LEGS

Laplacian-Enhanced Gaussian Splatting with a Nonlinear Weighted Loss

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Presentation outline

01 **Background and motivation** 03–07

Reconstruction context, related work and the supervision gap

02 **LEGS methodology** 08–10

Laplacian guidance and nonlinear weighting

03 **Experiments and results** 11–15

Evaluation protocol, ablation and pipeline transfer

04 **Conclusions and future work** 16–17

Key findings, evaluation scope and next steps

Image-based reconstruction for interactive 3D



Multi-view input

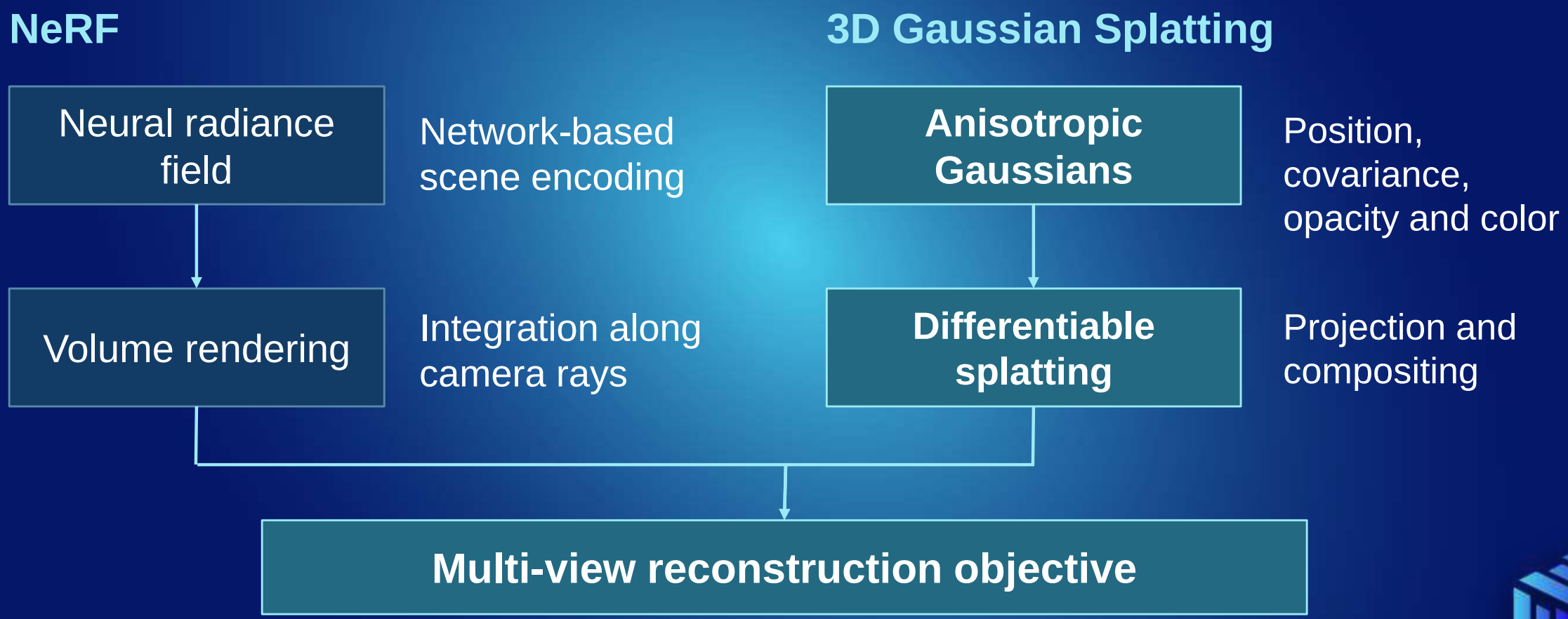
Images constrain the appearance of a 3D scene.

Local structure

Contours, corners and thin details contribute to visual fidelity.

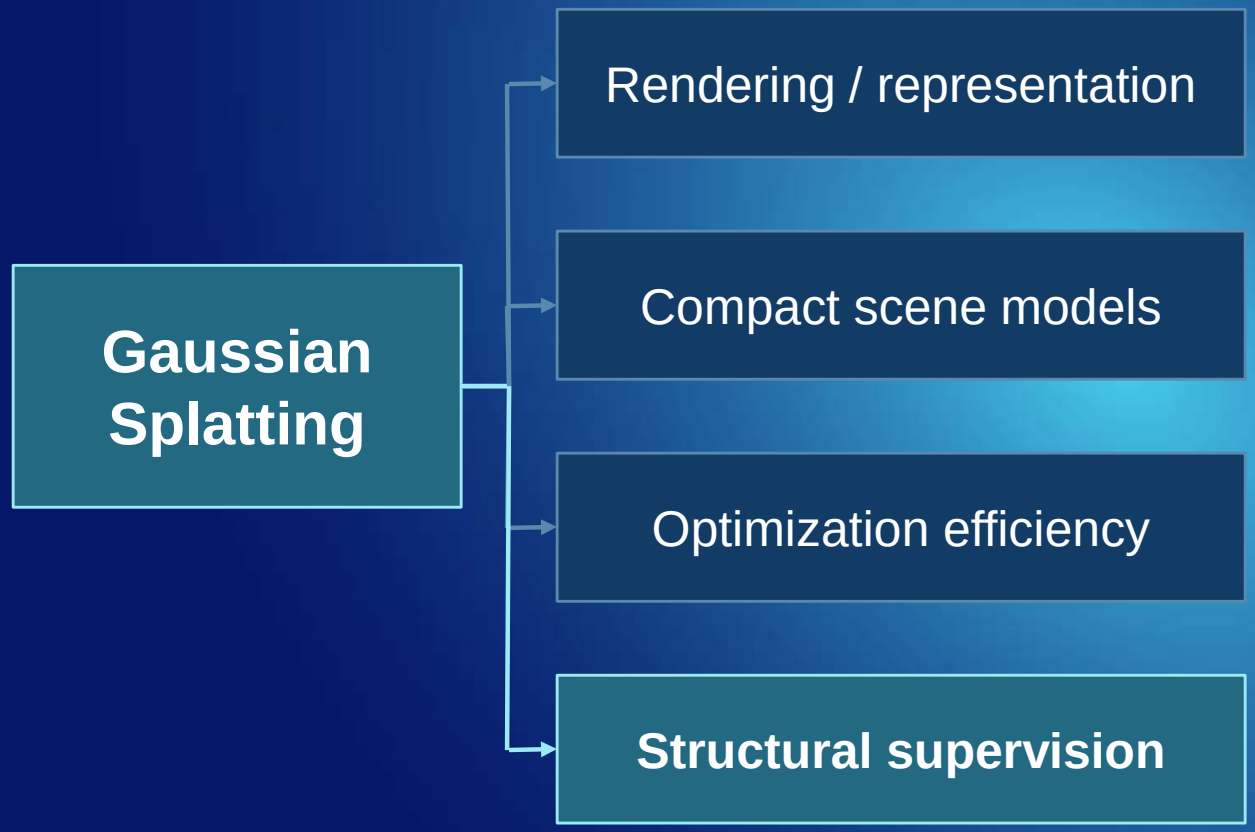
Research focus: local structure in Gaussian reconstruction.

Neural fields and explicit Gaussians



LEGS studies structural supervision within the Gaussian pipeline.

Research directions in Gaussian Splatting



Mip-Splatting: anti-aliasing
Scaffold-GS: structured, view-adaptive Gaussians

LightGaussian: Gaussian compression

FastGS and Faster-GS: training and optimization

EGGS: gradient guidance **LEGS: Laplacian + nonlinear weights**

LEGS changes the reconstruction loss while retaining the Gaussian pipeline.

Motivation: structural weighting of RGB error

Uniform photometric weighting

$$L = (1 - \lambda)\, \|U - F\|_1 + \lambda\, D_{SSIM}$$

The RGB term assigns equal basic spatial weight to smooth regions and structure-rich pixels.

EGGS adds first-order guidance

$$W_g = 1 + \beta\, \|\nabla F\|_p$$

Which structural cue should guide optimization?
How should response strength become a weight?

3DGS **Ground truth**



Source-marked details motivate structure-sensitive supervision.

LEGS separates two design choices

Method	Structural cue	Response-to-weight mapping
3DGS	Uniform spatial weight	Constant
EGGS	First-order gradient	Linear
LEGS-L	Laplacian magnitude	Linear
LEGS	**Laplacian magnitude**	**Nonlinear (C3)**

Loss-level integration

Retain the Gaussian representation, renderer and densification strategy.
Evaluate reconstruction quality and transfer to FastGS and FasterGS.



LEGS: a structural weighting path

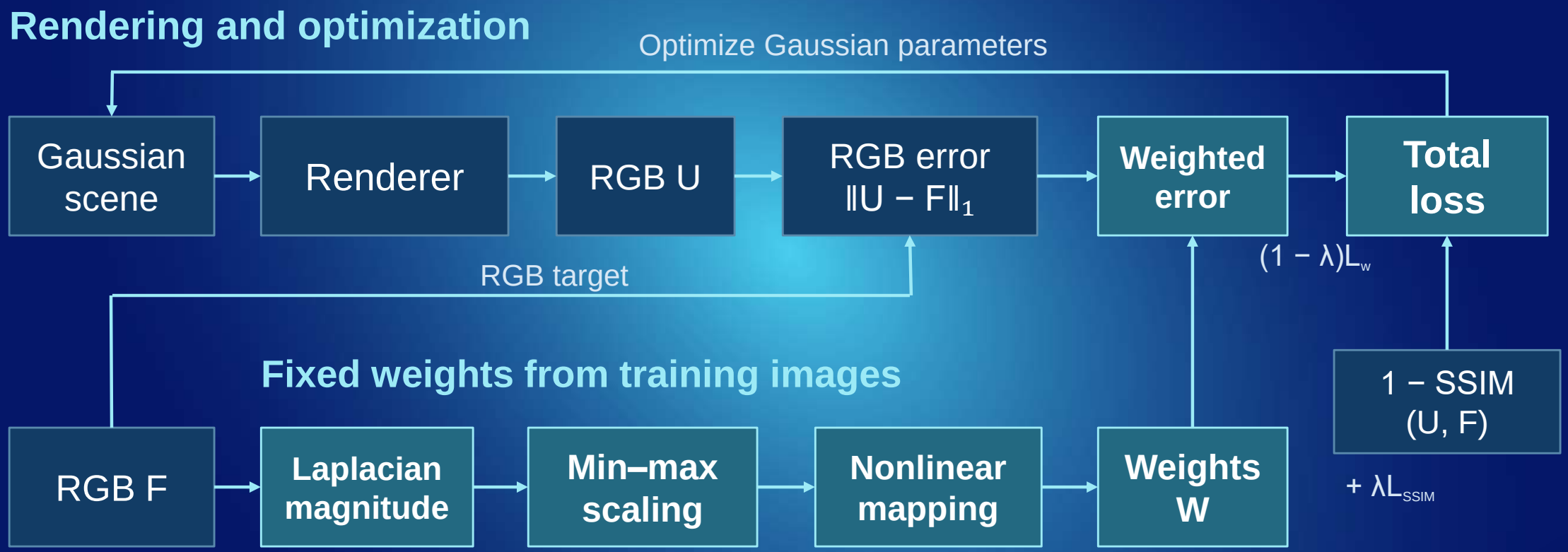


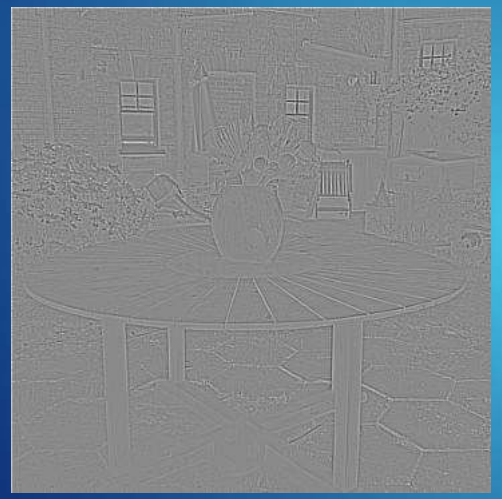
Image structure weights the RGB reconstruction error.

Laplacian structural guidance

Training RGB F



Laplacian response



Nonnegative response magnitude

$$E_\Delta(u,v) = \|\Delta F(u,v)\|_p$$

Aggregate the channel-wise response into one structural importance map.

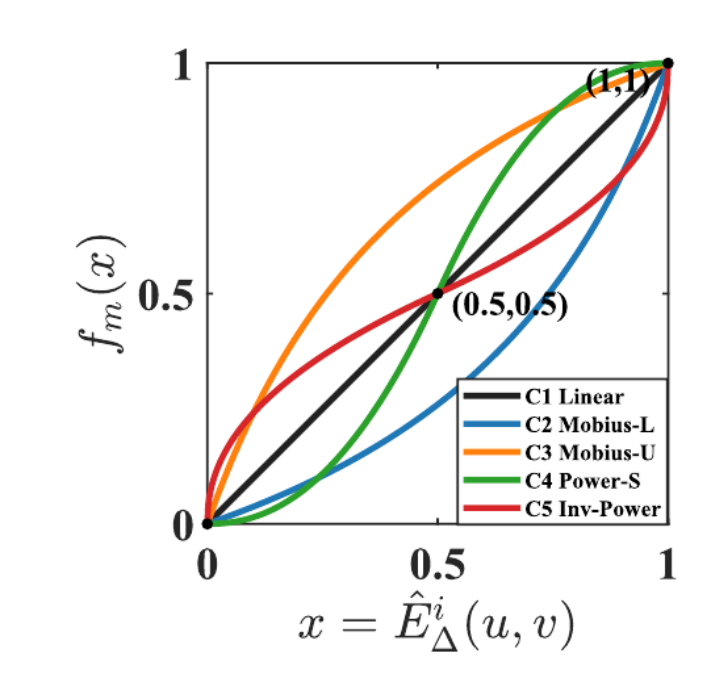
$$\Delta F = F_{xx} + F_{yy} = \mathrm{tr}(H_F)$$

Second-order spatial intensity variation in each RGB channel.

$$\hat{E}_\Delta = (E_\Delta - E_{\Delta,\min}) / (E_{\Delta,\max} - E_{\Delta,\min} + \varepsilon)$$

Spatial min/max within each image.
$\varepsilon > 0$ stabilizes the denominator.

Nonlinear weighted reconstruction objective



C1: linear reference
C2–C5: nonlinear alternatives

$$W_{\Delta,m} = 1 + \beta\, f_m(\hat{E}_\Delta)$$

f maps [0,1] to [0,1]. At β = 10, W lies in [1,11].

$$L_{w,m} = \text{mean}[W_{\Delta,m}\, \|U - F\|_1]$$

Average over training views and pixels.

$$L_{LEGS,m} = (1 - \lambda)L_{w,m} + \lambda L_{SSIM}$$

U: rendered RGB F: observed RGB
L_{SSIM}: mean structural dissimilarity

Selected: C3, β = 10. Fixed weights scale RGB-error gradients.

Source: LEGS, Fig. 2 and Eqs. (5)–(9). One mapping is used in each experiment.

Experimental design

Dataset	Evaluation coverage	Views used for metrics
Tanks and Temples	Train and Truck	Training views
Mip-NeRF360	Full dataset	Training views

Paired comparisons

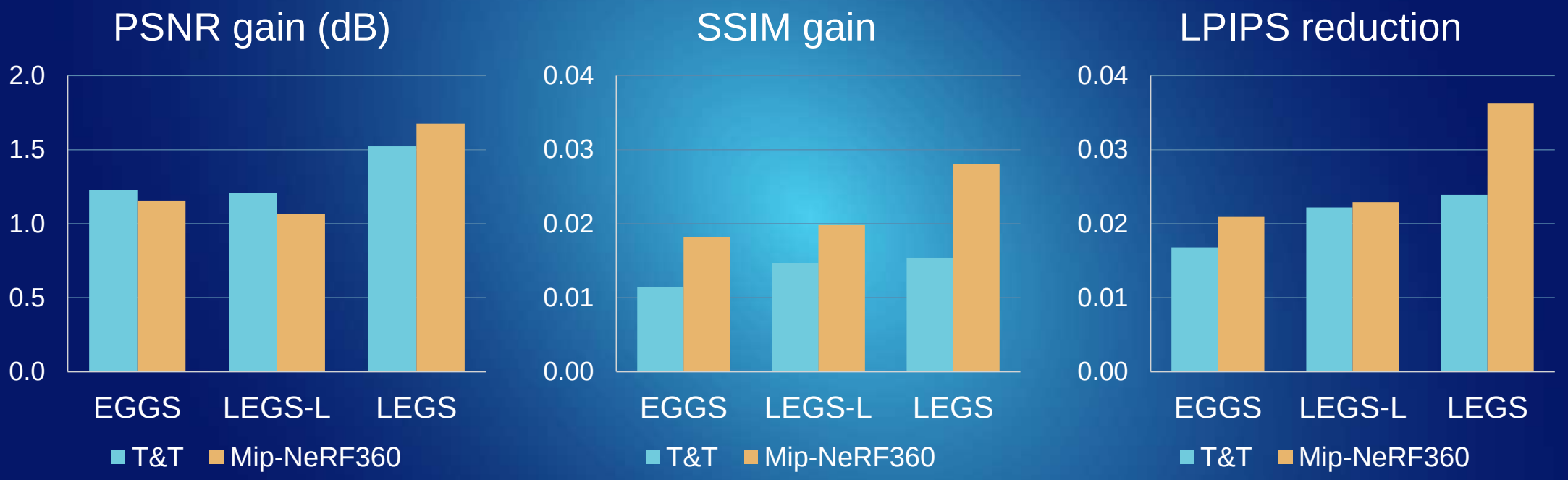
Baseline and modified pipelines share optimization and rendering settings.
PSNR and SSIM: higher is better.
LPIPS: lower is better.

Questions evaluated

Main quality: 3DGS, EGGS, LEGS-L
Components: β and mapping shape
Transfer: FastGS and FasterGS

The results quantify reconstruction of observed training views.

Quality gains across all three metrics



LEGS on Mip-NeRF360

31.0006 PSNR / 0.9010 SSIM / 0.1533 LPIPS

Up to +1.6764 dB over 3DGS and +0.5192 dB over EGGS.

Qualitative evidence of local structure

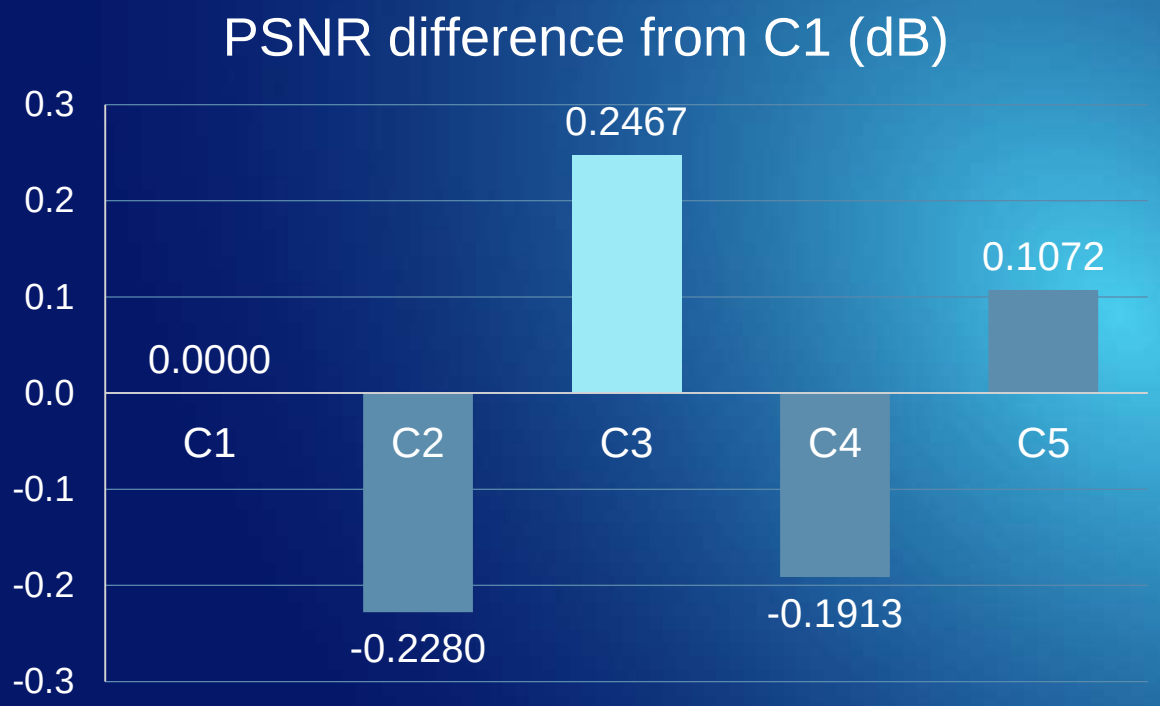
3DGS **EGGS** **LEGS** **Ground truth**



LEGS preserves clearer local boundaries and fine texture in the selected regions.

Embedded values are per-image PSNR / SSIM. These crops complement the aggregate metrics.

Mapping choice determines the benefit



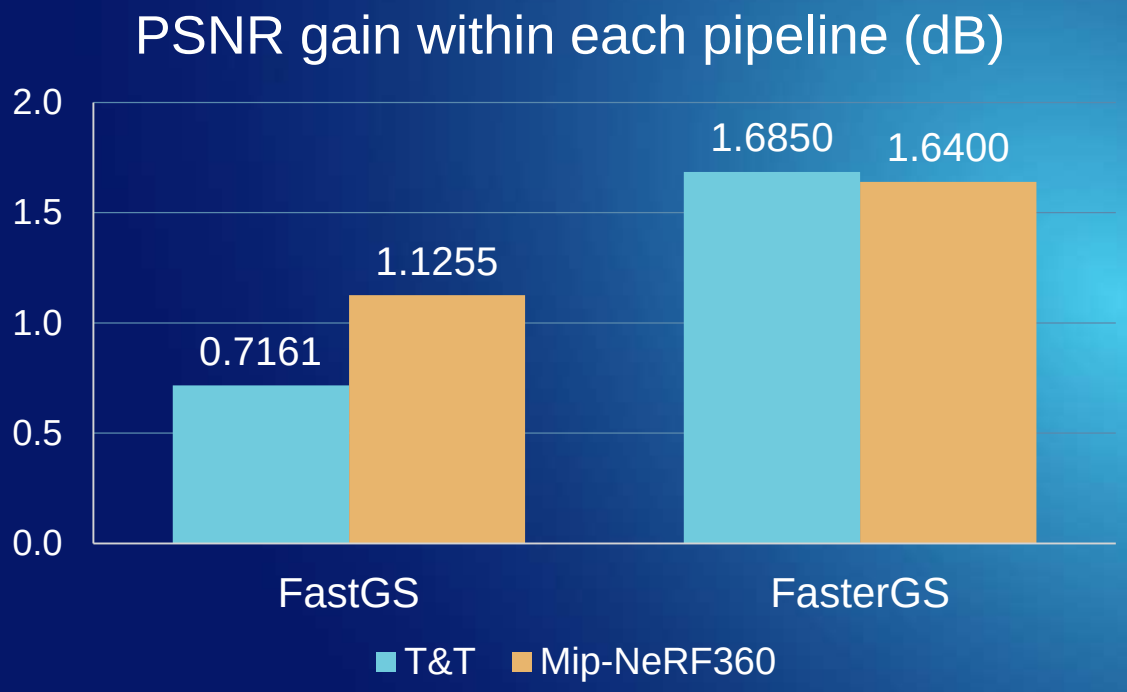
Mapping	SSIM ↑	LPIPS ↓
C1	0.9079	0.1291
C2	0.9059	0.1330
C3	**0.9092**	**0.1269**
C4	0.9069	0.1309
C5	0.9073	0.1293

C3 is best among the five tested mappings

C2 and C4 underperform C1 in PSNR. Nonlinearity alone does not ensure a gain.

Source: LEGS, Table 2 and §3.3. T&T training views. Mapping study at β = 10.

Transfer to efficient Gaussian pipelines



Pair / dataset	ΔSSIM ↑	ΔLPIPS ↓
FastGS / T&T	+0.0074	−0.0460
FastGS / 360	+0.0202	−0.0272
FasterGS / T&T	**+0.0175**	**−0.0270**
FasterGS / 360	**+0.0246**	**−0.0322**

360: Mip-NeRF360

All three metrics improve in both tested pipelines

Quality improves within each pipeline. Computational cost remains to be measured.

Scope and future research

Current evidence

Improved training-view reconstruction on two datasets,
with transfer to FastGS and FasterGS under paired settings.

Validation for interactive 3D use

Held-out novel-view quality
Repeated runs and uncertainty
Training time, memory and Gaussian count
Rendering FPS under matched conditions

Method development

Adaptive structural weighting
Compact scene representations
Noise and outlier robustness

Next: evaluate the balance between reconstruction quality and cost.

Conclusions

Second-order image structure

Laplacian magnitudes identify pixels for stronger reconstruction supervision.

Nonlinear response shaping

The selected mapping improves PSNR, SSIM and LPIPS across both reported datasets.

Integration through the loss

Quality gains extend to FastGS and FasterGS.
Generalization and computational cost are the next evaluation priorities.



Thank You!

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