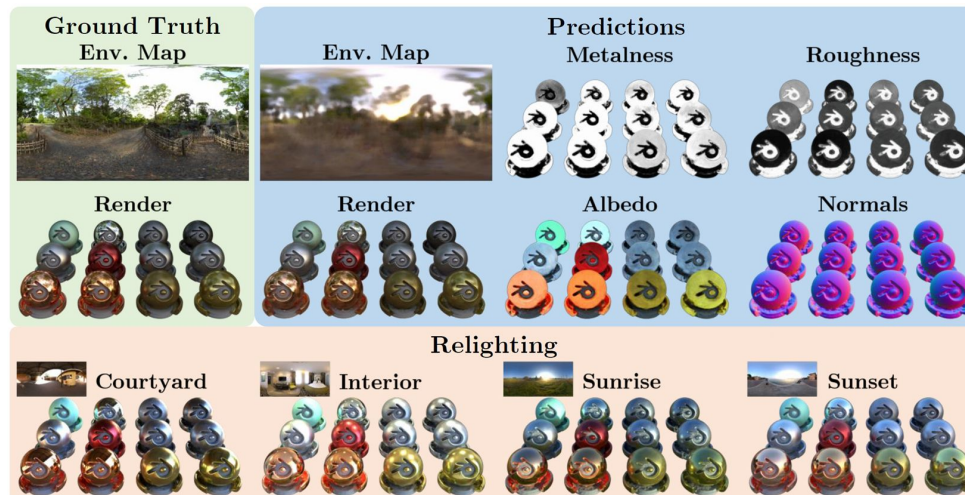


SplitNeRF: Split Sum Approximation Neural Field for Joint Geometry, Illumination, and Material Estimation

Jesus Zarzar, Bernard Ghanem



Introduction

Object Views

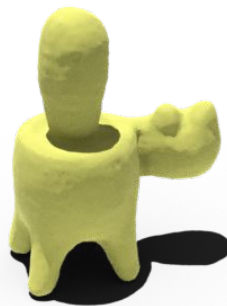


Introduction

Object Views



Geometry

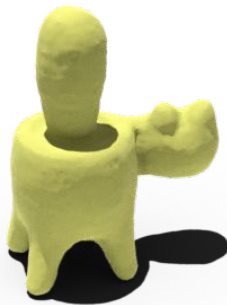


Introduction

Object Views



Geometry



Material Properties

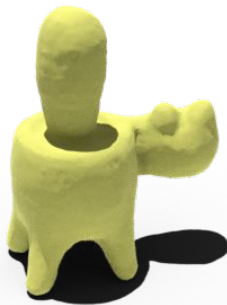


Introduction

Object Views



Geometry



Material Properties



Illumination



Introduction

Object Views

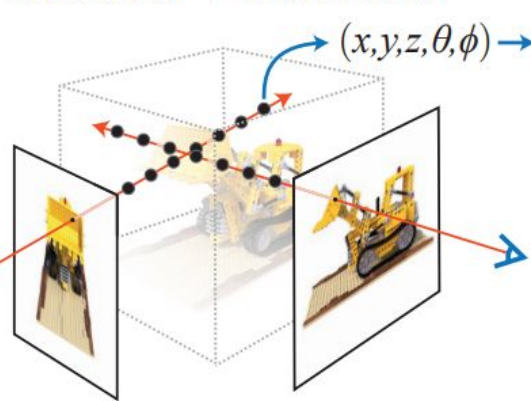


Relighting



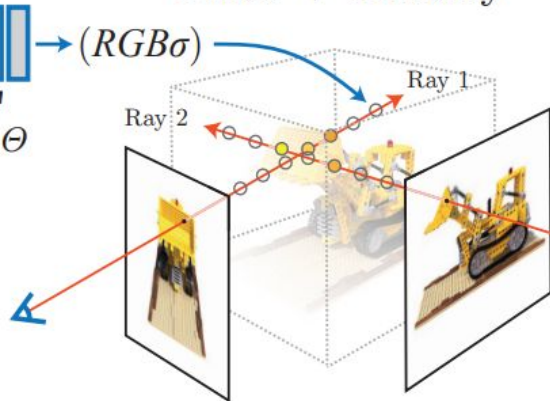
Background: NeRF

5D Input
Position + Direction



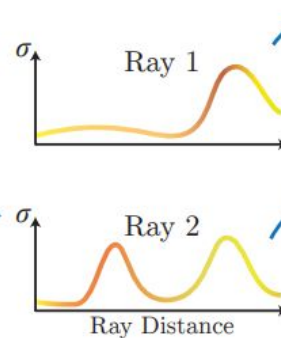
$(x, y, z, \theta, \phi) \rightarrow F_{\theta}$

Output
Color + Density



$(RGB\sigma)$

Volume
Rendering



Rendering
Loss

$$\| \text{Color} - \text{g.t.} \|_2^2$$

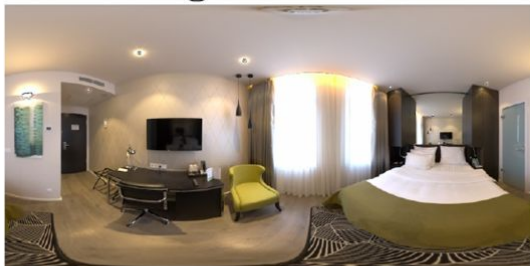
$$\| \text{Color} - \text{g.t.} \|_2^2$$

$$\hat{C}(\mathbf{r}; \theta) = \int_{t_n}^{t_f} T(t) \sigma(\mathbf{r}(t)) \hat{L}_o(\mathbf{r}(t), \mathbf{d}) dt, \quad \text{where } T(t) = \exp\left(-\int_{t_n}^t \sigma(\mathbf{r}(s)) ds\right).$$

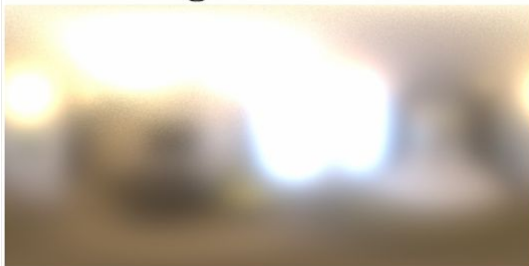
Background: PBR Shading

Split-Sum Approximation with Image-Based Lighting

Roughness = 0.0



Roughness = 0.5



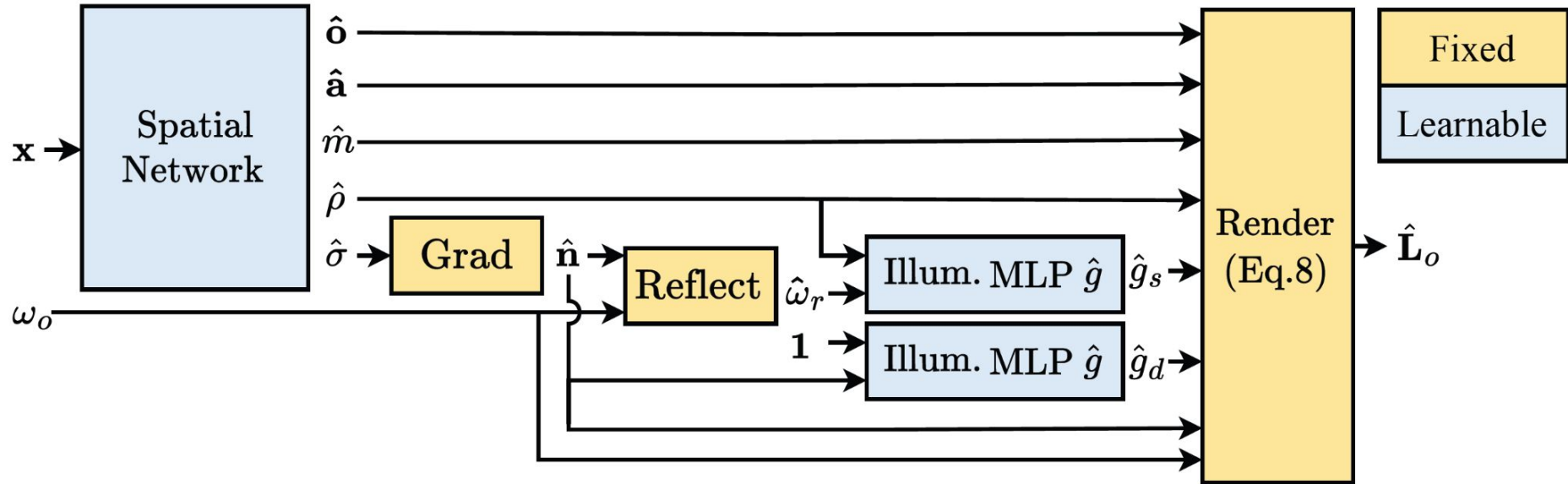
Roughness = 1.0



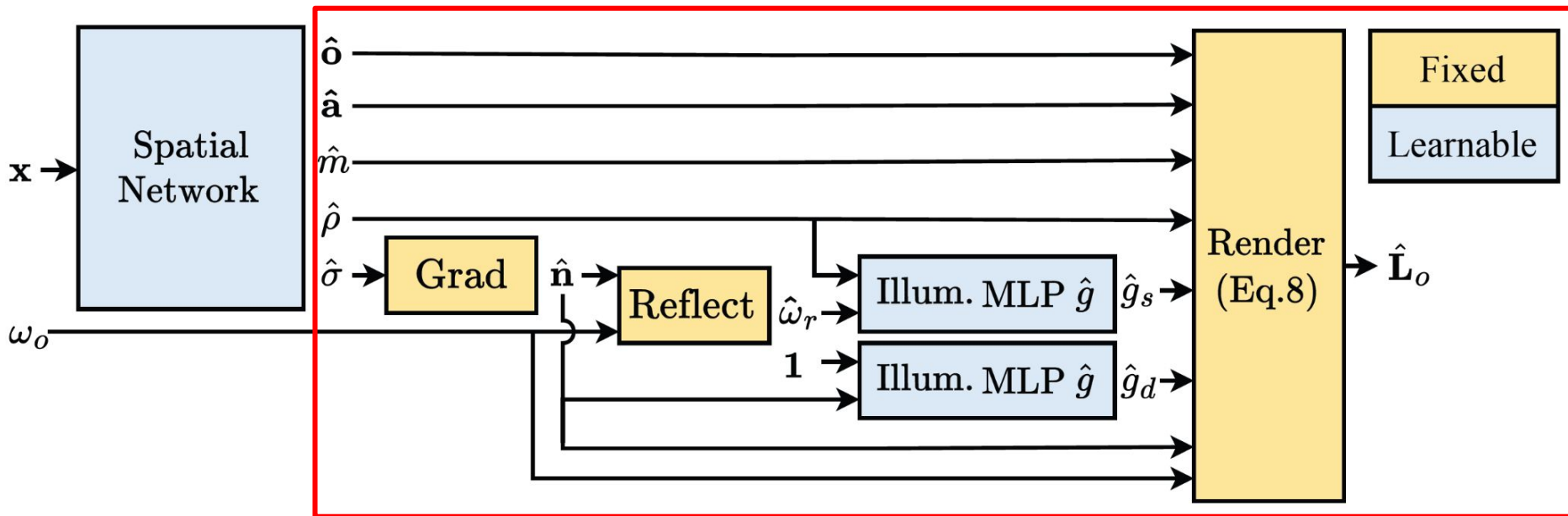
Contributions

1. A novel **MLP representation** for pre-integrated illumination regularized to be **physically accurate**.
2. **Self-occlusion approximation** for pre-integrated lighting with an additional MLP to improve material estimation.
3. Competitive **reconstruction and relighting quality** on both synthetic and **real data** with **~1 GPU-hour** training time.

Method: Pipeline

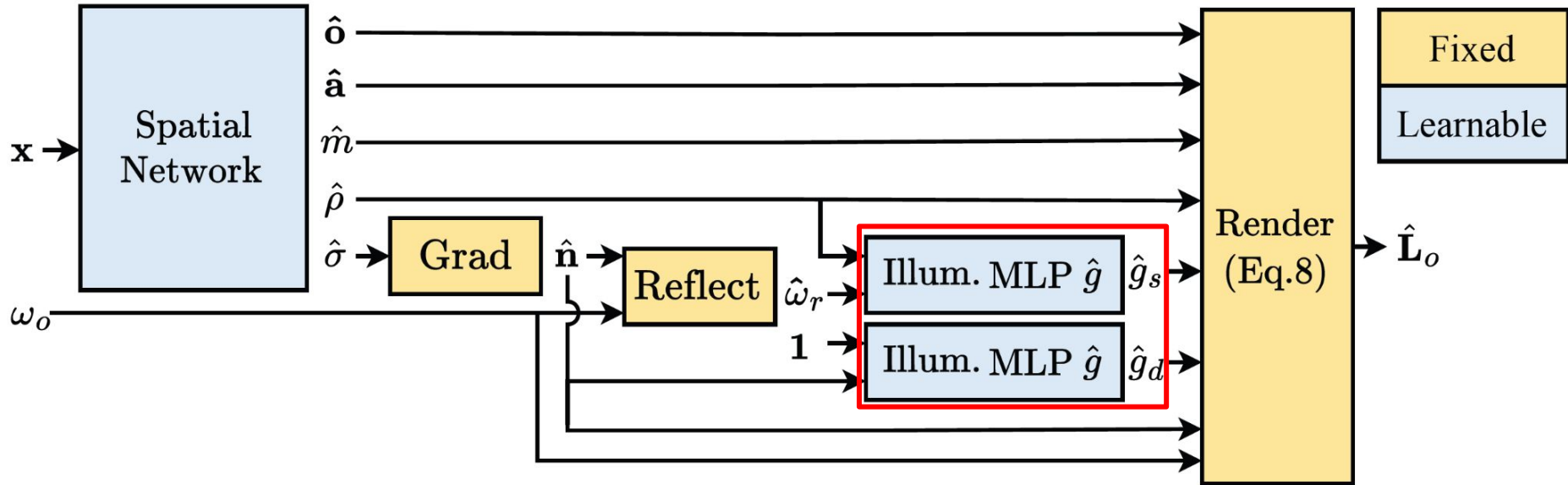


Method: Pipeline



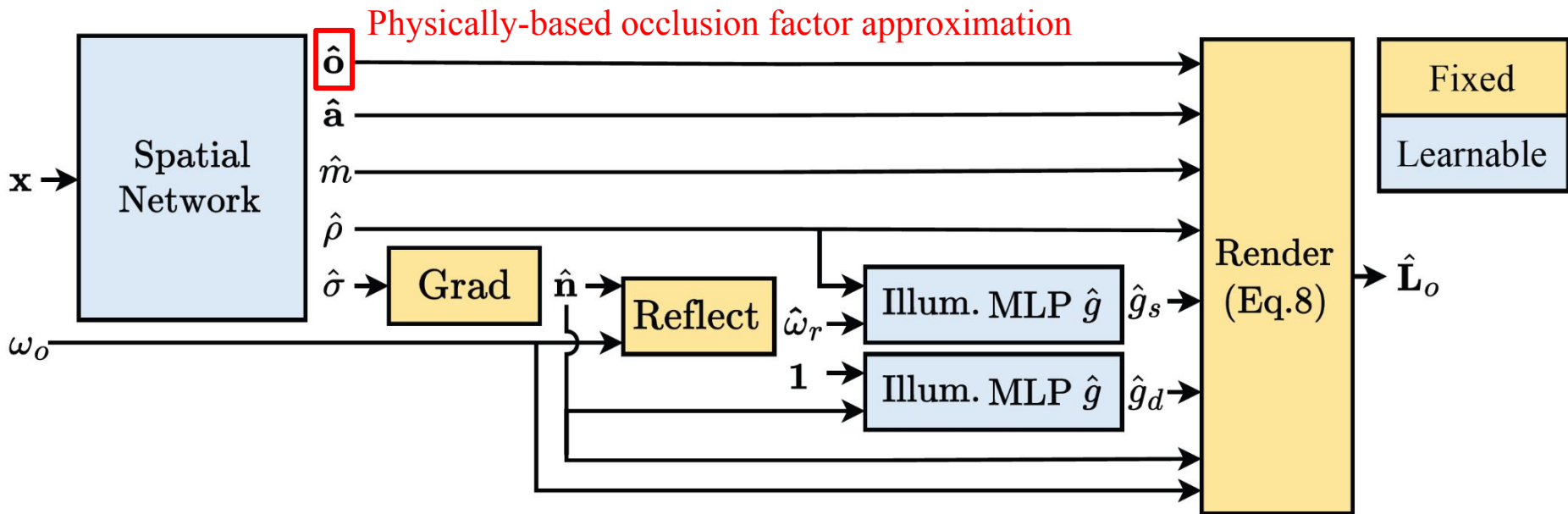
Physically-based radiance prediction

Method: Pipeline



Shared pre-integrated illumination network

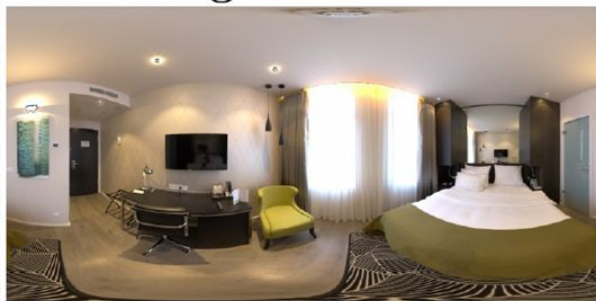
Method: Pipeline



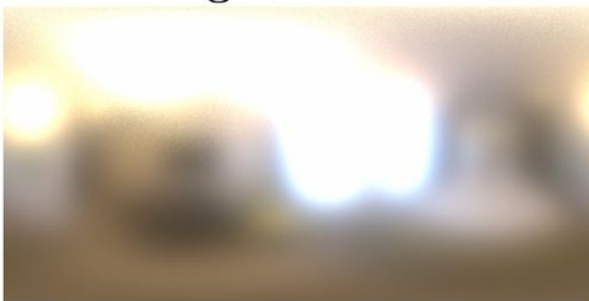
Method: MLP Illumination

Ground Truth

Roughness = 0.0



Roughness = 0.5



Roughness = 1.0



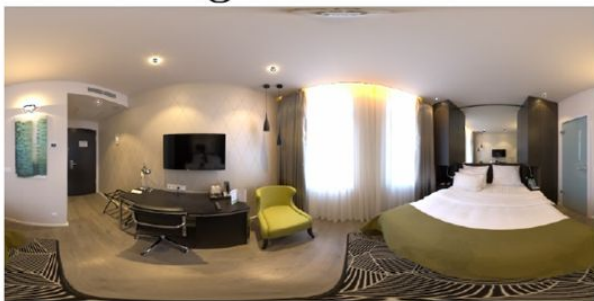
Ours



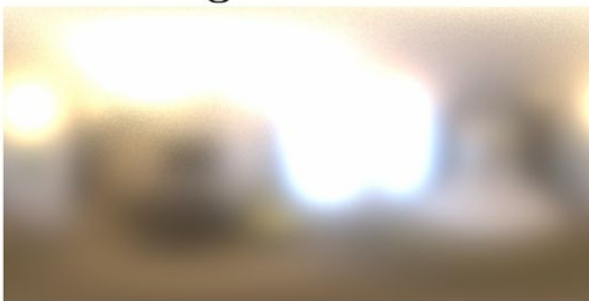
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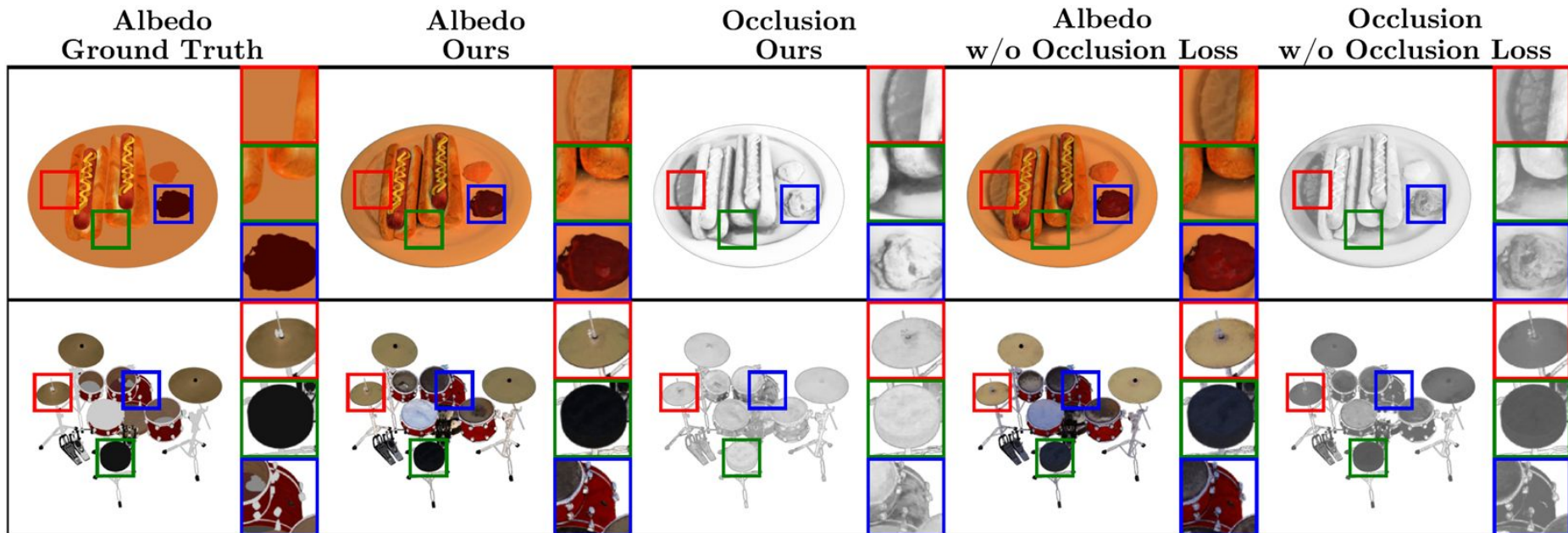


Ours



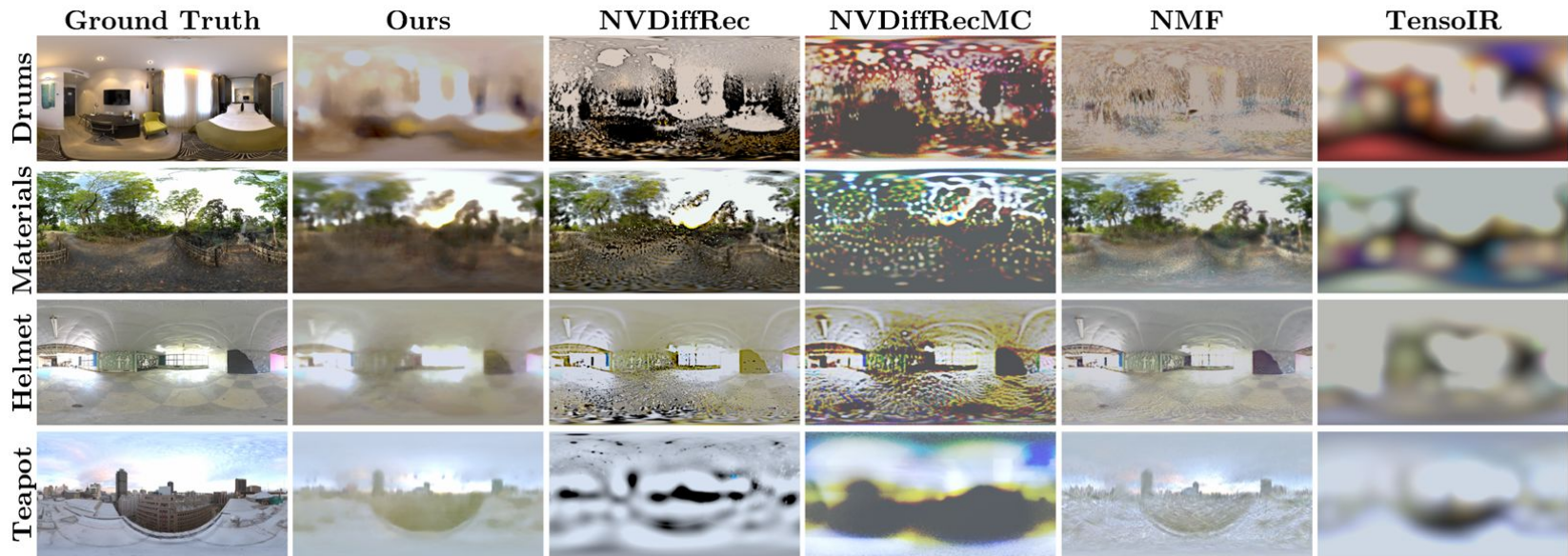
$$\mathcal{L}_D(\theta) = \frac{1}{|S|} \sum_{s \in S} |\hat{g}(s) - \bar{g}(s)|_2^2, \quad \bar{g}(s) = \frac{\sum_{\omega_i \in \Omega} D(\omega_i, \omega_s, \rho_s) \hat{g}(\omega_i, 0) \langle \omega_i, \omega_s \rangle}{\sum_{\omega_i \in \Omega} D(\omega_i, \omega_s, \rho_s) \langle \omega_i, \omega_s \rangle}$$

Method: Self-Occlusion Approximation



$$\mathcal{L}_o(\theta) = \frac{1}{|\mathcal{X}|} \sum_{x \in \mathcal{X}} w |\hat{o}(x) - \bar{o}(x)|_2^2, \quad \bar{o}_d(x) = \frac{\sum_{\omega_i \in \Omega} L_i V_i}{\sum_{\omega_i \in \Omega} L_i}, \quad \bar{o}_s(x) = \frac{\sum_{\omega_i \in \Omega} L_i V_i \langle \omega_i, n \rangle}{\sum_{\omega_i \in \Omega} L_i \langle \omega_i, n \rangle}$$

Results: Illumination Estimation



- Predicted illumination for our method and baselines for four different scenes.
- Our representation inherits **smoothness** from the MLP but still captures **high-frequency details** such as indoor objects, trees, and buildings.

Results: Real-Life Object Reconstruction



- Predictions on four scenes from the **real-life** CO3D dataset.
- Our method can successfully recover object geometry, material properties, and illumination for challenging scenes captured in the wild.

Results: Real-Life Object Reconstruction

Method	Normals	Albedo			Relighting			Average
	MAE ↓	PSNR ↑	SSIM ↑	LPIPS ↓	PSNR ↑	SSIM ↑	LPIPS ↓	Runtime
NerFactor	30.49	23.53	0.910	0.109	23.66	0.895	0.120	>20 hr.
NVDiffRec	26.47	23.05	0.901	0.123	21.88	0.880	0.111	0.98 hr.
NVDiffRecMC	25.98	23.84	0.918	0.114	24.06	0.902	0.099	2.95 hr.
NeRO	30.59	22.83	0.897	0.117	23.68	0.907	0.093	18.38 hr.
NMF	24.14	-	-	-	22.23	0.895	0.093	2.91 hr.
TensorIR	22.90	25.21	0.929	0.087	23.78	0.907	0.100	3.53 hr.
Ours	17.52	25.29	0.924	0.108	27.31	0.941	0.061	0.81 hr.

- Reconstruction and relighting quality of our method vs. baselines on the NerFactor dataset.
- Our method attains **competitive performances** across all metrics with the **lowest runtime**

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