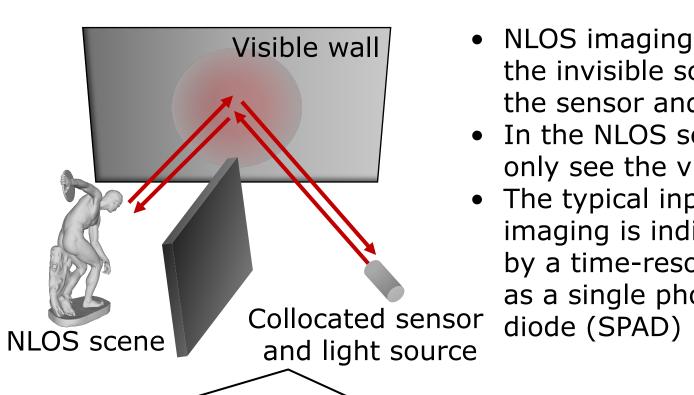


NLOS-NeuS: None-line-of-sight Neural Implicit Surface Takahiro Kushida Takuya Funatomi Yasuhiro Mukaigawa Yuki Fujimura



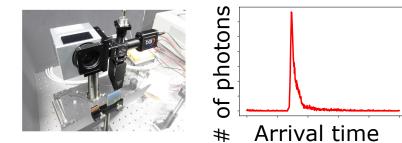


Non-line-of-sight (NLOS) imaging



- NLOS imaging is to reconstruct the invisible scene from the sensor and light source
- In the NLOS setup, the sensor only see the visible wall
- The typical input of the NLOS imaging is indirect light captured by a time-resolved sensor such as a single photon avalanche

Transient histogram captured by a SPAD



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

Related work

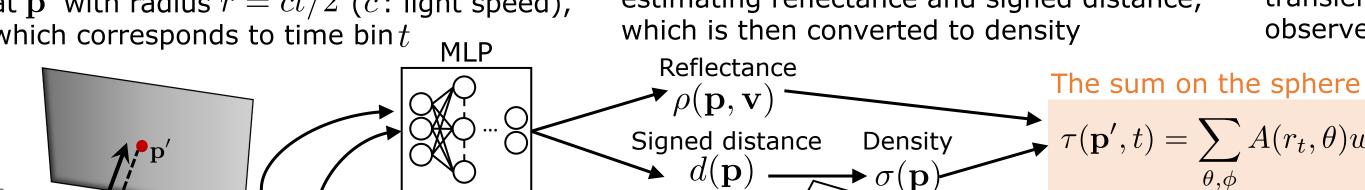
- DLCT [CVPR2020] is proposed for NLOS surface reconstruction with discretized voxel grid representation
- NeTF [ICCP2021] uses neural field similar to NeRF for NLOS imaging
- We propose a neural field approach for NLOS surface reconstruction with continuous implicit surface (signed distance function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

 $\sigma(\mathbf{p}) = \frac{1}{2} Sigmoid(-\frac{d(\mathbf{p})}{2})$

(2) MLP takes each sample point for (1) We sample points on a sphere centered estimating reflectance and signed distance, at \mathbf{p}' with radius r = ct/2 (c: light speed), which is then converted to density which corresponds to time bin t

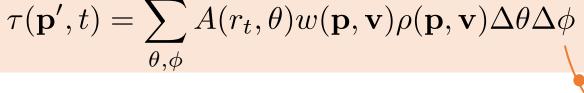


• We use the conversion proposed in StyleSDF [CVPR2022] because of its computational efficiency Positive distance (outside object)

- returns small density • α controls tightness, i.e., $\alpha \to 0$
- represents perfectly sharp surface

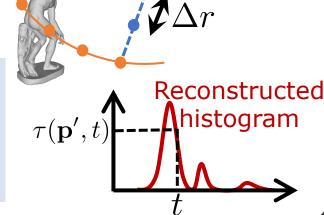
✓ Object

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



Volume rendering on a ray from the wall

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



Surface Normals

Key: Constraints for learning SDF in the NLOS setup

In the NLOS setup,

The object is not observed directly

 $\mathbf{p}(\mathbf{p}', r_t, \theta, \phi)$

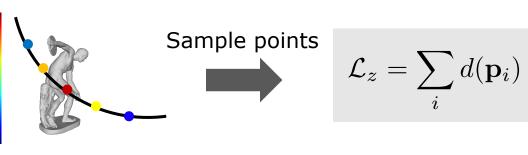
 Only one side of the object is observed from the wall This leads to incorrect SDF

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

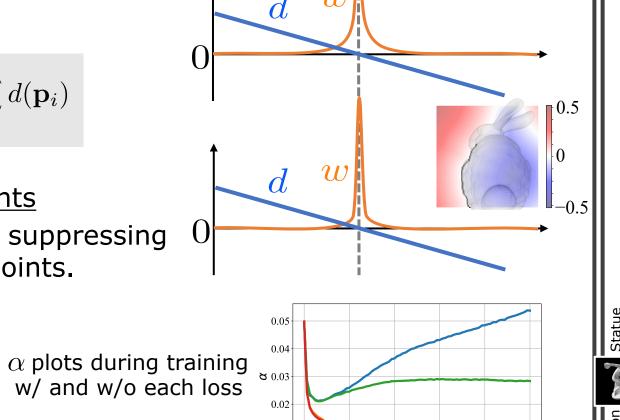


(2) Constraint on volume rendering weights By reducing α , we generate sharp w for suppressing β effects from non-zero signed distance points.

Specifically, we use

$$\mathcal{L}_{en} = \sum_{\mathbf{p}', heta, \phi} -\hat{o} \log_2 \hat{o} - (1 - \hat{o}) \log_2 (1 - \hat{o})$$
 where $\hat{o} = \sum_{\mathbf{r}}^{t_{max}} w(\mathbf{p}, \mathbf{v})$

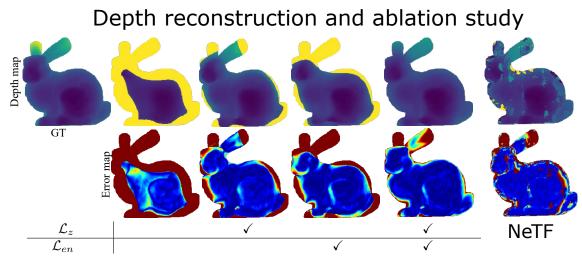
(Intuitively, all densities outside the object should be 0, mathematical discussion is in the supplementary)

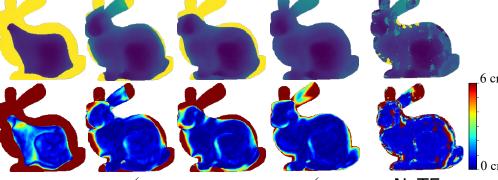


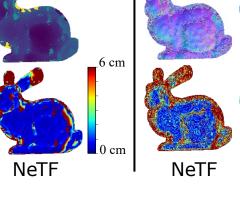
— only w/ \mathcal{L}_z

Experiments

- (1) Synthetic dataset (ZNLOS dataset [ICCP2019])
 - Scan region is 1m x 1m
 - 256 x 256 observed points
 - # of histogram time bins is 200







- (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)

