PAPER REVIEW

NeRO:

Neural Geometry and BRDF Reconstruction of Reflective Objects from Multiview Images

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POSTECH COMPUTER GRAPHICS

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

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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

Related Works

Liu, Yuan, et al. *SIGGRAPH*. 2023.
Wang, Peng, et al. *NIPS*. 2021.

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

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   - 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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   - 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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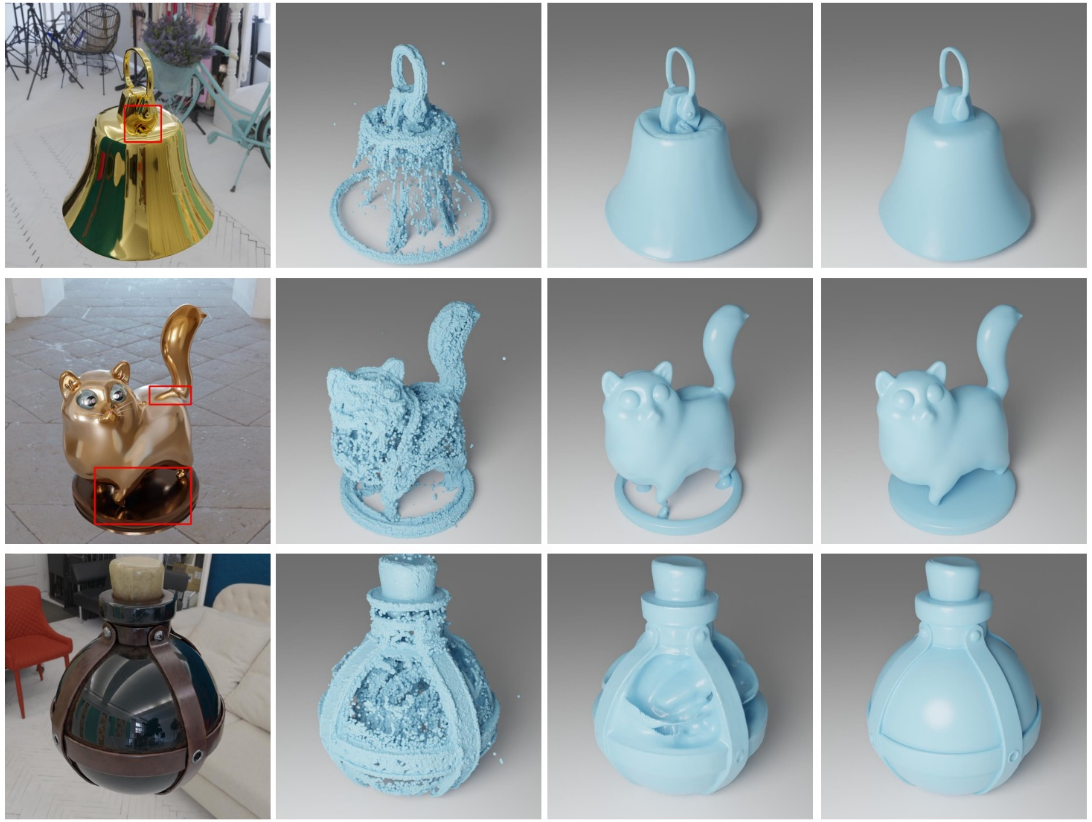

(a) Image (b) COLMAP (c) NeuS (f) Ours

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Related Works

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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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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)

(a) Image (d) Ref-NeRF (e) NDRMC* (f) Ours

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❖ Considering both direct and indirect lights,

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

Method

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

- We reconstruct the geometry of the reflective object by optimizing a neural SDF with the volume rendering

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- We reconstruct the geometry of the reflective object by optimizing a neural SDF with the volume rendering
- NeuS represents the object surface by an SDF encoded by an MLP network $g_{\mathrm{sdf}}(\mathbf{x})$
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- 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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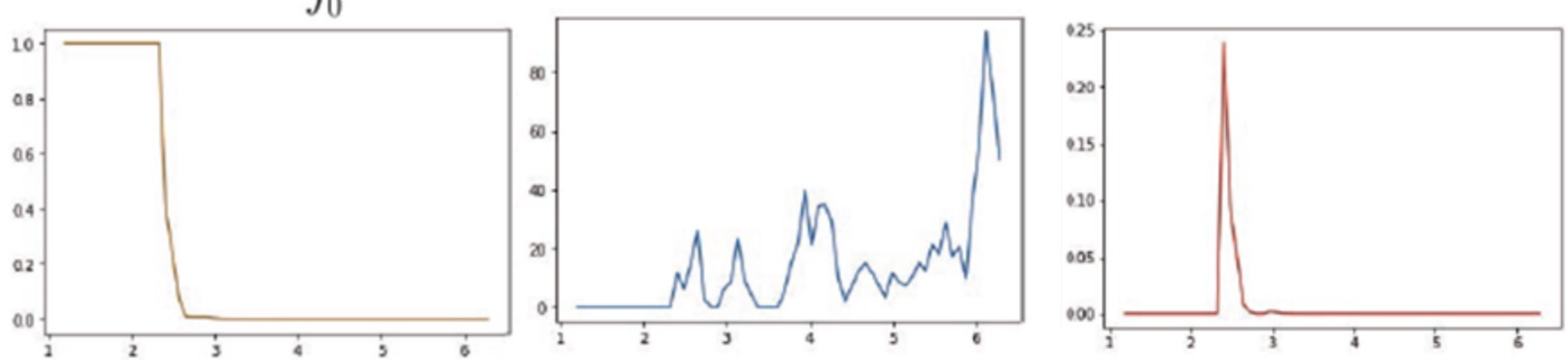
$$C(\mathbf{r}) = \int_{t_n}^{t_f} \underbrace{T(t)}_{\text{Accumulated Transmittance}} \underbrace{\sigma(\mathbf{r}(t))}_{\text{Volume Density}} \mathbf{c}(\mathbf{r}(t), \mathbf{d})dt\,, \quad \text{where } T(t) = \boxed{\exp\left(-\int_{t_n}^{t} \sigma(\mathbf{r}(s))ds\right)}$$

$$T(t) = \exp\left(-\int_0^t \sigma(s)ds\right) \qquad \sigma(t) \qquad w(t) = T(t)\sigma(t)$$



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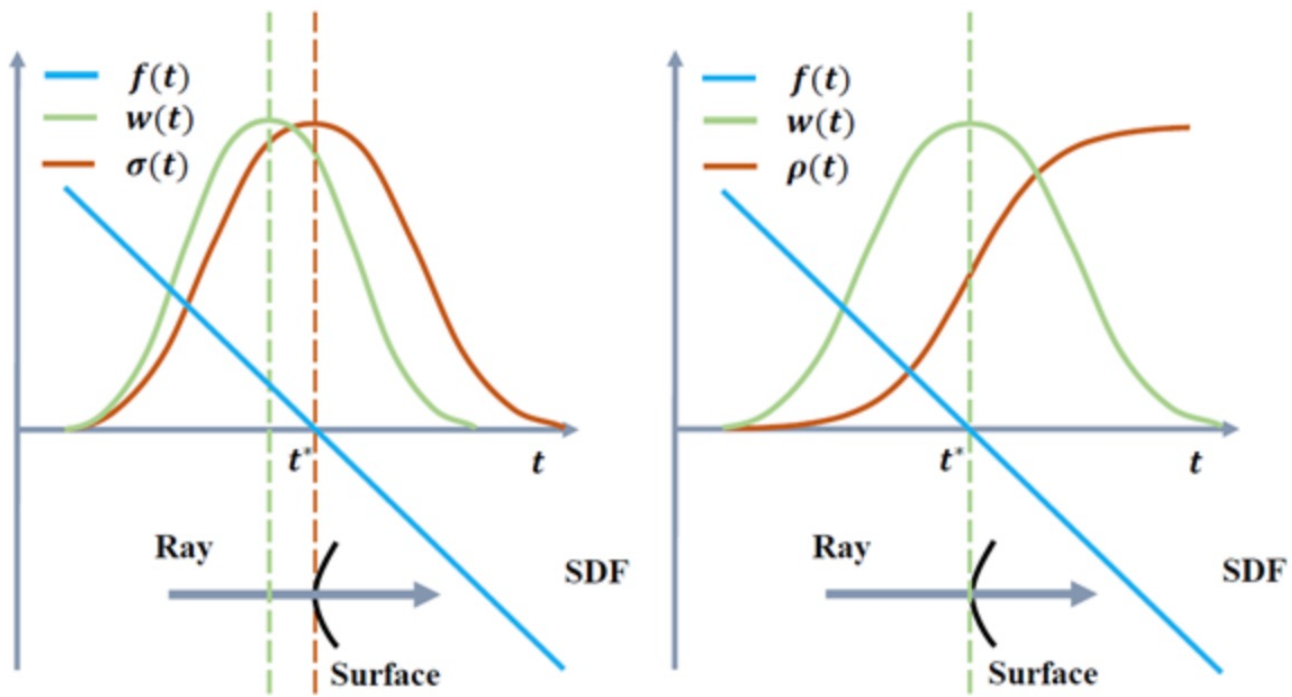
- weight for the j-th point, derived from the SDF value via the opaque density proposed in NeuS
    - Skip the math details (NeuS' Contribution)



(a) Naive Solution (b) Our Solution

Stage 1: Geometry Reconstruction

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

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

- We reconstruct the geometry of the reflective object by optimizing a neural SDF with the volume rendering
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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_{sdf} and g_{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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1. In NeRO, the normal **n** is computed from the gradient of the SDF

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1. In NeRO, the normal **n** is computed from the gradient of the SDF
2. 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)

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

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

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

Normal distribution function | D

Fresenel Term | F

Geometry term | G

Stage 1: Geometry Reconstruction

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 **n** is computed from the gradient of the SDF
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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 $[m, \rho, \mathbf{a}] = g_{\mathrm{material}}(\mathbf{p})$

Stage 1: Geometry Reconstruction

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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

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

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

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

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

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

Stage 1: Geometry Reconstruction

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) / SH : directional encoding using SH as basis

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

Stage 1: Geometry Reconstruction

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

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

Stage 1: Geometry Reconstruction

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

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Occlusion Loss

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

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
- Additional constraint using the neural SDF

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

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

Stage 1: Geometry Reconstruction

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

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

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

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

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)

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

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

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

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

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

Discussion

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

Deblur Module

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

Deblur Module

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