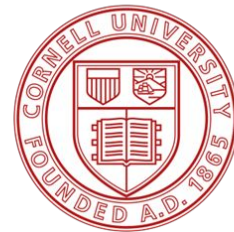
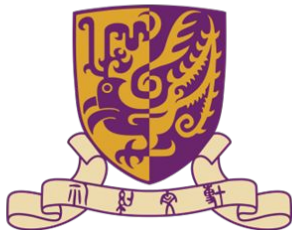


# GSDF: 3DGS Meets SDF for Improved Neural Rendering and Reconstruction

Mulin Yu, Tao Lu, Linning Xu, Lihan Jiang, Yuanbo Xiangli, Bo Dai



# Problem Statement

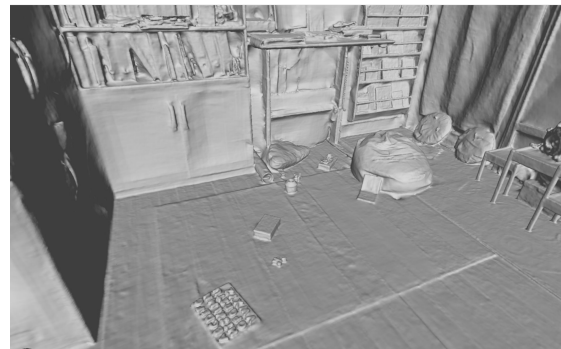
**Input:** Multi-view images and their poses



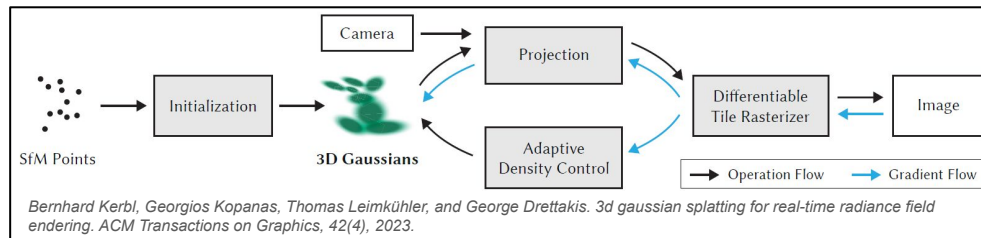
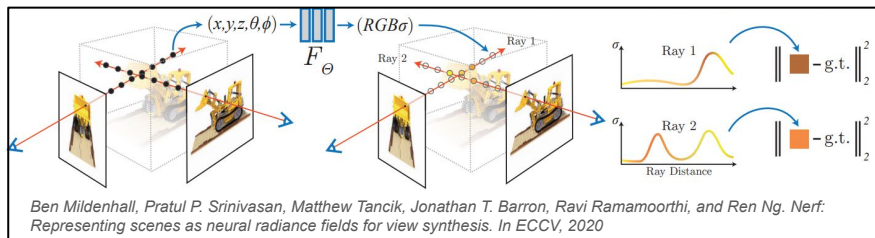
# Problem Statement

**Input:** Multi-view images and their poses

**Output:** A reconstructed model with accurate **geometry** and realistic **rendering** quality



# Related Work



**Neuralangelo: High-Fidelity Neural Surface Reconstruction**

Zhaoshuo Li, Thomas Müller, Alex Evans, Russell H Taylor, Mathias Unberath, Ming-Yu Liu, Chen-Hsuan Lin

Neuralangelo is a framework for high-fidelity 3D surface reconstruction from RGB video sequences. Using ubiquitous mobile devices, we enable users to create digital twins of both object-centric and large-scale real-world scenes with detailed 3D geometry.

**METHOD**

- Multi-resolution hash encoding
- Encoded feature
- MIP
- Volume rendering
- RGB (color)
- SDF (geometry)

**KEY INGREDIENTS**

- Numerical gradients for higher-order derivatives
- Tiler sampling
- Finite differences
- Coarse to fine approximation for progressive level of details
- Finite steps
- Encoded features

**Optimization objectives**

- Color: RGB synthesis loss
- Depth: Eikonal loss
- Feature: Curvature loss

DTU BENCHMARK

COMPARISON WITH BASELINE METHODS (DTU benchmarks)

Neuralangelo achieves state-of-the-art performance in DTU benchmarks, outperforming baselines like NeRF, NeRF++, and Gaussian Splatting.

Zhaoshuo Li, Thomas Müller, Alex Evans, Russell H Taylor, Mathias Unberath, Ming-Yu Liu, and Chen-Hsuan Lin. Neuralangelo: High-fidelity neural surface reconstruction. CVPR, pages 8456–8465, 2023.

**Sugar: Surface-aligned gaussian splatting for efficient 3d mesh reconstruction and high-quality mesh rendering.**

Antoine Guédon and Vincent Lepetit. arXiv preprint arXiv:2311.12775, 2023.

The figure shows a sequence of images: a real-world scene, a sparse point cloud, a mesh reconstruction, and a high-quality rendered scene with a yellow tractor and a table.

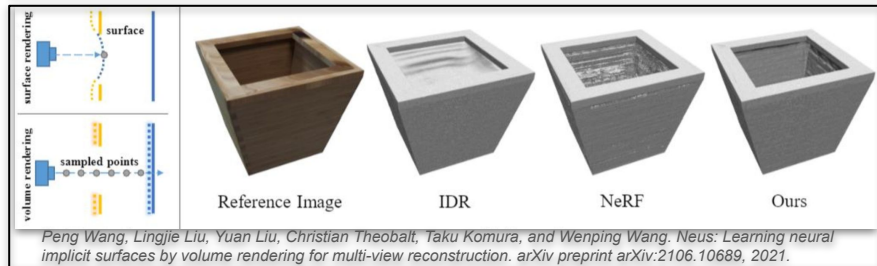
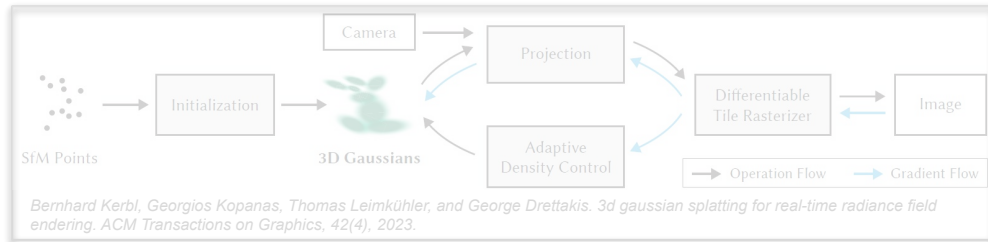
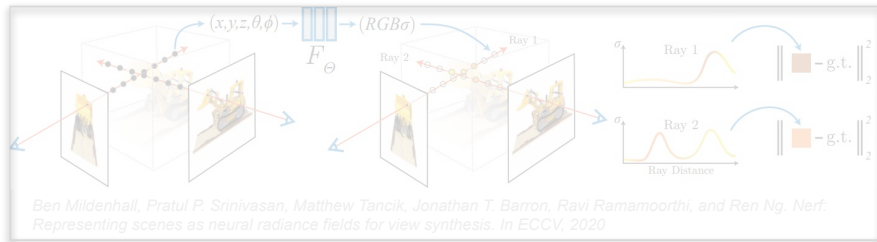
The figure compares normal maps for a disk and a surface. The disk normal map shows a smooth gradient, while the surface normal map shows more complex, irregular patterns. The rendered images show the corresponding 3D models.

Zelner, Batten, Voigt, Gelfand, Elias, Gaussian opacity fields for efficient and compact surface reconstruction in unbounded scenes. arXiv preprint arXiv:2404.10422 (2024)

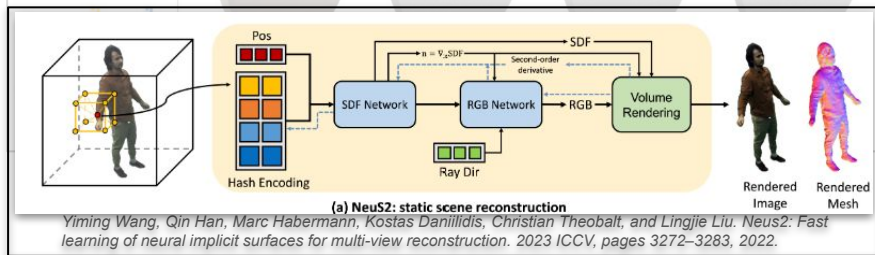
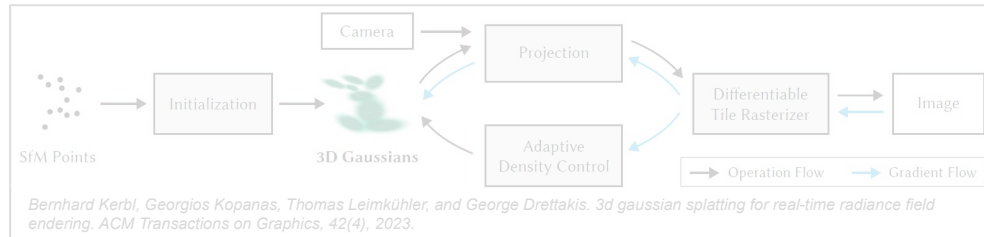
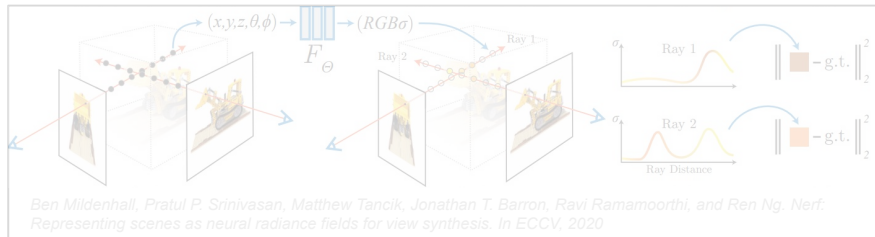




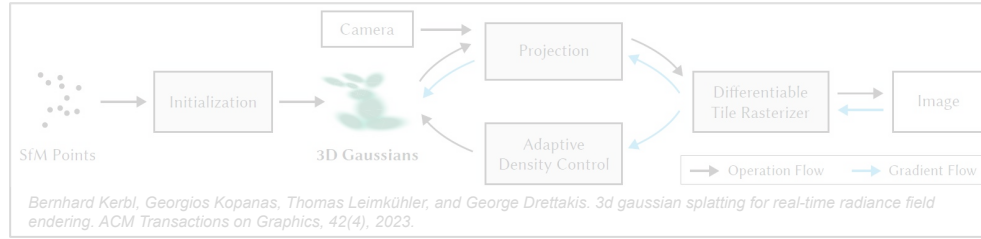
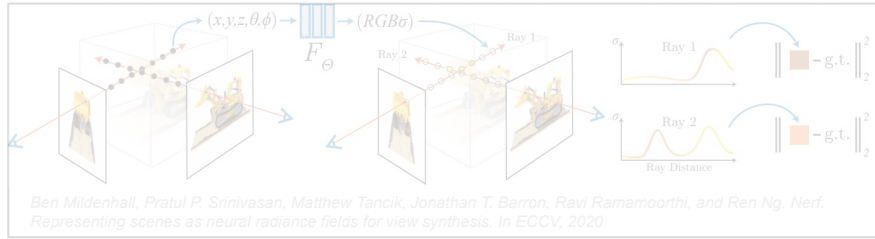
# Related Work



# Related Work



# Related Work



**Neuralangelo: High-Fidelity Neural Surface Reconstruction**

Zhaoshuo Li, Thomas Müller, Alex Evans, Russell H. Taylor, Mathias Unberath, Ming-Yu Liu, Chen-Hsuan Lin

Neuralangelo is a framework for high-fidelity 3D surface reconstruction from RGB video sequences. Using ubiquitous mobile devices, we enable users to create digital twins of both object-centric and large-scale real-world scenes with detailed 3D geometry.

**METHOD**

Multi-resolution hash encoding → Encoded feature → MLP → RGB (color) / SDF (geometry)

**KEY INGREDIENTS**

- Numerical gradients for higher-order derivatives
- Tile-size sampling
- Finite differences
- Coarse-to-fine optimization for progressive level of details
- Finite steps
- Encoded features

**Optimization objectives**

- $\mathcal{L}_{\text{color}}$ : RGB synthesis loss
- $\mathcal{L}_{\text{SDF}}$ : Eikonal loss
- $\mathcal{L}_{\text{TV}}$ : Curvature loss

**TANKS & TEMPLES DATASET**

**DTU BENCHMARK**

**COMPARISON WITH BASELINE METHODS**

DTU benchmark (DTU benchmarks)

Character distance (mm) ↓

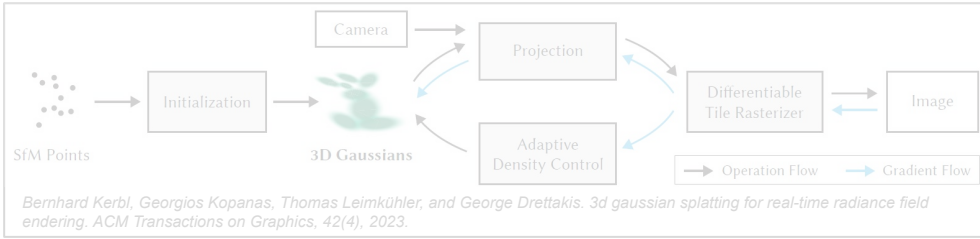
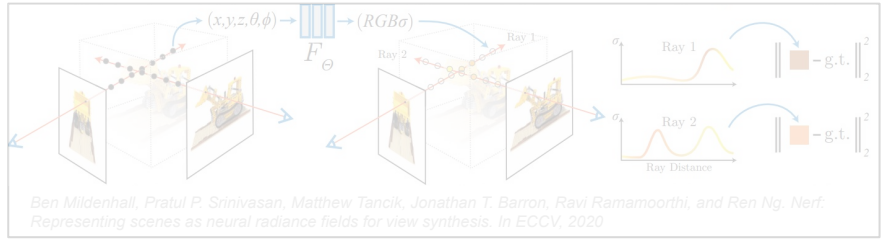
RMSE ↓

AS: analytical gradient  
AS+P: analytical gradient + coarse-to-fine optimization  
AS: analytical gradient  
Neuralangelo: numerical gradient + coarse-to-fine optimization

Zhaoshuo Li, Thomas Müller, Alex Evans, Russell H Taylor, Mathias Unberath, Ming-Yu Liu, and Chen-Hsuan Lin. *Neuralangelo: High-fidelity neural surface reconstruction*. *CVPR*, pages 8456–8465, 2023.



# Related Work



This block contains several research highlights in neural surface reconstruction:

- Neuralangelo: High-Fidelity Neural Surface Reconstruction** (CVPR 2023): A framework for high-fidelity 3D surface reconstruction from multi-view sequences. It uses observational model distillation and a novel digital terrain of both object-centric and large-scale real-world scenes with up to 3D points.
- Neuralangelo: High-Fidelity Neural Surface Reconstruction** (ICCV 2023): Learning of neural implicit surfaces for multi-view reconstruction.
- Neuralangelo: High-Fidelity Neural Surface Reconstruction** (CVPR 2023): A framework for high-fidelity 3D surface reconstruction from multi-view sequences.
- Neuralangelo: High-Fidelity Neural Surface Reconstruction** (CVPR 2023): A framework for high-fidelity 3D surface reconstruction from multi-view sequences.

Zhao Shuo Li, Thomas Müller, Alex Evans, Russell H Taylor, Mathias Unberath, Ming-Yu Liu, and Chen-Hsuan Lin. *Neuralangelo: High-fidelity neural surface reconstruction*. *CVPR*, pages 8456–8465, 2023.





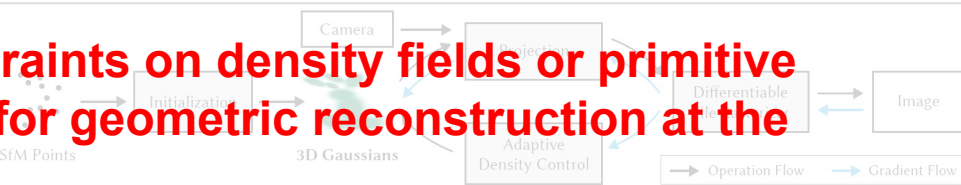




# Related Work

**Current methods impose strict constraints on density fields or primitive shapes, which enhances the affinity for geometric reconstruction at the sacrifice of rendering quality.**

Ben Mildenhall, Pratul P. Srinivasan, Matthew Tanaka, Jonathan T. Barron, Ravi Ramamoorthi, and Ren Ng. Nerf: Representing scenes as neural radiance fields for view synthesis. In ECCV, 2020.



Bernhard Kerbl, Georgios Kopanas, Thomas Leimkühler, and George Drettakis. 3d gaussian splatting for real-time radiance field rendering. ACM Transactions on Graphics, 42(4), 2023.

**Neuralangelo: High-Fidelity Neural Surface Reconstruction**  
 Yinyang Wang, Qin Han, Marc Habermann, Kostas Daniilidis, Christian Theobalt, and Lingjie Liu. Neus2: Fast learning of neural implicit surfaces for multi-view reconstruction. 2023 ICCV, pages 3272–3283, 2022.

**Neuralangelo: High-Fidelity Neural Surface Reconstruction**  
 Yinyang Wang, Qin Han, Marc Habermann, Kostas Daniilidis, Christian Theobalt, and Lingjie Liu. Neus2: Fast learning of neural implicit surfaces for multi-view reconstruction. 2023 ICCV, pages 3272–3283, 2022.

**COMPARISON WITH BASELINE METHODS (DTU benchmark)**

Method	Classification Accuracy (%)	Surface Error (mm)
Neuralangelo	~95	~0.5
Neuralangelo (w/o gradient)	~90	~1.0
Neuralangelo (w/o coarse to fine)	~85	~1.5
Neuralangelo (w/o numerical gradient)	~80	~2.0

Zhaoshuo Li, Thomas Müller, Alex Evans, Russell H Taylor, Mathias Unberath, Ming-Yu Liu, and Chen-Hsuan Lin. Neuralangelo: High-fidelity neural surface reconstruction. CVPR, pages 8456–8465, 2023.

**Sugar: Surface-aligned gaussian splating for efficient 3d mesh reconstruction and high-quality mesh rendering.**  
 Antoine Guédon and Vincent Lepetit. arXiv preprint arXiv:2311.12775, 2023.

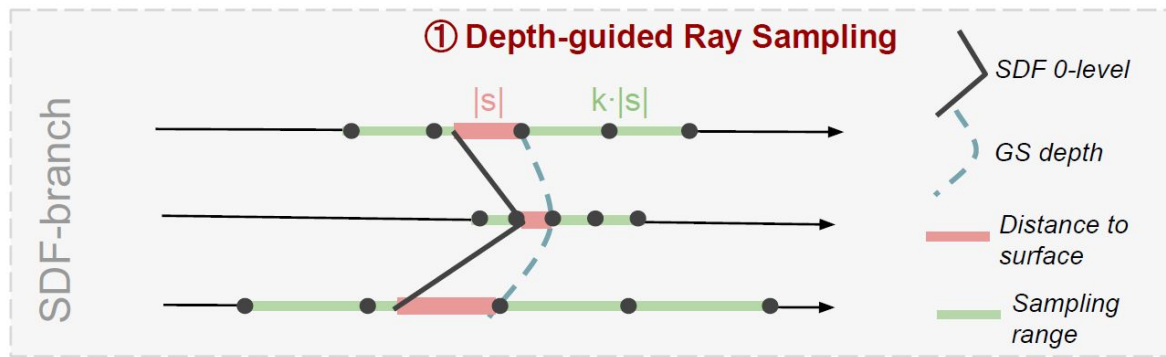
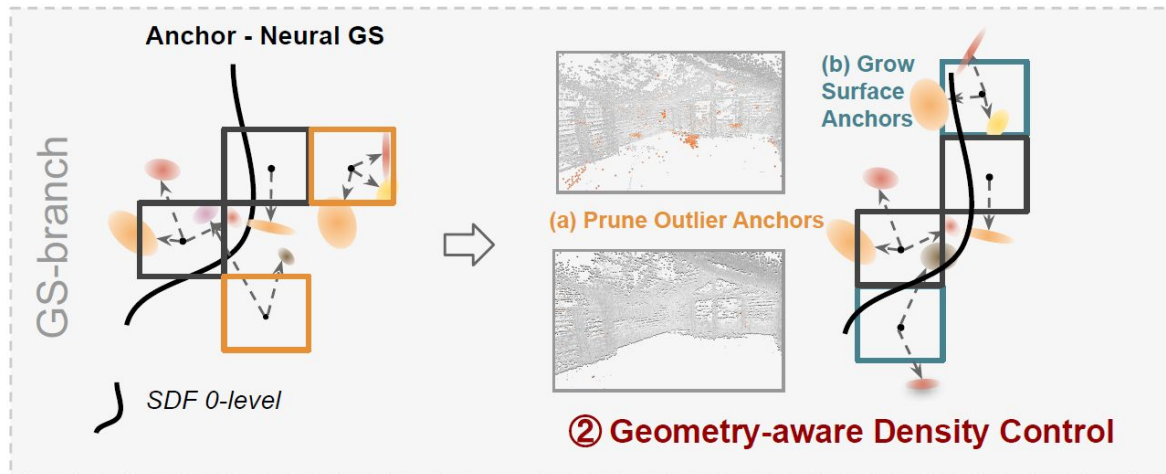
**2D gaussian splating for geometrically accurate radiance fields.**  
 Binbin Huang, Zehao Yu, Anpei Chen, Andreas Geiger, and Shenghua Gao. abs/2403.17888, 2024.

**Gaussian opacity fields: Efficient and compact surface reconstruction in unbounded scenes.**  
 Zehao Yu, Sattler Torsten, and Geiger Andreas. arXiv preprint arXiv:2404.10772 (2024).

Zehao Yu, Sattler Torsten, and Geiger Andreas. Gaussian opacity fields: Efficient and compact surface reconstruction in unbounded scenes. arXiv preprint arXiv:2404.10772 (2024).



# Two-branch Framework

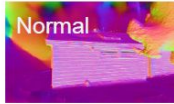


Rasterize



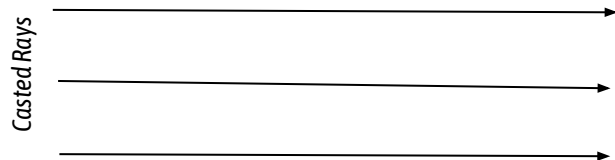
**③ Mutual Geometry Supervision**  
(w/ foreground mask)

Volume Rendering



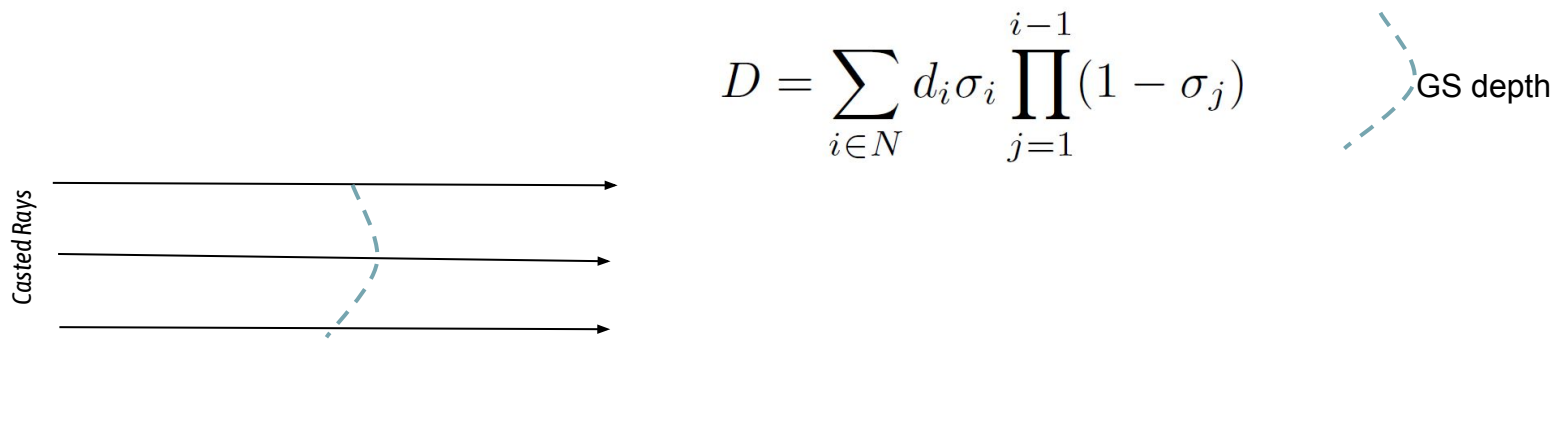
# GS → SDF: Depth Guided Ray Sampling

We leverage depth maps from the GS-branch to refine the ray sampling range for the SDF-branch.



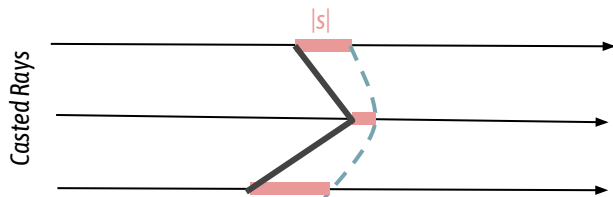
# GS → SDF: Depth Guided Ray Sampling

We leverage depth maps from the GS-branch to refine the ray sampling range for the SDF-branch.



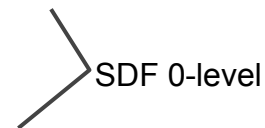
# GS → SDF: Depth Guided Ray Sampling

We leverage depth maps from the GS-branch to refine the ray sampling range for the SDF-branch.



$$D = \sum_{i \in N} d_i \sigma_i \prod_{j=1}^{i-1} (1 - \sigma_j)$$

$$s = \mathcal{F}_s(\vec{o} + D \cdot \vec{v})$$

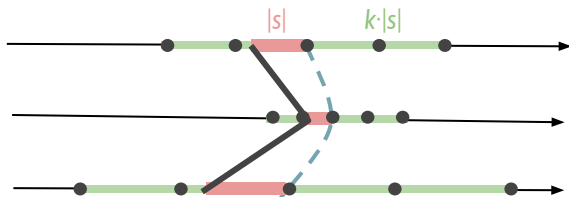




# GS → SDF: Depth Guided Ray Sampling

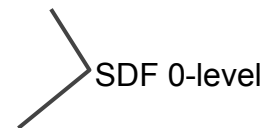
We leverage depth maps from the GS-branch to refine the ray sampling range for the SDF-branch.

Casted Rays



$$D = \sum_{i \in N} d_i \sigma_i \prod_{j=1}^{i-1} (1 - \sigma_j)$$

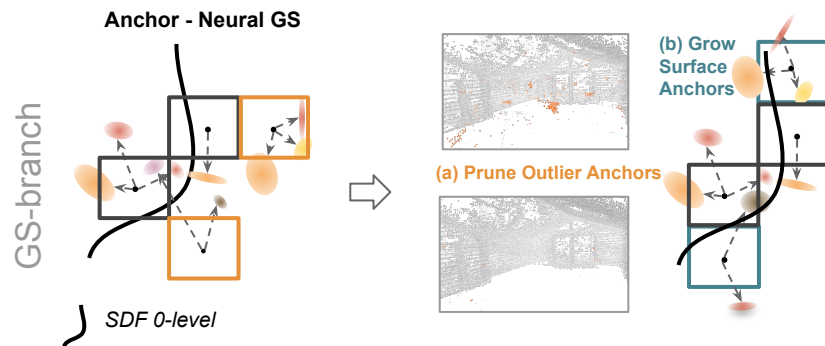
$$s = \mathcal{F}_s(\vec{o} + D \cdot \vec{v})$$



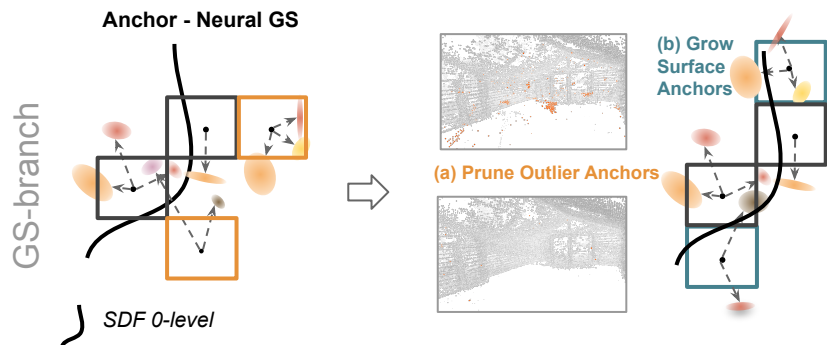
GS depth



# SDF → GS: Geometry-aware Gaussian Density Control

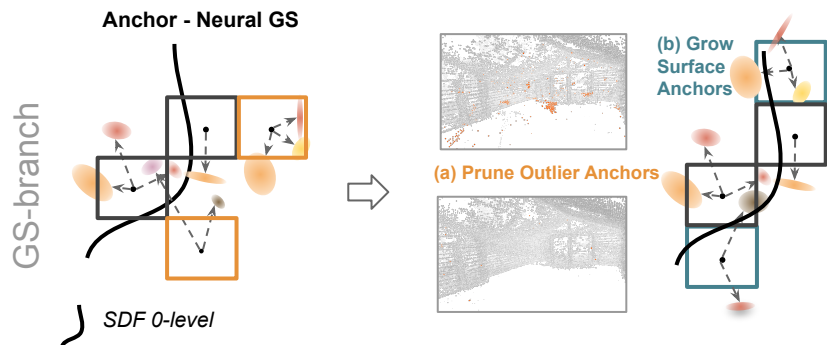


# SDF → GS: Geometry-aware Gaussian Density Control



$$\mu(s) = \exp(-s^2 / (2\sigma^2))$$

# SDF → GS: Geometry-aware Gaussian Density Control



$$\mu(s) = \exp(-s^2 / (2\sigma^2))$$

$$\epsilon_g = \nabla_g + \omega_g \mu(s)$$

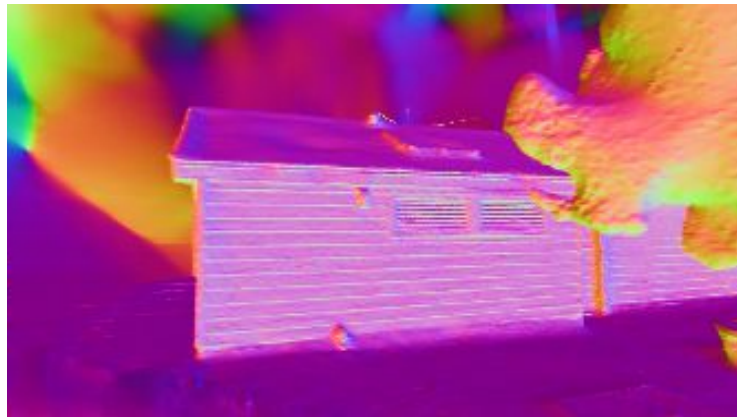
$$\epsilon_p = \sigma_a - \omega_p (1 - \mu(s))$$



# GS $\leftrightarrow$ SDF: Mutual Geometry Supervision

$$\mathcal{L}_{\text{mutual}} = \lambda_d \mathcal{L}_d + \lambda_n \mathcal{L}_n = \lambda_d \|D_{gs} - D_s\| + \lambda_n \left(1 - \frac{|N_{gs} \cdot N_s|}{\|N_{gs}\| \|N_s\|}\right)$$

GS Branch



SDF Branch



# Comparison

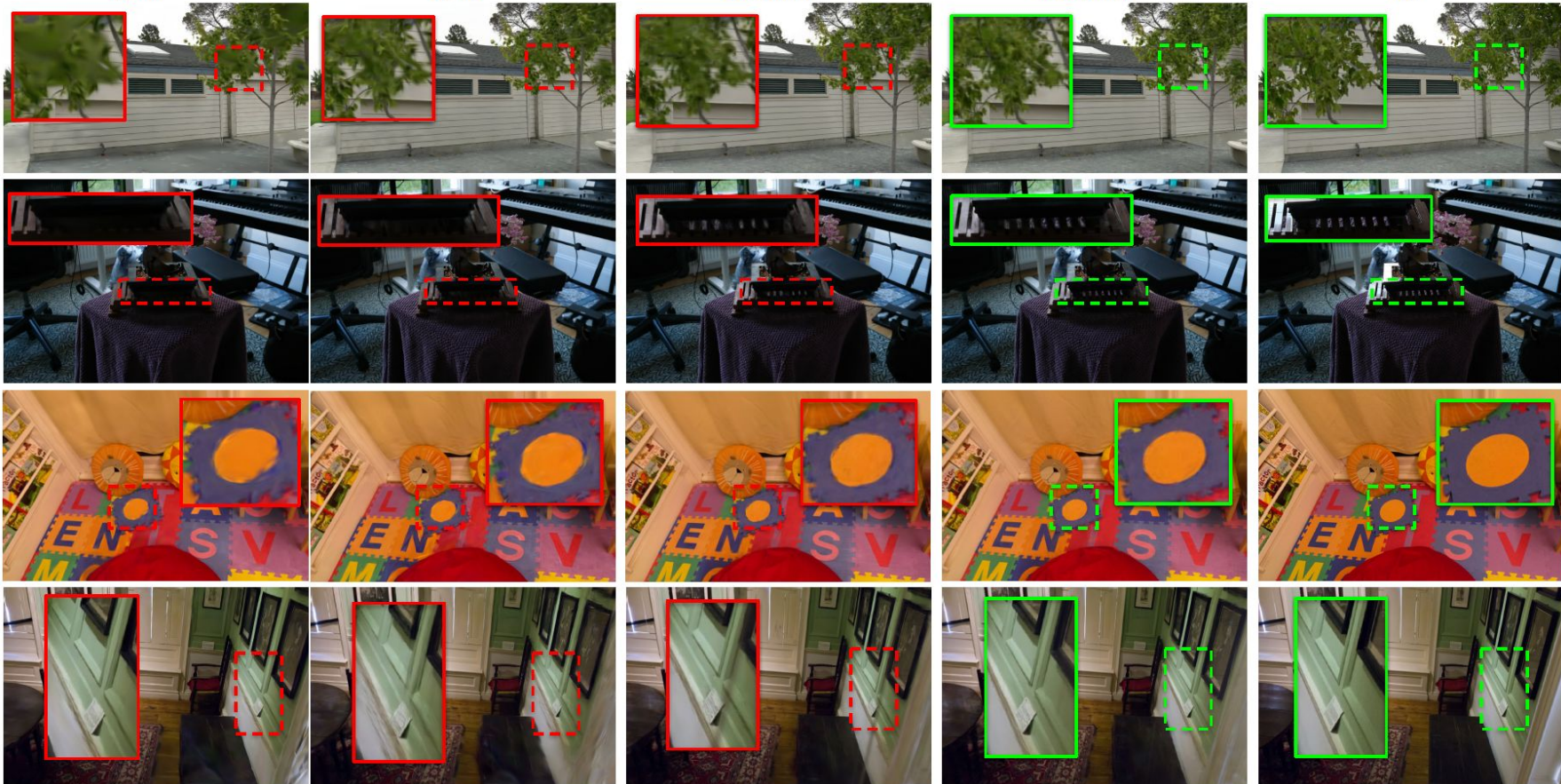
2D-GS

3D-GS

Scaffold-GS

GSDf (Ours)

GT

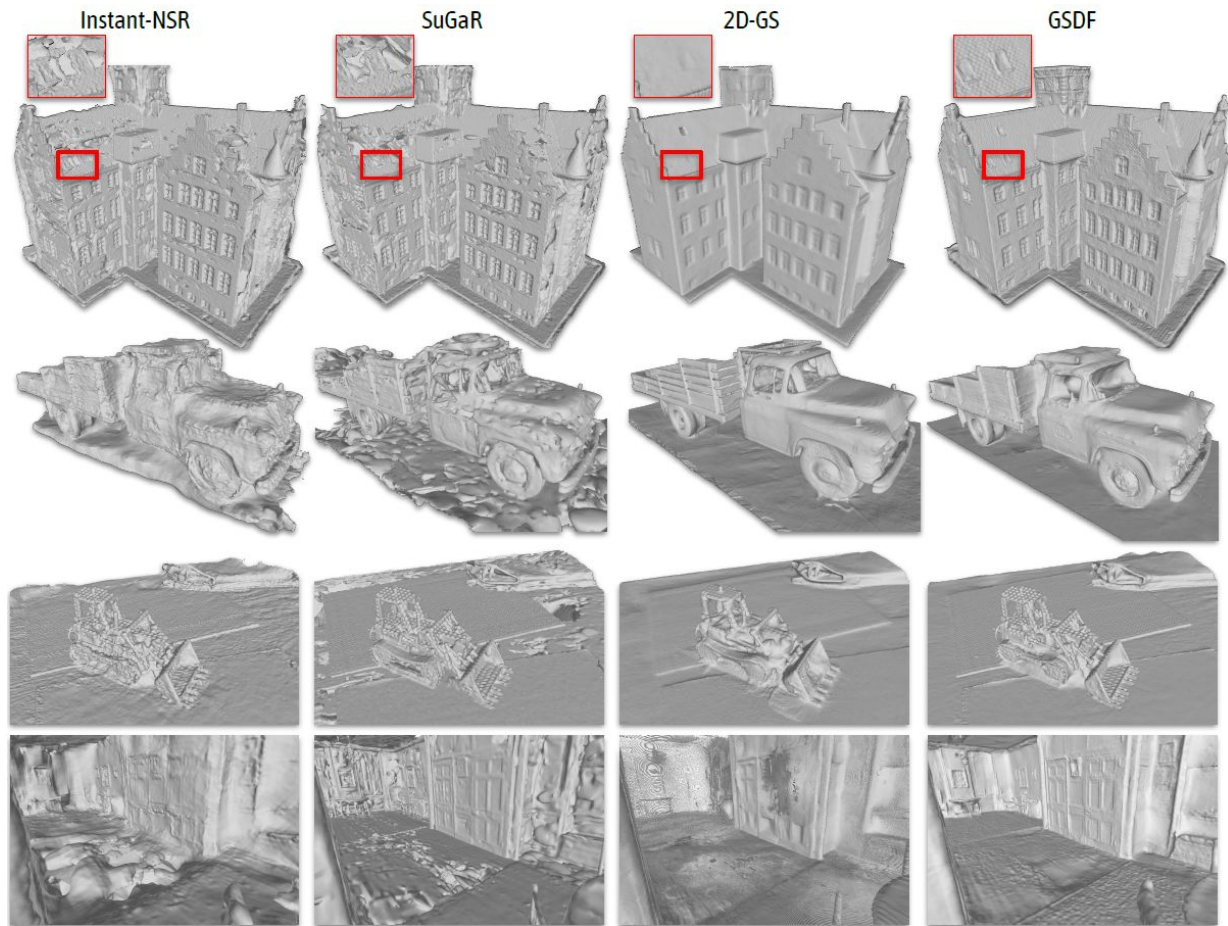




# Comparison - Random initialization



# Comparison



# Comparison



# Thanks!

<https://city-super.github.io/GSDF/>