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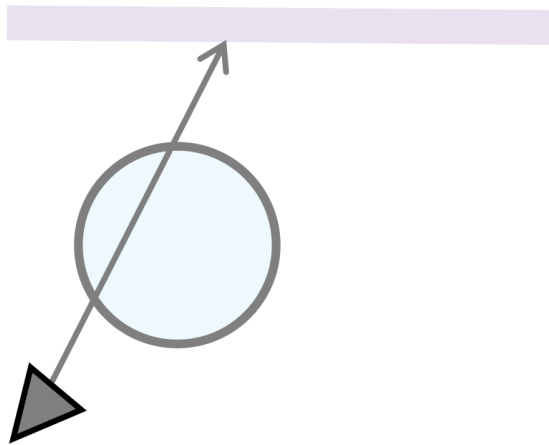
Ray Deformation Networks for Novel View Synthesis of Refractive Objects

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¹Australian National University ²RIOS Intelligent Machines

Traditional NeRF

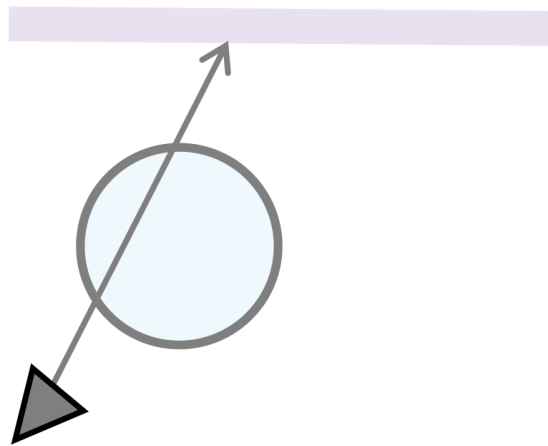
- ❑ NeRF methods learn the density field based on **light transports along straight path**



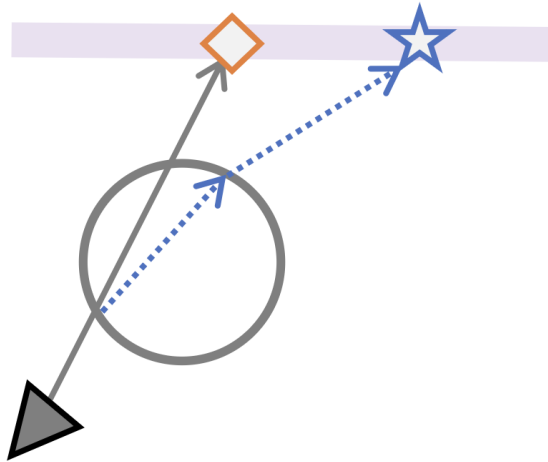
(a) Opaque Object

Traditional NeRF

□ Straight ray vs. Deformed ray



(a) Opaque Object



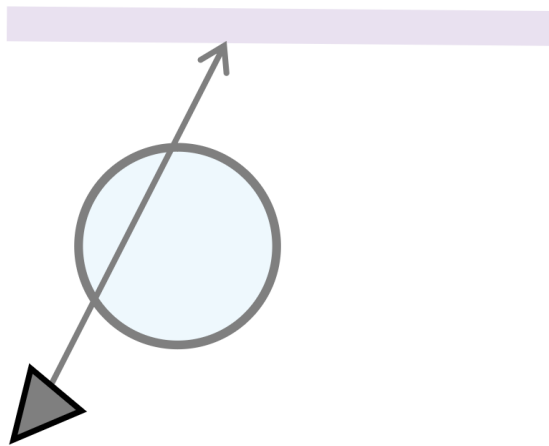
(b) Refractive Object



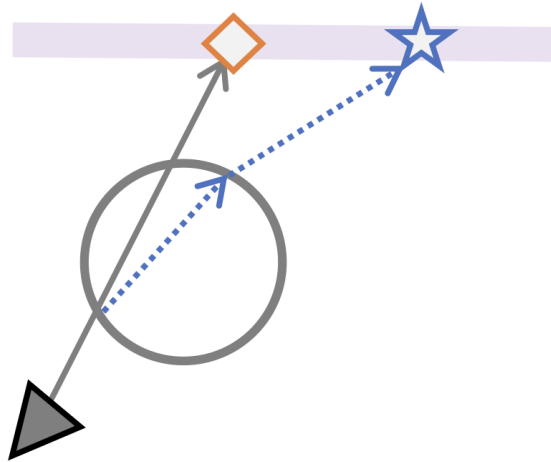
~~light transport along straight path~~

Ray Deformation

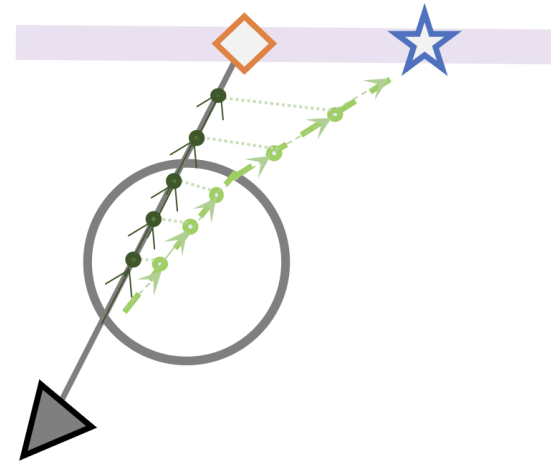
- We **bend the ray** by predicting offsets for the direction and position of each sample point along the ray



(a) Opaque Object



(b) Refractive Object



(c) Ray Deformation

Ray Deformation Network

- We **bend the ray** by predicting offsets for the direction and position of each sample point along the ray

Without making assumptions about **known geometry^[a]**, **refractive index^[a]**, **controlled setups^[b]**, or **infinitely distant background^[c]**.



(a) Opaque Object

(b) Refractive Object

(c) Ray Deformation

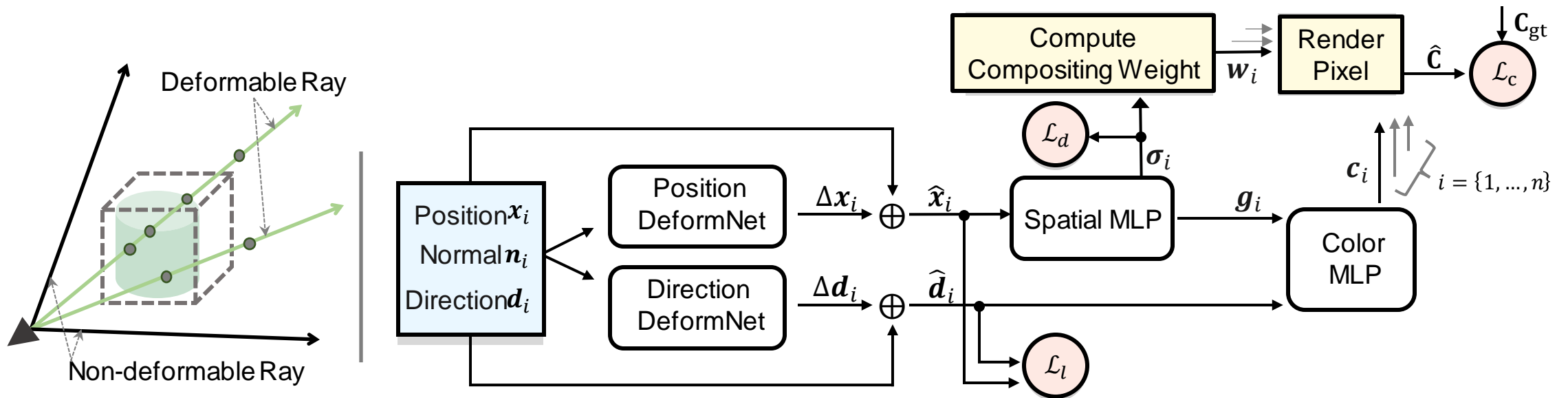
[a] Pan *et al.*, Sampling neural radiance fields for refractive objects. In *SIGGRAPH Asia 2022 Technical Communications*, 2022

[b] Li *et al.*, Neto: Neural re- construction of transparent objects with self-occlusion aware refraction-tracing. ICCV 2023

[c] Wang *et al.*, Nemto: Neural environment matting for novel view and relighting synthesis of transparent objects. In ICCV 2023

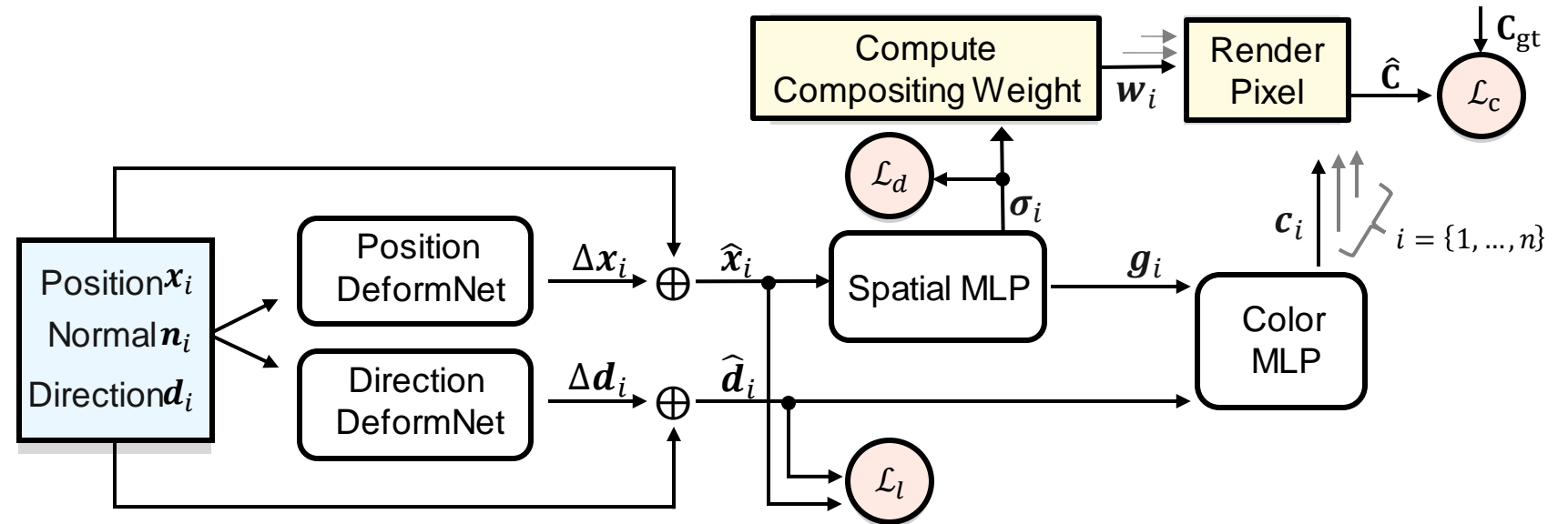
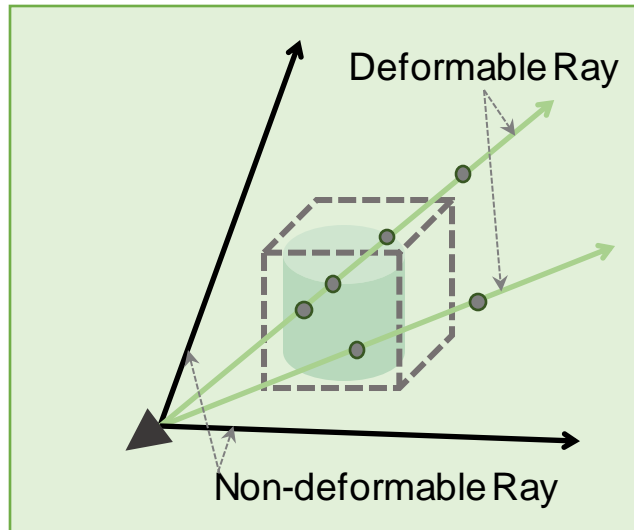
Ray Deformation NeRF

□ Framework



Ray Deformation NeRF

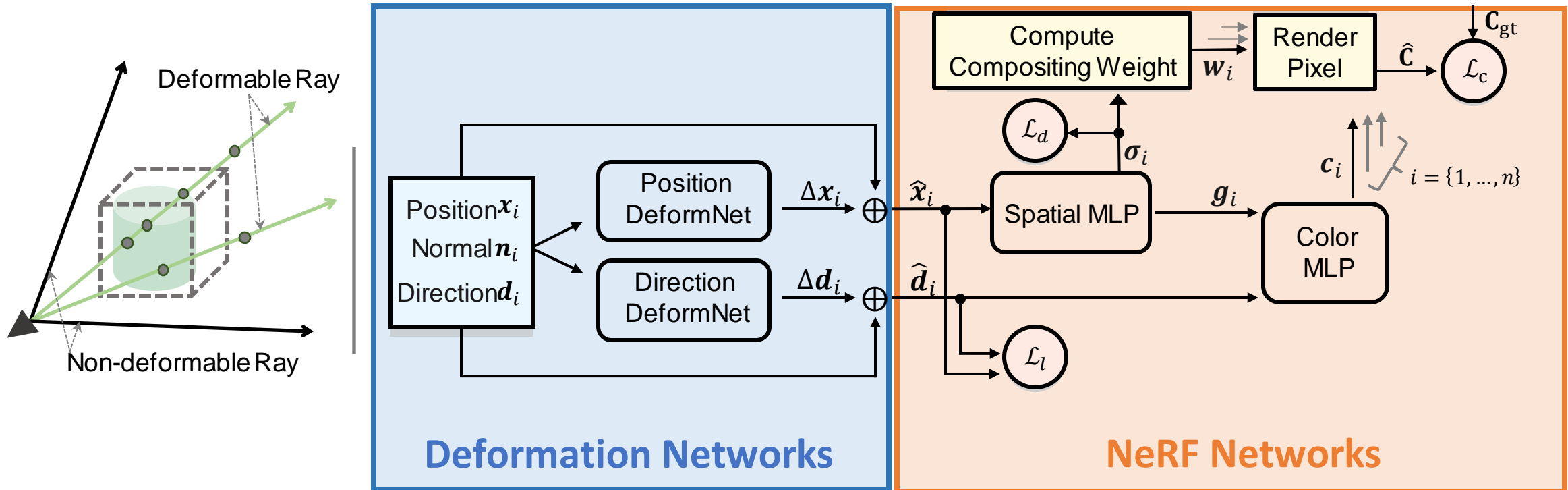
□ Framework



Roughly draw bounding boxes on several training views and project into 3D space with camera poses

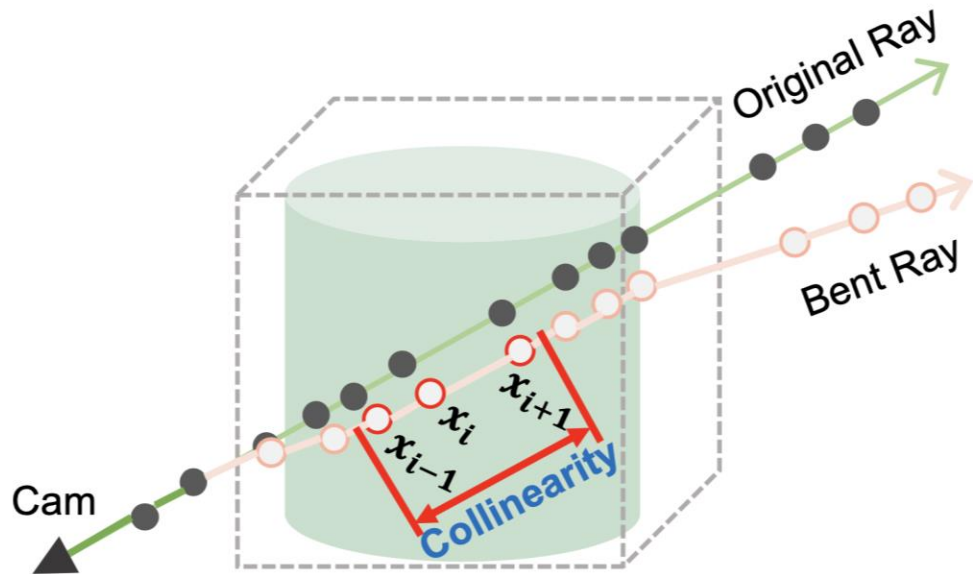
Ray Deformation NeRF

□ Framework



Ray Deformation NeRF

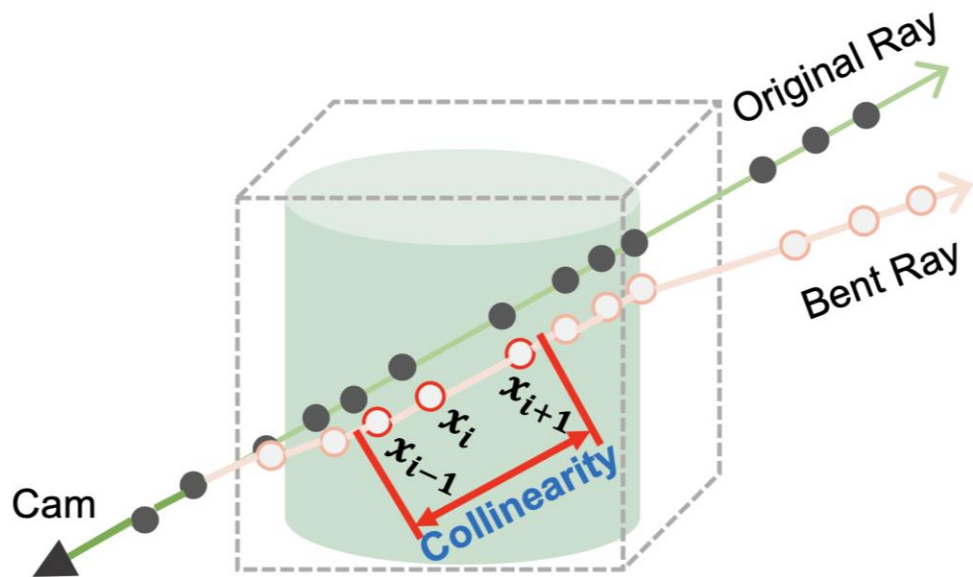
1) Collinearity Regularization



Snell's law: refracted rays are piece-wise linear

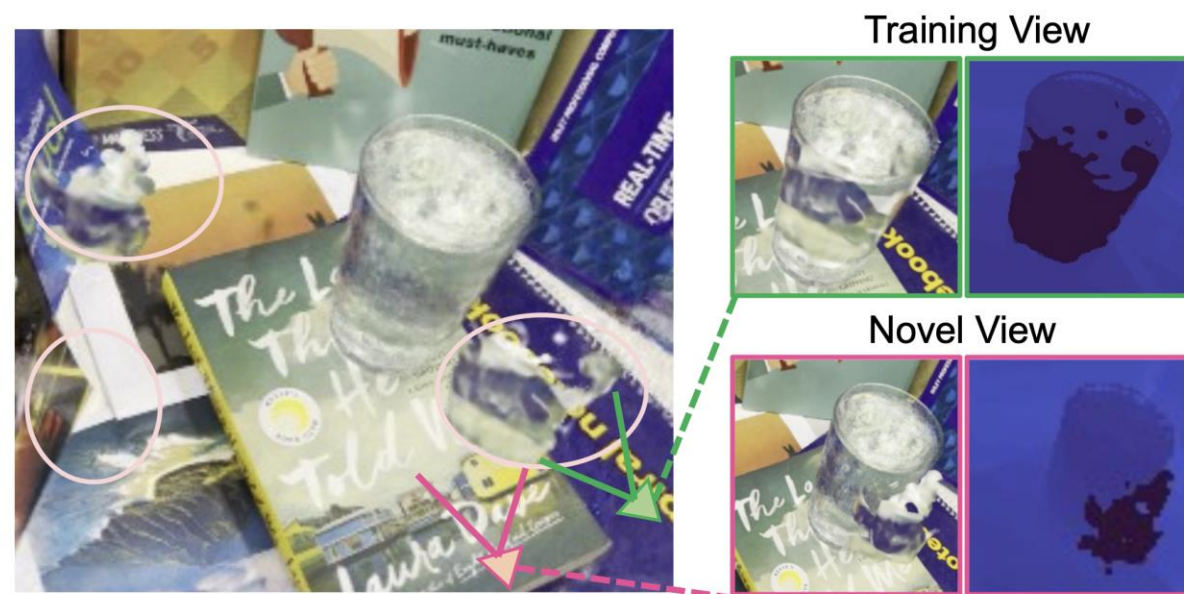
Ray Deformation NeRF

1) Collinearity Regularization



Snell's law: refracted rays are piece-wise linear

2) Near-Camera Density Penalty



NeRF tends to generate outliers near the camera

Promising Performance

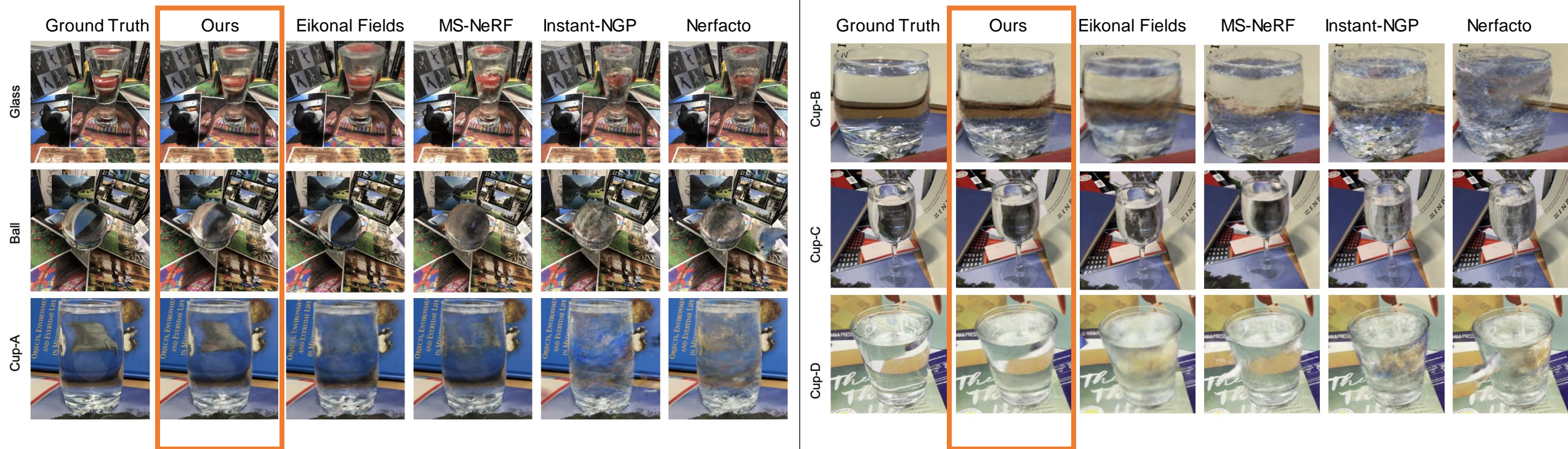
Model	Ball [4]			Glass [4]			Cup-A			Cup-B			Cup-C			Cup-D		
	PSNR	SSIM	LPIPS	PSNR	SSIM	LPIPS	PSNR	SSIM	LPIPS	PSNR	SSIM	LPIPS	PSNR	SSIM	LPIPS	PSNR	SSIM	LPIPS
TensoRF	21.41	0.735	0.187	20.49	0.695	0.226	25.96	0.856	0.184	23.12	0.823	0.230	27.57	0.888	0.1671	24.13	0.825	0.212
Instant-NGP	21.56	0.790	0.121	21.42	0.748	0.148	23.43	0.842	0.189	22.76	0.827	0.184	26.03	0.894	0.127	23.51	0.838	0.176
Nerfacto	21.67	0.797	0.113	22.14	0.774	0.121	23.24	0.846	0.168	21.37	0.808	0.209	25.69	0.893	0.114	22.67	0.835	0.177
MS-NeRF	22.35	0.810	0.105	21.83	0.781	0.119	27.43	0.890	0.113	24.83	0.859	0.142	28.84	0.910	0.099	25.51	0.870	0.137
SampleNeRFRO [†]	21.49	0.679	0.270	21.11	0.630	0.317	–	–	–	–	–	–	–	–	–	–	–	–
Eikonal Fields	21.64	0.699	0.217	20.92	0.663	0.262	26.11	0.832	0.214	25.27	0.818	0.242	24.62	0.811	0.282	24.33	0.777	0.256
Ours	23.30	0.822	0.092	23.54	0.795	0.103	29.33	0.894	0.104	27.04	0.867	0.128	30.11	0.916	0.093	27.09	0.871	0.137

(designed for refraction)

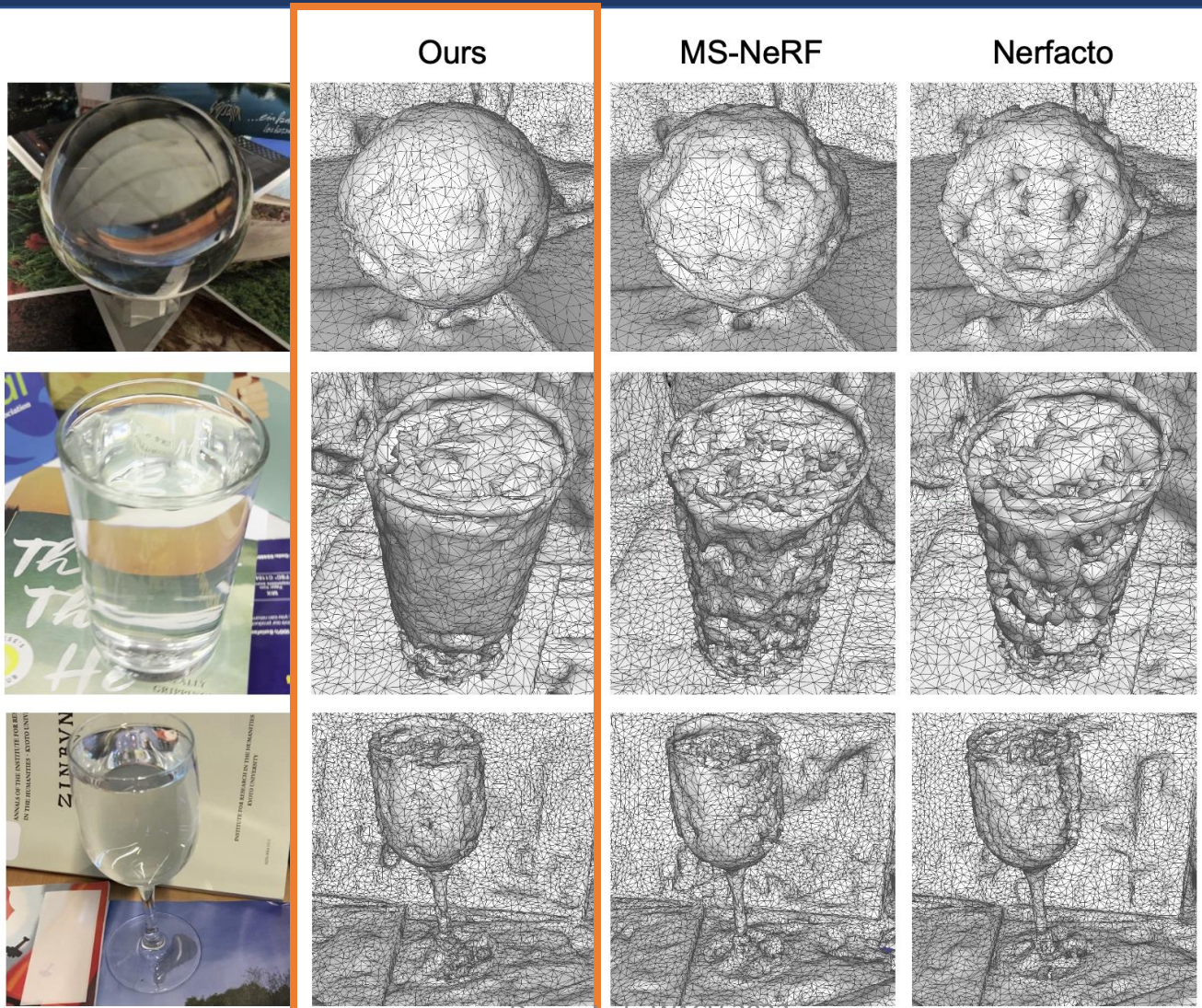
A higher PSNR/ SSIM denotes Higher performance

A Lower LPIPS denotes Higher performance

Improved Novel View Synthesis



Improved Geometry



Robust to Transparency Variation

Ground Truth



Ours



Test Set PSNR: **27.30**

MS-NeRF



Test Set PSNR: **25.79**

Nerfacto



Test Set PSNR: **23.14**



Test Set PSNR: **26.67**



Test Set PSNR: **24.90**



Test Set PSNR: **21.33**

Modelling Partially Refractive Objects

Ground Truth



Ours



Test Set PSNR: 27.51

MS-NeRF



Test Set PSNR: 26.40

Nerfacto



Test Set PSNR: 22.40



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