

PAPER REVIEW

# NeRO:

## Neural Geometry and BRDF Reconstruction of Reflective Objects from Multiview Images

Haeyun CHOI

✉ [heayun126@postech.ac.kr](mailto:heayun126@postech.ac.kr)

🏠 POSTECH PIAI Bldg., Office 341

🏠 [hae-koos.tistory.com](http://hae-koos.tistory.com)

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Liu, Yuan, et al. *SIGGRAPH*. 2023.

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# Introduction

Liu, Yuan, et al. *SIGGRAPH*. 2023.

Neural Geometry and BRDF Reconstruction of Reflective Objects from **Multiview Images**

## Input

- RGB images with known camera pose

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## Neural Geometry and BRDF Reconstruction of Reflective Objects from Multiview Images

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- RGB images with known camera pose
- No object masks or environment lights for reconstructing reflective objects in the MVS setting
  - Additional object masks (Godard et al. 2015)
  - Remove the reflections (Wu et al. 2018)
  - Constrained settings with known specular flows (Roth and Black 2006)
  - etc.

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### Output

- Triangular mesh with BRDF parameters
- Can be easily used in rendering software for various downstream applications such as relighting

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  - etc.

### Output

- Triangular mesh with BRDF parameters
- Can be easily used in rendering software for various downstream applications such as relighting

❖ NeRO can accurately reconstruct the geometry of reflective objects without any object mask. Then, NeRO uses more accurate sampling to recover the environment lights and the BRDF of the object.

# Related Works

Liu, Yuan, et al. *SIGGRAPH*. 2023.

Multiview 3D reconstruction : a fundamental task in computer graphics and vision

## 1. COLMAP

- Most methods rely on **view consistency** for stereo matching
- The reflection on glossy surfaces leads to inconsistent colors when observing the objects from different views

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Wang, Peng, et al. *NIPS*. 2021.

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## 2. Neural Reconstruction (NeuS)

- Model surfaces based on neural rendering
- Surface geometry is represented as an implicit function
  - a signed distance function encoded by a MLP
- Color function does not explicitly consider the underlying shading mechanism for reflection



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- Surface geometry is represented as an implicit function
  - a signed distance function encoded by a MLP
- **Color function does not explicitly consider the underlying shading mechanism for reflection**
- 즉, 현재 신경망은 반사 메커니즘을 정확히 모델링하지 않고, 단순히 색상과 Geometry 정보에 의존하여 재건하기에 Reflective objects를 재건하는 데에는 어려움이 존재한다.

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❖ NeRO explicitly incorporate the rendering equation into the neural reconstruction framework

❖ It enhances **the existing neural reconstruction framework** to capture the high-frequency specular color variations.

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## Related Works

Liu, Yuan, et al. *SIGGRAPH*. 2023.

However, incorporating the rendering equation in a neural reconstruction framework is not trivial

- With unknown surface locations and unknown environment lights,
- Integral of environment lights is intractable

# Related Works

Liu, Yuan, et al. *SIGGRAPH*. 2023.

Verbin, et al. *CVPR*. 2022.

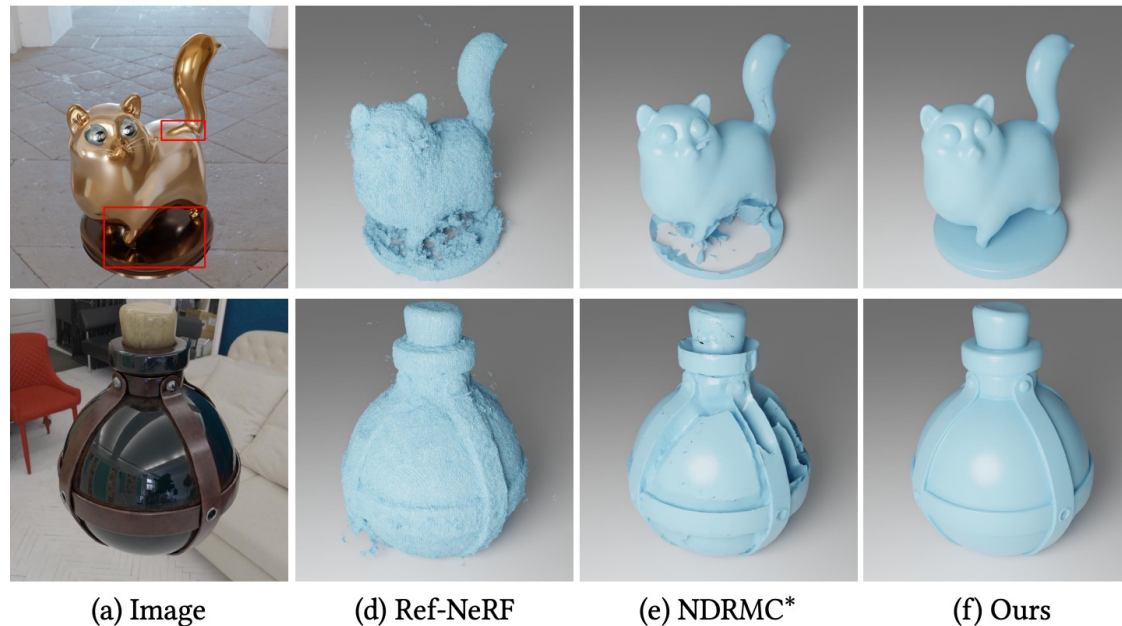
Hasselgren, et al. *NIPS*. 2022.

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- With unknown surface locations and unknown environment lights,
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## 3. Only Direct Lights (Ref-NeRF) / Object Masks (NDRMC)

- Rely on object masks to obtain a correct surface reconstruction
- Mainly designed for material estimation of objects **without strong specular reflections**
- Most of these methods simplify the rendering process to only consider the lights from distant regions (direct lights)



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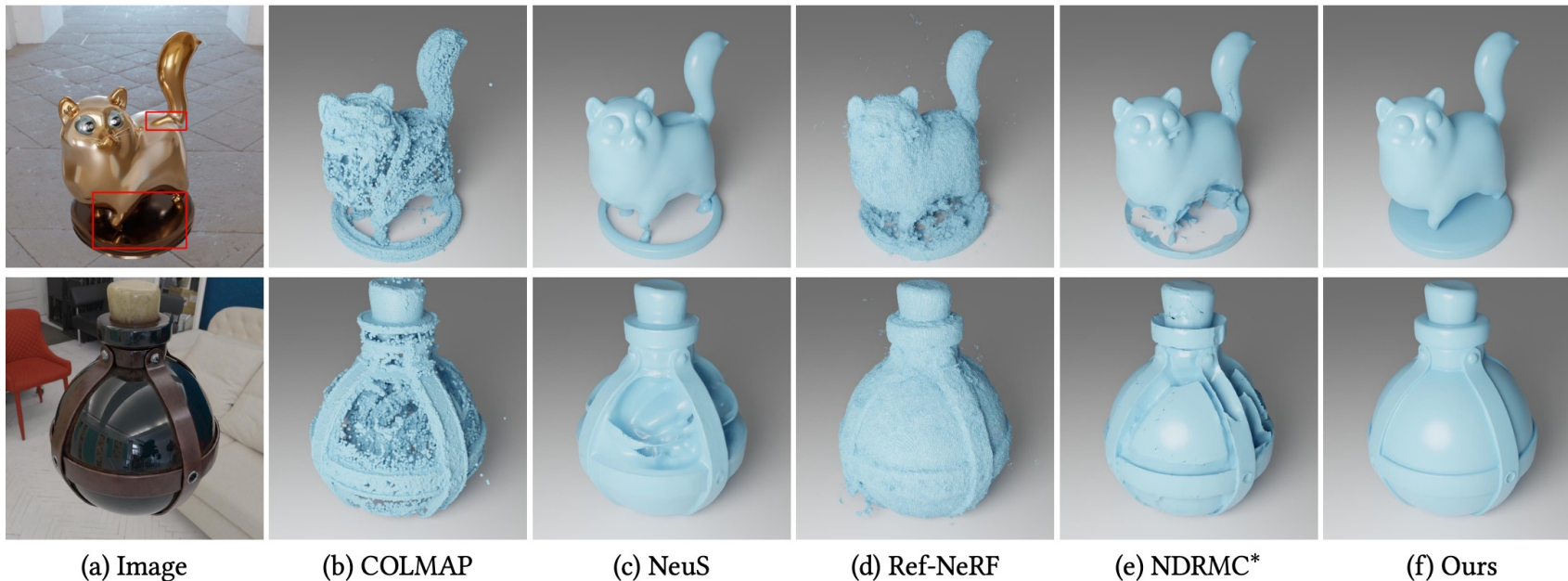
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- Most of these methods simplify the rendering process to only consider the lights from distant regions (direct lights)

❖ Considering both direct and indirect lights,

❖ reconstructing the unknown surfaces of reflective objects is still challenging.

# Method

Liu, Yuan, et al. *SIGGRAPH*. 2023.

NeRO: Reconstructing both the geometry and the BRDF of reflective objects from only posed RGB images

- Key Component

- A novel light representation (Two MLPs to encode the radiance of direct & indirect lights respectively)
- Occlusion probability to determine whether direct or indirect lights should be used in the rendering
- Based on them, 2-stage strategy for a tractable evaluation of the rendering equation



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### Stage 1 (Geometry Reconstruction)

- NeuS / Micro-facet BRDF / Split-sum Approximation / Integrated Directional Encoding (Ref-NeRF)
- Evaluating the rendering equation,
- it produces accurate geometry reconstruction with compromised environment lights and surface BRDF estimation

### Stage 2 (BRDF Estimation)

- Fixed geometry, It improves the estimated BRDF
- by more accurately evaluating the rendering equation with Monte Carlo sampling

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Liu, Yuan, et al. *SIGGRAPH*. 2023.

NeuS / Micro-facet BRDF / Split-sum Approximation / Integrated Directional Encoding

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- NeuS represents the object surface by an SDF encoded by an MLP network  $g_{\text{sdf}}(\mathbf{x})$
- Then, volume rendering is applied to render images from the neural SDF

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- Then, volume rendering is applied to render images from the neural SDF
- Given a camera ray, we sample  $n$  points on the ray
- Then, the rendered color for this camera ray is computed by  $\hat{\mathbf{c}} = \sum_n w_j \mathbf{c}_j \quad \mathbf{c}_j = g_{\text{color}}(\mathbf{p}_j, \mathbf{v})$
- weight for the  $j$ -th point, derived from the SDF value via the opaque density proposed in NeuS

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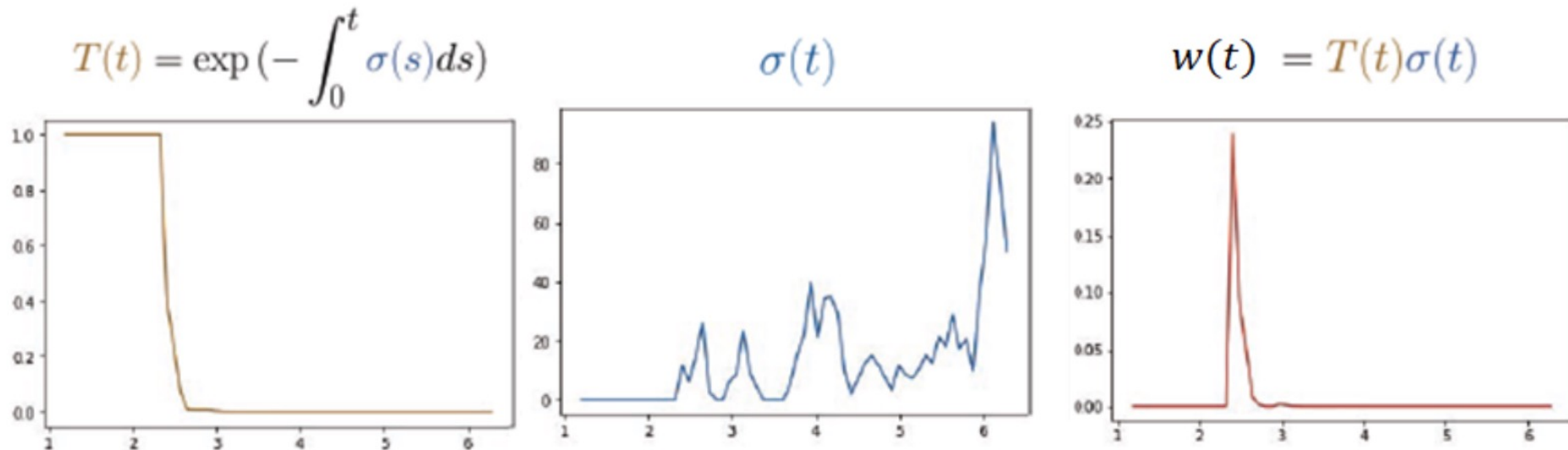
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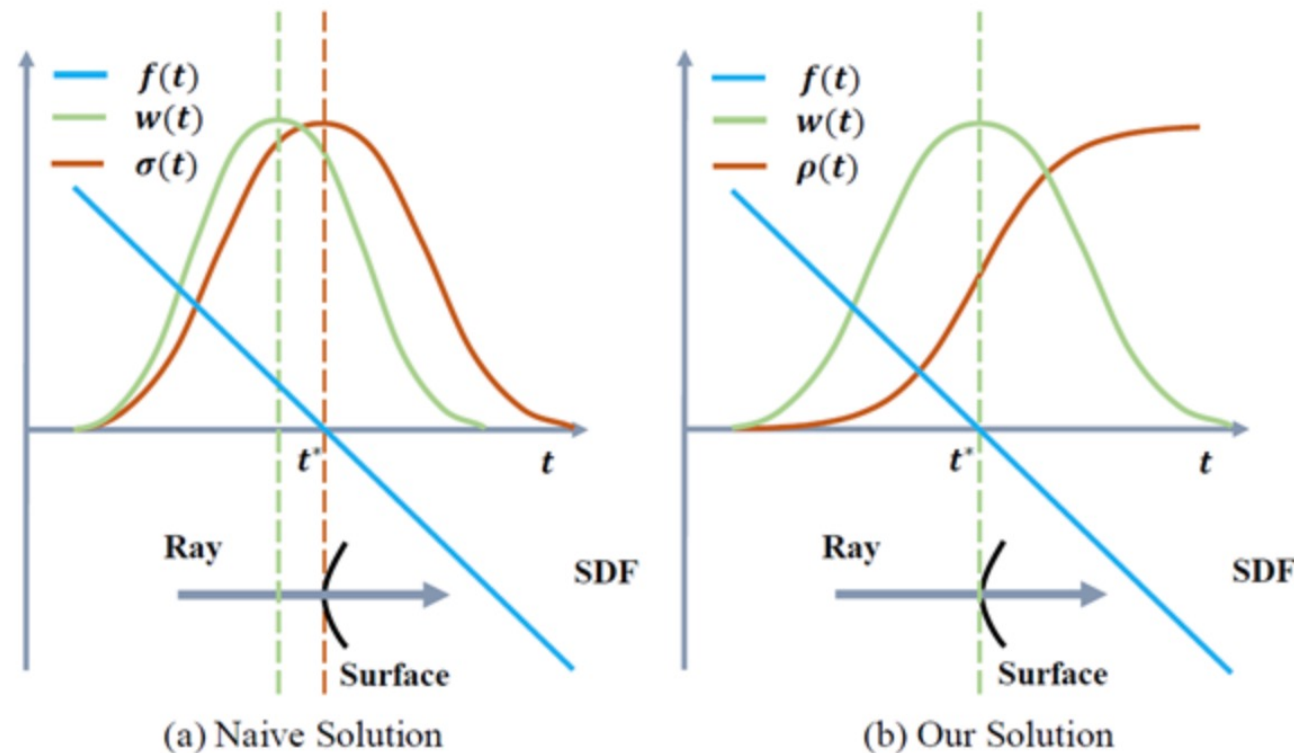
$$C(\mathbf{r}) = \int_{t_n}^{t_f} \underbrace{T(t)}_{\text{Accumulated Transmittance}} \underbrace{\sigma(\mathbf{r}(t))}_{\text{Volume Density}} \underbrace{\mathbf{c}(\mathbf{r}(t), \mathbf{d})}_{\text{Color}} dt, \quad \text{where } T(t) = \exp\left(-\int_{t_n}^t \sigma(\mathbf{r}(s)) ds\right)$$



# Stage 1: Geometry Reconstruction

Liu, Yuan, et al. SIGGRAPH. 2023.

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- weight for the  $j$ -th point, **derived from the SDF value via the opaque density proposed in NeuS**
  - Skip the math details (NeuS' Contribution)



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Liu, Yuan, et al. SIGGRAPH. 2023.

NeuS / Micro-facet BRDF / Split-sum Approximation / Integrated Directional Encoding

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- weight for the  $j$ -th point, derived from the SDF value via the opaque density proposed in NeuS
- By minimizing color difference,  $g_{\text{sdf}}$  and  $g_{\text{color}}$  are learned

❖ To enable the color function to correctly represent the specular colors on the reflective surfaces,

❖ NeRO replaces the color function of NeuS with the shading function using a Micro-facet BRDF



# Stage 1: Geometry Reconstruction

Liu, Yuan, et al. SIGGRAPH. 2023.

NeuS / Micro-facet BRDF / Split-sum Approximation / Integrated Directional Encoding

- Replace the color function of NeuS with the shading function using a Micro-facet BRDF

$$\mathbf{c}(\omega_o) = \int_{\Omega} L(\omega_i) f(\omega_i, \omega_o) (\omega_i \cdot \mathbf{n}) d\omega_i,$$

Outgoing view direction |  $w_0 = -\mathbf{v}$

Surface normal |  $\mathbf{n}$

Input light direction |  $w_i$

BRDF function |  $f(w_i, w_o) \in [0, 1]^3$

Radiance of incoming lights |  $L(w_i) \in [0, +\infty]^3$

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- In NeRO, the normal  $\mathbf{n}$  is computed from the gradient of the SDF
- The BRDF function consists of a diffuse and a specular part
  - D, F, and G are all determined by the metalness  $m$ , the roughness  $p$ , and the albedo  $a$  (Appendix)

$$f(\omega_i, \omega_o) = \underbrace{(1 - m) \frac{a}{\pi}}_{\text{diffuse}} + \underbrace{\frac{DFG}{4(\omega_i \cdot \mathbf{n})(\omega_o \cdot \mathbf{n})}}_{\text{specular}}$$

Metalness |  $m \in [0, 1]$  / Weight for the diffuse part  $1 - m$

Albedo color |  $a \in [0, 1]^3$

Normal distribution function |  $D$

Fresnel Term |  $F$

Geometry term |  $G$

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Liu, Yuan, et al. SIGGRAPH. 2023.

NeuS / Micro-facet BRDF / Split-sum Approximation / Integrated Directional Encoding

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1. In NeRO, the normal  $\mathbf{n}$  is computed from the gradient of the SDF
2. The BRDF function consists of a diffuse and a specular part

---

In summary, the BRDF of the point is specified by the metalness, the roughness, and the albedo

All of them are predicted by a material MLP in NeRO  $[m, \rho, \mathbf{a}] = g_{\text{material}}(\mathbf{p})$

# Stage 1: Geometry Reconstruction

Liu, Yuan, et al. SIGGRAPH. 2023.

NeuS / Micro-facet BRDF / Split-sum Approximation / Integrated Directional Encoding

- Diffuse part BRDF / Specular Part BRDF 각각 아래 식에 대입

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$$\mathbf{c}(\omega_o) = \mathbf{c}_{\text{diffuse}} + \mathbf{c}_{\text{specular}},$$

$$\mathbf{c}_{\text{diffuse}} = \int_{\Omega} (1 - m) \frac{\mathbf{a}}{\pi} L(\omega_i) (\omega_i \cdot \mathbf{n}) d\omega_i,$$

$$\mathbf{c}_{\text{specular}} = \int_{\Omega} \frac{DFG}{4(\omega_i \cdot \mathbf{n})(\omega_o \cdot \mathbf{n})} L(\omega_i) (\omega_i \cdot \mathbf{n}) d\omega_i.$$

- Evaluating the integrals above for every sample point in the volume rendering is intractable
- To do so, Split-sum Approximation / Integrated Directional Encoding (Ref-NeRF)

# Stage 1: Geometry Reconstruction

Liu, Yuan, et al. SIGGRAPH. 2023.

NeuS / Micro-facet BRDF / Split-sum Approximation / Integrated Directional Encoding

- Split-sum Approximation

$$\mathbf{c}(\omega_o) = \mathbf{c}_{\text{diffuse}} + \mathbf{c}_{\text{specular}},$$

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---


$$\mathbf{c}_{\text{specular}} \approx \underbrace{\int_{\Omega} L(\omega_i) D(\rho, \mathbf{t}) d\omega_i}_{L_{\text{specular}}} \cdot \underbrace{\int_{\Omega} \frac{DFG}{4(\omega_o \cdot \mathbf{n})} d\omega_i}_{M_{\text{specular}}}, \quad \mathbf{c}_{\text{diffuse}} = \mathbf{a}(1 - m) \underbrace{\int_{\Omega} L(\omega_i) \frac{\omega_i \cdot \mathbf{n}}{\pi} d\omega_i}_{L_{\text{diffuse}}},$$

- The only two unknowns are light integrals  $L_{\text{diffuse}}$  and  $L_{\text{specular}}$ .

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Liu, Yuan, et al. SIGGRAPH. 2023.

NeuS / Micro-facet BRDF / Split-sum Approximation / Integrated Directional Encoding

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- Light Representation (Page 17. Key Component)

$$L(\omega_i) = [1 - s(\omega_i)] g_{\text{direct}}(SH(\omega_i)) + s(\omega_i) g_{\text{indirect}}(SH(\omega_i), \mathbf{p}),$$



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- The only two unknowns are light integrals  $L_{\text{diffuse}}$  and  $L_{\text{specular}}$ .

- Light Representation (Page 17. Key Component) / SH : directional encoding using SH as basis

$$L(\omega_i) = [1 - s(\omega_i)] g_{\text{direct}}(SH(\omega_i)) + s(\omega_i) g_{\text{indirect}}(SH(\omega_i), \mathbf{p}),$$

- Two MLPs  $g_{\text{direct}}$  and  $g_{\text{indirect}}$
- Probability that the ray from the point  $\mathbf{p}$  to the direction  $w_i$  is occluded |  $s(w_i) \in [0, 1]$
- Note that  $s(w_i) = g_{\text{occ}}(SH(w_i, \mathbf{p}))$  is also predicted by an MLP  $g_{\text{occ}}$

# Stage 1: Geometry Reconstruction

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## Occlusion Loss

- Occlusion Prob : To determine whether direct lights or indirect lights will be used in rendering

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Liu, Yuan, et al. SIGGRAPH. 2023.

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## Occlusion Loss

- Occlusion Prob : To determine whether direct lights or indirect lights will be used in rendering
- Additional constraint using the neural SDF

We compute its occlusion probability  $s_{\text{march}}$  by ray-marching in the neural SDF  $g_{\text{SDF}}$  and enforce the consistency

$$\ell_{\text{occ}} = \|s_{\text{march}} - s\|_1.$$

# Stage 1: Geometry Reconstruction

Liu, Yuan, et al. SIGGRAPH. 2023.

NeuS / Micro-facet BRDF / Split-sum Approximation / Integrated Directional Encoding (Appendix)

$$\mathbf{c}_{\text{specular}} \approx \underbrace{\int_{\Omega} L(\omega_i) D(\rho, \mathbf{t}) d\omega_i}_{L_{\text{specular}}} \cdot \underbrace{\int_{\Omega} \frac{DFG}{4(\omega_o \cdot \mathbf{n})} d\omega_i}_{M_{\text{specular}}}, \quad \mathbf{c}_{\text{diffuse}} = \mathbf{a}(1 - m) \underbrace{\int_{\Omega} L(\omega_i) \frac{\omega_i \cdot \mathbf{n}}{\pi} d\omega_i}_{L_{\text{diffuse}}},$$

$$L(\omega_i) = [1 - s(\omega_i)] g_{\text{direct}}(SH(\omega_i)) + s(\omega_i) g_{\text{indirect}}(SH(\omega_i), \mathbf{p});$$

$$\begin{aligned} L_{\text{specular}} &\approx [1 - s(\mathbf{t})] \int_{\Omega} g_{\text{direct}}(SH(\omega_i)) D(\rho, \mathbf{t}) d\omega_i + \\ &\quad s(\mathbf{t}) \int_{\Omega} g_{\text{indirect}}(SH(\omega_i), \mathbf{p}) D(\rho, \mathbf{t}) d\omega_i \\ &\approx [1 - s(\mathbf{t})] g_{\text{direct}} \left( \int_{\Omega} SH(\omega_i) D(\rho, \mathbf{t}) d\omega_i \right) + \\ &\quad s(\mathbf{t}) g_{\text{indirect}} \left( \int_{\Omega} SH(\omega_i) D(\rho, \mathbf{t}) d\omega_i, \mathbf{p} \right). \end{aligned}$$

## Stage 2: BRDF Estimation

Liu, Yuan, et al. SIGGRAPH. 2023.

### Stage 2 (BRDF Estimation)

- **Fixed geometry**, It improves the estimated BRDF (metalness, albedo, roughness)
- by more accurately evaluating the rendering equation with **Monte Carlo sampling**

### Fixed Geometry

- We **only** need to evaluate the rendering equation **on surface points**
- Thus, it is feasible to apply Monte Carlo sampling to compute the equations (5), (6)

$$\mathbf{c}_{\text{diffuse}} = \int_{\Omega} (1 - m) \frac{\mathbf{a}}{\pi} L(\omega_i) (\omega_i \cdot \mathbf{n}) d\omega_i, \quad (5)$$

$$\mathbf{c}_{\text{specular}} = \int_{\Omega} \frac{DFG}{4(\omega_i \cdot \mathbf{n})(\omega_o \cdot \mathbf{n})} L(\omega_i) (\omega_i \cdot \mathbf{n}) d\omega_i. \quad (6)$$

## Stage 2: BRDF Estimation

Liu, Yuan, et al. *SIGGRAPH*. 2023.

### Stage 2 (BRDF Estimation)

$$\mathbf{c}_{\text{diffuse}} = \int_{\Omega} (1 - m) \frac{\mathbf{a}}{\pi} L(\omega_i) (\omega_i \cdot \mathbf{n}) d\omega_i, \quad (5)$$

$$\mathbf{c}_{\text{specular}} = \int_{\Omega} \frac{DFG}{4(\omega_i \cdot \mathbf{n})(\omega_o \cdot \mathbf{n})} L(\omega_i) (\omega_i \cdot \mathbf{n}) d\omega_i. \quad (6)$$

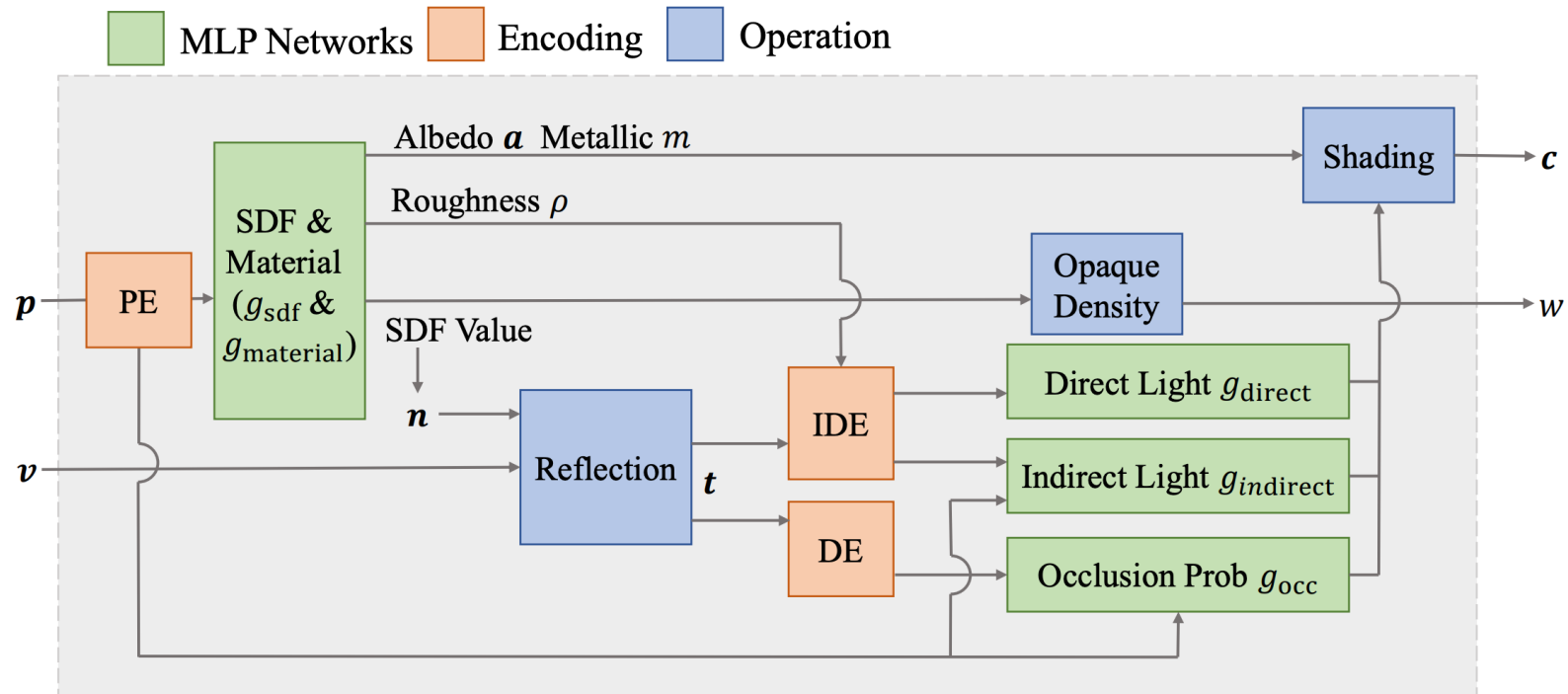
$$\mathbf{c}_{\text{diffuse}} = \frac{1}{N_d} \sum_i^{N_d} (1 - m) \mathbf{a} L(\omega_i),$$

$$\mathbf{c}_{\text{specular}} = \frac{1}{N_s} \sum_i^{N_s} \frac{FG(\omega_o \cdot \mathbf{h})}{(\mathbf{n} \cdot \mathbf{h})(\mathbf{n} \cdot \omega_o)} L(\omega_i),$$

# Discussion

Liu, Yuan, et al. SIGGRAPH. 2023.

## Interim Assumption



- 기존 Deblur-NeRF 방식처럼 Ray 여러 개 쏘서 Rendering 하기에는 Computation Inefficient
- GT Sharp Image 없는 Setting 활용

# Milestone

Liu, Yuan, et al. *SIGGRAPH*. 2023.

## Week 1 (240108 ~ 240112)

- ~~NeRO Paper Review~~
- ~~NeRO Train~~
- 어떤 데이터를 어떻게 찍을 것인지
- BLK 360 활용법

## Week 2 (240115 ~ 240119)

- 240115 (월) 백남준 아트센터 출장
- 데이터 처리 및 활용 방안

## Week 3 (240122 ~ 240126)

- 프로젝트 방향성 확정
  - Add deblur module to the NeRO
  - Just utilized data



# Milestone

Liu, Yuan, et al. *SIGGRAPH*. 2023.

## Week 4 (240129 ~ 240202)

- 프로젝트 수행
- IPIU 2024 참석 : 240131 (수) ~ 240202 (금)
- TBD

## Week 5 (240205 ~ 240209)

- 프로젝트 수행
- TBD

## Week 6 (240212 ~ 240216)

- 발표 준비
- 과제 발표회 : 2월 15일 목요일, 우면사옥 뉴미디어 회의실
- 수료식 : 2월 16일 금요일, 우면사옥 4F 타운 홀

# Milestone

Liu, Yuan, et al. *SIGGRAPH*. 2023.

## Week 4 (240129 ~ 240202)

- 프로젝트 수행
- IPIU 2024 참석 : 240131 (수) ~ 240202 (금)
- TBD

## Week 5 (240205 ~ 240209)

- 프로젝트 수행
- TBD

## Week 6 (240212 ~ 240216)

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- 과제 발표회 : 2월 15일 목요일, 우면사옥 뉴미디어 회의실
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*End of Document.*