CRAYM:Neural Field Optimization via Camera RAY Matching

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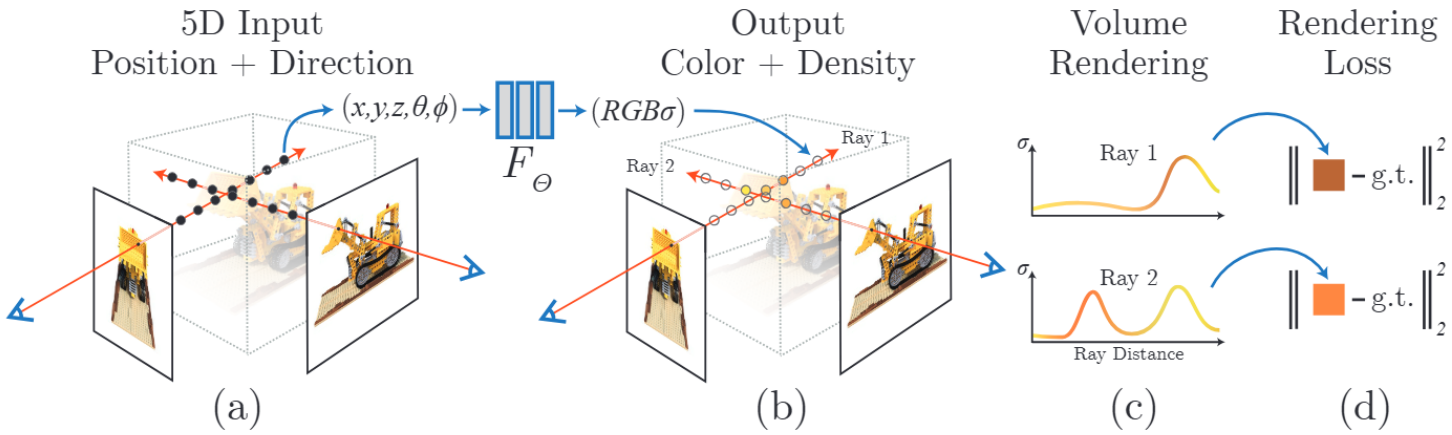
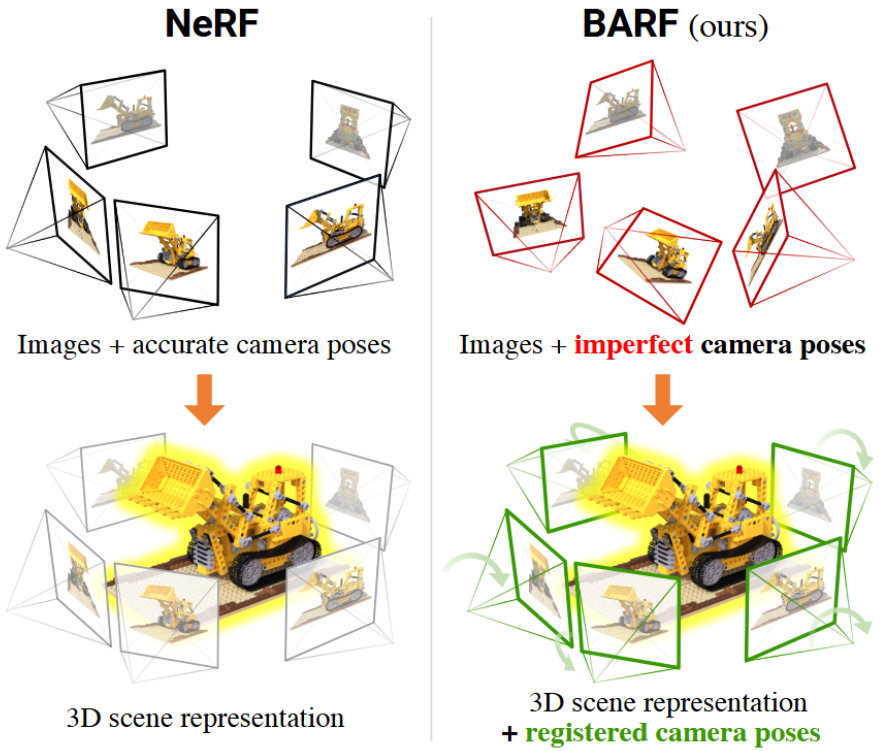
Introduction

Background

The established or obtained camera poses can be noisy

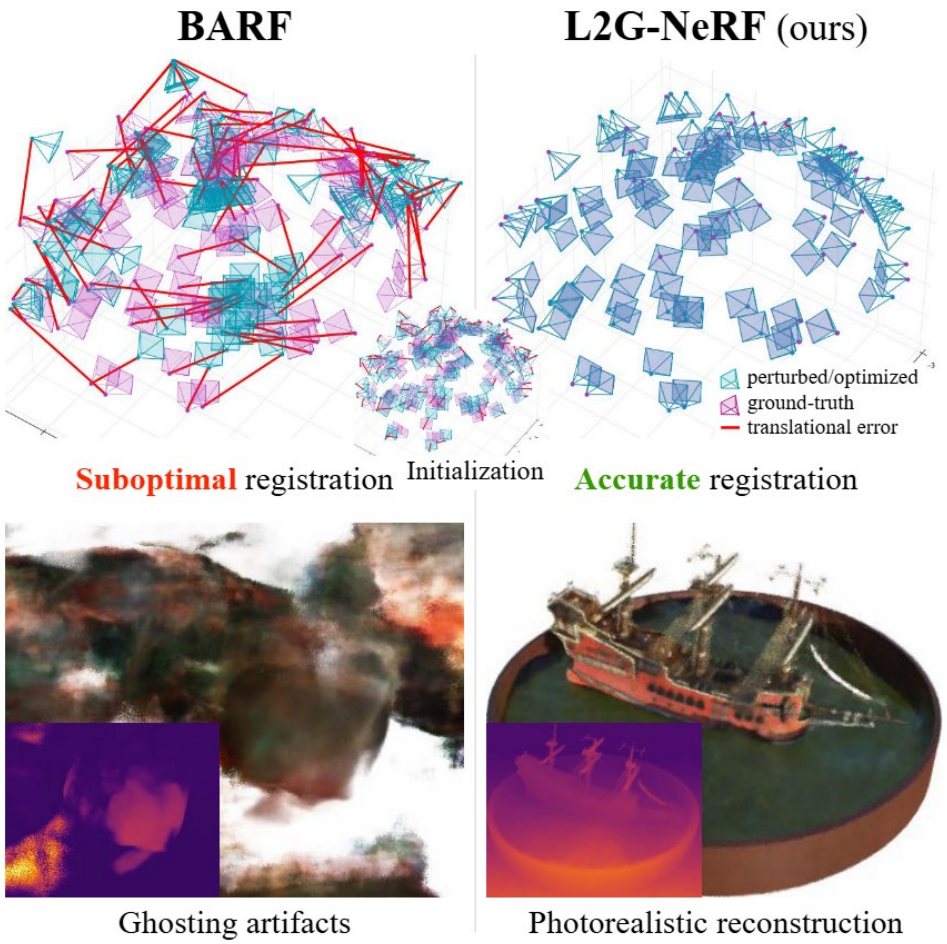




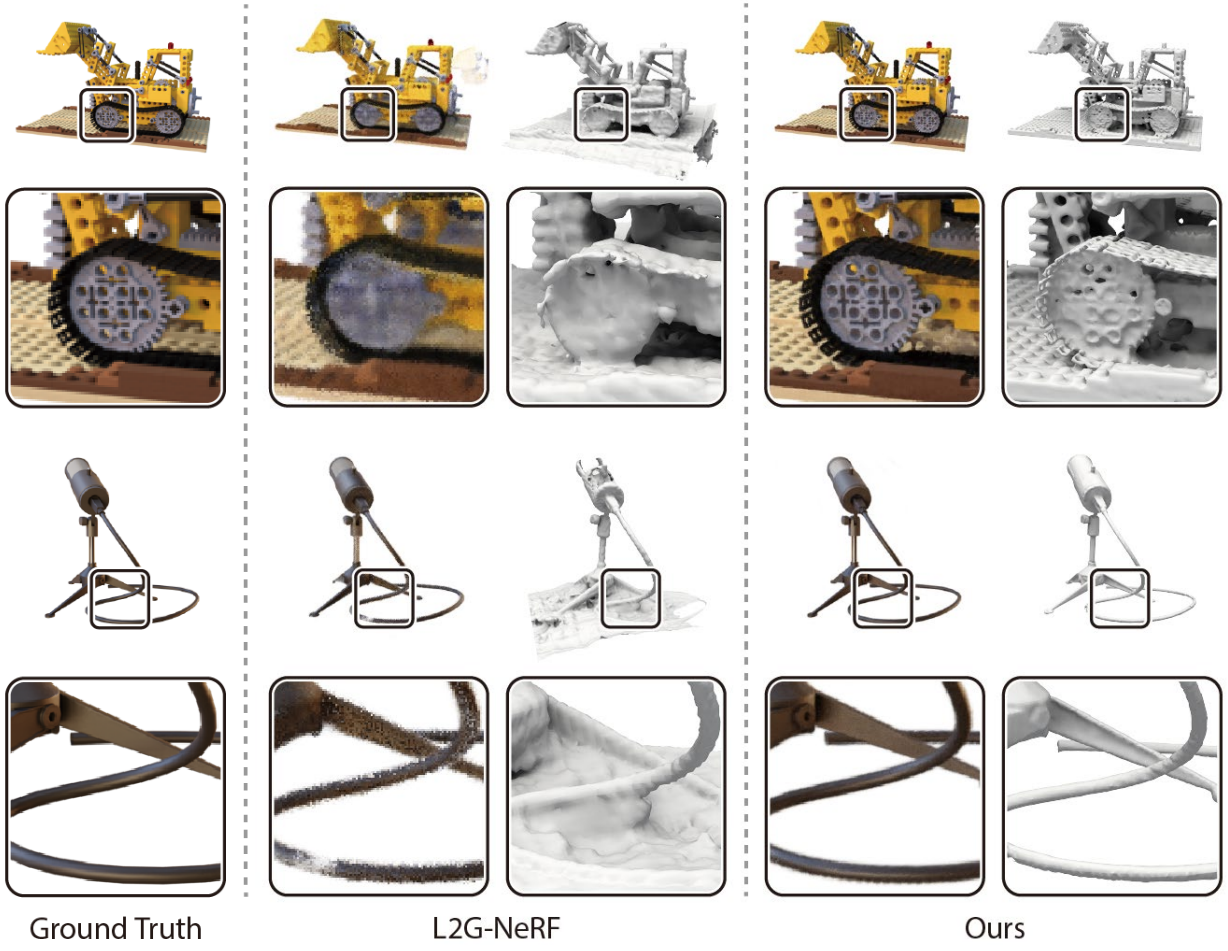
Mildenhall B, Srinivasan P P, Tancik M, et al. NeRF: Representing scenes as neural radiance fields for view synthesis. ECCV, 2020.

Lin, Chen-Hsuan, et al. BARF: Bundle-adjusting neural radiance fields. ICCV, 2021.

Bundle-Adjusting Neural Fields



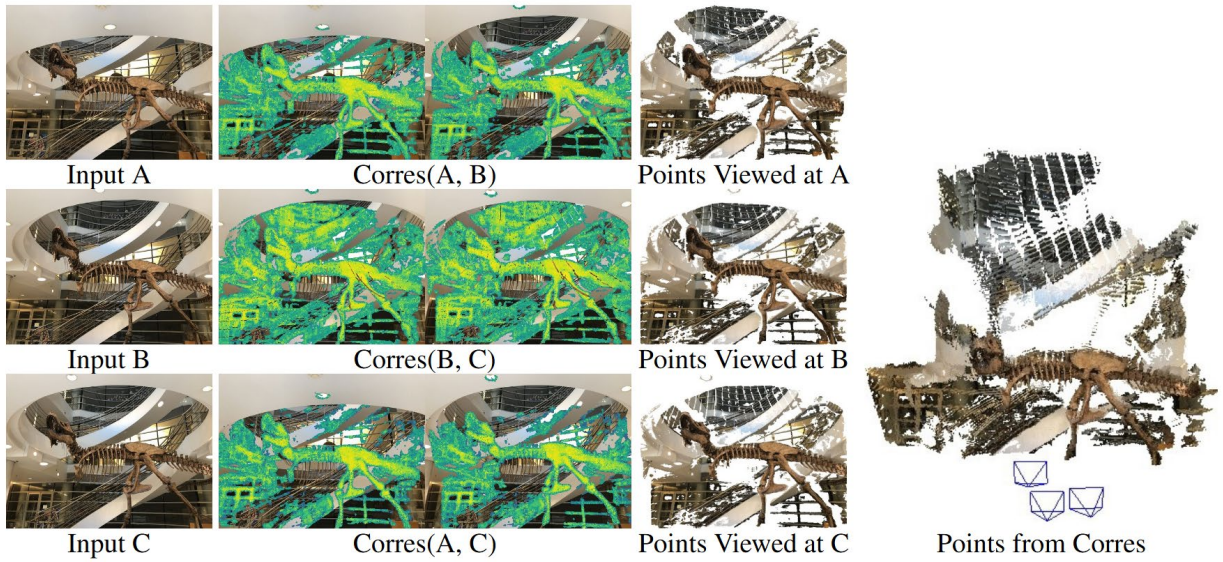
L2G-NeRF



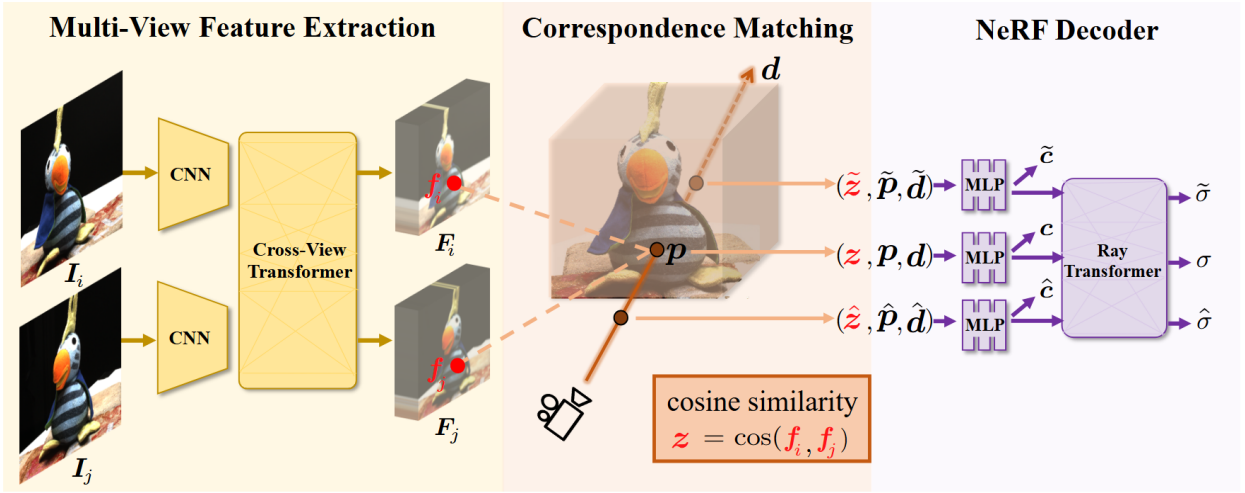
CRAYM

Chen Y, Chen X, Wang X, et al. Local-to-global registration for bundle-adjusting neural radiance fields. CVPR 2023.

Bundle-Adjusting Neural Fields



CorresNeRF

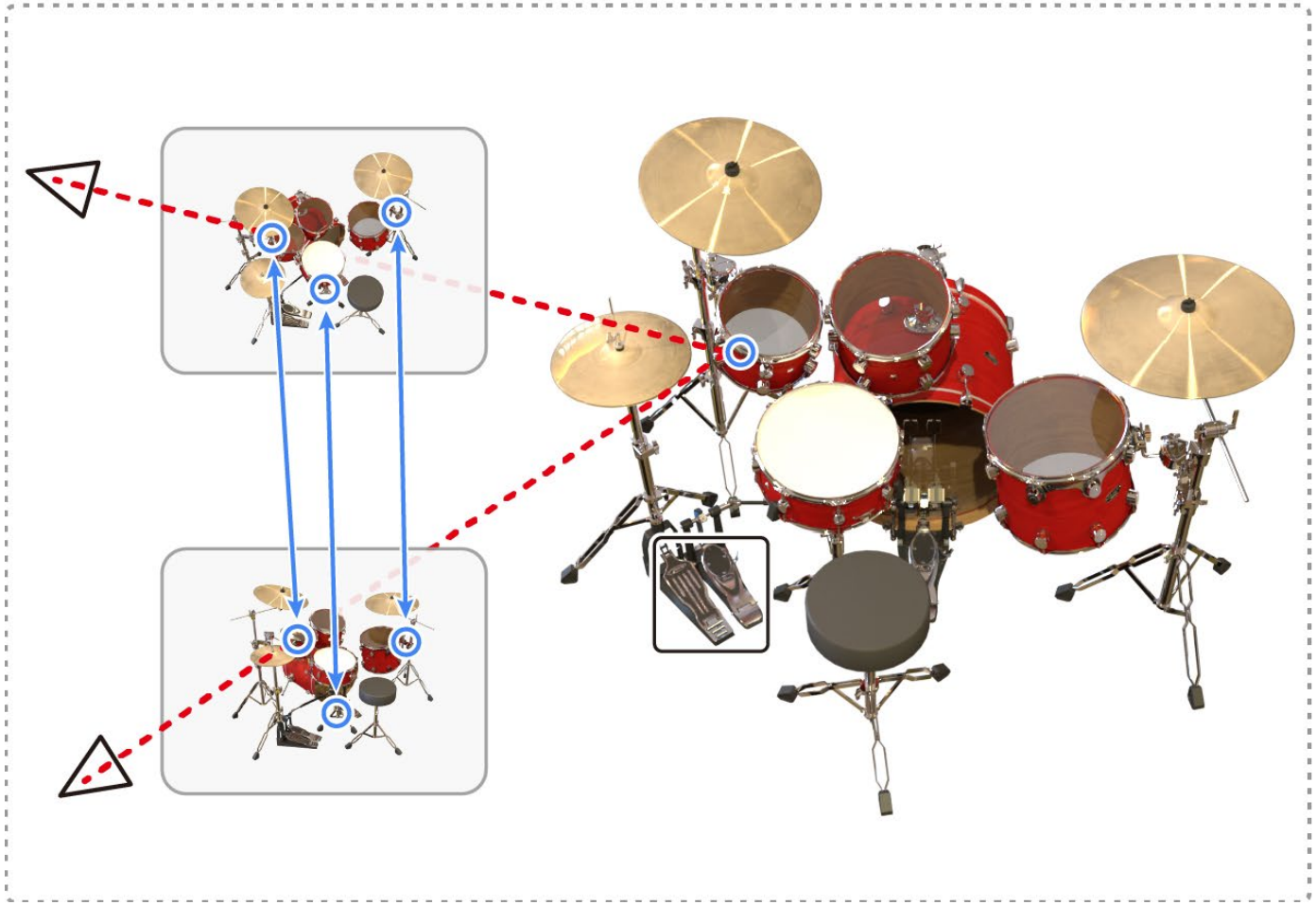


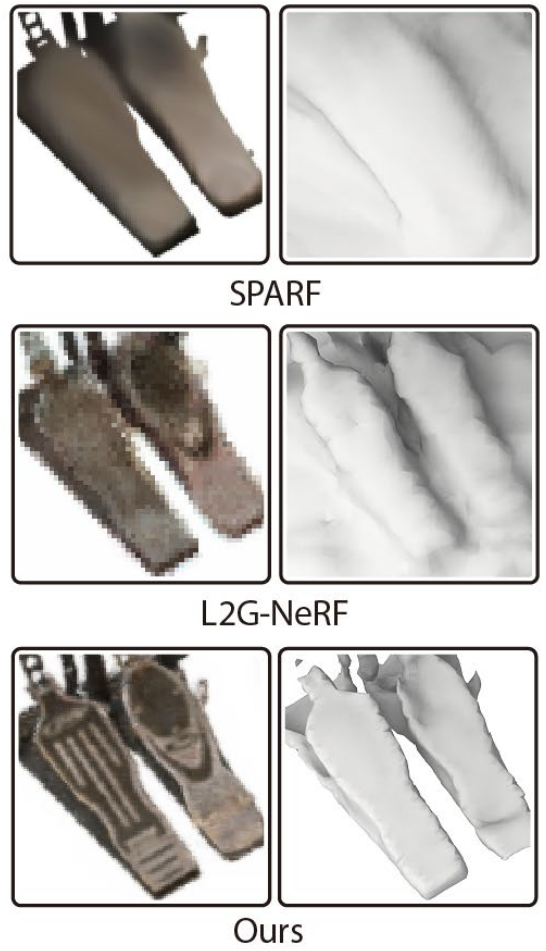
MatchNeRF

Lao Y, Xu X, Liu X, et al. Corresnerf: Image correspondence priors for neural radiance fields. NeurIPS 2023.

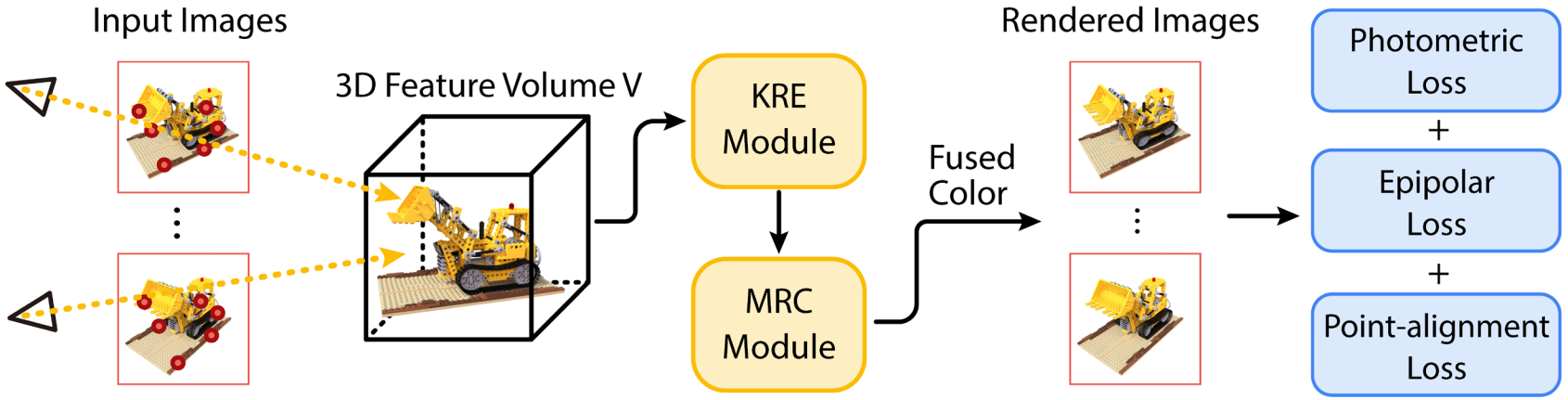
Chen, Yuedong, et al. Explicit correspondence matching for generalizable neural radiance fields. Arxiv 2023.

Motivation



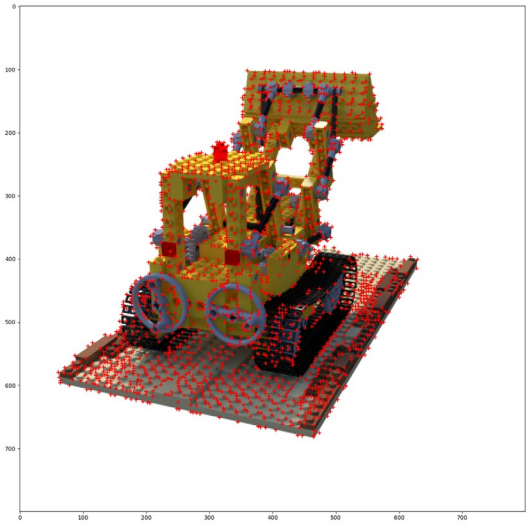


Pipeline

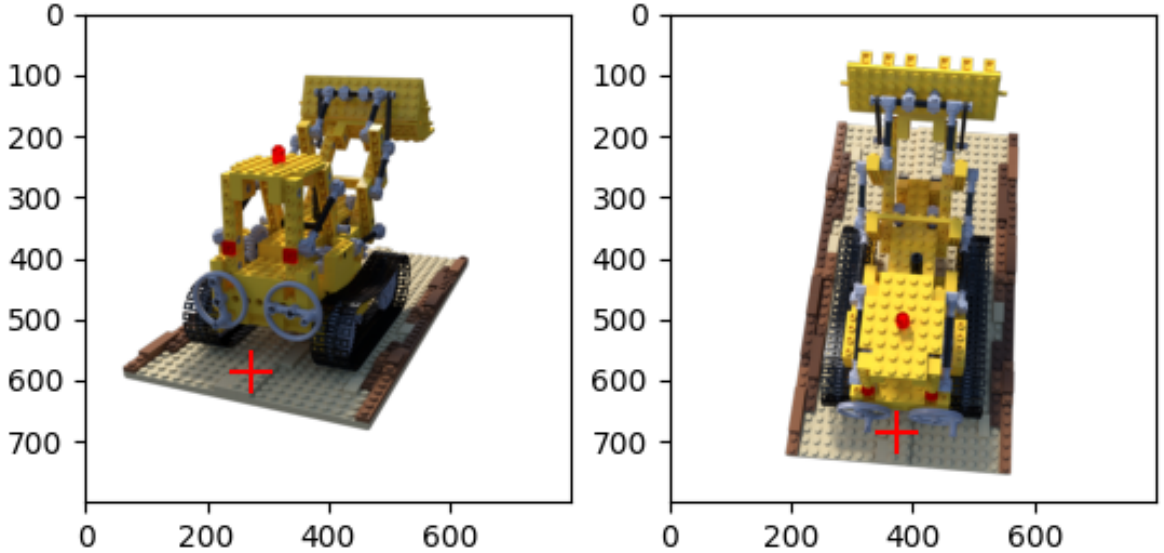


$$f(p) = \mathcal{M}(\mathcal{V}(p))$$

where $\mathcal{M}$ is the progressive feature mask

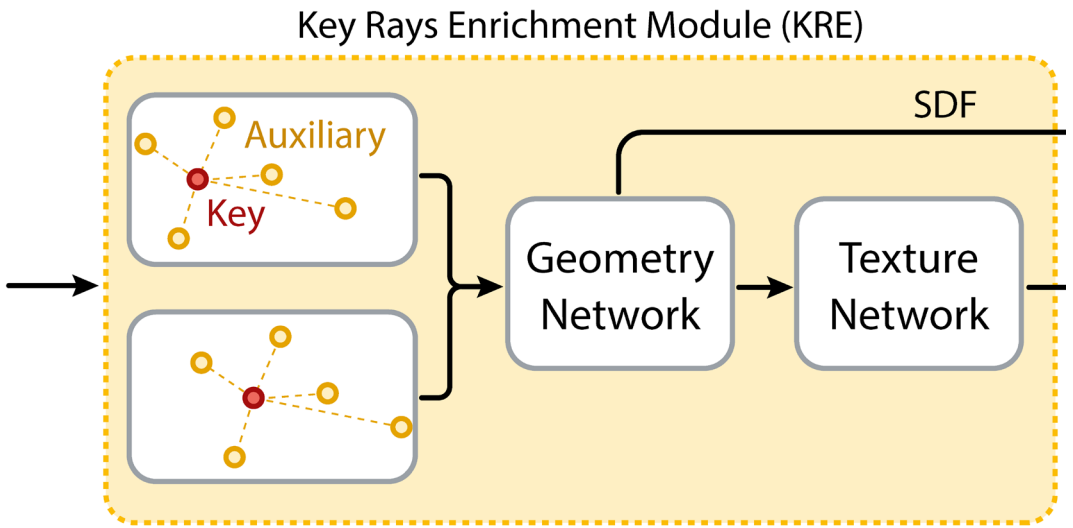


Extracted Keypoints



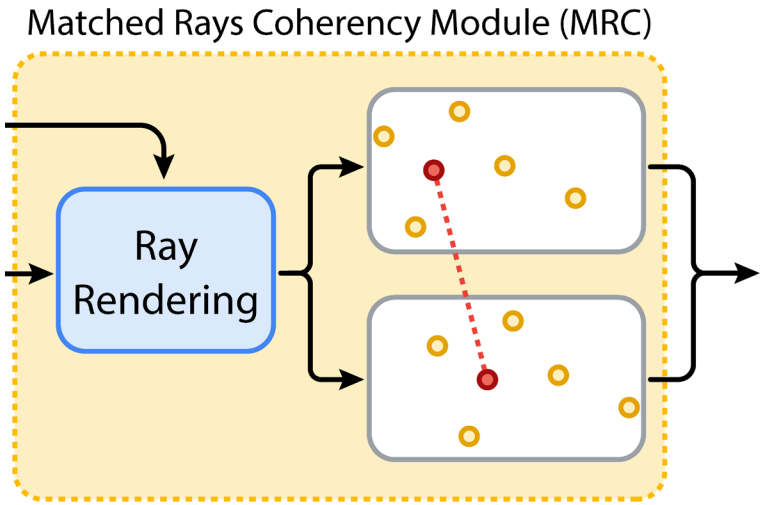
A pair of matched keypoints

Key Rays Enrichment



$$f'(p_k) = \sum_j g(f(p_k), f(q_j)),$$

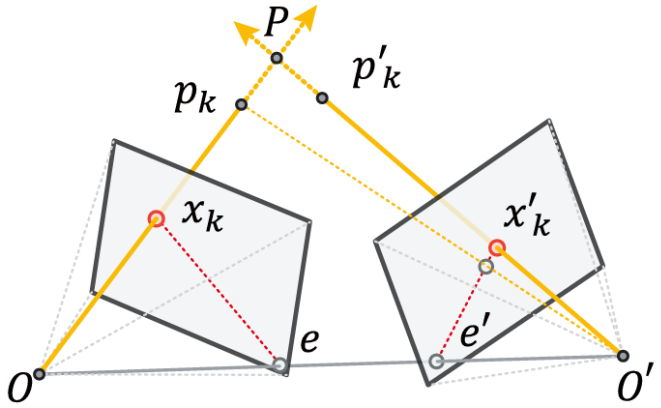
Matched Rays Coherency



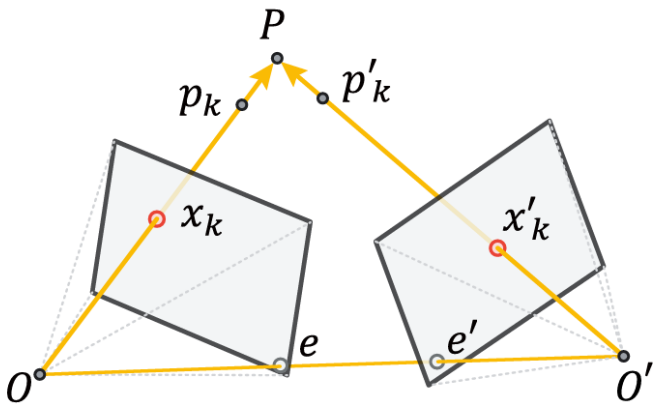
$$f(\mathbf{r_k}) = \int_0^\infty \mathcal{T}(p_k)\sigma(p_k)f''(p_k)dt.$$

$$\mathbf{c}(\mathbf{r}_k) = w\mathbf{c}(\mathbf{r}'_k) + (1-w)\mathbf{c}(\mathbf{r}_k),$$

Losses



(a) Epipolar Loss



(b) Point-alignment Loss

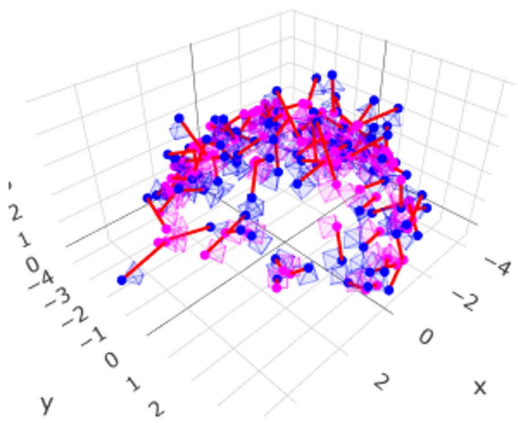
$$L_e = \frac{1}{N_k}\sum_{i=1}^{N_k} \mathrm{Dist}(Proj(p_k), e'x'_k).$$

$$L_a = \frac{1}{N_k}\sum_{i=1}^{N_k} \mathrm{Dist}(p_k, p'_k).$$

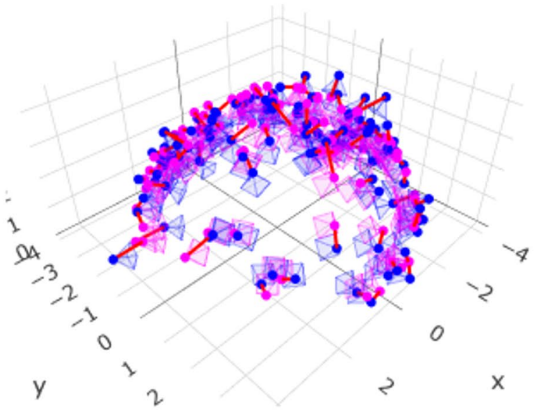
$$L = \lambda_1 * L_p + \lambda_2 * L_s + \lambda_3 * L_e + \lambda_4 * L_a,$$

Results

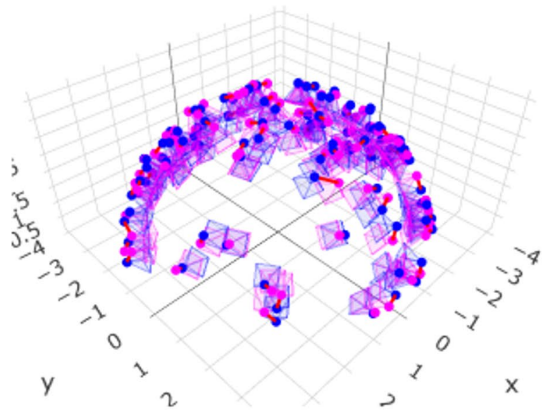
Pose alignment



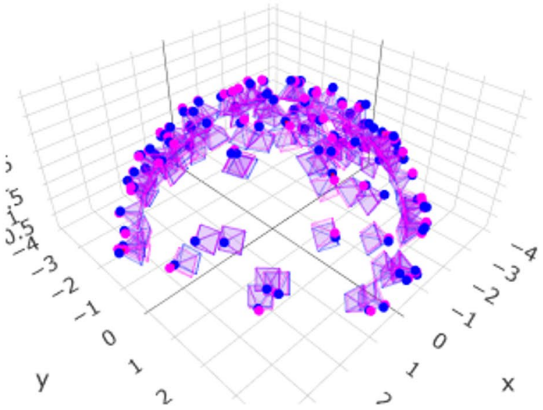
Initial Poses



BARF



L2G-NeRF



Ours

Table 1: Poses registration errors evaluated on the LEGO scene in the NeRF-Synthetic dataset [26].

Method		Rotation (°) ↓	Translation ↓
BARF [21]	ICCV′21	9.02	0.81
SPARF [32]	CVPR23′21	10.64	0.53
L2G-NeRF [5]	CVPR23′21	2.90	**0.10**
CRAYM (ours)		**1.21**	0.19

NeRF-Synthetic dataset

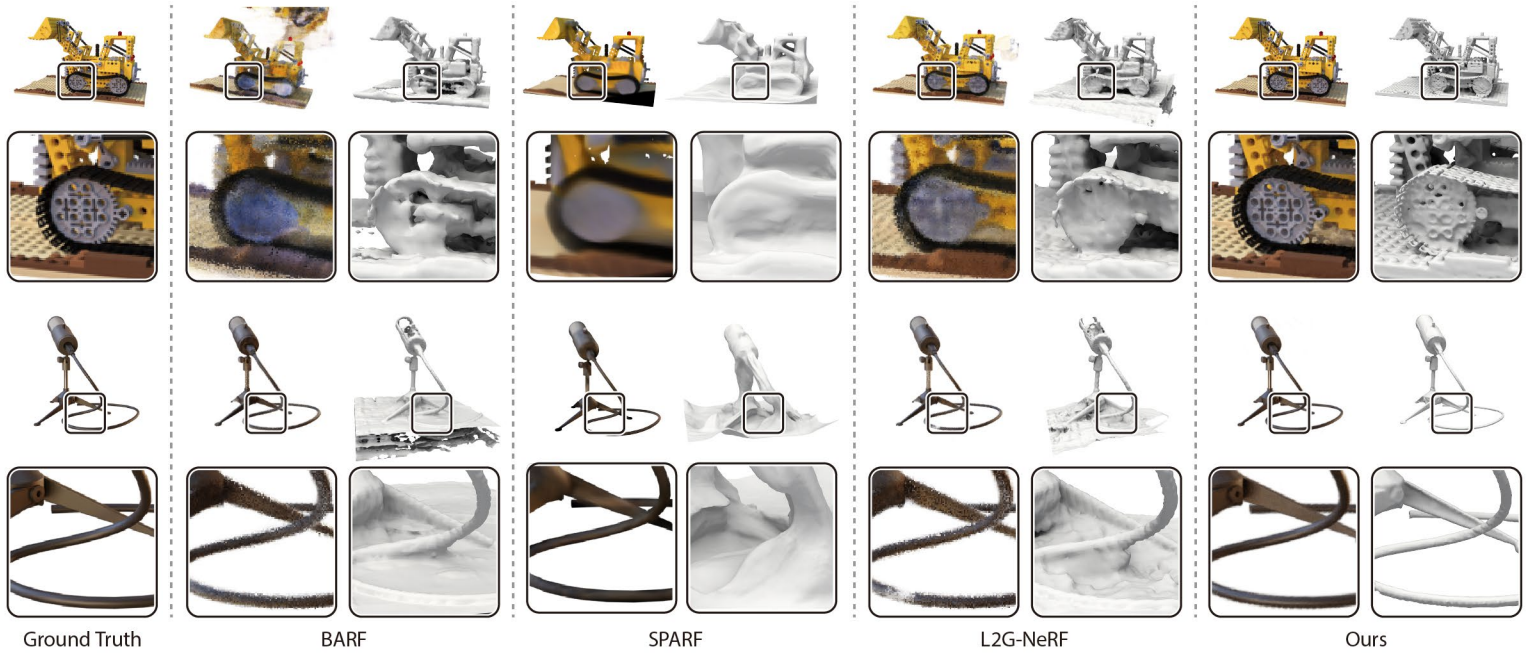


Table 2: Results on the NeRF-Synthetic dataset.

Metrics	Method	PSNR↑	SSIM↑	LPIPS↓	CD↓
Chair	NeRF [26]	16.69	0.77	0.39	2.23
	BARF [21]	28.55	0.93	0.06	0.09
	SPARF [32]	23.80	0.87	0.19	0.14
	L2G-NeRF [5]	30.99	0.95	0.05	0.10
	CRAYM (ours)	**34.18**	**0.98**	**0.02**	**0.06**
Hotdog	NeRF [26]	15.07	0.74	0.42	N/A
	BARF [21]	30.12	0.95	0.04	0.38
	SPARF [32]	29.10	0.93	0.13	0.07
	L2G-NeRF [5]	34.56	0.97	0.03	0.38
	CRAYM (ours)	**36.42**	**0.98**	**0.02**	**0.05**
LEGO	NeRF [26]	11.11	0.60	0.58	0.58
	BARF [21]	22.54	0.79	0.12	**0.04**
	SPARF [32]	22.47	0.80	0.25	0.09
	L2G-NeRF [5]	27.71	0.91	0.06	0.12
	CRAYM (ours)	**31.60**	**0.96**	**0.03**	**0.04**
Mic	NeRF [26]	13.08	0.73	0.53	0.48
	BARF [21]	30.37	0.96	**0.05**	0.28
	SPARF [32]	28.36	0.91	0.17	0.24
	L2G-NeRF [5]	30.91	0.97	**0.05**	0.17
	CRAYM (ours)	**31.02**	**0.97**	**0.05**	**0.04**
Mean	NeRF [26]	13.29	0.68	0.49	0.64
	BARF [21]	23.09	0.84	0.18	0.24
	SPARF [32]	23.90	0.84	0.23	0.18
	L2G-NeRF [5]	28.62	0.93	0.07	0.17
	CRAYM (ours)	**30.34**	**0.95**	**0.05**	**0.06**

Real scenes

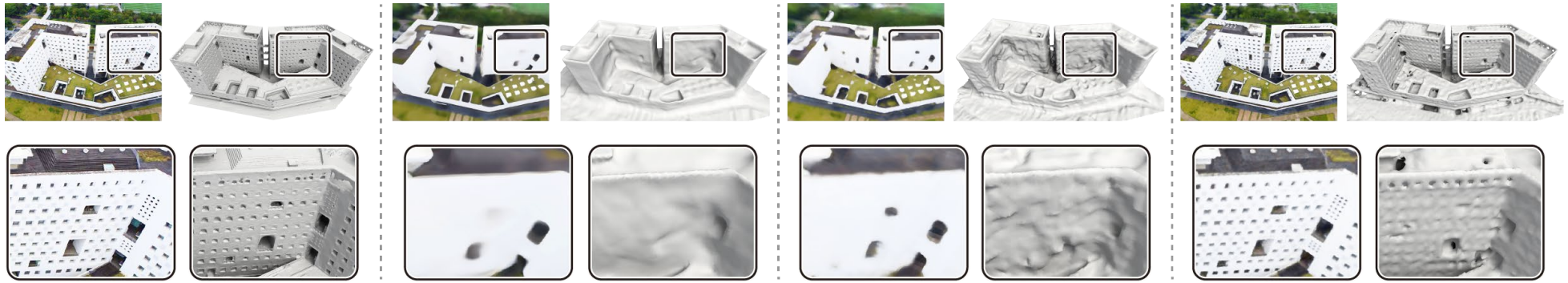


Table 3: Qualitative comparison on novel view synthesis on the LLFF dataset [25].

	PSNR ↑				SSIM ↑				LPIPS ↓			
	BARF [21]	L2G-NeRF [5]	BAA-NGP [23]	CRAYM (ours)	BARF [21]	L2G-NeRF [5]	BAA-NGP [23]	CRAYM (ours)	BARF [21]	L2G-NeRF [5]	BAA-NGP [23]	CRAYM (ours)
Fern	23.88	24.57	19.37	**24.83**	0.71	0.75	0.50	**0.79**	0.31	0.26	0.38	**0.25**
Flower	24.29	24.90	**25.16**	25.04	0.71	0.74	**0.81**	0.76	0.20	0.17	**0.10**	0.13
Fortress	29.06	29.27	29.24	**29.39**	0.82	0.84	0.83	**0.85**	0.13	**0.11**	0.14	0.12
Horns	23.29	23.12	19.71	**23.30**	0.74	0.74	0.72	**0.75**	0.29	0.26	**0.24**	**0.24**
Leaves	18.91	19.02	**19.96**	19.57	0.55	0.56	**0.68**	0.60	0.35	0.33	**0.23**	0.29
Orchids	19.46	19.71	12.45	**19.81**	0.57	**0.61**	0.14	0.59	0.29	0.25	0.42	**0.23**
Room	32.05	32.25	29.72	**32.44**	0.94	**0.95**	0.90	0.91	0.10	**0.08**	0.12	0.09
T-rex	22.92	23.49	**24.56**	23.68	0.78	0.80	**0.86**	0.83	0.20	0.16	0.11	**0.10**
Mean	24.23	24.54	22.52	**24.76**	0.73	0.75	0.68	**0.76**	0.23	0.20	0.22	**0.18**

Table 4: Results on the real scenes PolyTech and ArtSci in the UrbanScene3D [22] dataset.

Scene	Method	PSNR↑	SSIM↑	LPIPS↓	CD↓
PolyTech	NeuS [34]	14.27	0.42	0.71	0.10
	PET-NeuS [37]	13.64	0.40	0.75	0.07
	CRAYM (ours)	**22.51**	**0.63**	**0.43**	**0.01**
ArtSci	NeuS [34]	13.49	0.33	0.89	0.10
	PET-NeuS [37]	15.18	0.36	0.88	0.08
	CRAYM (ours)	**19.37**	**0.42**	**0.63**	**0.02**

Ablation studies

Table 5: Comparing different methods at varying noise levels.

Method	PSNR↑	SSIM↑	LPIPS↓	CD↓
w/o Noise				
NeRF [26]	29.08	0.94	0.04	0.34
NeuS [34]	21.18	0.82	0.09	0.04
BARF [21]	28.33	0.93	0.05	0.36
SPARF [32]	22.73	0.80	0.25	0.09
PET-NeuS [37]	21.37	0.82	0.14	0.10
L2G-NeRF [5]	27.94	0.92	0.06	0.14
CRAYM (ours)	**32.72**	**0.97**	**0.02**	**0.03**
Low Noise Level				
NeRF [26]	24.86	0.88	0.09	0.34
NeuS [34]	21.76	0.83	0.14	0.05
BARF [21]	28.32	0.93	0.05	0.36
SPARF [32]	22.55	0.80	0.25	0.09
PET-NeuS [37]	21.34	0.82	0.11	0.55
L2G-NeRF [5]	27.75	0.92	0.06	0.21
CRAYM (ours)	**32.68**	**0.97**	**0.02**	**0.04**
High Noise Level				
NeRF [26]	11.36	0.81	0.56	0.57
NeuS [34]	N/A	N/A	N/A	N/A
BARF [21]	14.48	0.69	0.29	0.04
SPARF [32]	22.47	0.80	0.25	0.09
PET-NeuS [37]	N/A	N/A	N/A	N/A
L2G-NeRF [5]	27.71	0.91	0.06	0.12
CRAYM (ours)	**31.60**	**0.96**	**0.03**	**0.03**

Table 6: Ablation of major modules and losses.

Method	PSNR↑	SSIM↑	LPIPS↓	CD↓
L2G-NeRF [5]	27.71	0.91	0.06	0.12
NeuS2 [35]	26.83	0.86	0.17	0.08
Baseline	27.30	0.91	0.10	0.06
+ KRE	28.64	0.93	0.07	0.05
+ KRE + MRC	30.41	0.95	0.04	**0.04**
+ L_e	29.43	0.92	0.07	0.05
+ L_e + L_a	29.95	0.94	0.06	**0.04**
Our full pipeline	**31.60**	**0.96**	**0.03**	**0.04**

Conlusion

Limitations:

1. Randomly initialized poses
2. Messy inner structures
3. Dense matching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THANKS