Poster ID: WED-PM-016

Code available

Inverse Rendering of Translucent Objects using Physical and Neural Renderers

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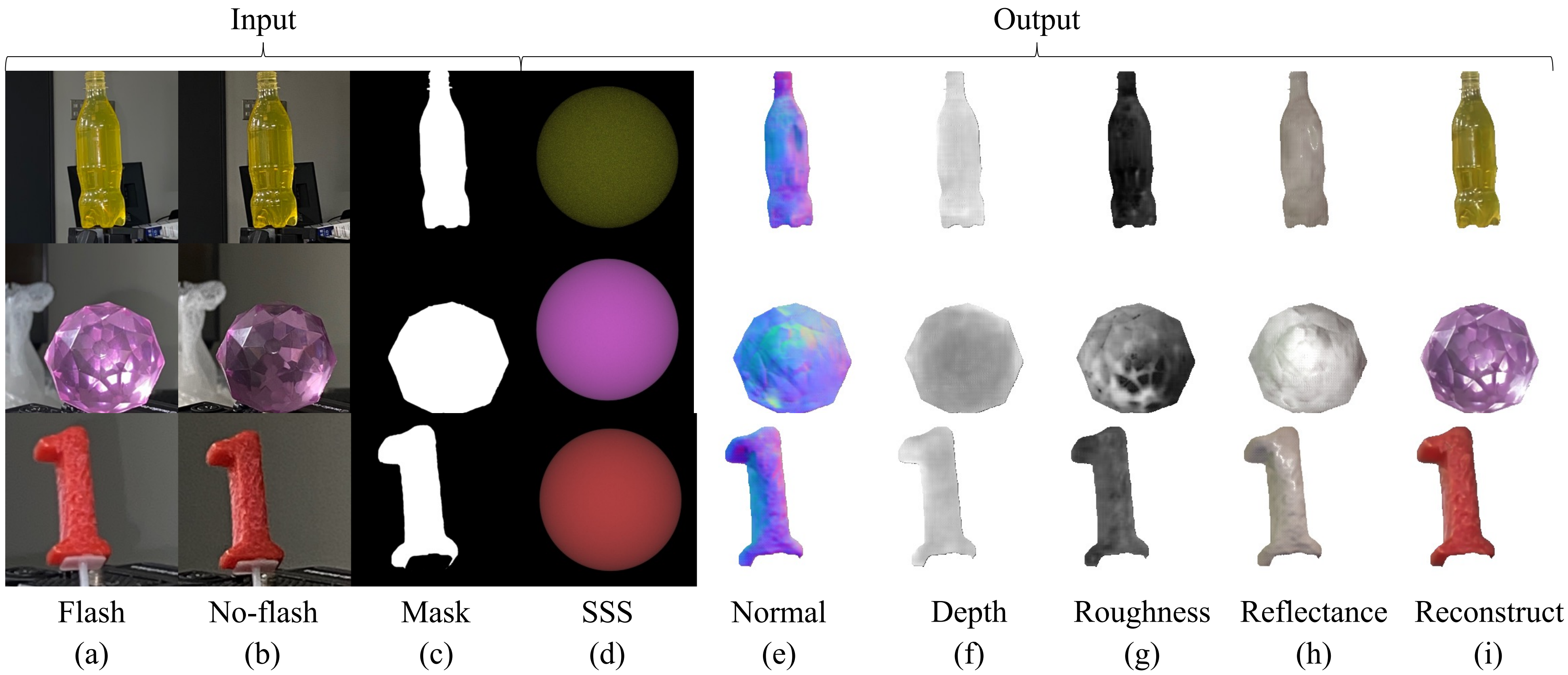
Osaka University



Quick Preview

Translucent objects

Surface

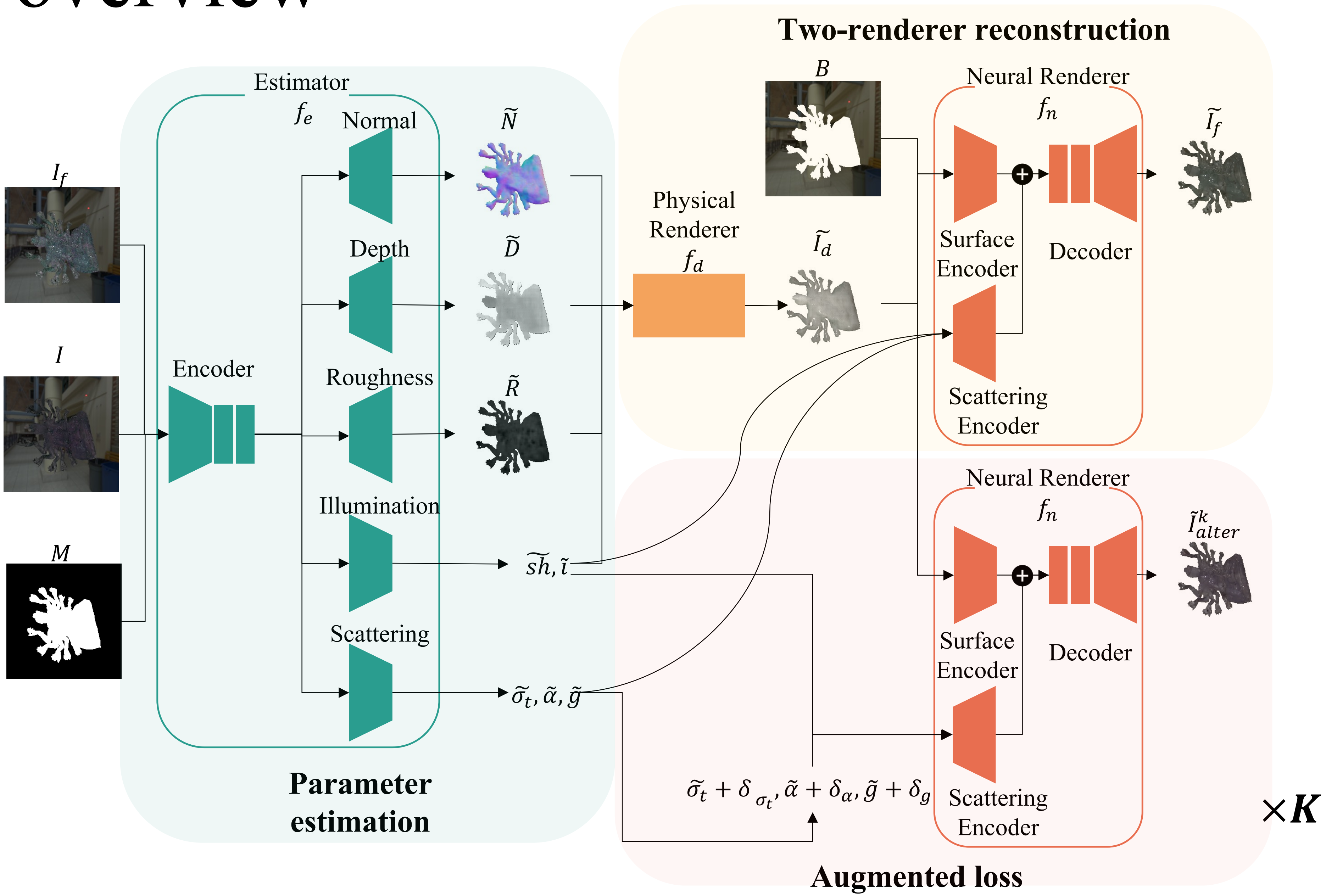
Volume

Surface or Volume?

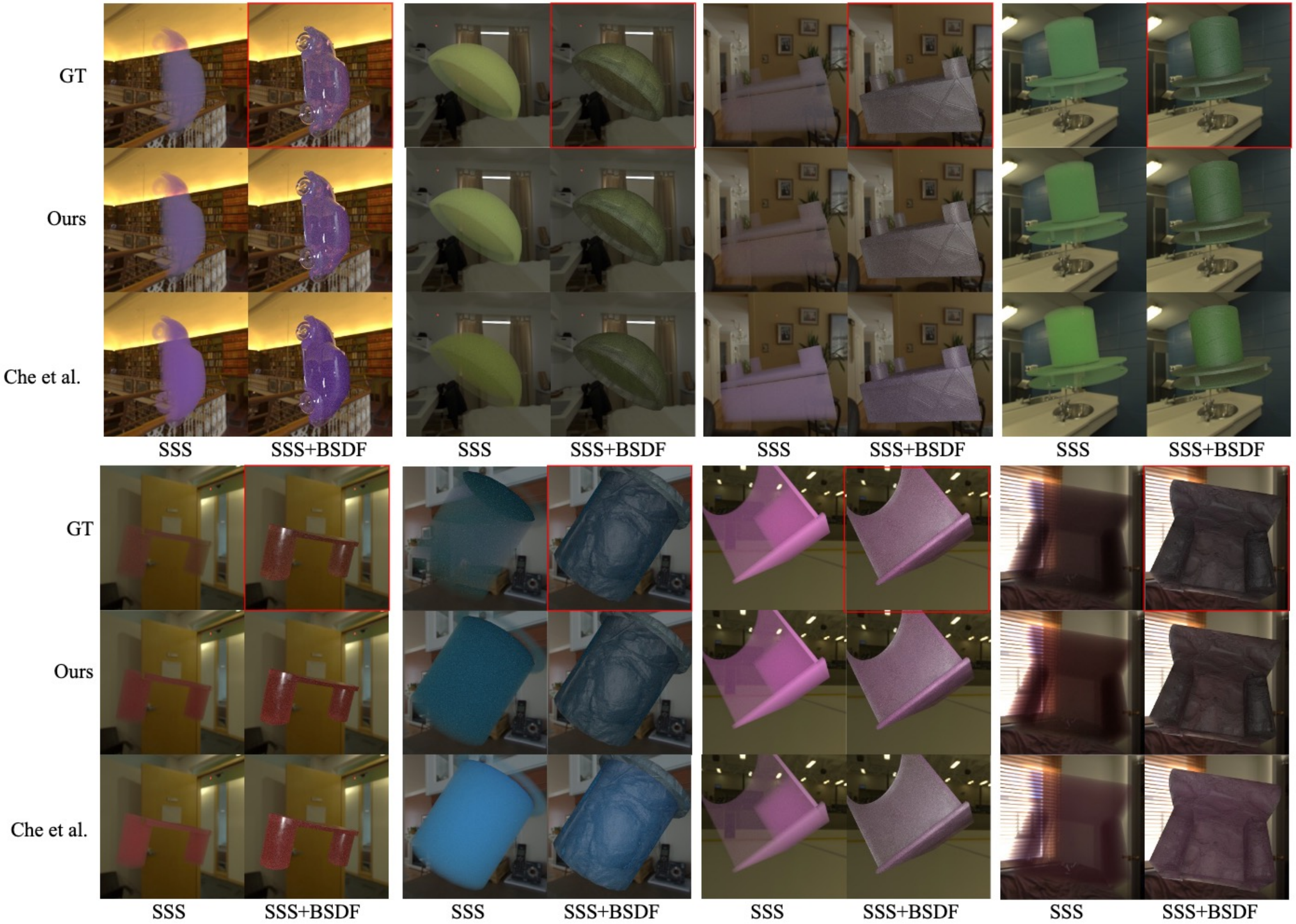
Existing inverse rendering works.

Our target objects

Model overview



Qualitative results



Re-rendered images using estimated SSS parameters.

Quantitative results

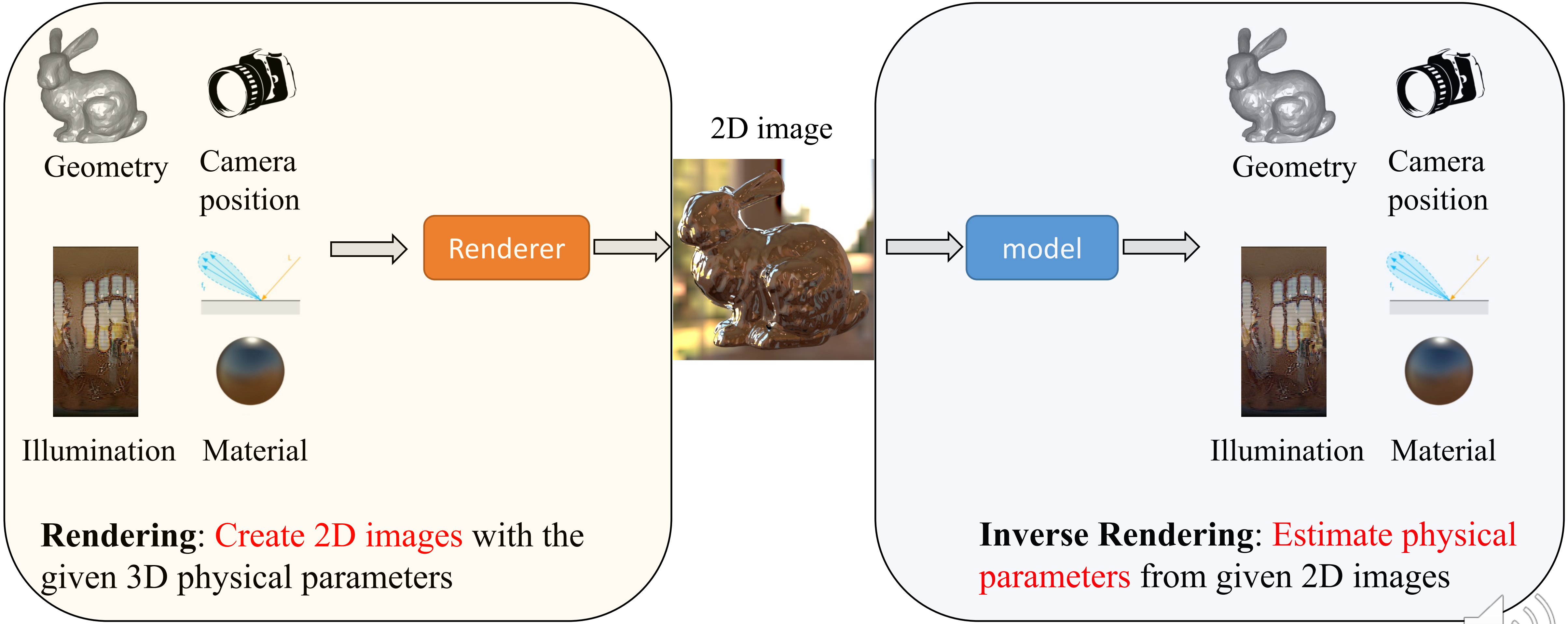
Table 1. MAE results on 17140 test scenes. For each element we report mean(std) value. The scale of mean is 1×10^0, and std is 1×10^{-3}.

	Geometry		BSDF	Illumination			SSS	
	N	D	R	sh	i	σ_t	α	g
Baseline	.0918(.4395)	.0705(.4443)	.0811(.5303)	.1083(.6571)	.0912(1.042)	.1670(.7904)	.1061(.5792)	.1762(.8811)
2R	.0916(.3009)	.0697(.3617)	.0811(.4903)	.1064(.8984)	.0908(.7697)	.1675(1.072)	.1057(.4191)	.1777(2.562)
2R-AUG	.0913(.1768)	.0699(1.271)	.0807(.2714)	.1105(8.926)	.0893(1.151)	.1619(.9635)	.1040(.1578)	.1703(.8856)
Che *et al.* [11]	-	-	-	-	-	.1828	.1115	.2123
Full model	**.0894**(.1532)	**.0646**(.3283)	**.0769**(.2659)	**.0989**(1.017)	**.0804**(1.736)	**.1590**(.2286)	**.1002**(.5185)	**.1655**(.3932)

Baseline: Re-renderer the image only using a neural network
2R: Use a physically-based renderer and a neural renderer
2R-AUG: Use two renderers and Augment loss
Full model: add two-shot to 2R-AUG

Details

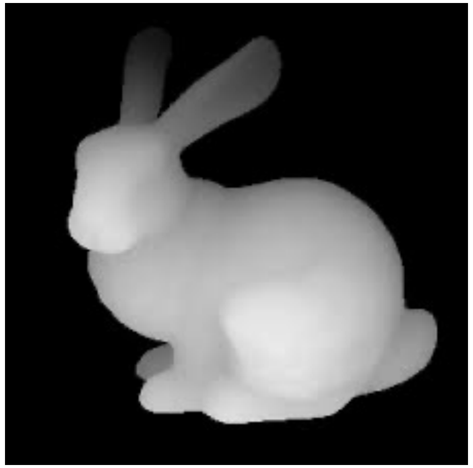
Rendering & Inverse Rendering



Geometry

Fine

Coarse



Surface normal

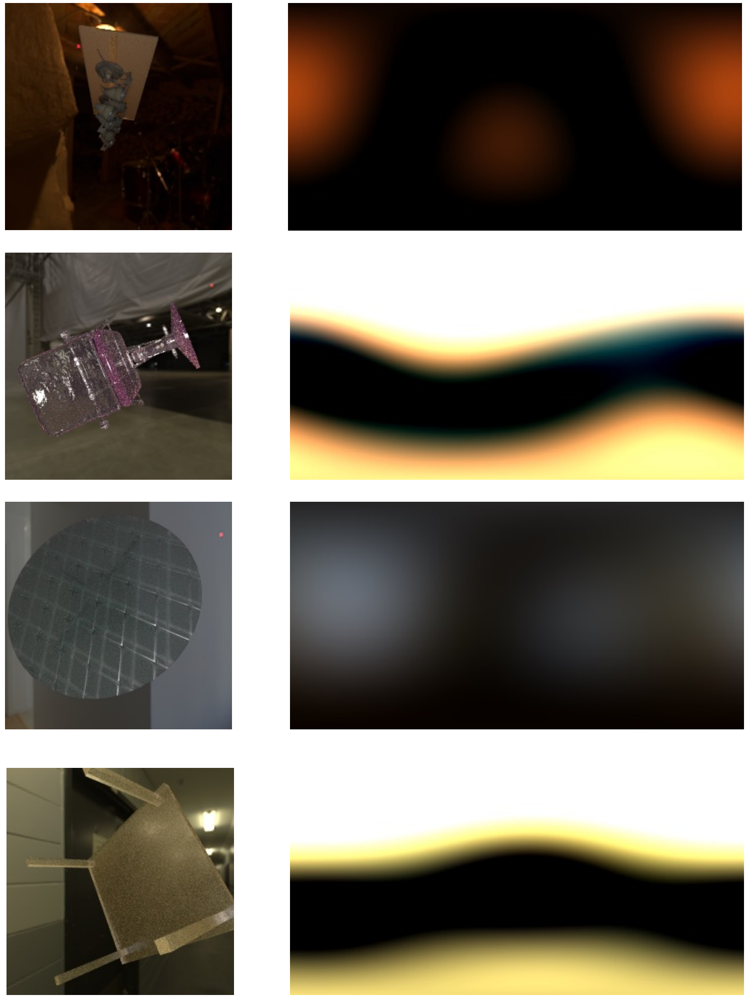
Depth

This work

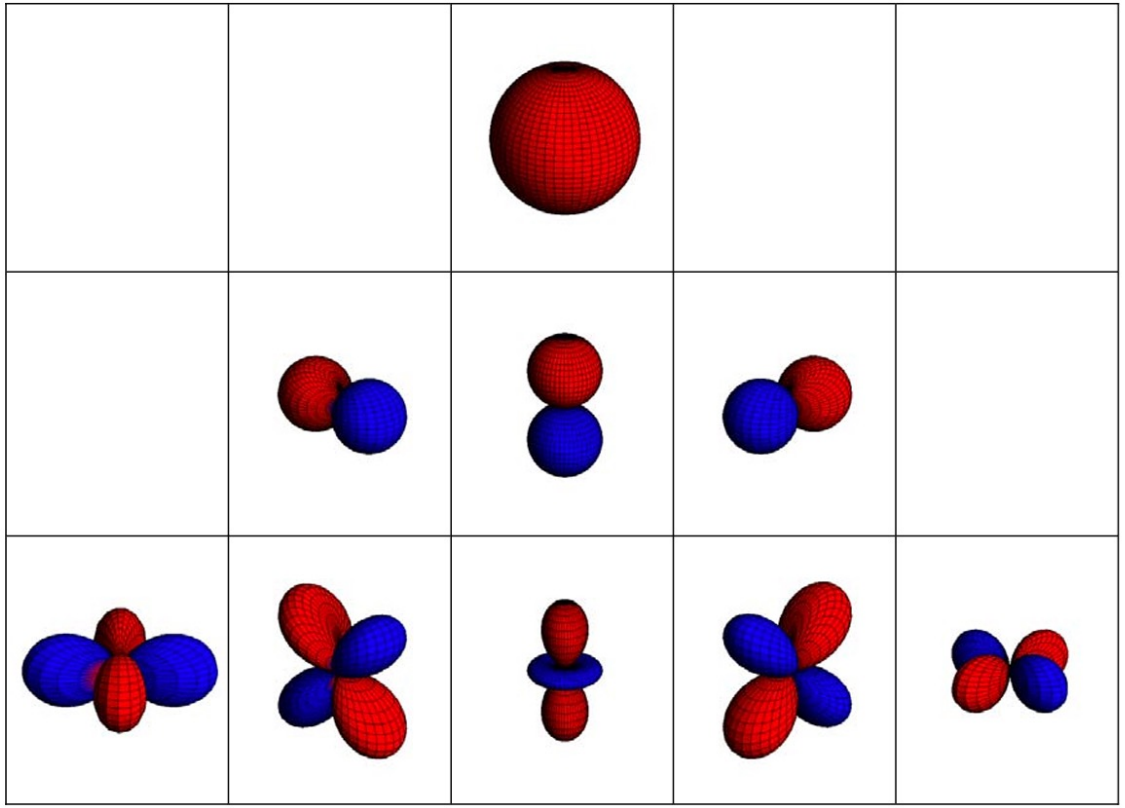
Illumination

Scene

Spherical harmonics illumination



Spherical harmonics basis

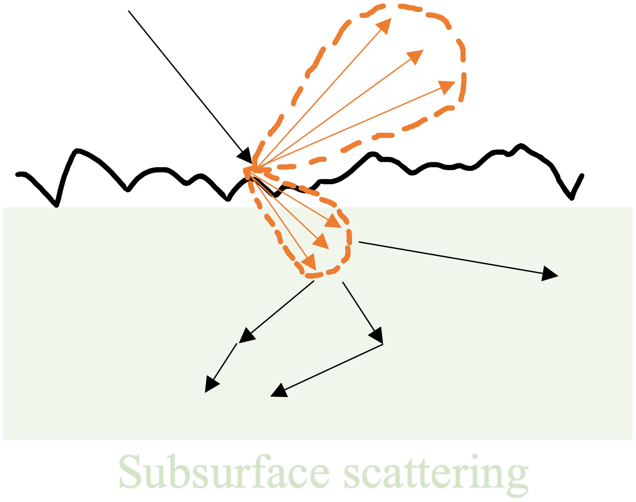


- http://www.ppsloan.org/publications/StupidSH36.pdf

Material

Translucent objects

Our material model

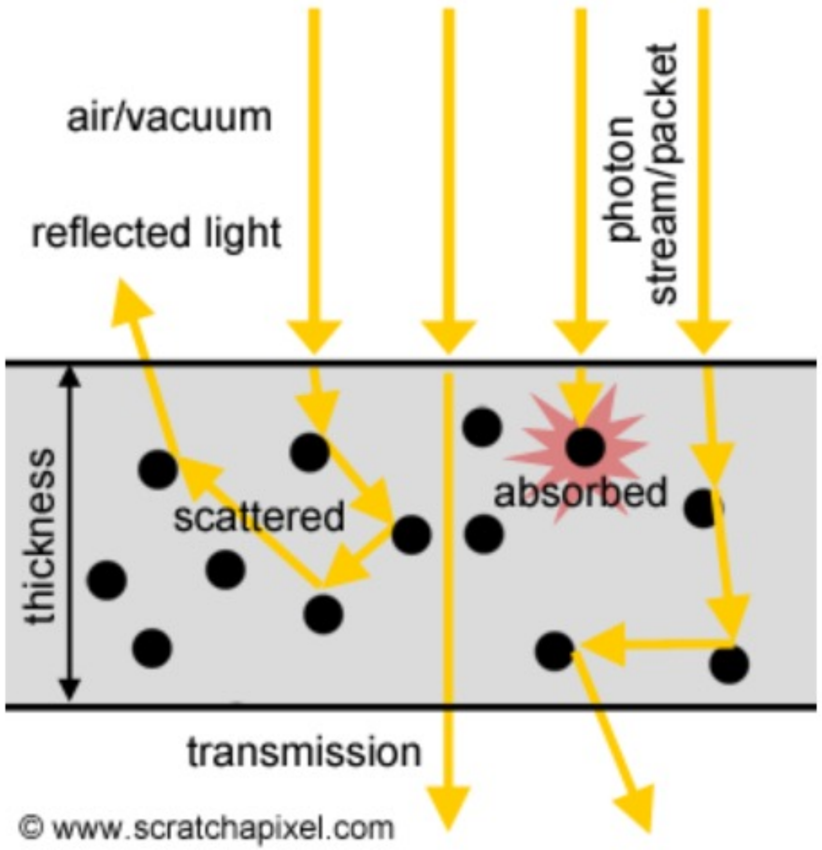


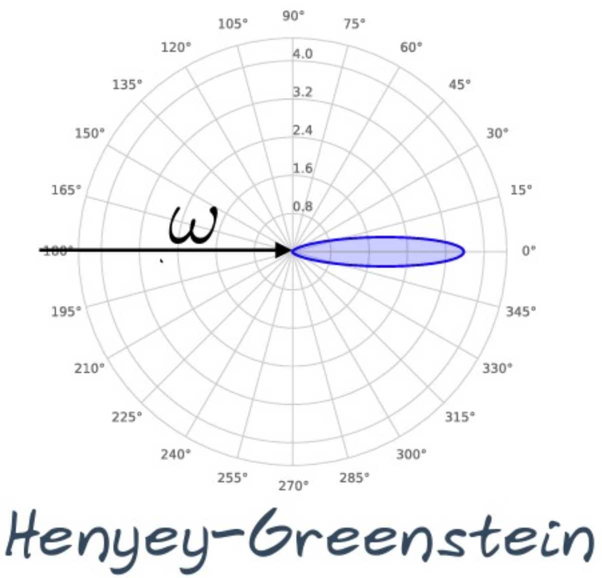
Sptially-varying
dielectric BSDF

Homogeneous
Subsurface scattering
(RTE)

Subsurface scattering

An important physical phenomenon that occurs inside translucent objects





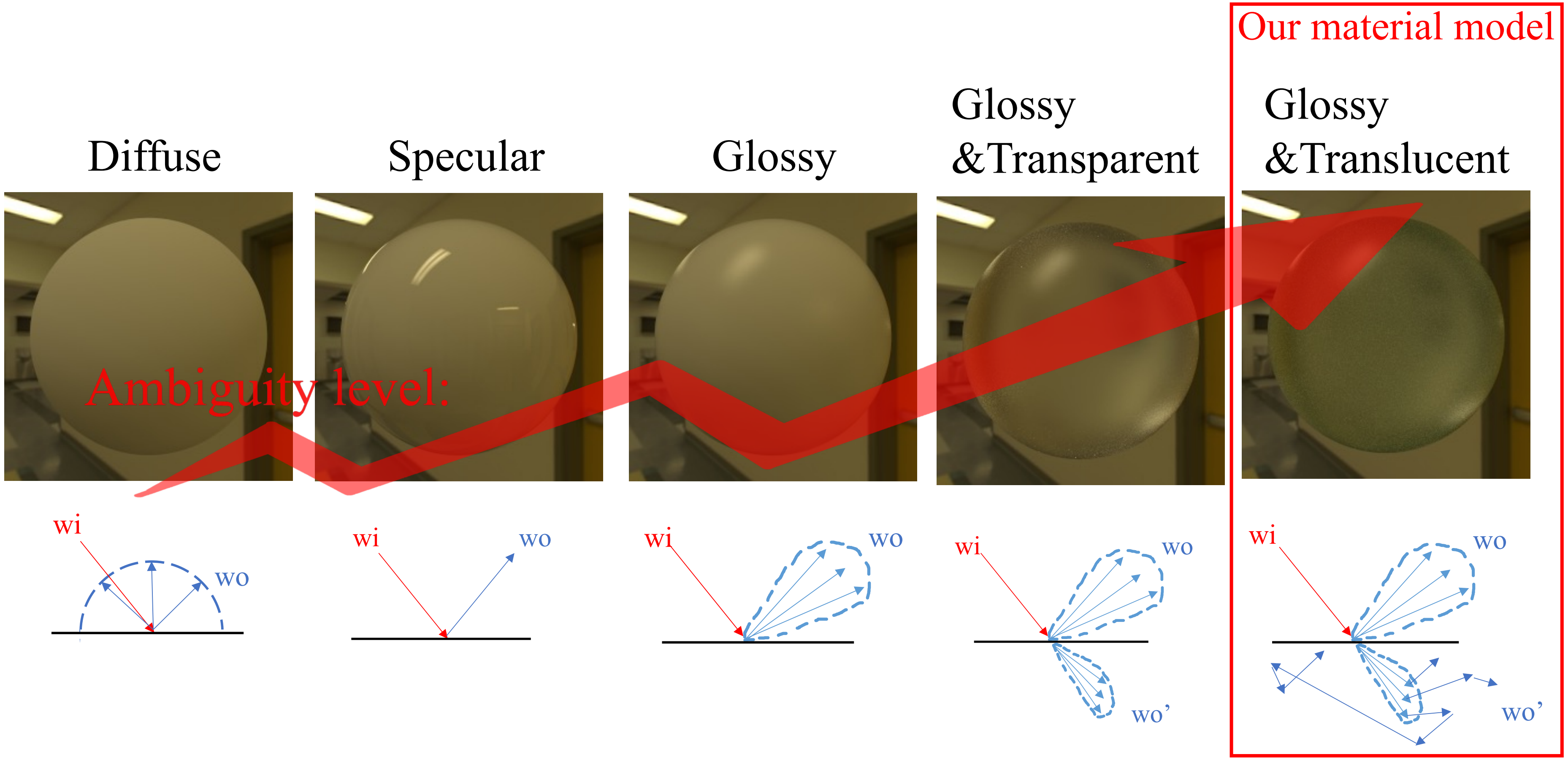
https://jannovak.info/publications/VolumeCourse/index.html

σ_t: extinction coefficent

α : volumetic albedo

g: phase fuction parameter

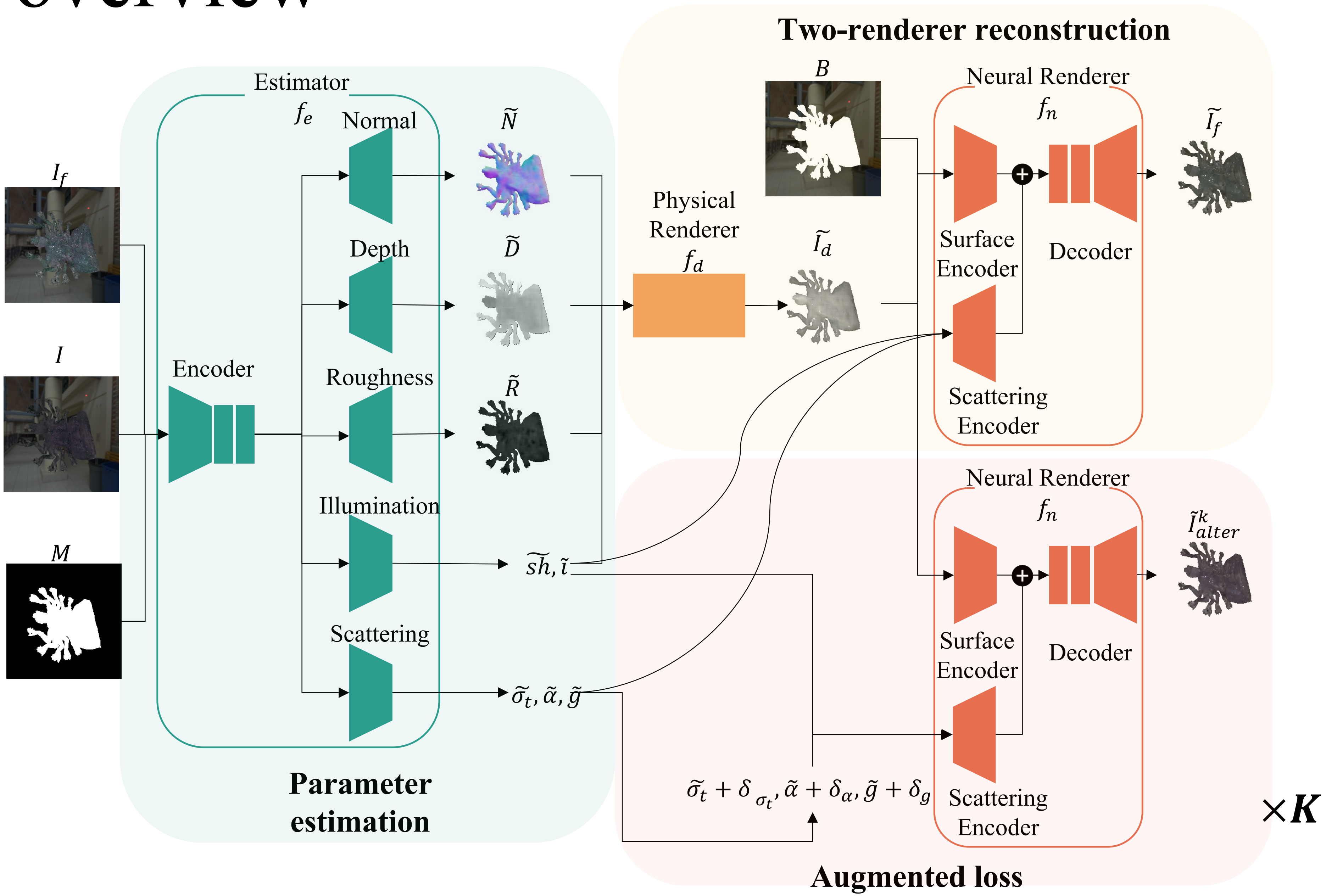
Challenges: complex material introduce more ambiguity



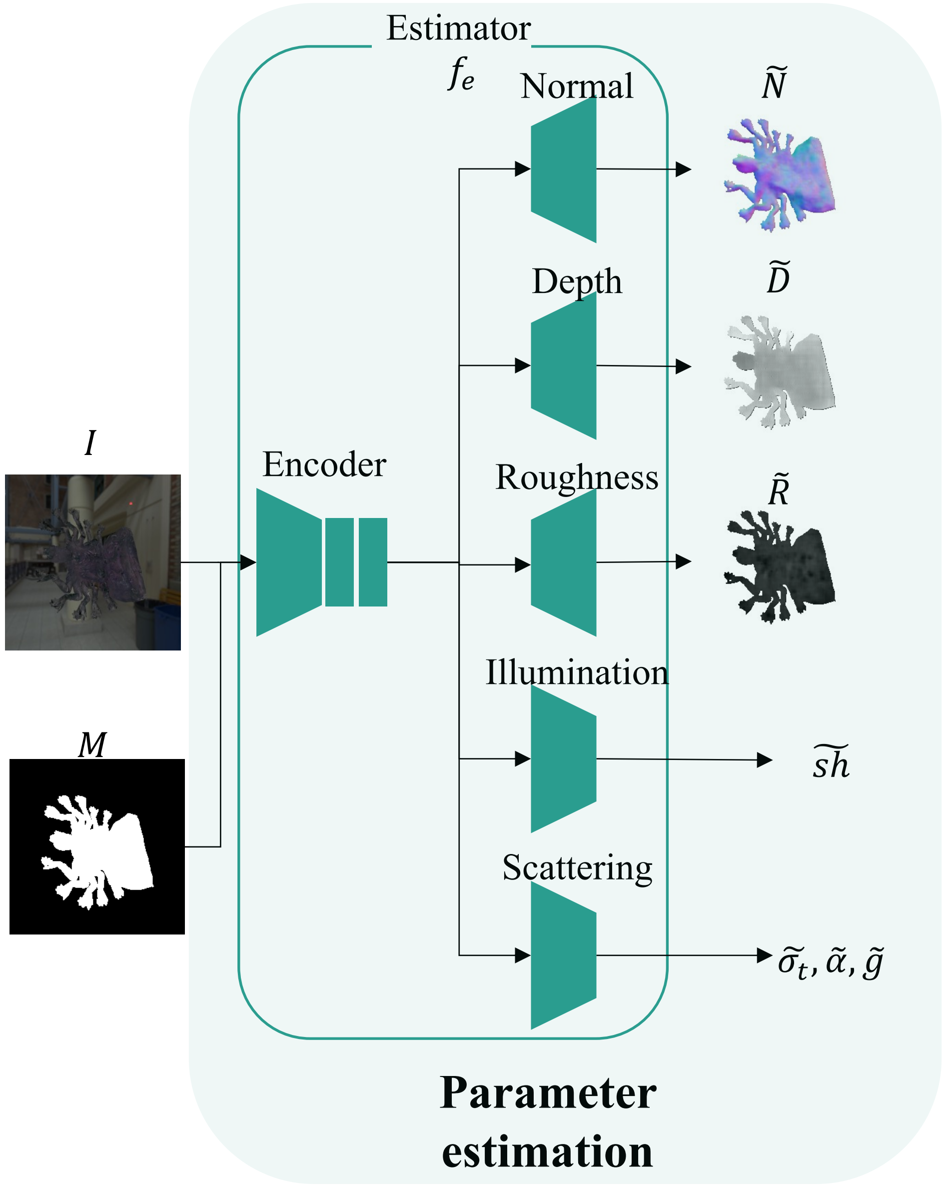
Translucent objects exhibit surface reflection and subsurface scattering at the same time!

Multi-path,
Multi-bounce scattering

Model overview



Estimator



Input:

- Image I
- Mask M

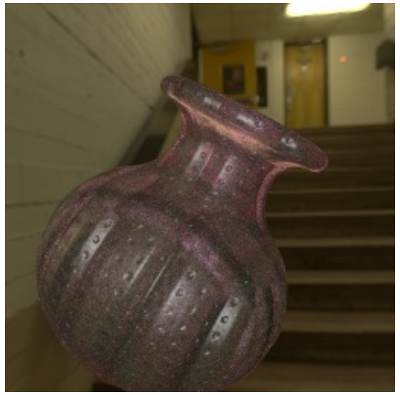
Out put:

- Surface normal $\tilde{N}$
- Depth $\tilde{D}$
- Roughness $\tilde{R}$
- Illumination $\widetilde{sh}$
- Subsurface scattering parameter $\tilde{\sigma}_t, \tilde{\alpha}, \tilde{g}$

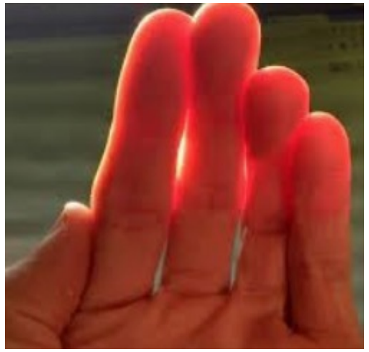
Improvement: flash and no-flash inputs

w/o flashlight

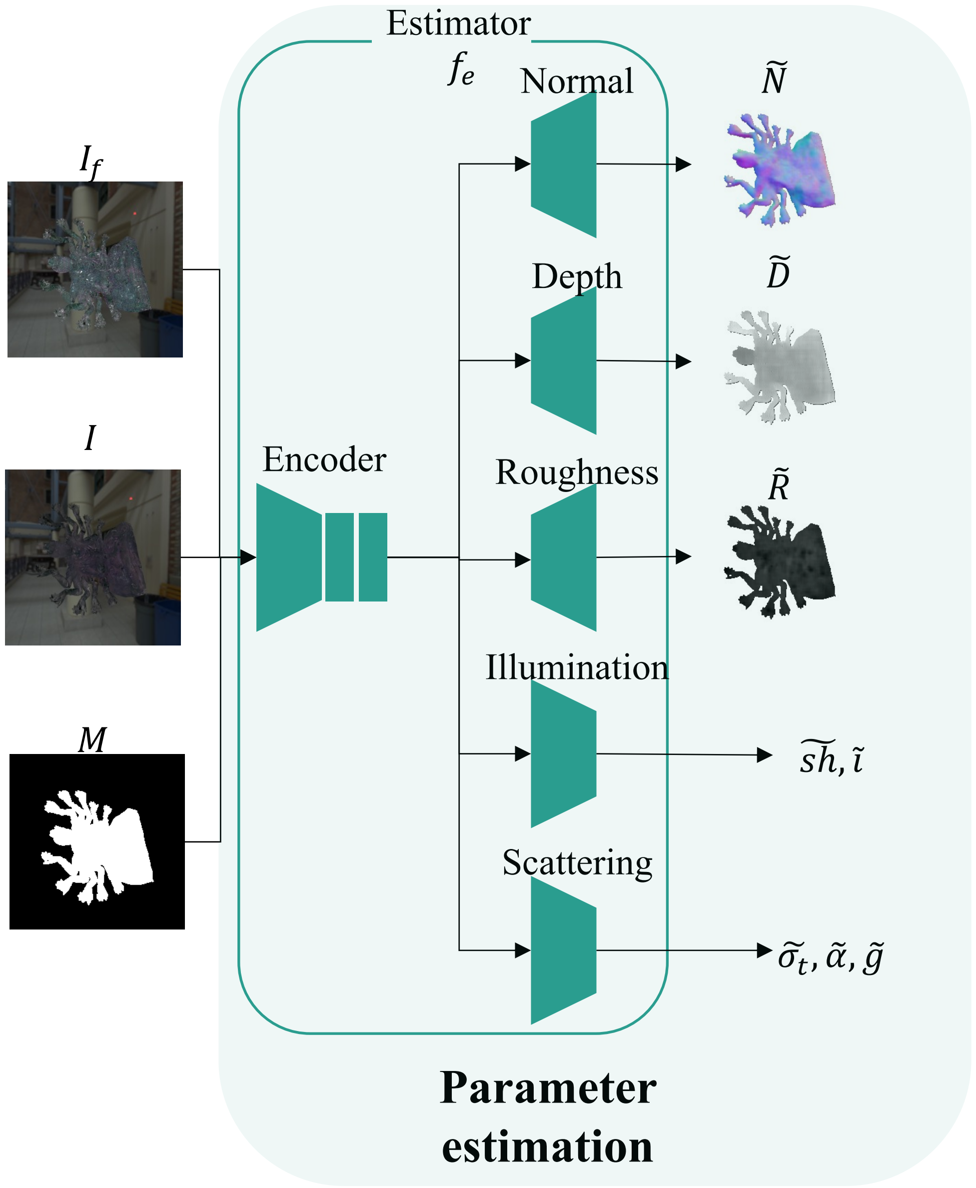
w/ flashlight



Motivation of using flash and no-flash images:
- the appearance of translucent object is significantlly affected by the illumiantion



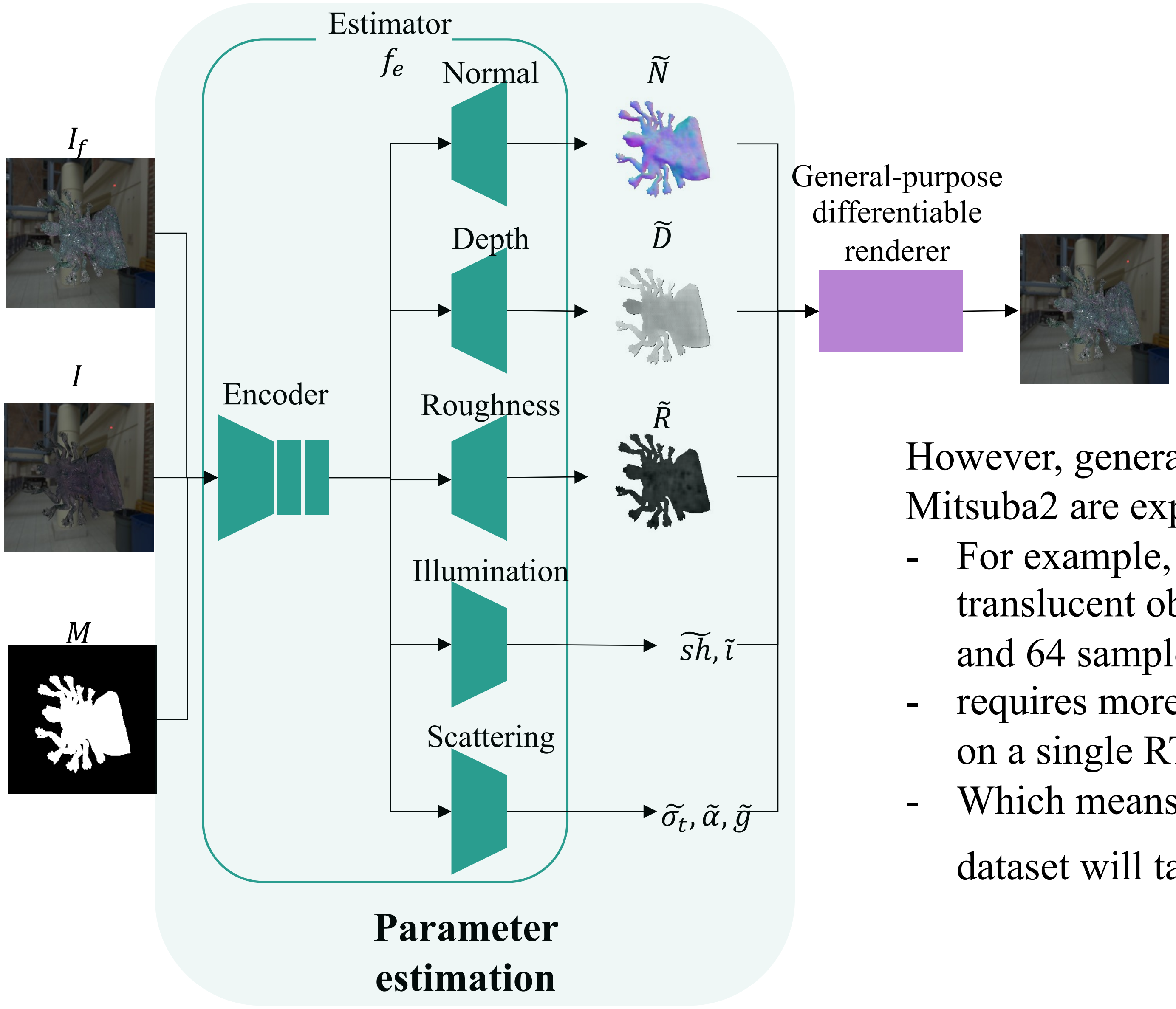
Two-shot inputs



Improvements:

- Adding a flash image I_f as input
- Also estimate a flashlight intensity $\tilde{\imath}$

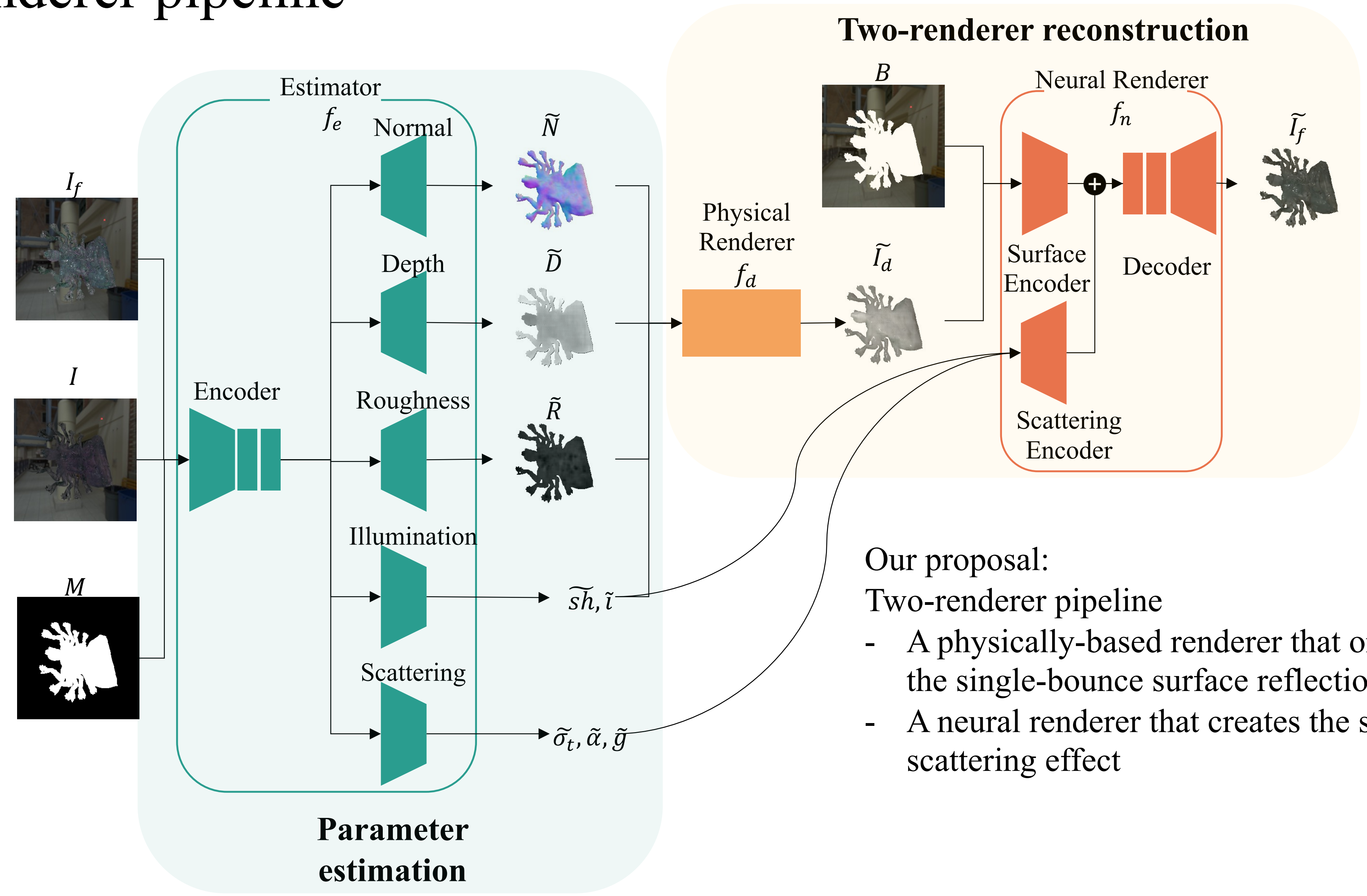
Using a general-purpose renderer for reconstruction loss?



However, general-purpose differentiable renderers like Mitsuba2 are expensive:

- For example, differentiable rendering of a single translucent object image with 256x256 resolution and 64 samples per pixel (spp)
- requires more than 5 seconds and 20 GB memory on a single RTX3090 GPU.
- Which means the training of 20 epochs on our 117K dataset will take **115 DAYs!!**

Two-renderer pipeline

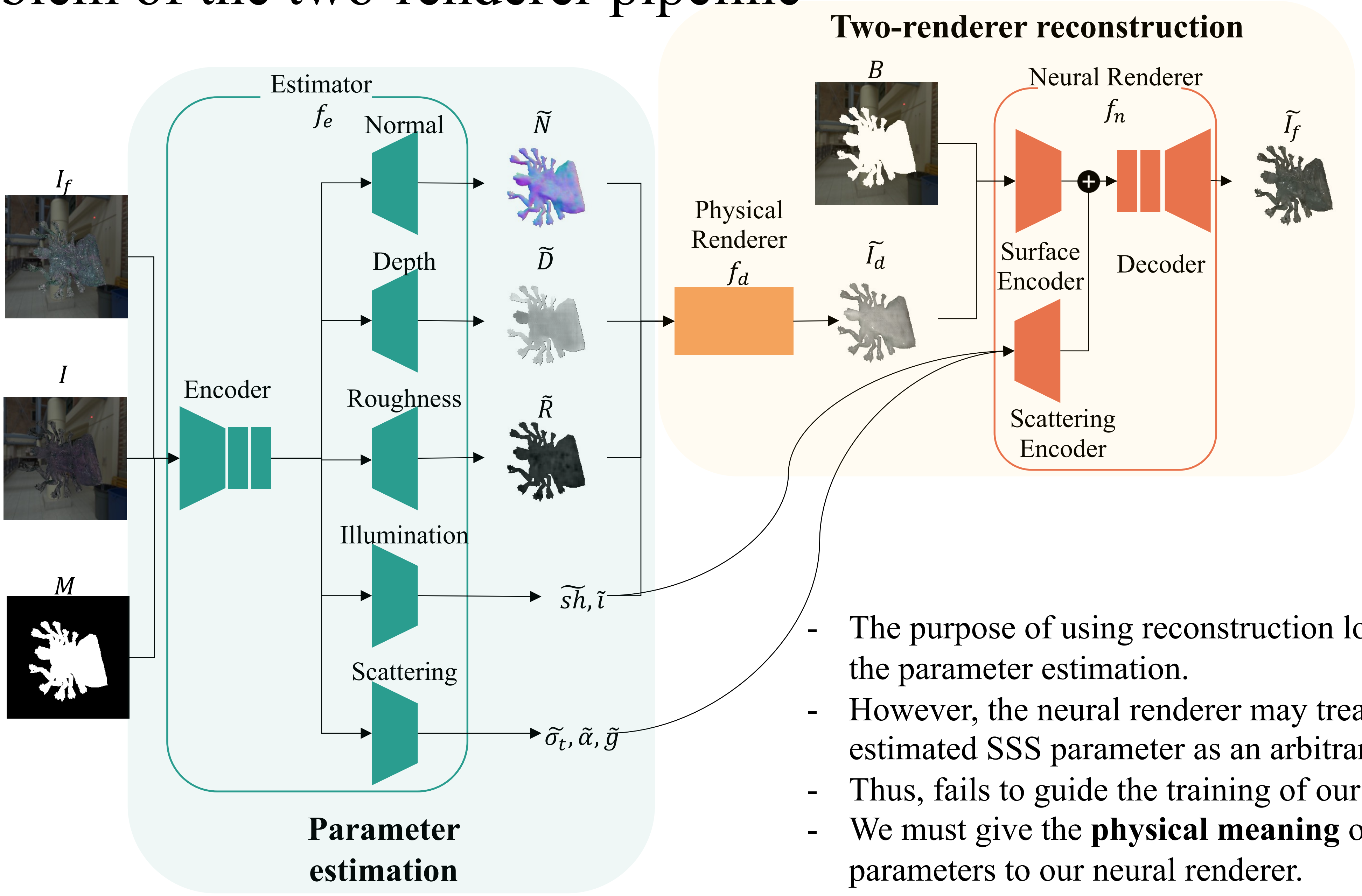


Our proposal:

Two-renderer pipeline

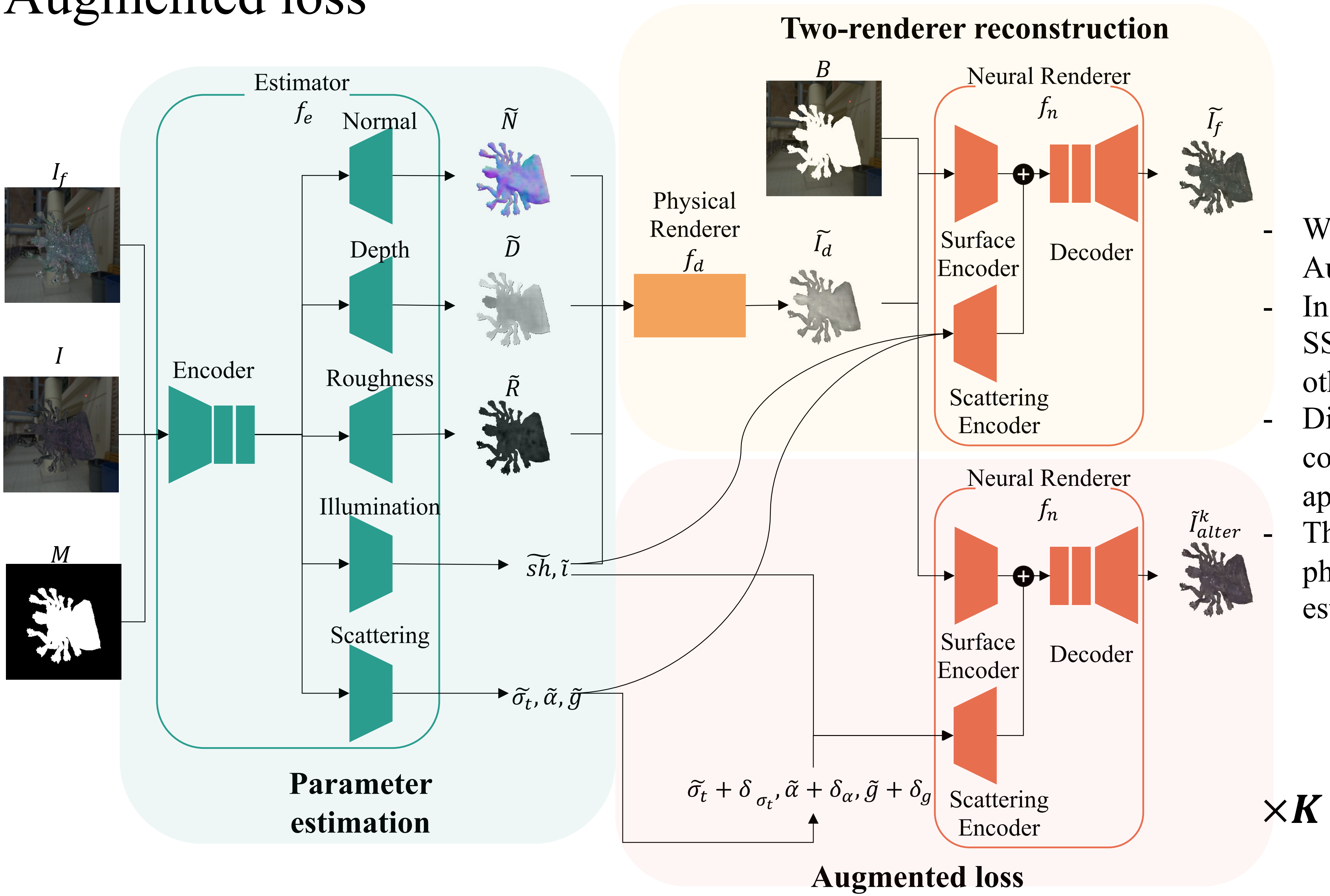
- A physically-based renderer that only renderer the single-bounce surface reflection
- A neural renderer that creates the subsurface scattering effect

One problem of the two-renderer pipeline



- The purpose of using reconstruction loss is to assist the parameter estimation.
- However, the neural renderer may treat the estimated SSS parameter as an arbitrary latent code.
- Thus, fails to guide the training of our Estimator.
- We must give the **physical meaning** of SSS parameters to our neural renderer.

Augmented loss

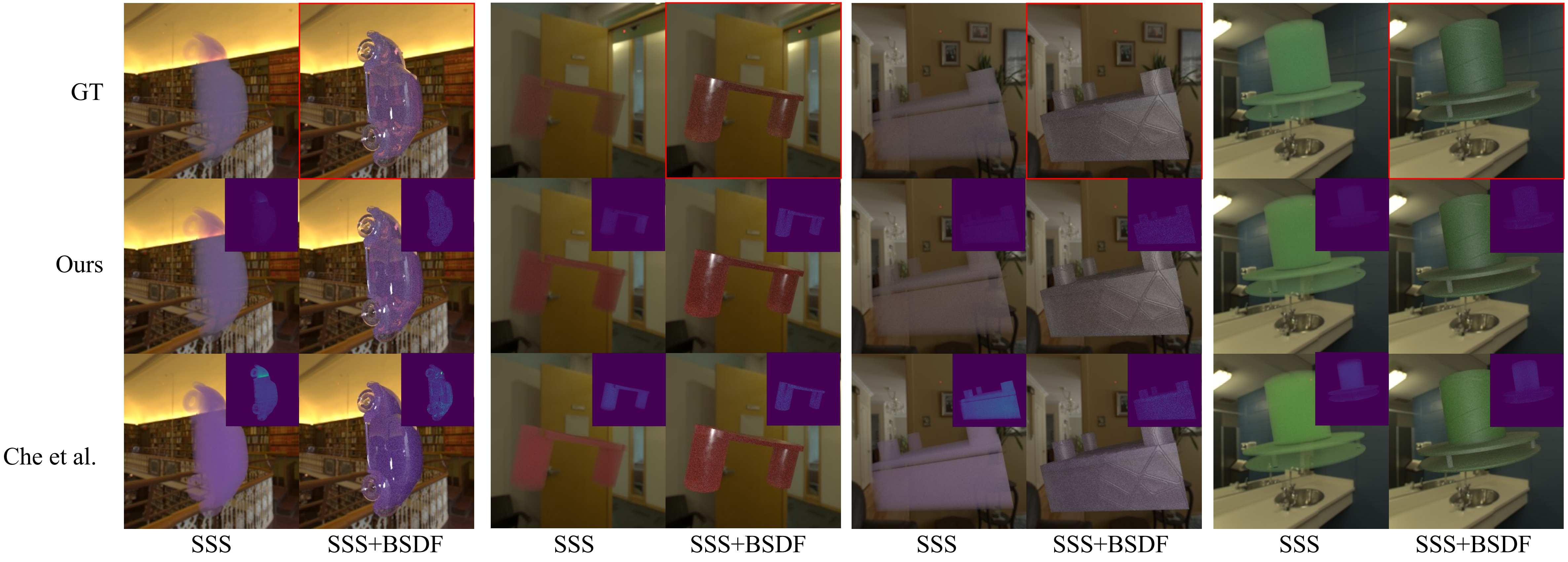


- We add K branches of Augmented loss.
- In each branch, we edit the SSS parameters and keep the other parameter the same.
- Different SSS parameters correspond to different appearances.
- This gives the explicit physical meaning of the estimated SSS parameters.

Our translucent objects dataset

- We construct a large-scale synthetic dataset consisting of more than 117K translucent scenes.
- Each scene contains
    - a human-created 3D model
    - and is rendered with a spatially-varying microfacet BSDF,
    - homogeneous SSS,
    - under an environment illumination.

Visual comparison with an existing inverse scattering work



Re-rendered images using estimated SSS parameters.

Ablation study

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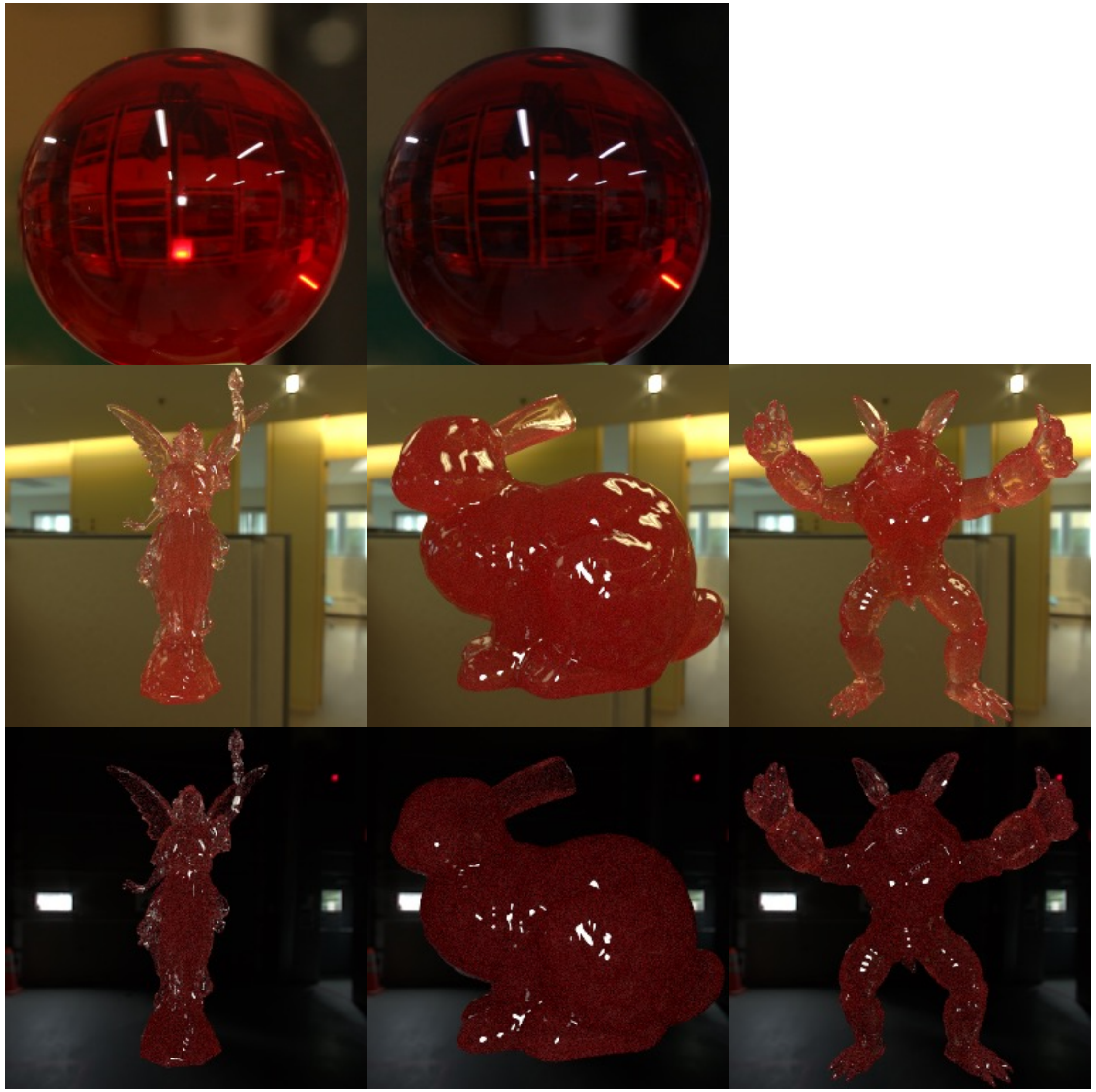
Application: Material acquisition

Input

Illumination 1

Illumination 2



Application: Material editing

Thank you!