NLOS-NeuS: None-line-of-sight Neural Implicit Surface

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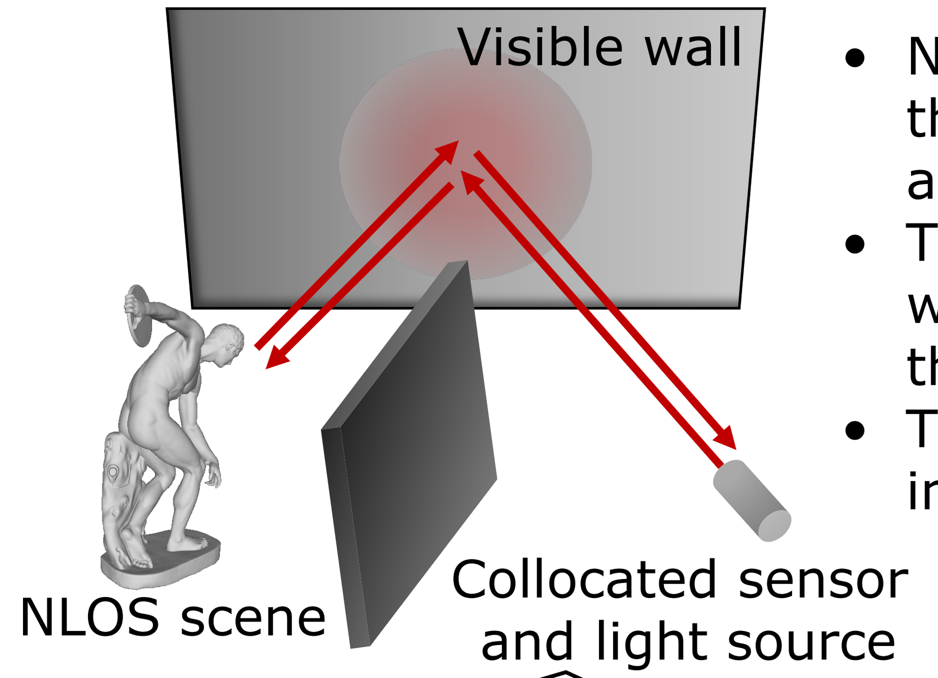
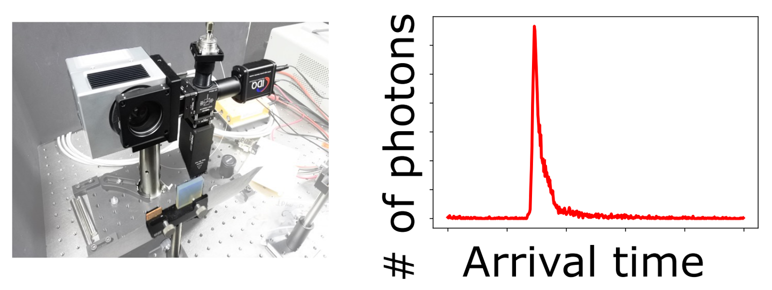
Project page

Non-line-of-sight (NLOS) imaging



- NLOS imaging is to reconstruct the invisible scene from the sensor and light source
- The sensor can only see the visible wall, and we use indirect light through the wall
- The typical input of the NLOS imaging is a transient histogram

Single photon avalanche diode (SPAD)



- Photon counts at each arrival time
- The time resolution is from [ns] to [ps]

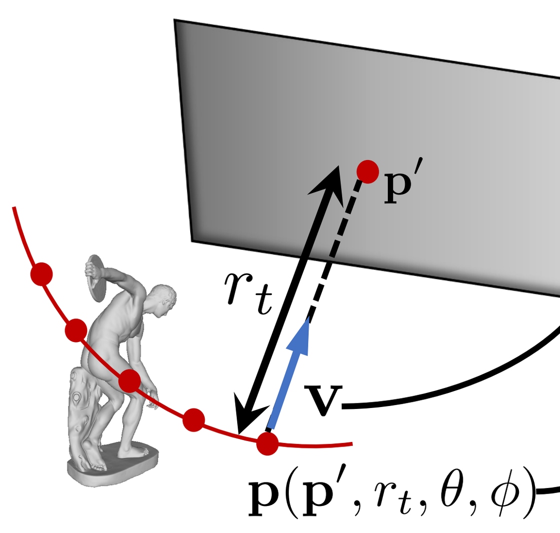
Related work

- DLCT [CVPR2020] is proposed for NLOS surface reconstruction with discretized voxel grid representation
- NeTF [ICCP2021] uses neural field similar to NeRF for NLOS imaging
- We propose a neural field approach for NLOS surface reconstruction with continuous implicit surface (signed distance function (SDF))

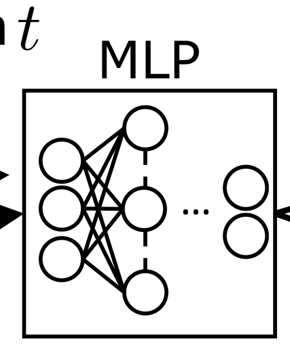
Method	Scene representation	Output geometry
LCT [Nature2018]	Voxel grid	Volumetric density
DLCT [CVPR2020]	Voxel grid	Volumetric density + surface normals
NeTF [ICCP2021]	Neural field	Volumetric density
NLOS-NeuS (Ours)	**Neural field**	**Implicit surface (SDF)**

Overview: Volume rendering for transient histogram

(1) We sample points on a sphere centered at $\mathbf{p}'$ with radius $r = ct/2$ (c: light speed), which corresponds to time bin t



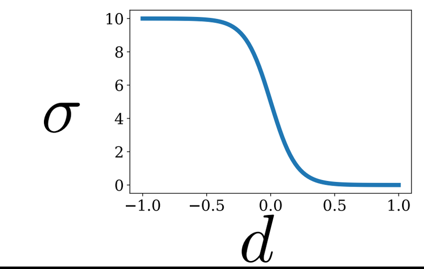
(2) MLP takes each sample point for estimating reflectance and signed distance, which is then converted to density



Reflectance $\rho(\mathbf{p}, \mathbf{v})$

Signed distance $d(\mathbf{p})$ → Density $\sigma(\mathbf{p})$

$$\sigma(\mathbf{p}) = \frac{1}{\alpha} Sigmoid(-\frac{d(\mathbf{p})}{\alpha})$$



- We use the conversion proposed in StyleSDF [CVPR2022] because of its computational efficiency
- Positive distance (outside object) returns small density
- α controls tightness, i.e., $\alpha \to 0$ represents perfectly sharp surface

(3) We apply volume rendering to reconstruct transient histogram, which is compared to the observed histogram to compute a training loss

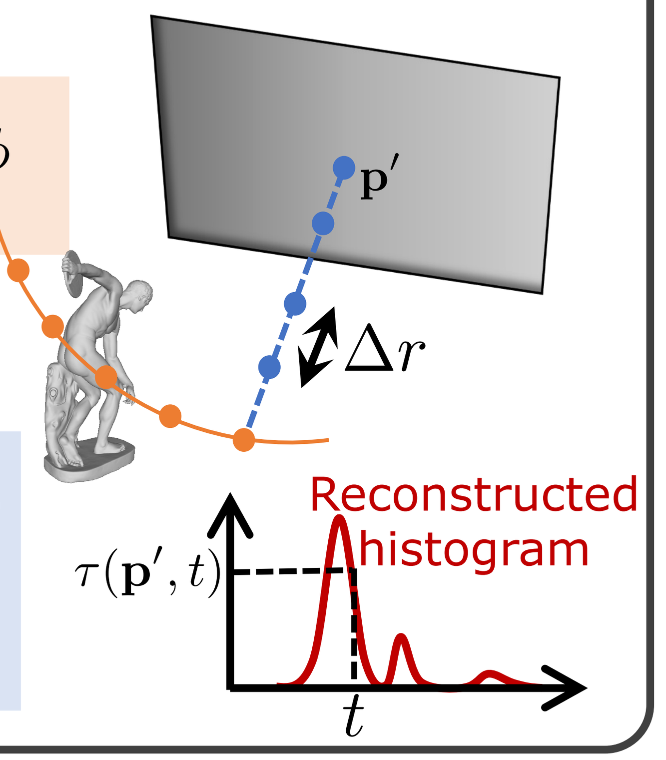
The sum on the sphere

$$\tau(\mathbf{p}', t) = \sum_{\theta, \phi} A(r_t, \theta) w(\mathbf{p}, \mathbf{v}) \rho(\mathbf{p}, \mathbf{v}) \Delta\theta \Delta\phi$$

Volume rendering on a ray from the wall

$$w(\mathbf{p}, \mathbf{v}) = \sum_{s=t_{min}}^{t} T_s \left(1 - \exp\{-\sigma(\mathbf{p}(\mathbf{p}', r_s, \theta, \phi))\Delta r_s\}\right)$$

$$T_s = \exp\left\{-\sum_{u=t_{min}}^{s-1} \sigma(\mathbf{p}(\mathbf{p}', r_u, \theta, \phi))\Delta r_u\right\}$$



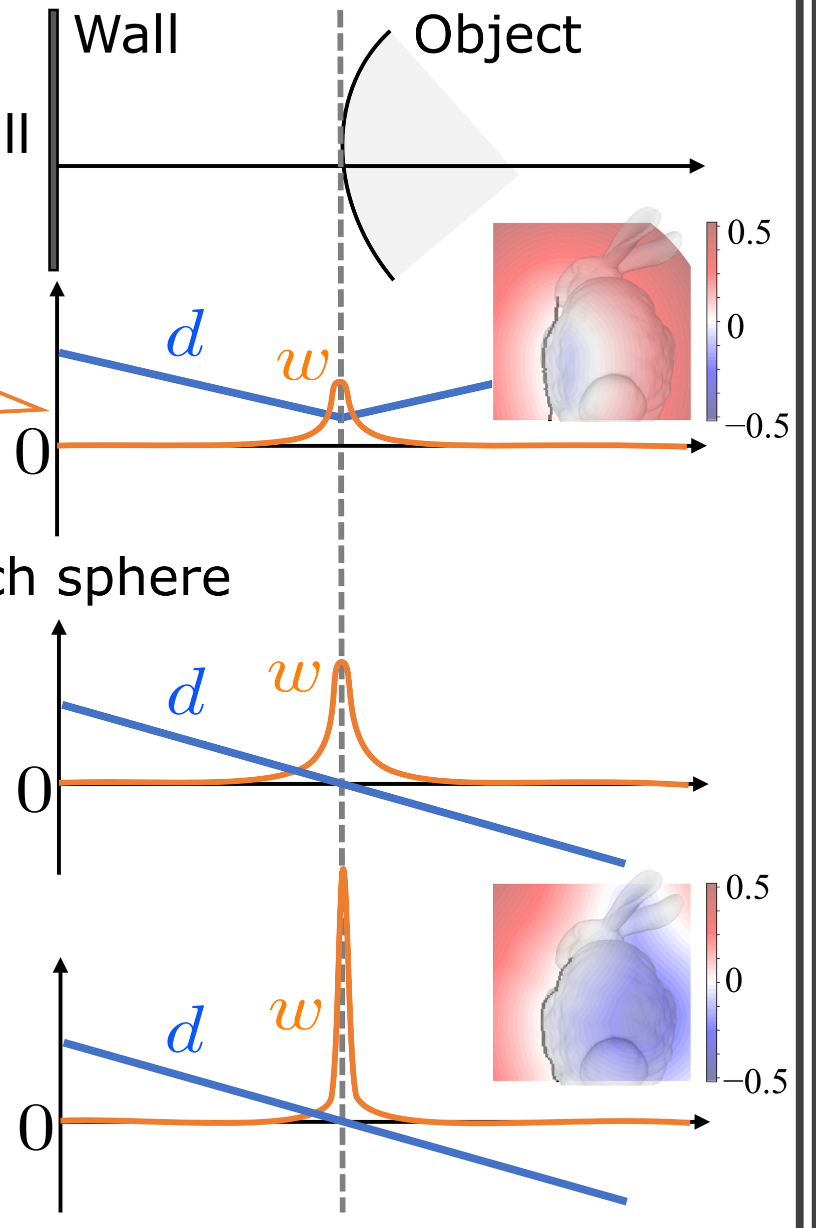
Key: Constraints for learning SDF in the NLOS setup

In the NLOS setup,

- The object is not observed directly
- Only one side of the object is observed from the wall

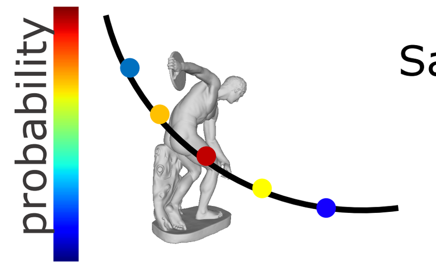
This leads to incorrect SDF

Common failure case:
Volume rendering weight is the highest at a point with non-zero signed distance



(1) Self-supervised zero level-set learning

During training, we compute PDF based on $w\rho$ on each sphere
The signed distances at sampled points with the PDF are forced to be 0



Sample points

$$\mathcal{L}_z = \sum_i d(\mathbf{p}_i)$$

(2) Constraint on volume rendering weights

By reducing α, we generate sharp w for suppressing effects from non-zero signed distance points.

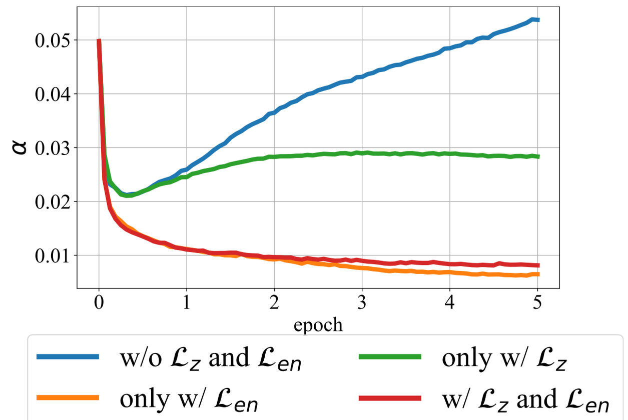
Specifically, we use

$$\mathcal{L}_{en} = \sum_{\mathbf{p}', \theta, \phi} -\hat{o}\log_2 \hat{o} - (1 - \hat{o})\log_2(1 - \hat{o})$$

where $\hat{o} = \sum_{t=t_{min}}^{t_{max}} w(\mathbf{p}, \mathbf{v})$

(Intuitively, all densities outside the object should be 0, mathematical discussion is in the supplementary)

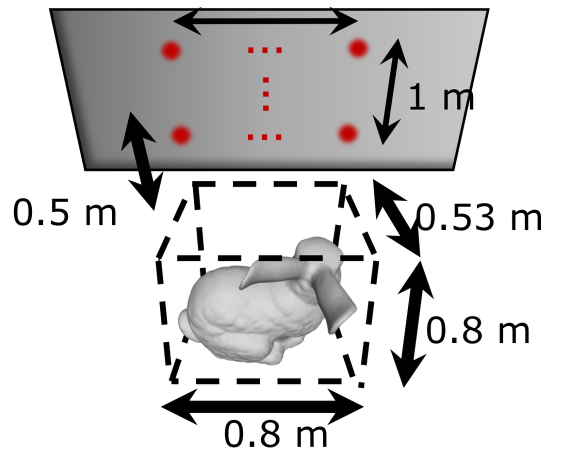
α plots during training w/ and w/o each loss



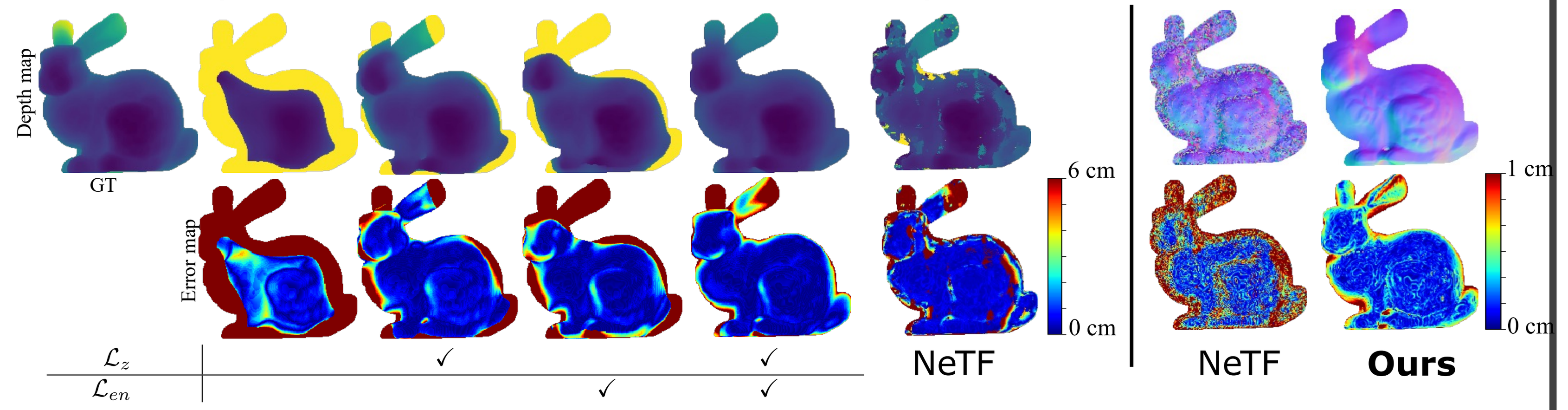
Experiments

(1) Synthetic dataset (ZNLOS dataset [ICCP2019])

- Scan region is 1m x 1m
- 256 x 256 observed points
- # of histogram time bins is 200

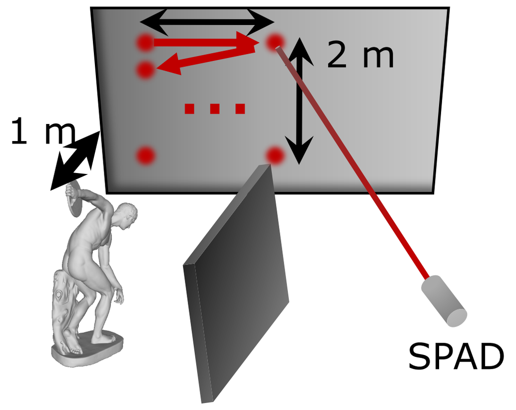


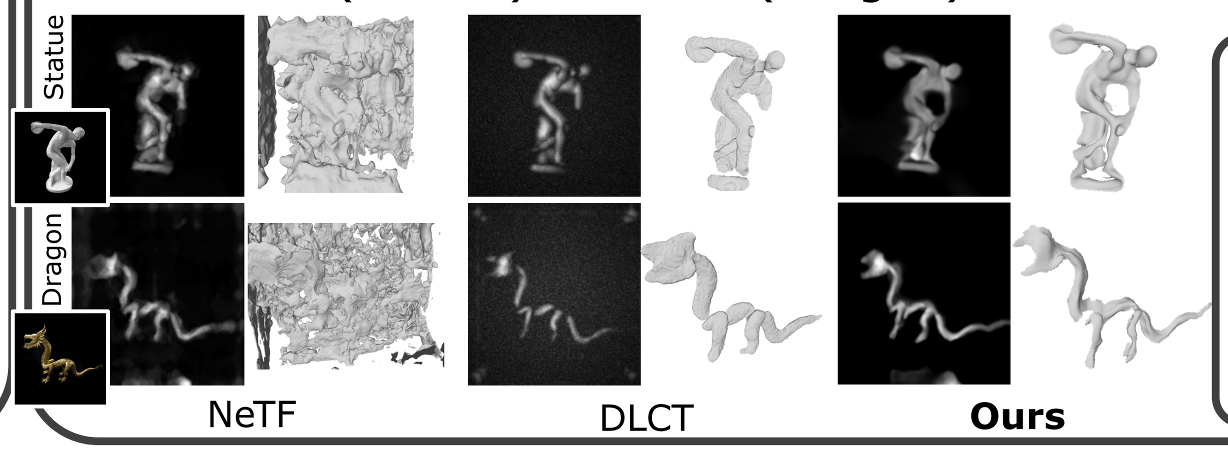
Depth reconstruction and ablation study Surface Normals



(2) Real dataset (f-k dataset [SIGGRAPH2019])

- Captured by SPAD
- Scan region is 2m x 2m
- 256 x 256 observed points
- # of histogram time bins is 160 (Statue) and 120 (Dragon)





Challenging scene (limitation)

Thin structures are difficult for SDF representation