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Rapid and Physically-Based Gaussian Splatting of Unknown Space Objects in Low Earth Orbit

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S2S **From Sea to Space** **Advancing Perception in Harsh Domains**

Introduction

Motivation

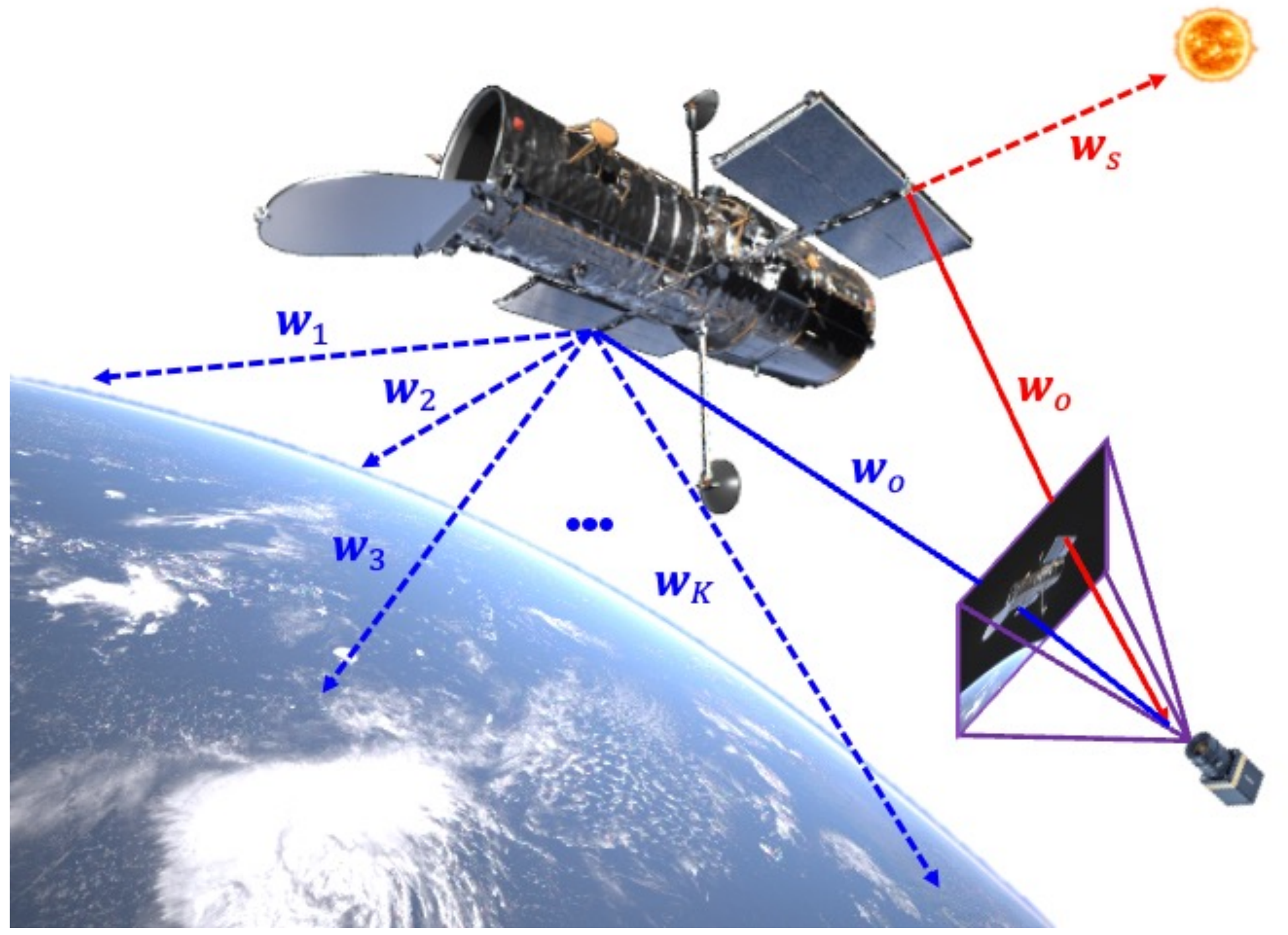
- Accurate Novel View Synthesis (NVS) and 3D reconstruction of unknown LEO targets require both geometric and photometric consistency under complex space illumination
- Existing NeRF [1] and Gaussian Splatting [2] approaches rely on static or simplified lighting assumptions, limiting realism and robustness in space environments

Contribution

- Physically-based 2D Gaussian Splatting [3] pipeline that explicitly models known Sun and Earth illumination in LEO
- BRDF-based deferred shading framework that enables efficient material-aware 3D reconstruction
- Supports realistic rendering of challenging appearance effects, including specular reflections and Earth-induced illumination

Overview

$$L_o(\boldsymbol{w}_o, \boldsymbol{x}) = V(\boldsymbol{x}) L_{\mathrm{S}} f(\boldsymbol{w}_{\mathrm{S}}, \boldsymbol{w}_o, \boldsymbol{x})(\boldsymbol{w}_{\mathrm{S}} \cdot \boldsymbol{n}) + \sum_{i \in S_L} L_{\mathrm{E}}(\boldsymbol{w}_i) f(\boldsymbol{w}_i, \boldsymbol{w}_o, \boldsymbol{x})(\boldsymbol{w}_i \cdot \boldsymbol{n}) \Delta\Omega$$



References

[1] B. Mildenhall, P. P. Srinivasan, M. Tancik, J. T. Barron, R. Ramamoorthi, and R. Ng, "NeRF: Representing scenes as neural radiance fields for view synthesis," *ECCV* (2020).
[2] B. Kerbl, G. Kopanas, T. Leimkuehler, and G. Drettakis, "3D gaussian splatting for real-time radiance field rendering," *ACM Trans. Graph.*, vol. 42, no. 4 (2023).
[3] B. Huang, Z. Yu, A. Chen, A. Geiger, and S. Gao, "2D gaussian splatting for geometrically accurate radiance fields," *ACM SIGGRAPH* (2024).
[4] S. Kheradmand, D. Rebain, G. Sharma, W. Sun, Y.-C. Tseng, H. Isack, A. Kar, A. Tagliasacchi, and K. M. Yi, "3d gaussian splatting as markov chain monte carlo," *Advances in Neural Information Processing Systems* (2024).
[5] T. H. Park and S. D'Amico, "Improved 3D gaussian splatting of unknown spacecraft structure using space environment illumination knowledge," *International Conference on Space Robotics* (2025).
[6] S. Velkei, C. Goldschmidt, and K. Vass. "A large-scale, physically-based synthetic dataset for satellite pose estimation," *arXiv preprint arXiv:2506.12782* (2025).

Methodology

Physically-Based Rendering

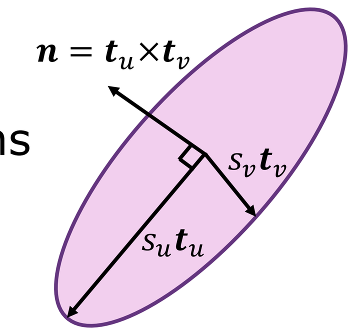
- Each Gaussian learns material parameters $\boldsymbol{a}$: albedo, ρ: roughness, m: metallicity
- Model outgoing radiance using rendering equation and analytical Disney principled BRDF

$$L_o(\boldsymbol{w}_o, \boldsymbol{x}) = \int_{\Omega_+} L_i(\boldsymbol{w}_i, \boldsymbol{x}) f(\boldsymbol{w}_i, \boldsymbol{w}_o, \boldsymbol{x})(\boldsymbol{w}_i \cdot \boldsymbol{n}) d\boldsymbol{w}_i$$

$$f(\boldsymbol{w}_i, \boldsymbol{w}_o, \boldsymbol{x}) = \frac{1-m}{\pi}\boldsymbol{a} + \frac{D(\boldsymbol{h})F(\boldsymbol{h}, \boldsymbol{w}_o)G(\boldsymbol{n}, \boldsymbol{w}_i, \boldsymbol{w}_o)}{4(\boldsymbol{w}_i \cdot \boldsymbol{n})(\boldsymbol{w}_o \cdot \boldsymbol{n})}$$

2D Gaussian Splatting

- Inherently defines normal vectors ($\boldsymbol{n}$)
- MCMC densification [4] to control # Gaussians



Leveraging Illumination Prior

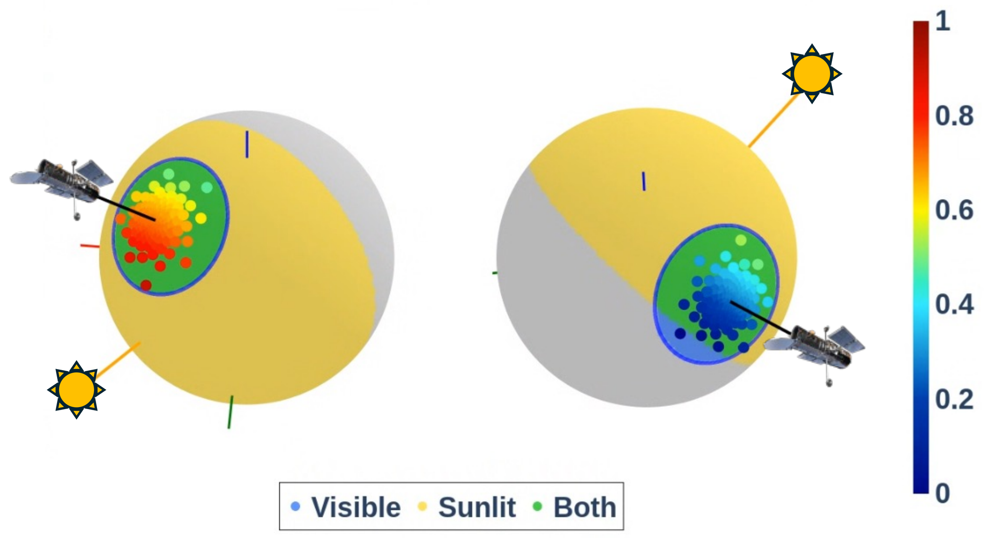
Decompose rendering equation into

- **Sun** as primary source at infinite distance
- **Earth** as secondary, predominantly diffuse source
- Shadow splatting for self-occlusion due to Sun

Both positions are assumed ***known*** from onboard AOCS

Incident Earth rays

- K rays computed via fixed Fibonacci sampling
- Radiance scales by $\max(0, \boldsymbol{w}_{\mathrm{S}} \cdot \boldsymbol{n}_i^{\mathrm{E}})$, i.e., dot product between Sun vector and outward normal at sample's surface location



Deferred Shading

- Rasterize material parameters ($\boldsymbol{a}$, ρ, m) via splatting, then evaluate BRDF per each pixel
- Custom CUDA implementation of fused BRDF for batched incoming radiance from the Earth surface

Key Optimization Objectives

- Since BRDF returns radiance, work directly with HDR data

$$\mathcal{L}_{\mathrm{HDR}}(\hat{\boldsymbol{L}}, \boldsymbol{L}) = \frac{\|\hat{\boldsymbol{L}} - \boldsymbol{L}\|_1}{\mathrm{sg}(\hat{\boldsymbol{L}}) + \varepsilon}$$

- Smoothness loss – ensure smoothness of materials (ρ, m) in homogeneous regions

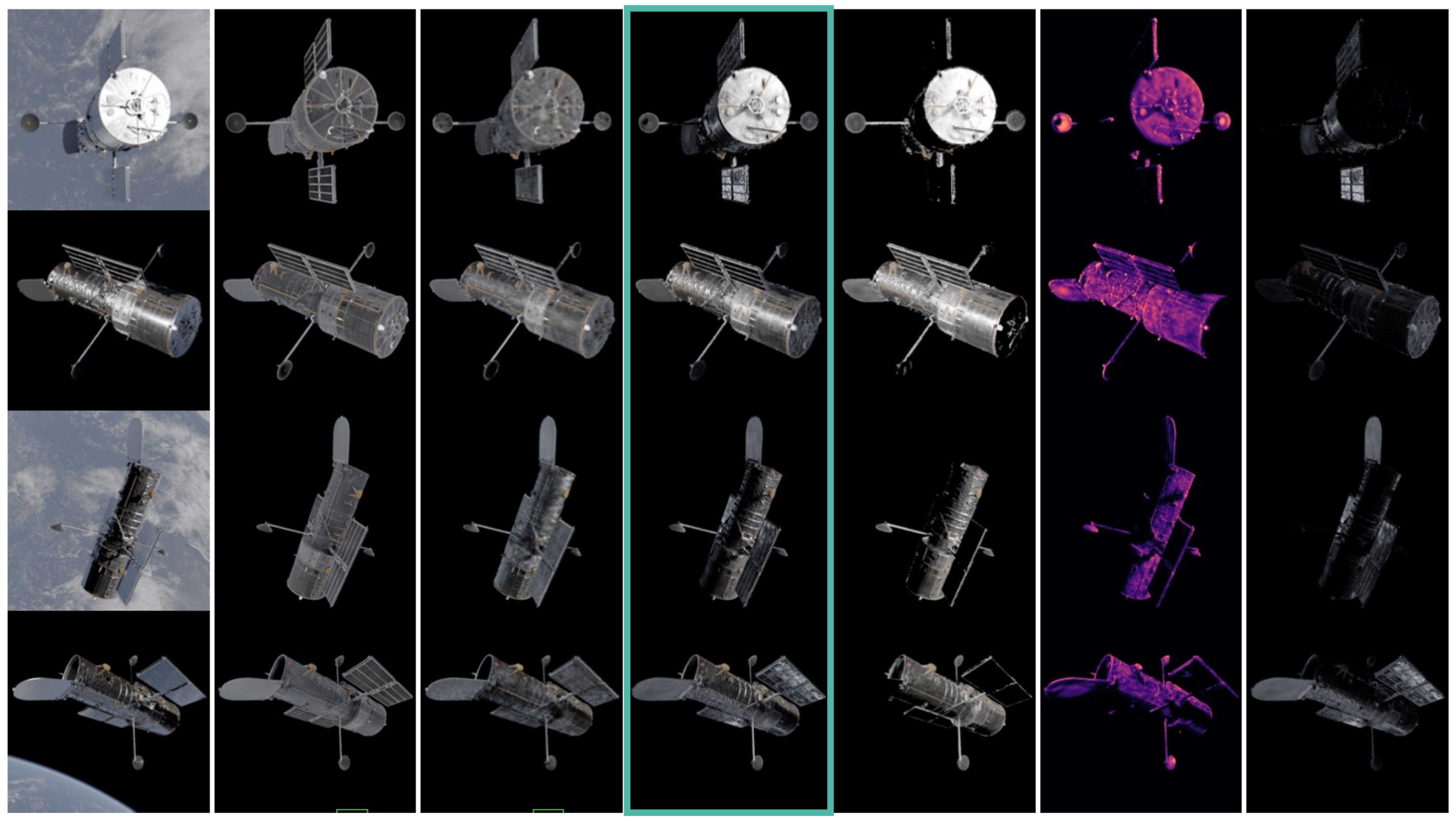
$$\mathcal{L}_{\mathrm{smooth}} = \sum_i \|\nabla\lambda(\boldsymbol{p}_i)\| \exp(-\|\nabla \boldsymbol{L}(\boldsymbol{p}_i)\|)$$

Experiments

Dataset & Training

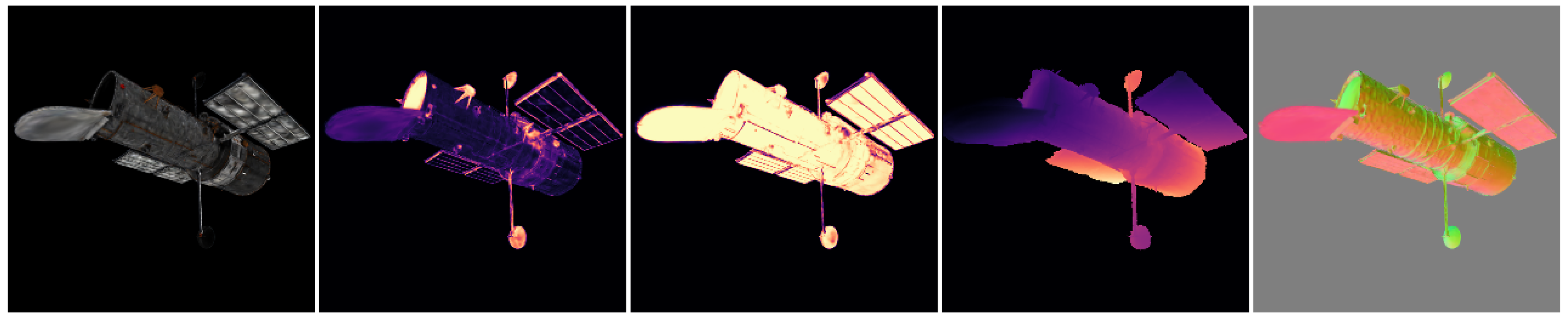
- Trained (1K images) and tested (100 images) on HDR images of the **DLVS³-HST** [6]
  - During evaluation, converted to LDR via μ-law (μ = 5,000)
- Trained for 20,000 steps with fixed number of Gaussians (250K) and $K = 16$

NVS Results



Ground-Truth | 3DGS [2, 4] | Park & D'Amico [5] | Ours | L_{sun} | Shadow (V) | L_{earth}

Material Decomposition



albedo | roughness | metallic | depth | normal

Ablation Studies

Config.	S	E	SSIM (↑)	PSNR (↑)	LPIPS (↓)	Train Time
3DGS [35]	✗	✗	0.9701	27.49	0.0230	3.5 min
Ref. [17]	✓	✗	0.9724	29.42	0.0238	7.2 min
Ours	✗	✗	0.9695	28.84	0.0254	6.5 min
Ours	✓	✗	0.9714	29.47	0.0252	8.1 min
Ours	✗	✓	0.9741	30.56	0.0217	6.9 min
Ours	✓	✓	**0.9763**	**31.51**	**0.0212**	9.0 min

S: Shadow splatting. **E**: Earth albedo sampling.

- Modeling Earth albedo significantly improves performance
- Diminishing return w.r.t. computation as more rays are used with BRDF