LightNeuS: Neural Surface Reconstruction in Endoscopy Using Illumination Decline

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Introduction

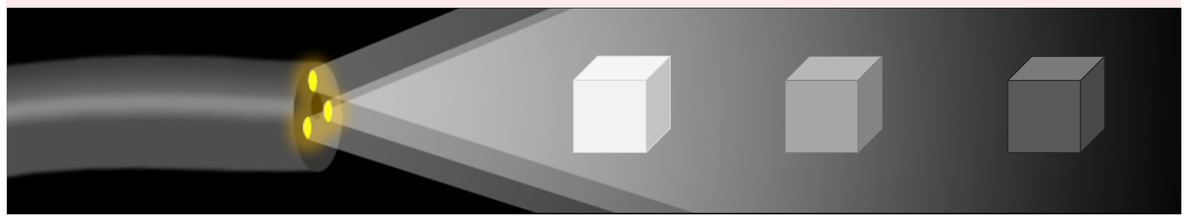
Goal:

3D reconstruction from **monocular endoscopes.**

Key insights:

❖ **Signed distance function (SDF)** is **watertight**.

❖ **Illumination declines** with **distance**.



NeuS

We build on Neural implicit Surfaces (NeuS) [1]

❖ NeuS fails with illumination changes.

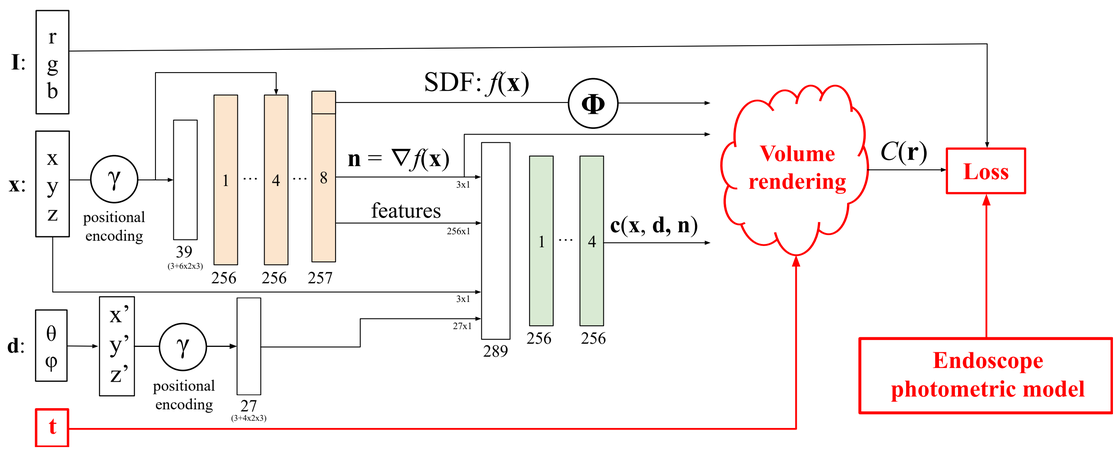
❖ Endoscopes can only capture few viewing directions.

LightNeuS

❖ Exploit the relation of **brightness** $\mathcal{I}$ **and depth** t

$$\mathcal{I}(\mathbf{x}) = \left(\frac{L_e}{t^2} \, \mathrm{BRDF}(\mathbf{x}, \mathbf{d}) \, \cos(\theta) \, g \right)^{1/\gamma}$$

❖ Introduce a **calibrated photometric model** of the endoscope's camera and light source.



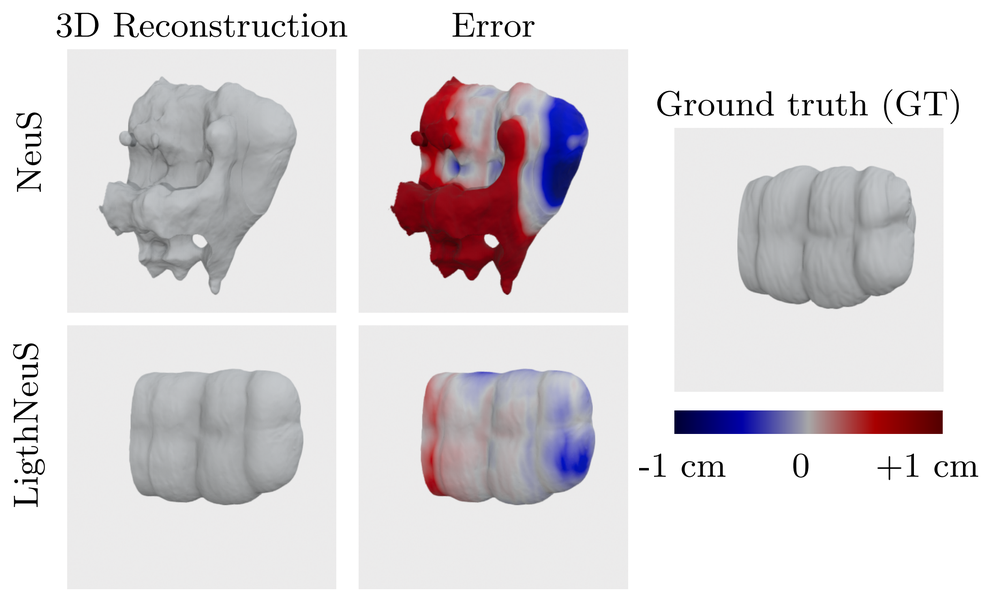


Fig 1. Benefits of illumination decline.

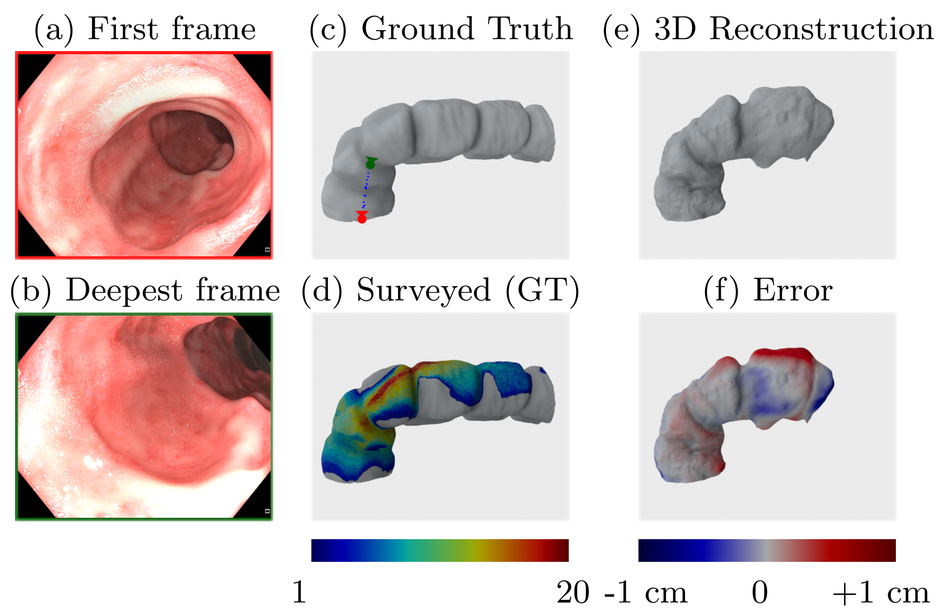


Fig 2. Reconstructing partially observed regions.

Takeaway

❖ **Exploiting the illumination** is key.

❖ **Accuracies** in the range of **3 mm.**

❖ Reconstruction of **unseen portions.**

References

[1] Wang, P. et al., *"NeuS: Learning neural implicit surfaces by volume rendering for multi-view reconstruction"*. NeurIPS (2021)

[2] Bobrow, T.L et al., *"Colonoscopy 3D video dataset with paired depth from 2D-3D registration"*. (2022)

Quantitative results

Excellent accuracy on phantom imagery in the C3VD dataset [2]

❖ Different sections of the colon anatomy: Cecum, Descending, Sigmoid, Transverse.

❖ Reconstruction **mean error of 2.80 mm.**

		NeuS		LightNeuS (ours)																				
	Sequence	C1a	C4b	C1a	C1b	C2a	C2b	C2c	C3a	C4a	C4b	D4a	S1a	S2a	S3a	S3b	T1a	T1b	T2a	T2b	T4a	Mean	*T2c*	*T3a*	*T3b*	*T4b*	*Mean*
Sur.	MedAE	4.53	10.6	0.95	4.85	1.40	3.26	2.57	1.12	1.90	1.41	2.66	4.23	1.19	2.57	3.63	3.43	2.33	2.24	2.16	1.15	**2.39**	*5.07*	*6.39*	*11.0*	*1.75*	***6.04***
	MAE	5.07	10.6	1.48	5.11	1.54	3.65	3.00	2.54	2.14	1.63	3.26	4.33	1.89	2.68	4.16	3.47	2.72	2.28	2.30	2.31	**2.80**	*5.45*	*8.65*	*12.1*	*6.70*	***8.23***
	RMSE	6.40	11.6	2.01	5.63	1.87	4.39	3.74	5.49	2.92	2.10	4.08	4.96	2.78	3.18	4.81	4.07	3.34	2.58	2.70	3.79	**3.58**	*6.48*	*10.7*	*14.4*	*11.3*	***10.7***
Ext.	MedAE	4.68	5.35	0.83	4.89	1.41	3.32	2.54	1.27	1.91	1.45	4.50	4.01	1.40	2.87	3.54	3.38	2.69	2.19	2.12	1.29	**2.53**	*4.44*	*6.54*	*13.6*	*8.00*	***8.16***
	MAE	6.24	6.74	1.26	5.10	1.56	3.70	3.01	3.83	2.18	1.72	6.61	4.19	2.36	3.27	4.64	3.31	3.21	2.22	2.28	2.22	**3.15**	*5.36*	*8.10*	*14.1*	*10.4*	***9.47***
	RMSE	8.77	8.56	1.72	5.60	1.90	4.42	3.77	7.96	2.95	2.20	9.32	4.87	3.96	4.04	6.10	3.86	3.96	2.55	2.69	3.32	**4.18**	*6.78*	*9.94*	*15.9*	*13.9*	***11.6***

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