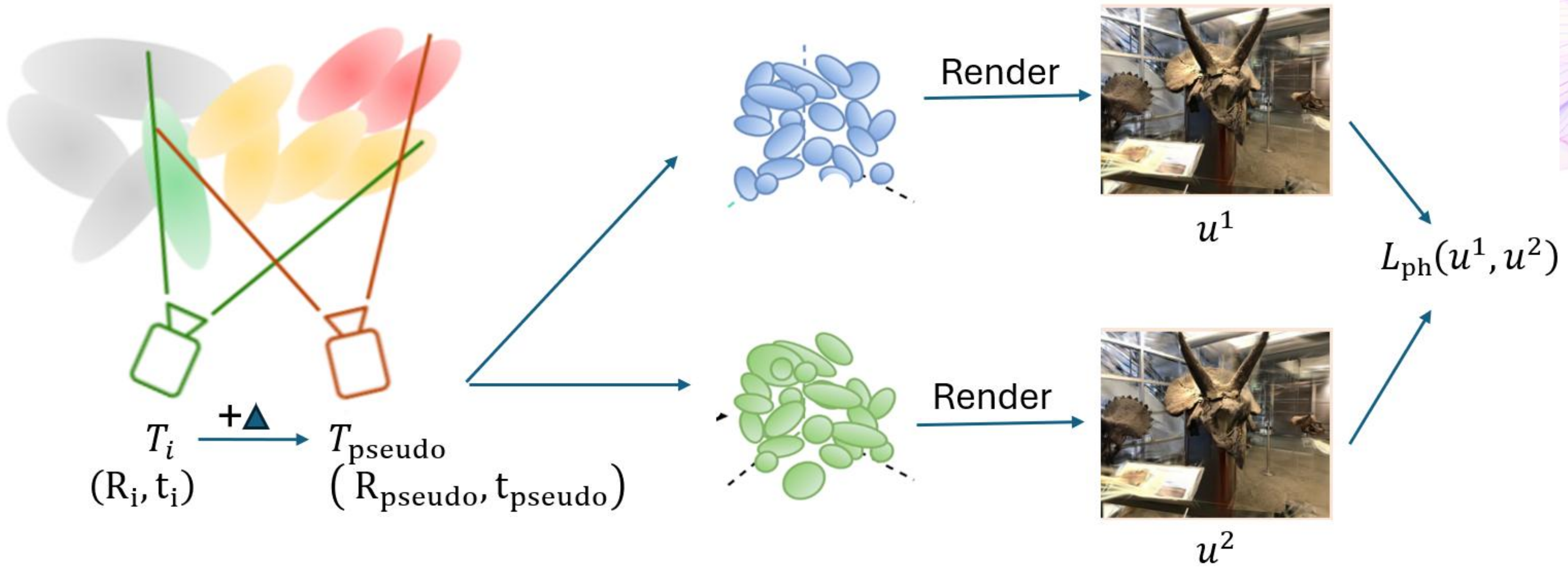
Example (Details Preservation)



Method


Initial Training
Alternate Densification Training
Two Gaussian Models
Low Densification
High Densification
Low Densification
High Densification
SFM Points
Combined Loss
Photometric Loss
Combined Loss
Photometric Loss
more iterations
Iterations
0
N_W
$N_W + N_L$
$N_W + N_L + N_H$
$N_W + 2N_L + N_H$
....
Warm-Up Phase
Low Densification Phase
High Densification Phase
Low Densification Phase
High Densification Phase

Pseudo-view consistency + Depth Loss



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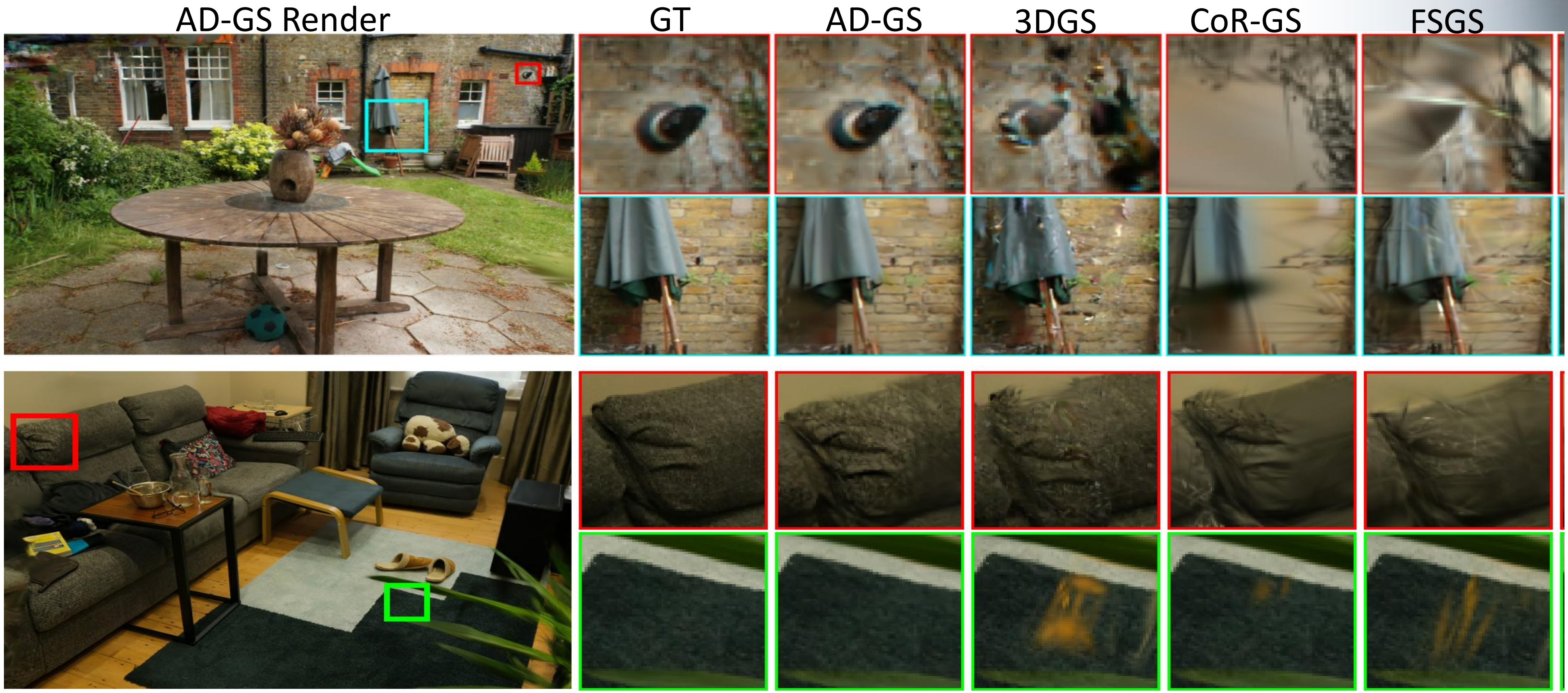
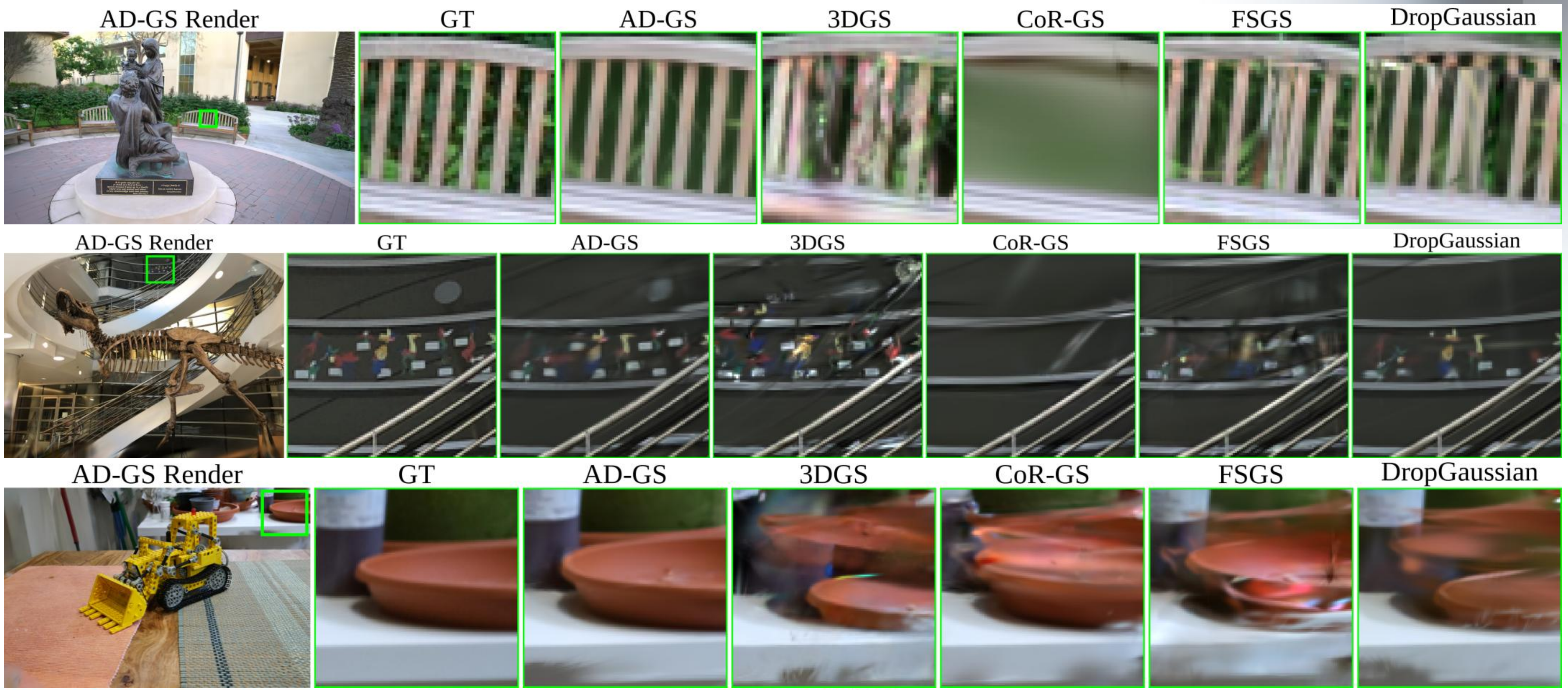
Qualitative Results

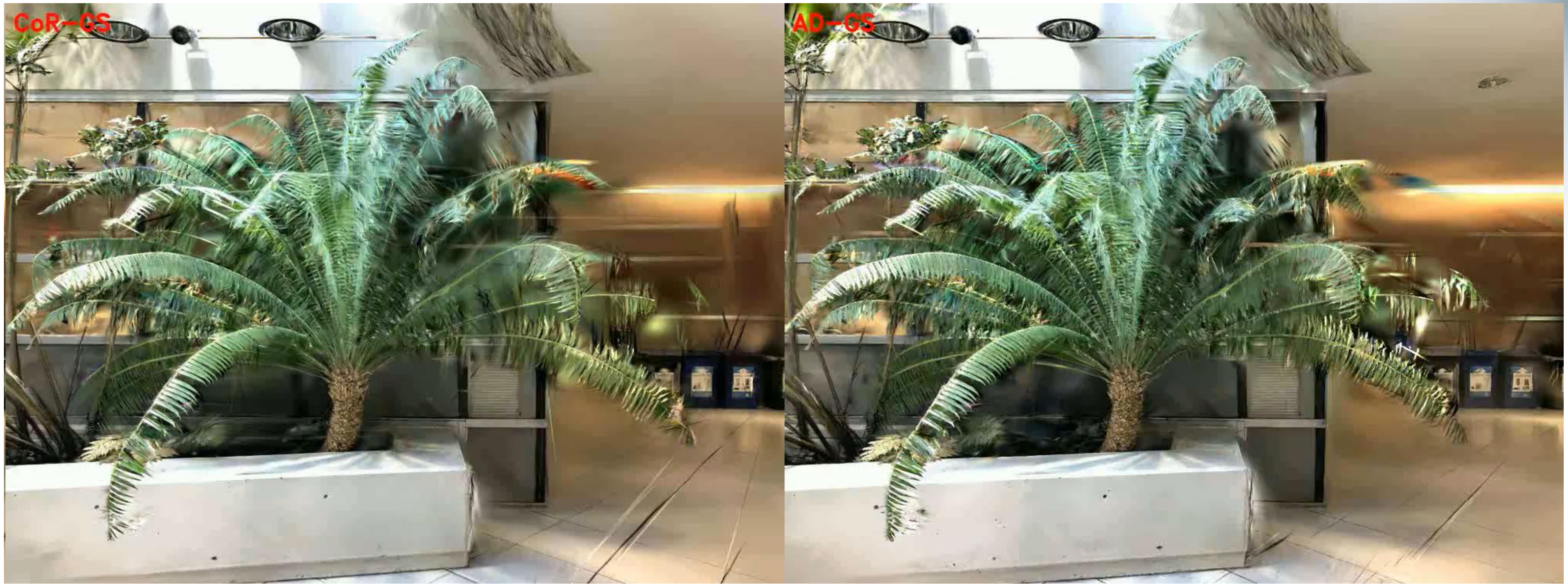


Qualitative Results



3DGS vs AD-GS

CoR-GS vs AD-GS



FSGS vs AD-GS

DropGaussian vs AD-GS

Quantitative Results

Tanks & Temples

Model	PSNR ↑			SSIM ↑			LPIPS ↓		
	3-view	6-view	9-view	3-view	6-view	9-view	3-view	6-view	9-view
3DGS	16.992	22.393	24.492	0.556	0.788	0.850	0.352	0.182	0.141
FSGS	19.644	26.436	28.488	0.637	0.847	0.888	0.312	0.168	0.139
CoR-GS	19.246	26.273	28.489	0.650	0.849	0.891	0.342	0.175	0.132
DropGaussian	19.475	26.452	28.488	0.652	0.852	0.891	0.320	0.173	0.138
AD-GS (Ours)	19.724	27.139	28.964	0.678	0.867	0.902	0.285	0.142	0.113

LLFF

Model	PSNR ↑			SSIM ↑			LPIPS ↓		
	3-view	6-view	9-view	3-view	6-view	9-view	3-view	6-view	9-view
3DGS	18.90	22.57	24.02	0.632	0.757	0.799	0.269	0.182	0.151
FSGS	19.50	23.25	24.56	0.655	0.776	0.815	0.269	0.185	0.151
CoR-GS	19.59	23.33	24.75	0.674	0.780	0.817	0.271	0.187	0.152
DropGaussian	19.72	23.52	24.89	0.674	0.786	0.824	0.266	0.182	0.148
AD-GS (Ours)	20.06	23.54	25.02	0.699	0.793	0.830	0.237	0.170	0.142

Quantitative Results

Mip-NeRF360

Model	PSNR ↑		SSIM ↑		LPIPS ↓	
	12-view	24-view	12-view	24-view	12-view	24-view
3DGS	17.36	22.06	0.496	0.701	0.403	0.253
FSGS	18.51	23.11	0.547	0.720	0.411	0.275
CoR-GS	19.42	23.20	0.579	0.728	0.410	0.272
DropGaussian	19.18	23.28	0.575	0.732	0.412	0.277
AD-GS(Ours)	19.66	23.68	0.593	0.750	0.386	0.249

Conclusion

- AD-GS: alternating densification for sparse-input 3DGS, by alternating between high and low densification phases.
- Low densification: prune + geometry-aware regularization
- High densification: aggressive photometric growth.
- Delivers state-of-the-art performance on challenging benchmarks.

For paper, code and more, visit : gurutvapatle.github.io/publications/2025/ADGS.html

Take-Away

- AD-GS shows that densification matters as much as how you densify.
- Reliable surface structure can emerge purely from image-domain supervision.
- Training dynamics matter as much as the underlying 3D representation.
- AD-GS as a general training schedule and this idea of alternating optimization may be useful beyond just Gaussian Splatting.

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Thank You!