

# SC-OmniGS: Self-Calibrating Omnidirectional Gaussian Splatting

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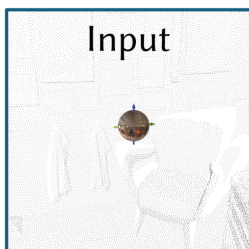
<sup>1</sup>The Hong Kong University of Science and Technology

<sup>2</sup>Sun Yat-sen University

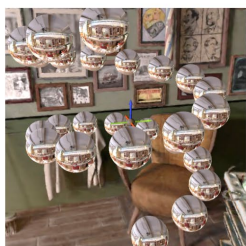
<sup>3</sup>ICT, University of Southern California

\* Equal Contribution

Homepage : <https://www.chenyingshu.com/sc-omnigs/>



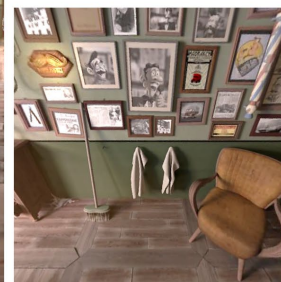
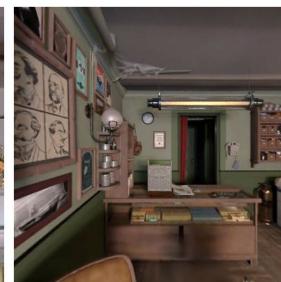
SC-OmniGS



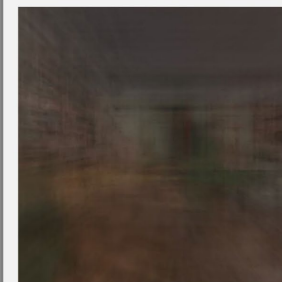
Side view



Center view with training camera visualization



Other novel views



w/o calibration

# Motivation

## ***Robust omnidirectional radiance field reconstruction***

is challenging due to:

1. Non-ideal camera model

360° Capturing



Sparse and wide-baseline  
360° image dataset [1]

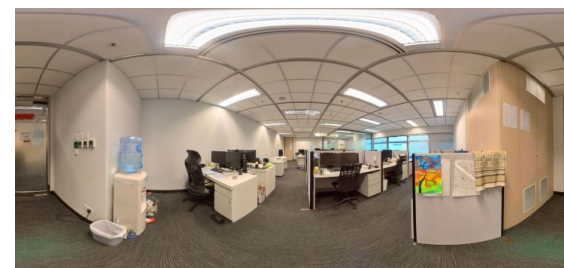


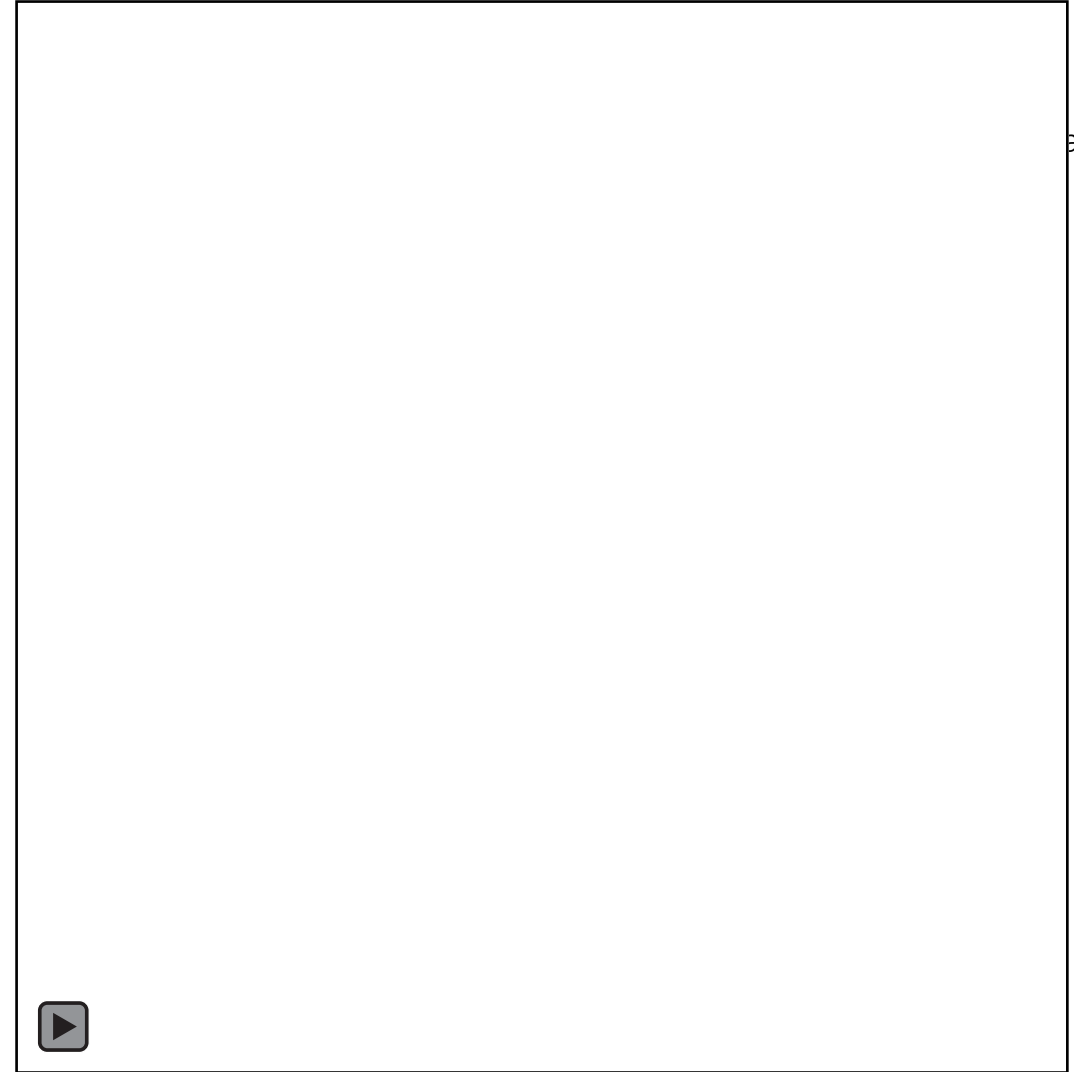
Image distortion

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2. Reliance on camera estimation,  
e.g., structure from motion (SfM)



CamP [2] adds joint camera optimization to NeRF training

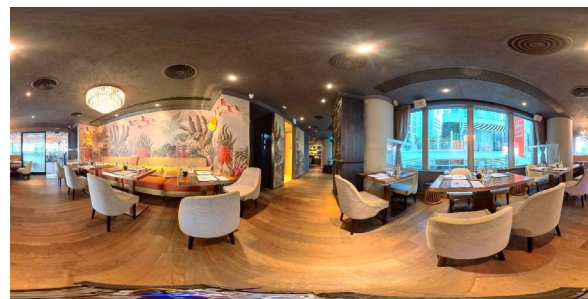


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equirectangular  
to cube map



6 perspective  
images



SC-OmniGS (Ours)



Naïve solution:  
cube map + calibration [3]

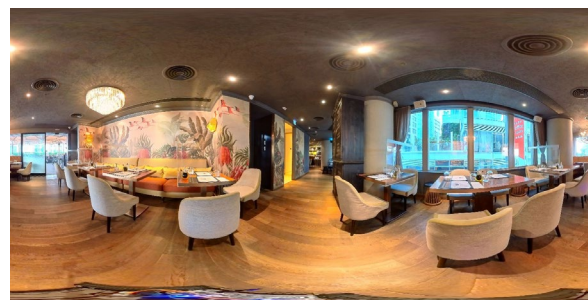


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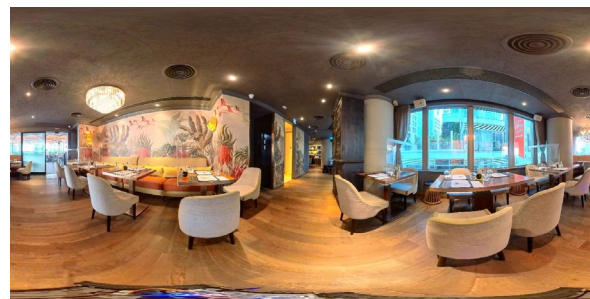
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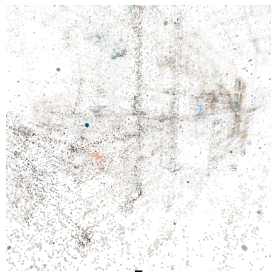
SC-OmniGS (Ours)



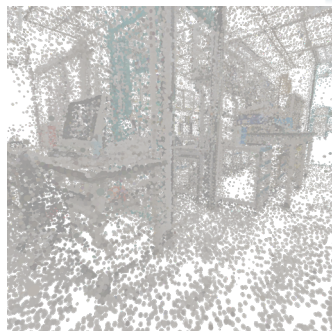
Naïve solution:  
cube map + calibration [3]

# Methodology: Overview of SC-OmniGS Optimization Flow

Initialization with  
coarse/random points




3D Gaussians 



Differentiable  
Omnidirectional  
Rasterizer




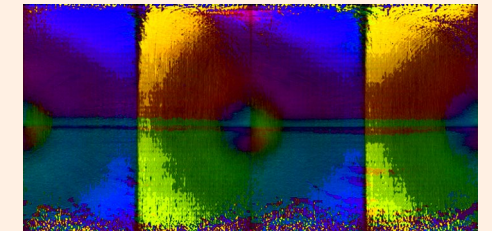
Camera  
Poses 





Omnidirectional  
Image Input




Differentiable  
Omnidirectional Camera Model 



Forward Flow 

Backward Flow 

Trainable 

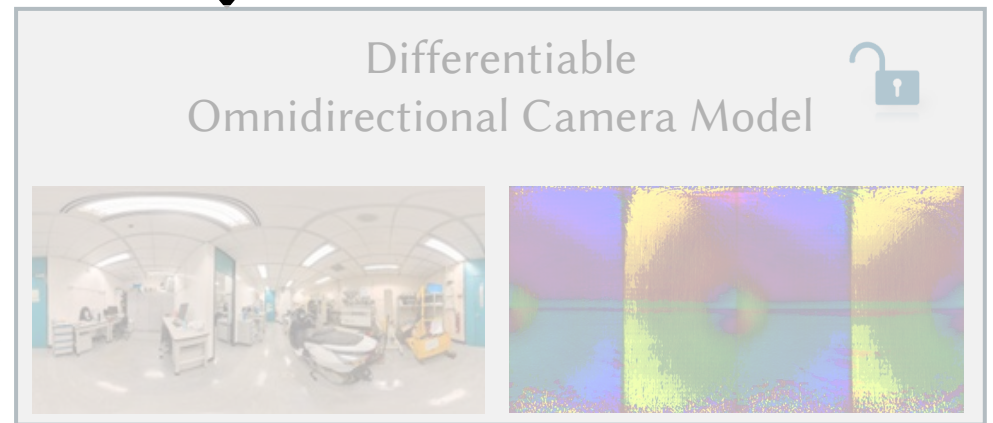
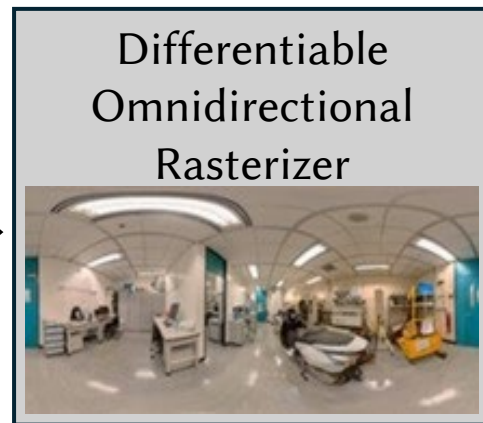
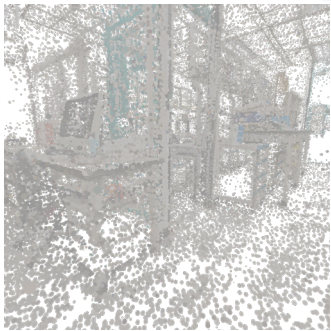


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3D Gaussians



Omnidirectional  
Image Input



Forward Flow →  
Backward Flow →  
Trainable 🔓

$\mathcal{L}$

# Methodology: Gradients of Omnidirectional Camera Pose

## Omnidirectional Gaussian Splatting (OmniGS)[4]

- Equirectangular projection  $\phi^o$ :

$$\mathbf{u} = \phi^o(\mathbf{x}) = \begin{bmatrix} f_x^o \cdot \arctan2(x, z) + c_x^o \\ f_y^o \cdot \arcsin(y/d) + c_y^o \end{bmatrix} = \begin{bmatrix} \frac{W}{2\pi} \cdot \arctan2(x, z) + \frac{W}{2} \\ \frac{H}{\pi} \cdot \arcsin(y/d) + \frac{H}{2} \end{bmatrix}$$

- Rendered color of pixel  $\mathbf{u}$  in an omnidirectional image:

$$\mathbf{C}^o(\mathbf{u}) = \sum_{i \in \mathcal{N}} c_i \alpha_i^o \prod_{j=1}^{i-1} (1 - \alpha_j^o), \quad \alpha_j^o = \sigma_j \cdot \mathbf{r}_{2D}^o(\mathbf{u})$$

↓ derivation

## Gradients of camera pose $\mathbf{T}$ :

Part 1:  $\frac{\partial c}{\partial \mathbf{T}'} = \frac{\partial c}{\partial dir} \cdot \frac{\partial dir}{\partial \mathbf{T}'} = \frac{\partial c}{\partial dir} \cdot \left[ \frac{\partial dir}{\partial \mathbf{R}} \cdot \frac{\partial \mathbf{R}}{\partial \mathbf{q}} \quad \frac{\partial dir}{\partial \mathbf{t}} \right]$

Part 2:  $\frac{\partial \mathbf{r}_{2D}^o}{\partial \mathbf{T}'} = \left[ \frac{\partial \mathbf{r}_{2D}^o}{\partial \mathbf{u}_i} \cdot \frac{\partial \mathbf{u}_i}{\partial \mathbf{T}'} \quad \frac{\partial \mathbf{r}_{2D}^o}{\partial \mathbf{J}_i^o} \cdot \frac{\partial \mathbf{J}_i^o}{\partial \mathbf{T}'} \quad \frac{\partial \mathbf{r}_{2D}^o}{\partial \mathbf{R}} \cdot \frac{\partial \mathbf{R}}{\partial \mathbf{T}'} \right] = \left[ \frac{\partial \mathbf{r}_{2D}^o}{\partial \mathbf{u}_i} \cdot \frac{\partial \mathbf{u}_i}{\partial \mathbf{x}_i}, \quad \frac{\partial \mathbf{r}_{2D}^o}{\partial \mathbf{J}_i^o} \cdot \frac{\partial \mathbf{J}_i^o}{\partial \mathbf{x}_i} \right] \cdot \left[ \frac{\partial \mathbf{x}_i}{\partial \mathbf{R}} \cdot \frac{\partial \mathbf{R}}{\partial \mathbf{q}}, \quad \frac{\partial \mathbf{x}_i}{\partial \mathbf{t}} \right] + \frac{\partial \mathbf{r}_{2D}^o}{\partial \mathbf{R}} \cdot \frac{\partial \mathbf{R}}{\partial \mathbf{q}}$

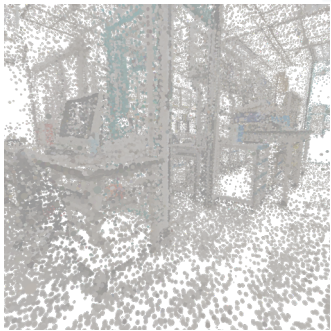


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coarse/random points



3D Gaussians



Differentiable  
Omnidirectional  
Rasterizer



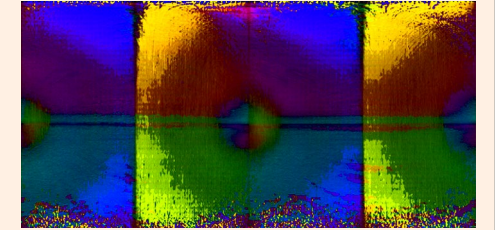
Camera  
Poses

$\mathcal{L}$

Omnidirectional  
Image Input



Differentiable  
Omnidirectional Camera Model



Forward Flow →  
Backward Flow ⇐  
Trainable 🔓





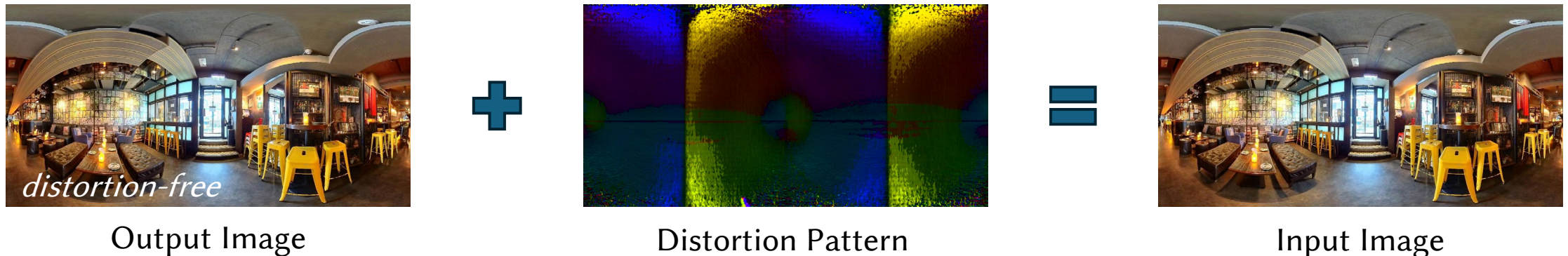
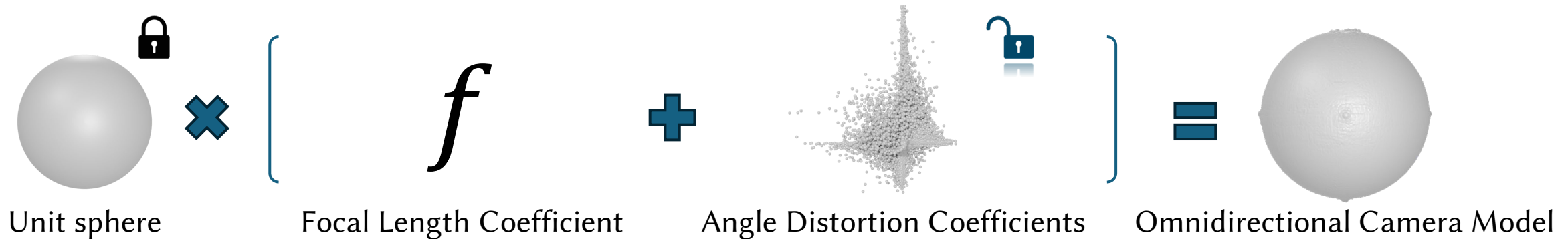
# Methodology: Differentiable Omnidirectional Camera Model

- The **generic** omnidirectional camera model  $\Theta$  is defined as:

$$\Theta := S \cdot f_t + S \odot D.$$

$S \in \mathbb{R}^{H \times W \times 3}$  is a spherical grid; angle distortion coefficients  $D \in \mathbb{R}^{H \times W \times 3}$  are initialized to zeros; for simplicity, we fix focal length coefficient  $f_t$  to 1.

Frozen   
Trainable 



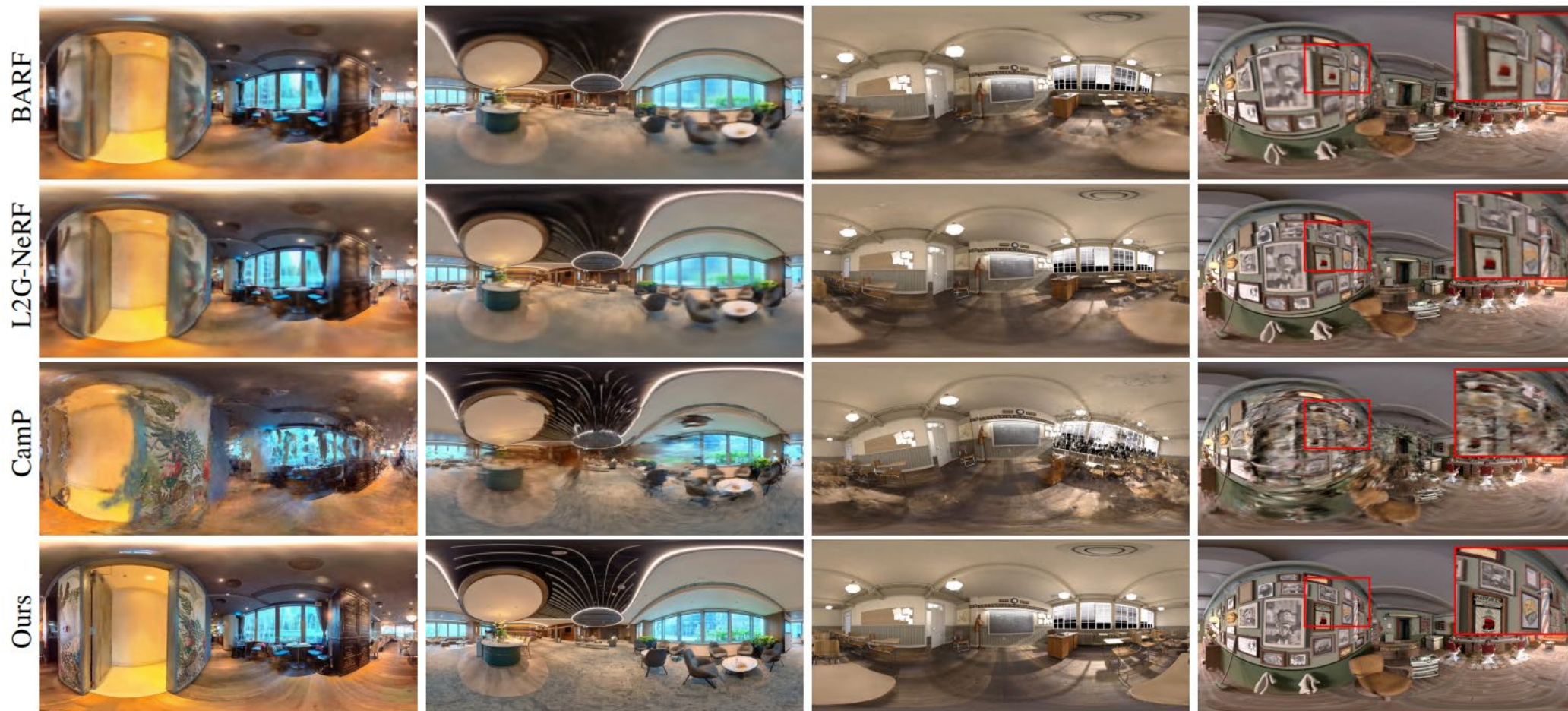
# Result Comparisons

**Quantitative comparisons** on real-world dataset 360Roam. “Perturb” indicates perturbed camera poses as inputs, “train” and “test” indicate training and test views, respectively. We mark the best two results with **first** and **second**.

	On 360Roam	Perturb	train			test			Input images
			PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓	
Calibration Non-calibration methods	3D-GS [20]	×	23.943	0.744	0.223	20.791	0.684	0.261	Perspective images
	OmniGS [22]	×	28.517	0.861	<b>0.137</b>	24.212	0.768	<b>0.176</b>	360-degree images
	OmniGS [22]	✓	22.111	0.705	0.334	15.619	0.455	0.489	
	BARF [23]	✓	21.699	0.594	0.465	20.200	0.572	0.481	Perspective images
	L2G-NeRF [8]	✓	21.797	0.598	0.460	20.507	0.576	0.473	
	CamP [28]	✓	24.592	0.735	0.264	14.253	0.438	0.573	
	SC-OmniGS (Ours)	✓	<b>29.232</b>	<b>0.872</b>	0.147	<b>24.910</b>	<b>0.790</b>	0.188	360-degree images



# Result Comparisons



(a) Canteen

(b) Innovation

(c) Classroom<sup>†</sup>

(d) Barbershop<sup>†</sup>

**Qualitative comparisons** of 360-degree novel views among calibration methods. Our results outperform in both rendering quality and camera accuracy. <sup>†</sup> indicates training from scratch without camera priors.



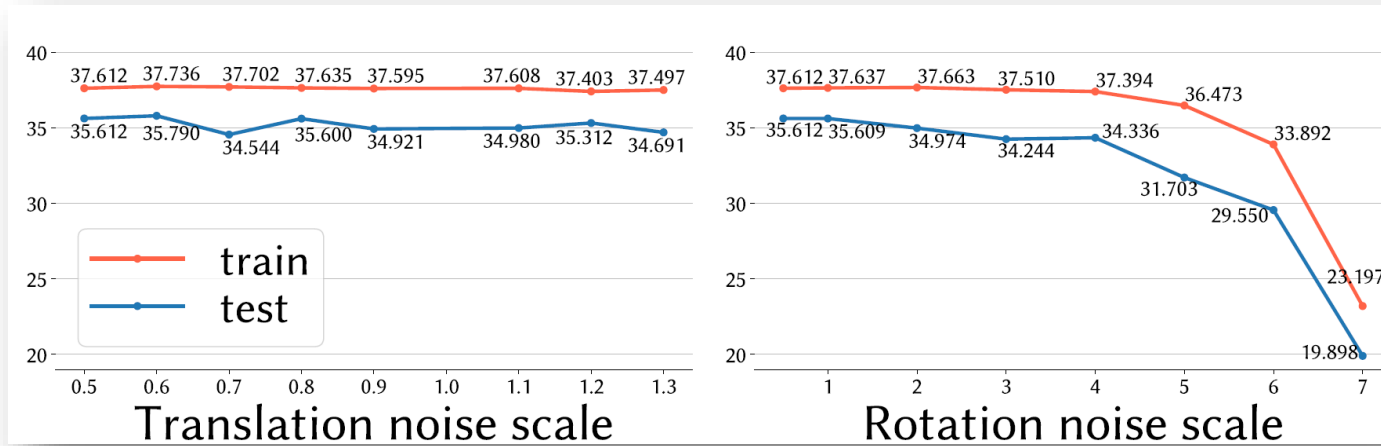
# Ablation Study

**Ablation study** on real scene **Center** of 360Roam, in terms of the optimization of camera model, camera pose, or both. “Perturb” indicates perturbed camera poses, “train” and “test” indicate training and test views, respectively. We mark the best two results with **first** and **second**.

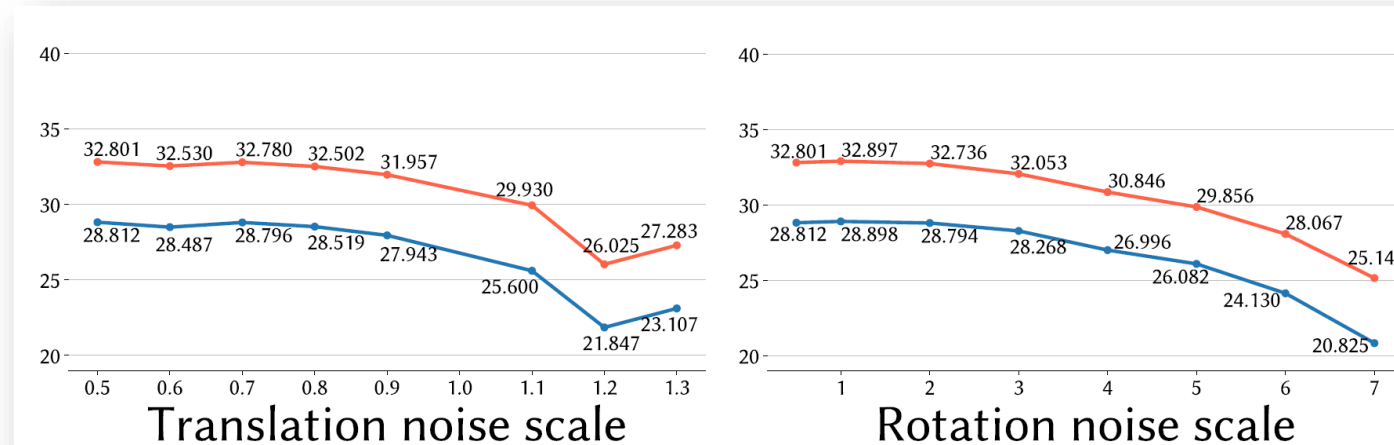
Calibration	w/o Perturb						w/ Perturb					
	train			test			train			test		
	PSNR $\uparrow$	SSIM $\uparrow$	LPIPS $\downarrow$	PSNR $\uparrow$	SSIM $\uparrow$	LPIPS $\downarrow$	PSNR $\uparrow$	SSIM $\uparrow$	LPIPS $\downarrow$	PSNR $\uparrow$	SSIM $\uparrow$	LPIPS $\downarrow$
none	28.728	0.848	0.170	24.264	0.763	0.213	22.740	0.717	0.372	15.597	0.510	0.553
+camera model	<b>30.230</b>	<b>0.877</b>	<b>0.153</b>	25.123	0.795	<b>0.195</b>	22.743	0.730	0.408	15.702	0.543	0.568
+pose	28.334	0.837	0.191	24.906	0.781	0.224	28.130	0.834	0.198	24.739	0.777	0.233
+camera model+pose	30.035	0.872	0.169	<b>25.802</b>	<b>0.813</b>	0.203	<b>29.706</b>	<b>0.867</b>	<b>0.177</b>	<b>25.304</b>	<b>0.799</b>	<b>0.220</b>

360-degree real-scene data:  
Imperfect camera model exhibits distortion

(a) Synthetic scene

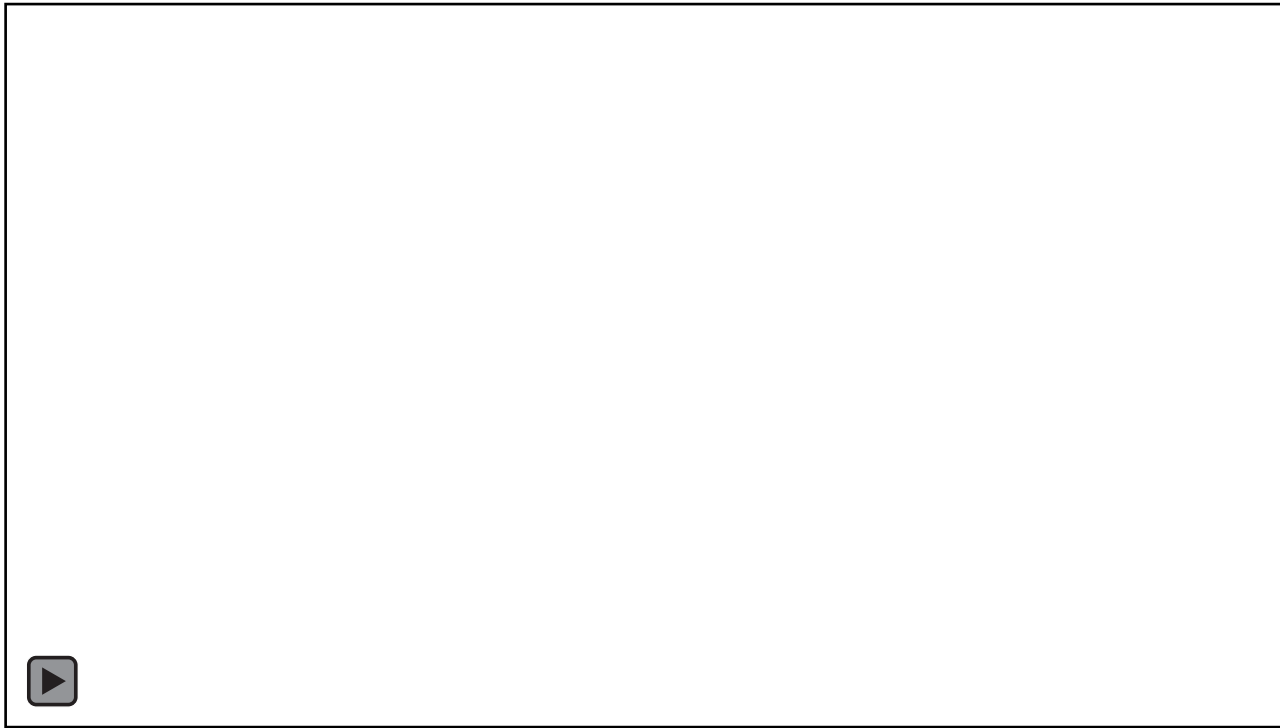


(b) Real world scene

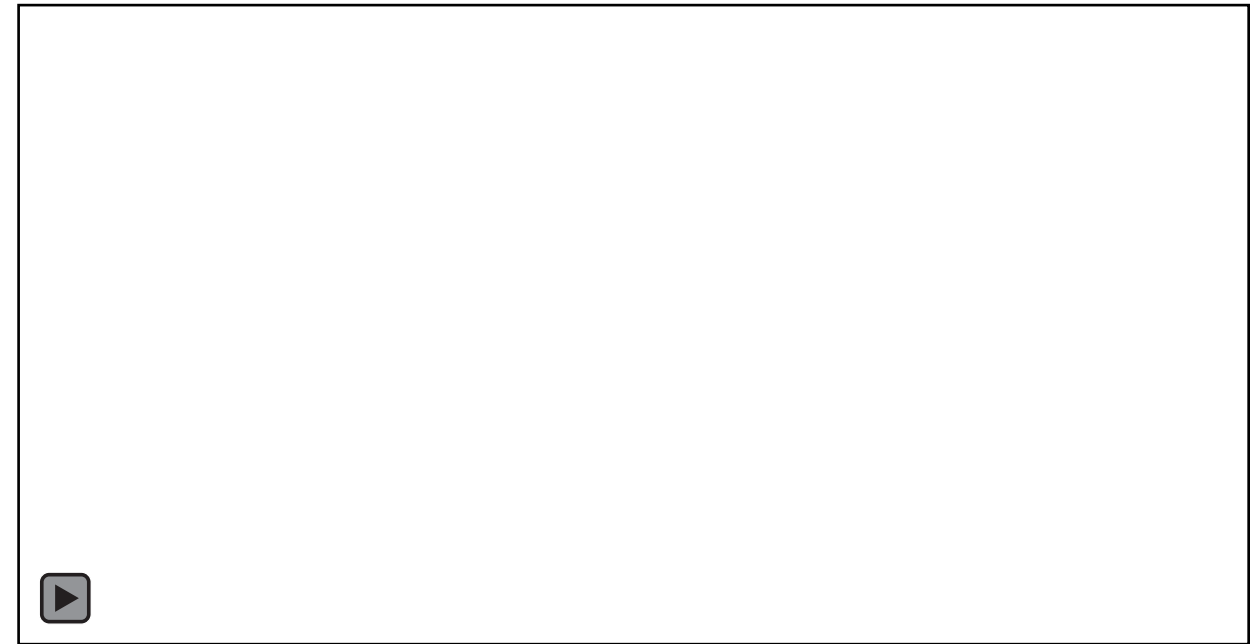


Robustness with different level camera perturbations (PSNR $\uparrow$ ).

# Ablation Study – real-time rendering comparisons



Perspective novel views



Omnidirectional novel views



Thank You