SIGGRAPH ASIA 2022 DAEGU

Light Probe Based Real-time Global Illumination

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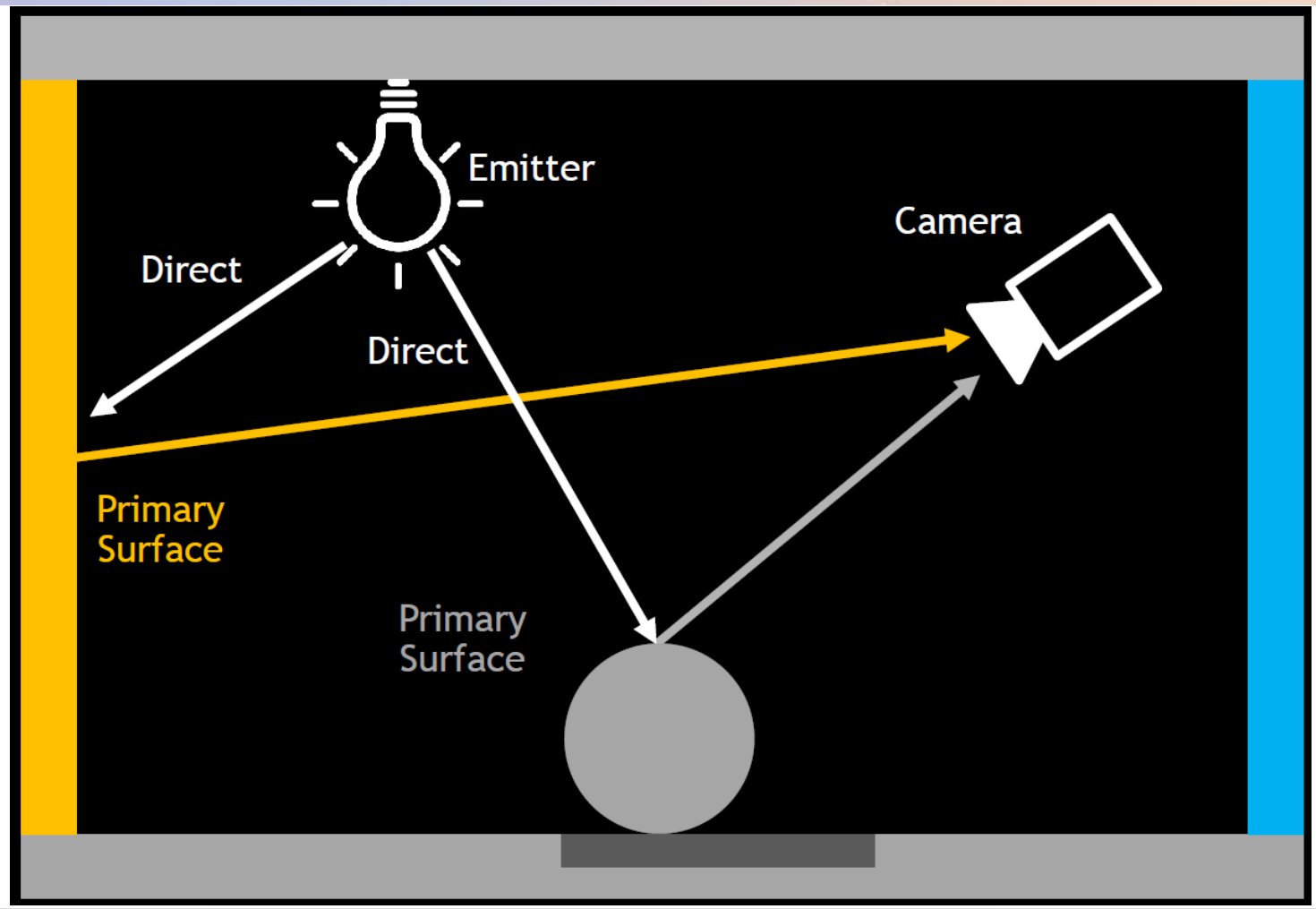
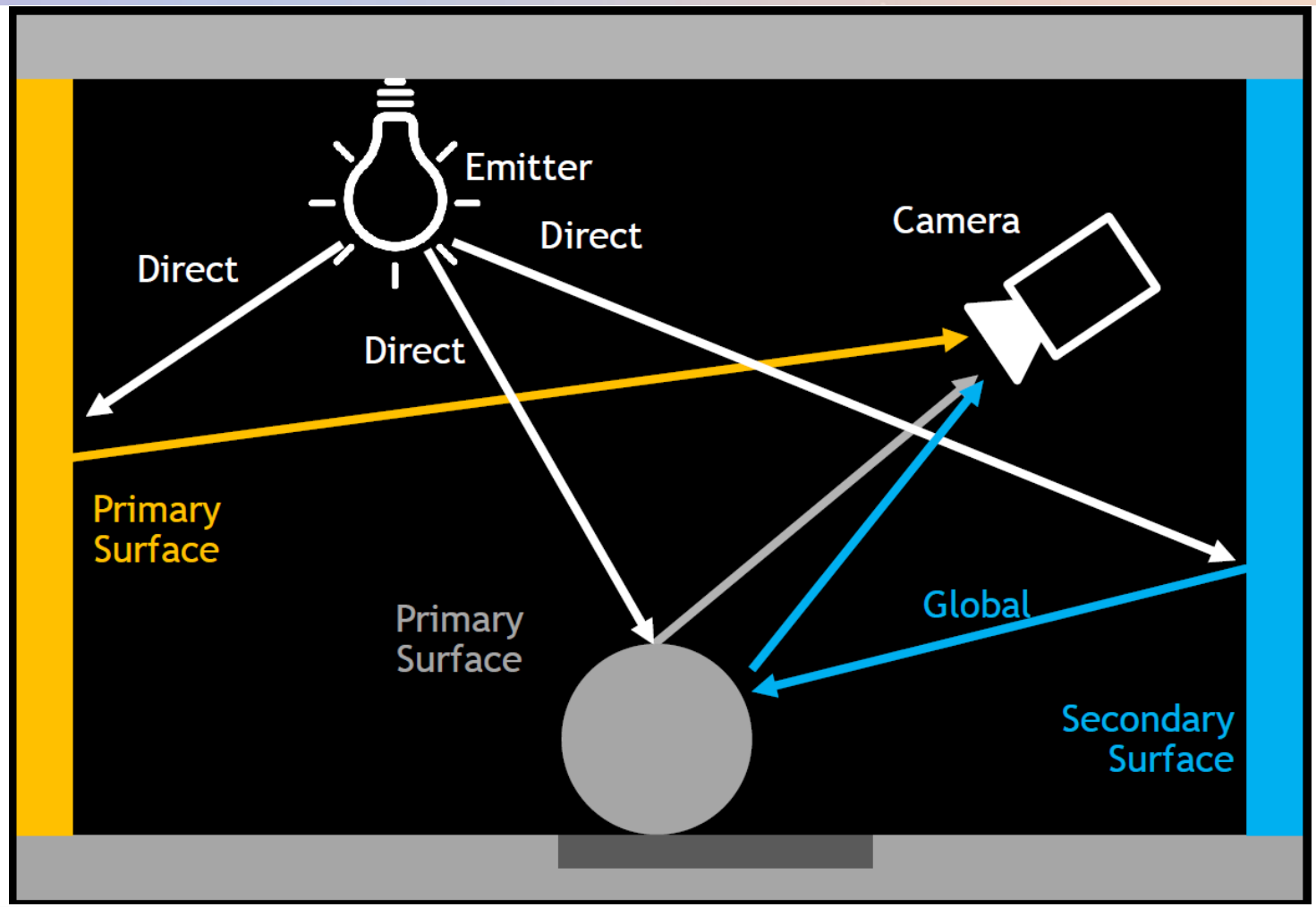
Background

Direct Illumination

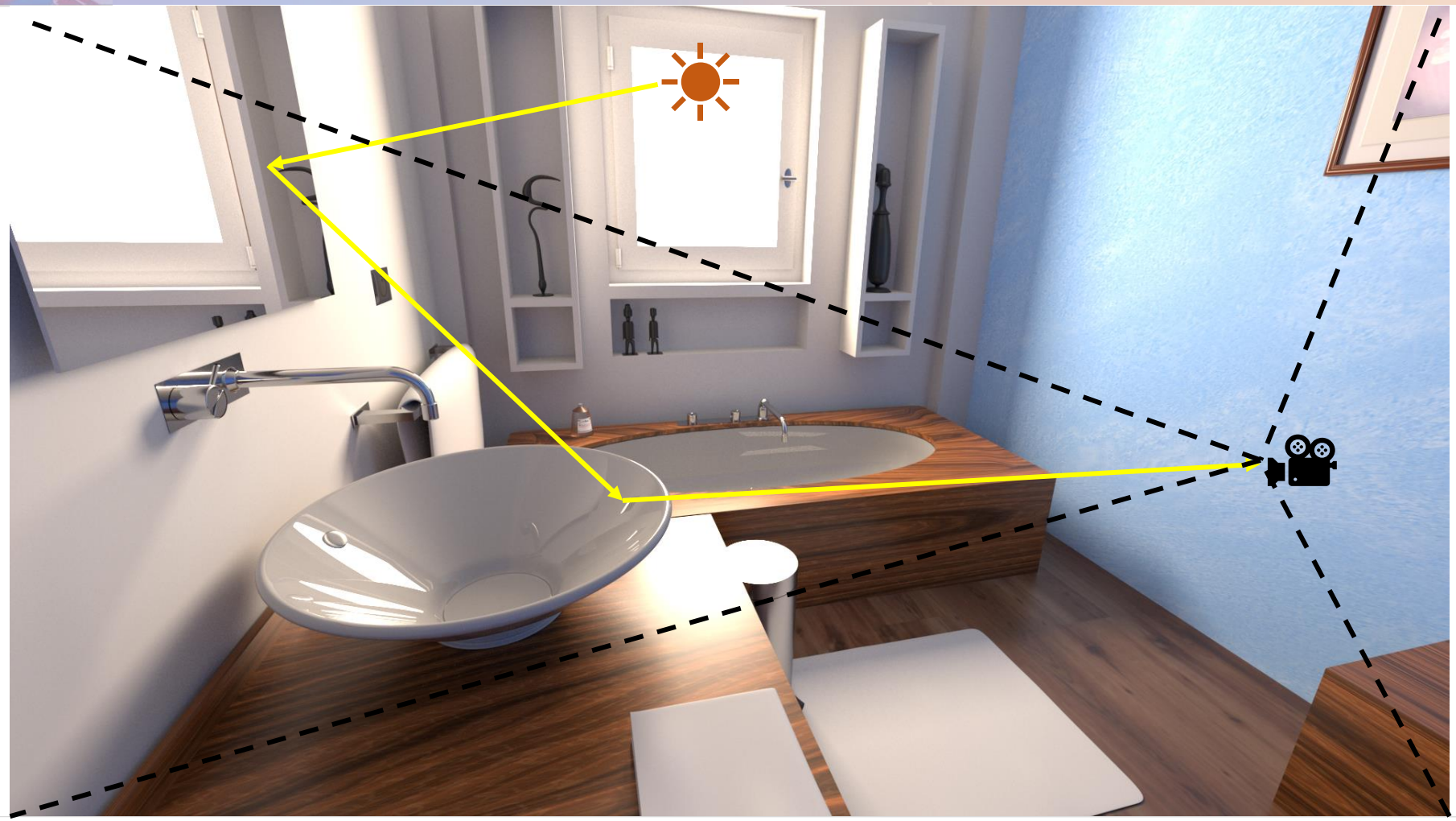


Direct Illumination

Indirect Illumination



Indirect Illumination

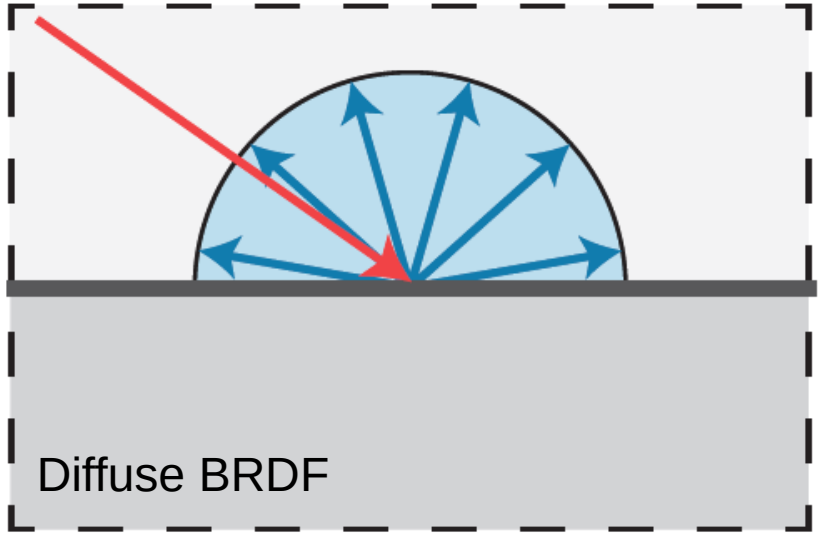


Indirect Illumination

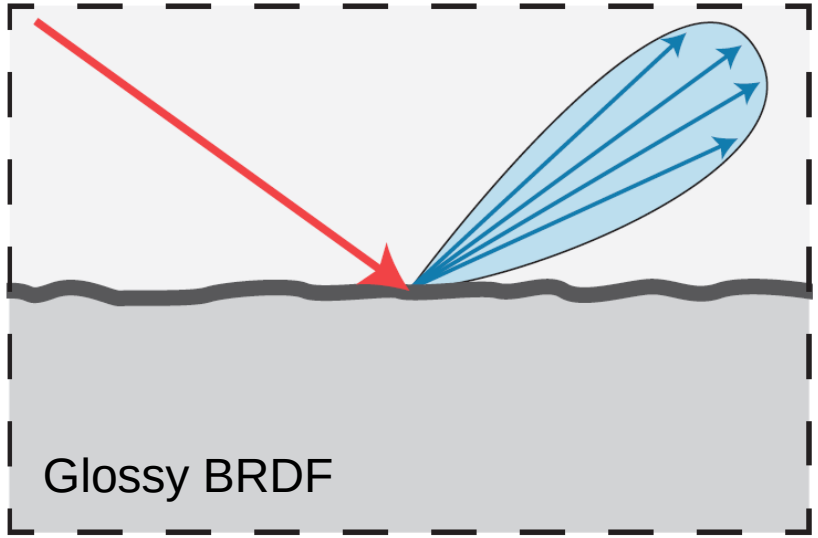
Indirect Illumination

Diffuse and Glossy Reflection

$$L_o(p,\omega_o) = L_e(p,\omega_o) + \int_\Omega \boxed{f_r(p,\omega_i,\omega_o)} L_i(p,\omega_i) n \cdot \omega_i d\omega_i$$



View-independent



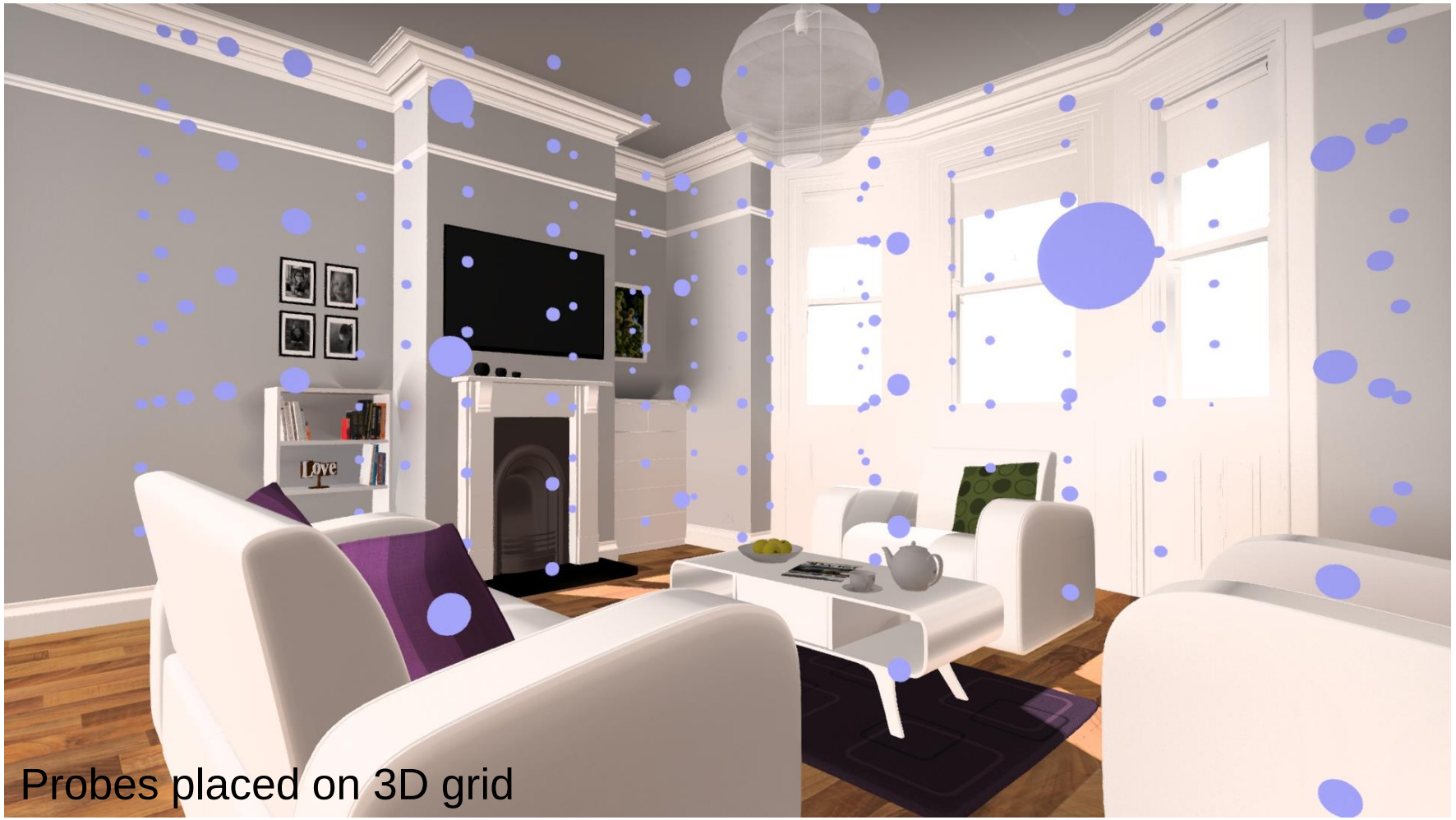
View-dependent

Real-time Rendering

$$L_o(p,\omega_o) = L_e(p,\omega_o) + \int_\Omega f_r(p,\omega_i,\omega_o) L_i(p,\omega_i) n \cdot \omega_i d\omega_i$$

To much cost to solve the equation at real-time!!!

Light Probe Based Real-time Global Illumination



Probes placed on 3D grid

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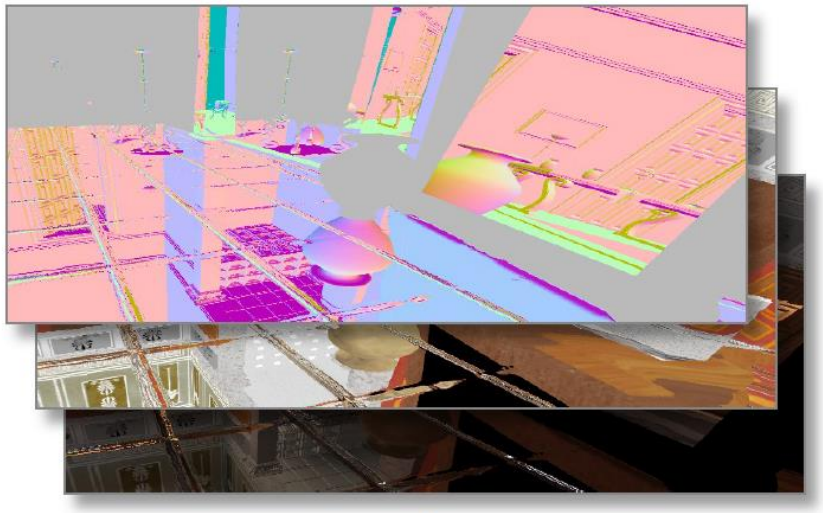
Dynamic Diffuse Global Illumination (DDGI)

[Majercik et al. 2019]

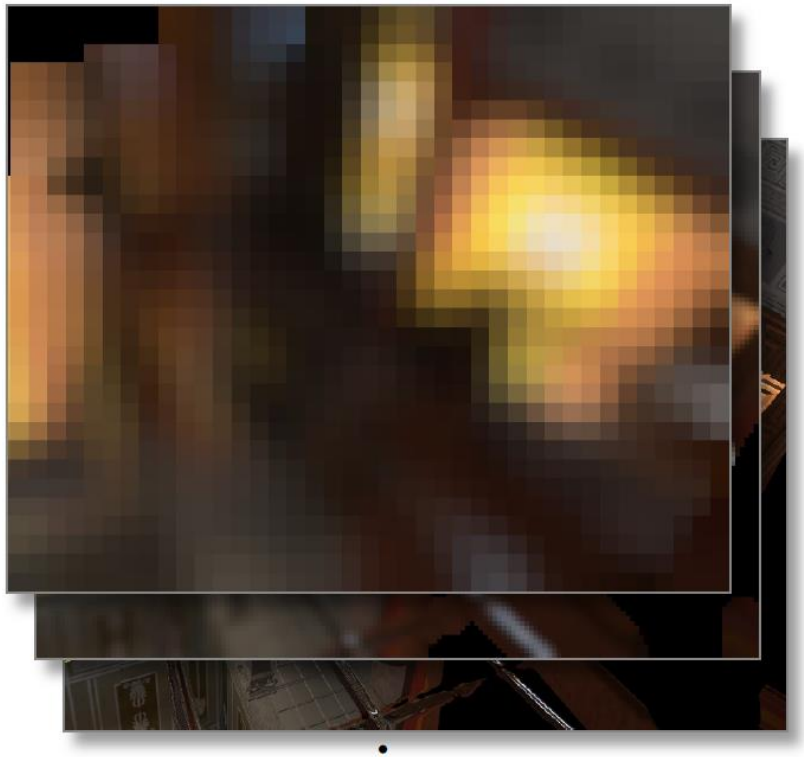
Typical Glossy Reflection Solution



⋮

1. Ray Trace

Trace and shade perfect mirror rays at full resolution X, ½ resolution Y



⋮

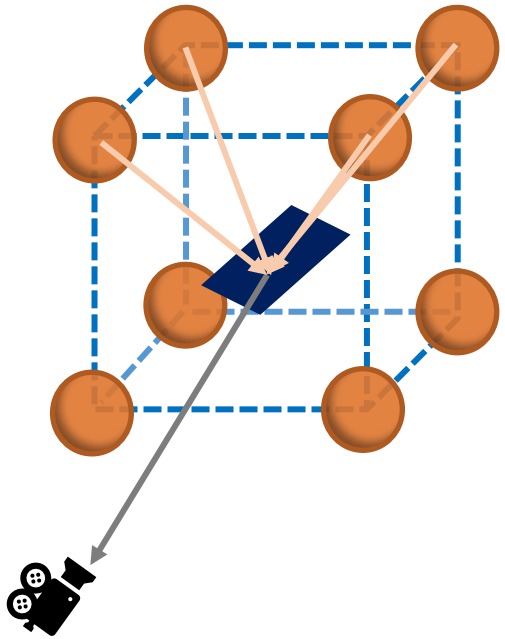
2. Blur

Bilateral filter into MIPs, respecting edges

3. Sample

Sample in screen-space based on primary roughness and total reflection distance

Diffuse Gathering



Gather light probes near shading point

DDGI [Majercik et al. 2019]

Result

Offline Path Tracing

DDGI

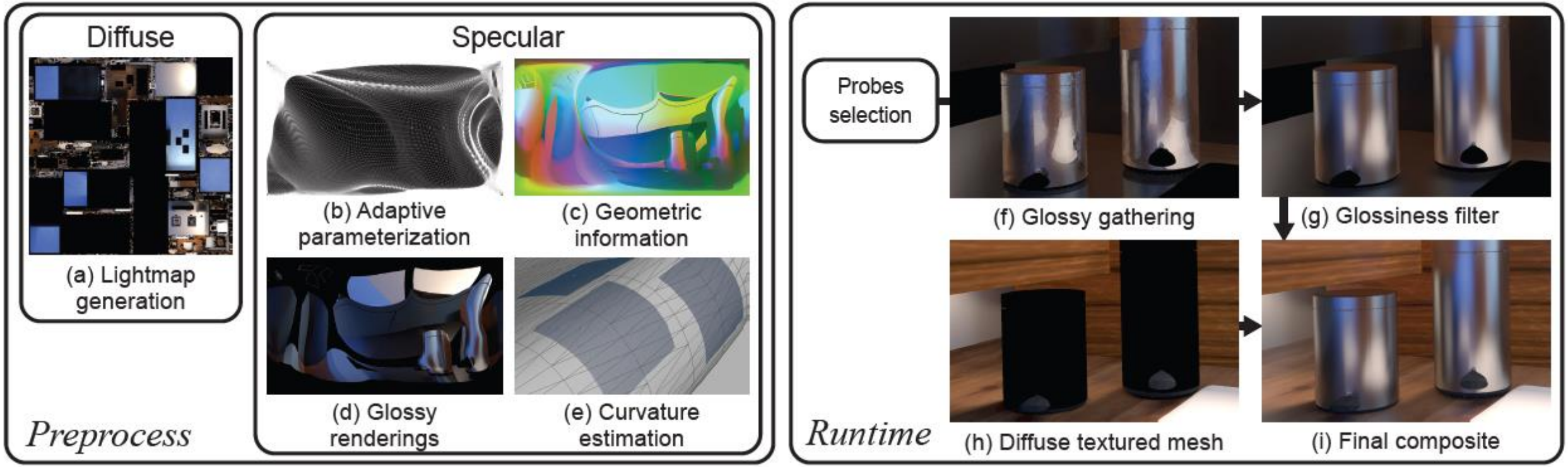
Pros & Cons

- Light-weight probes guarantee fast dynamic update
- Tricks and estimation make it physically incorrect
- Light paths are simplified and long glossy paths are usually excluded

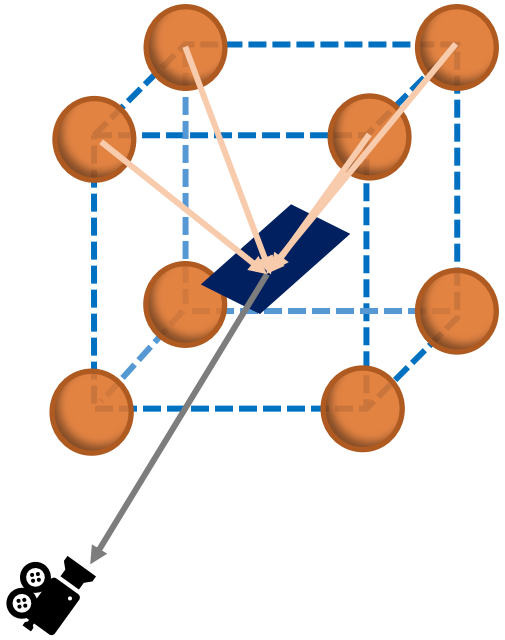
Glossy Probe Reprojection (GPR)

[Rodriguez et al. 2020]

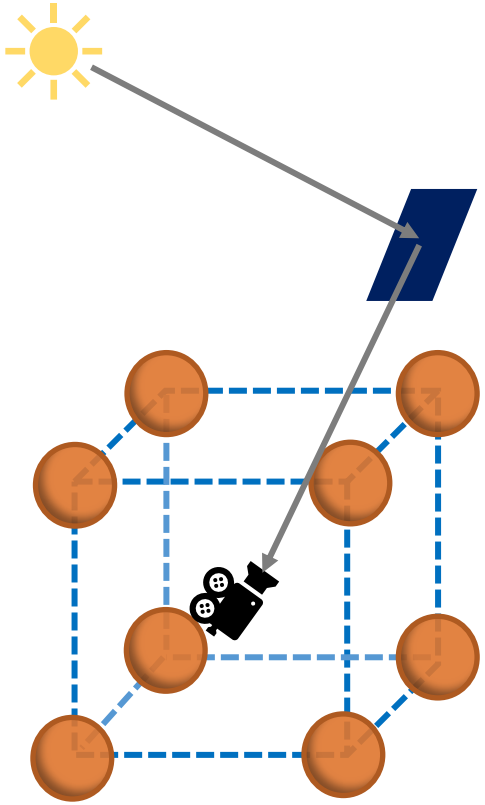
Pipeline


Diffuse
(a) Lightmap generation
Specular
(b) Adaptive parameterization
(c) Geometric information
(d) Glossy renderings
(e) Curvature estimation
Preprocess
Probes selection
(f) Glossy gathering
(g) Glossiness filter
(h) Diffuse textured mesh
(i) Final composite
Runtime

Probe Reprojection



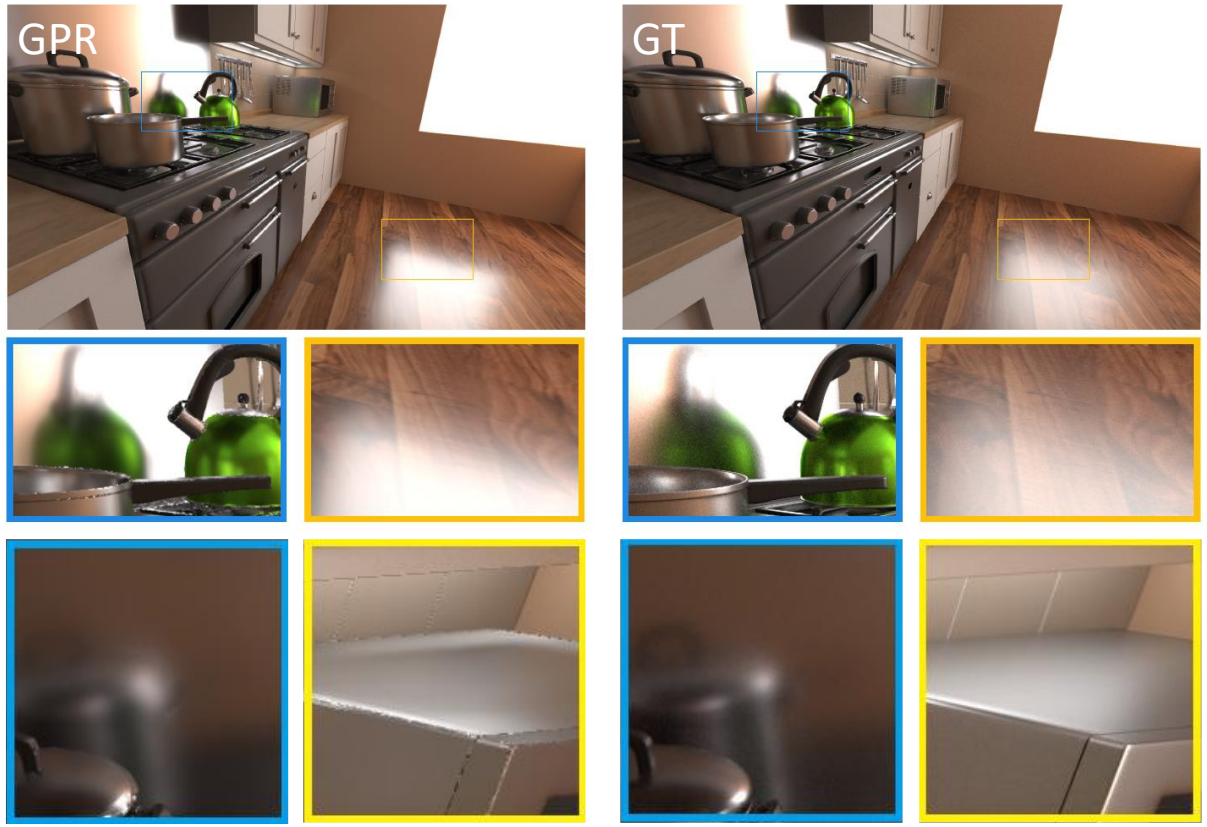
DDGI's diffuse solution



GPR's glossy solution

Pros & Cons

- Can handle all light paths in static scenes
- Large burden in the precomputation step
- Artifacts may occur due to the heuristic gathering and filtering process



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2022 DAEGU, KOREA

Efficient Light Probes for Real-time Global Illumination

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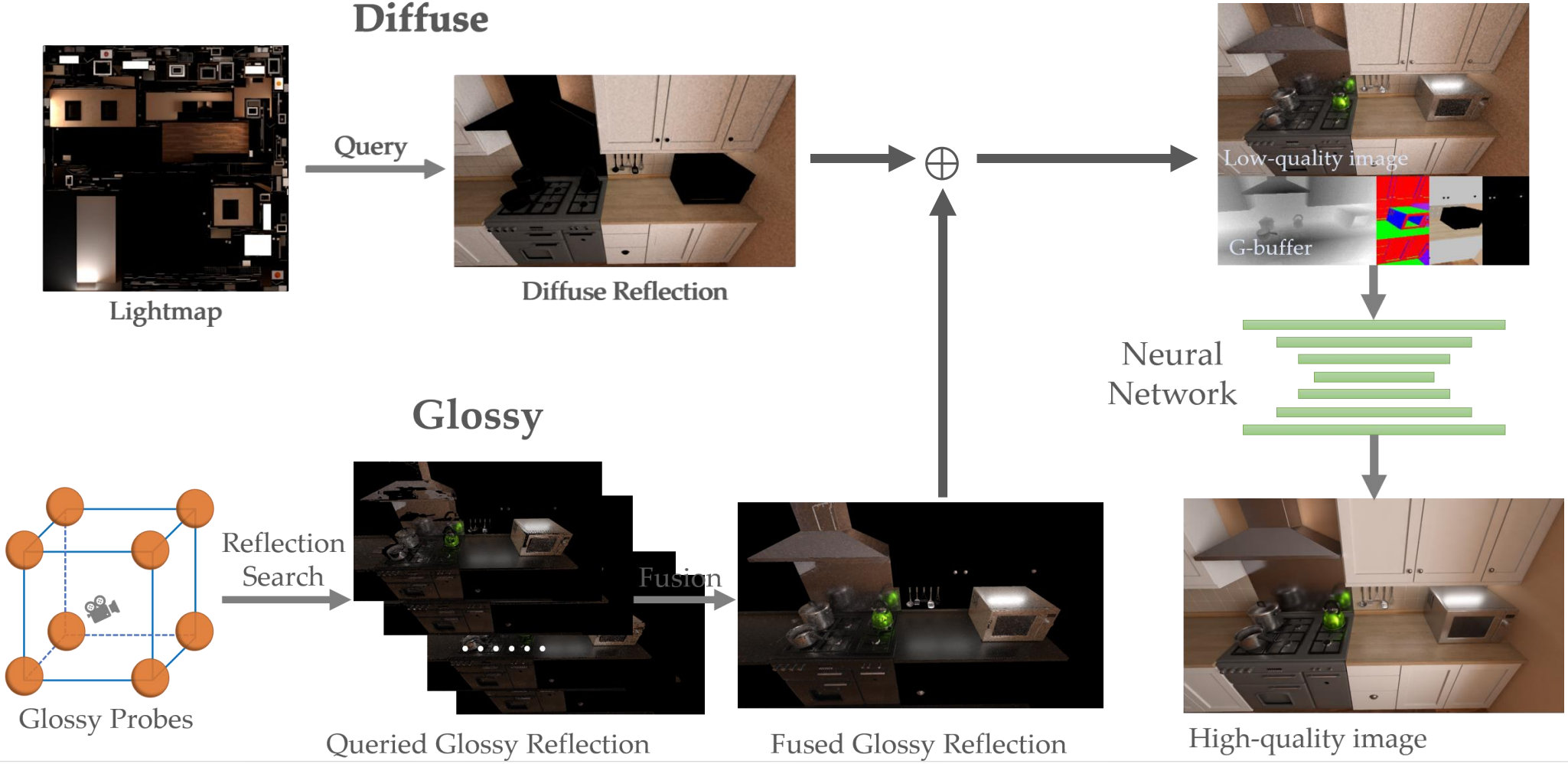
[1] State Key Lab for Novel Software Technology, Nanjing University

[2] University of California, Santa Barbara

Our Method

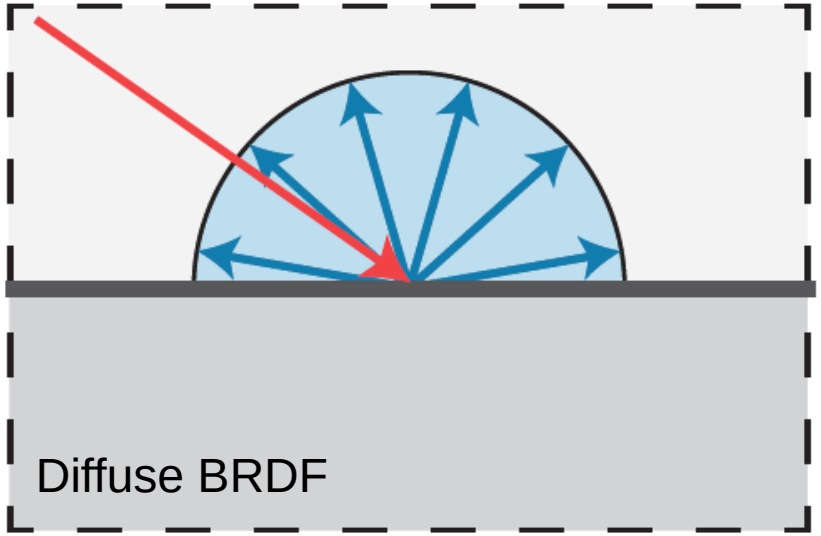
- A **gradient-based reflection search algorithm** that corrects parallax changes
- A **neural network** that recovers high-quality images from low-quality inputs.
- Reproducing **high-quality GI** with complex glossy light paths at **real time** (over 30fps at 1080p resolution)
- Substantial **reduction of precomputation cost**

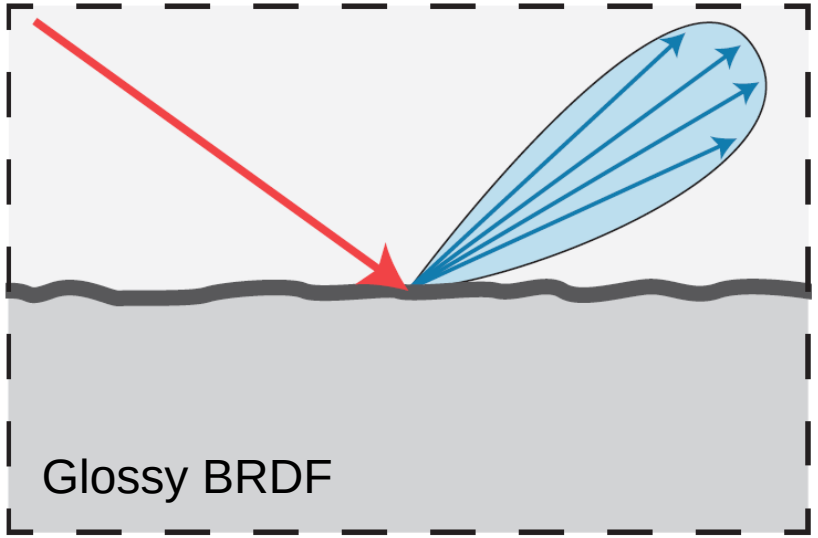
Overview


Diffuse
Lightmap
Query
Diffuse Reflection
Low-quality image
G-buffer
Neural
Network
Glossy
Glossy Probes
Reflection
Search
Queried Glossy Reflection
Fusion
Fused Glossy Reflection
High-quality image

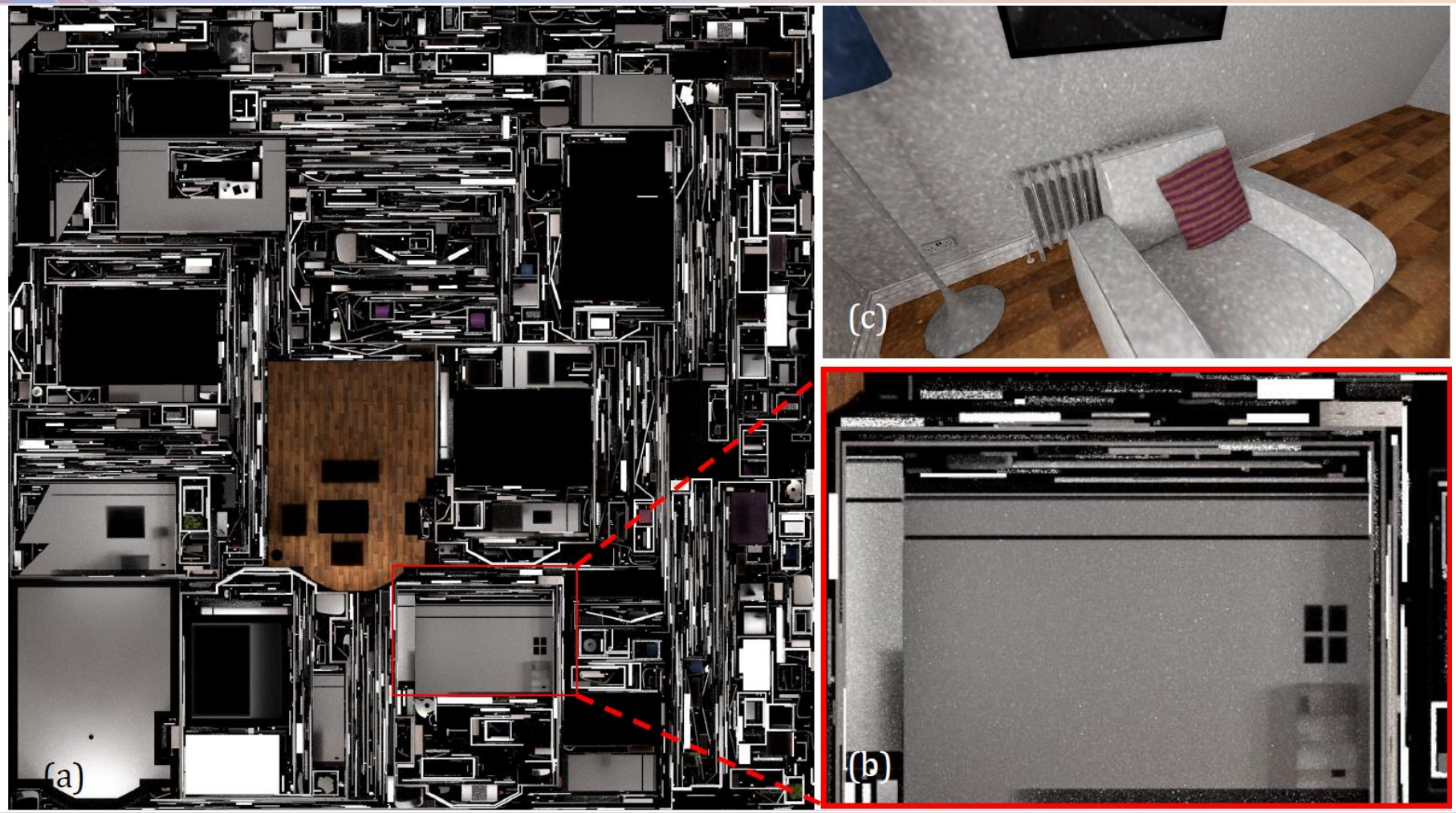
Split Reflection

$$L_o(p,\omega_o) = L_e(p,\omega_o) + \int_\Omega \boxed{f_r(p,\omega_i,\omega_o)} L_i(p,\omega_i) n \cdot \omega_i d\omega_i$$





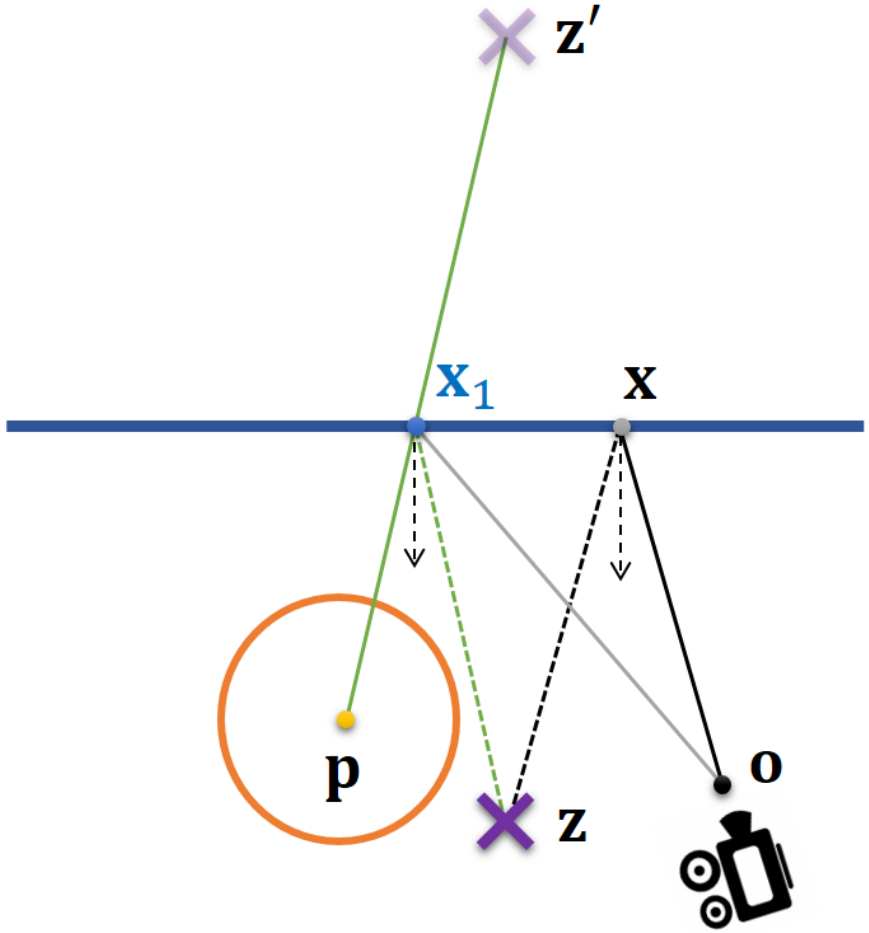
Lightmap for Diffuse Reflection



Gradient-based Search Algorithm

Probes Arranged on 3D Grid

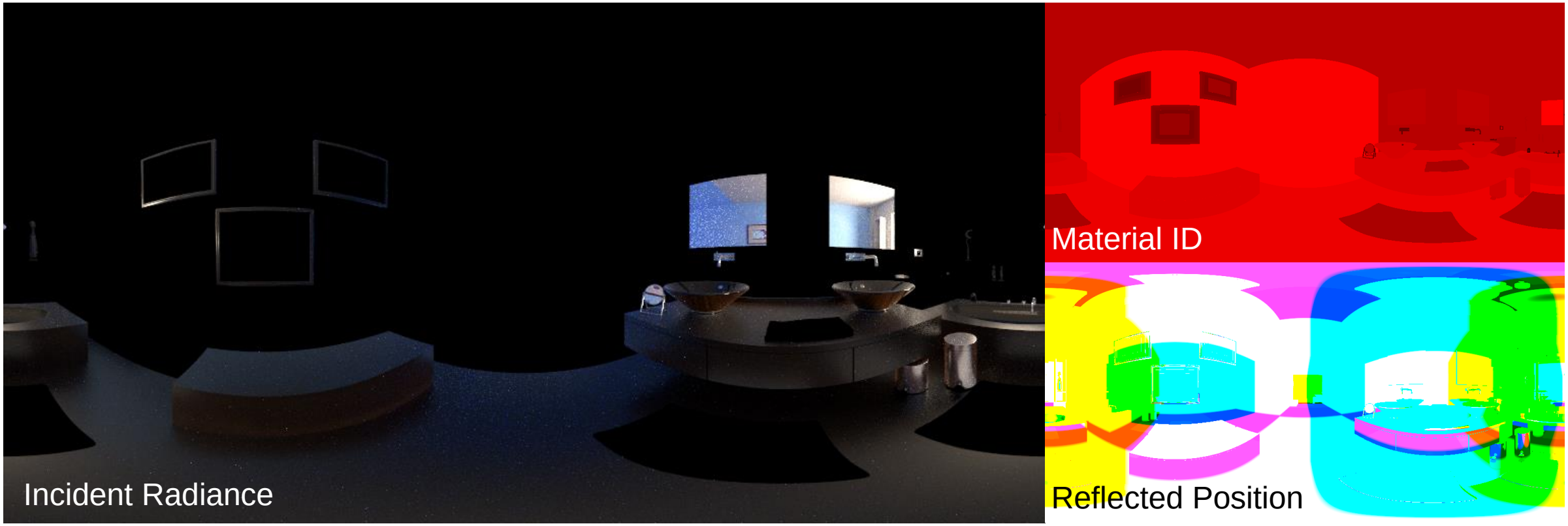
Gradient-based Search Algorithm



Gradient-based Search Algorithm

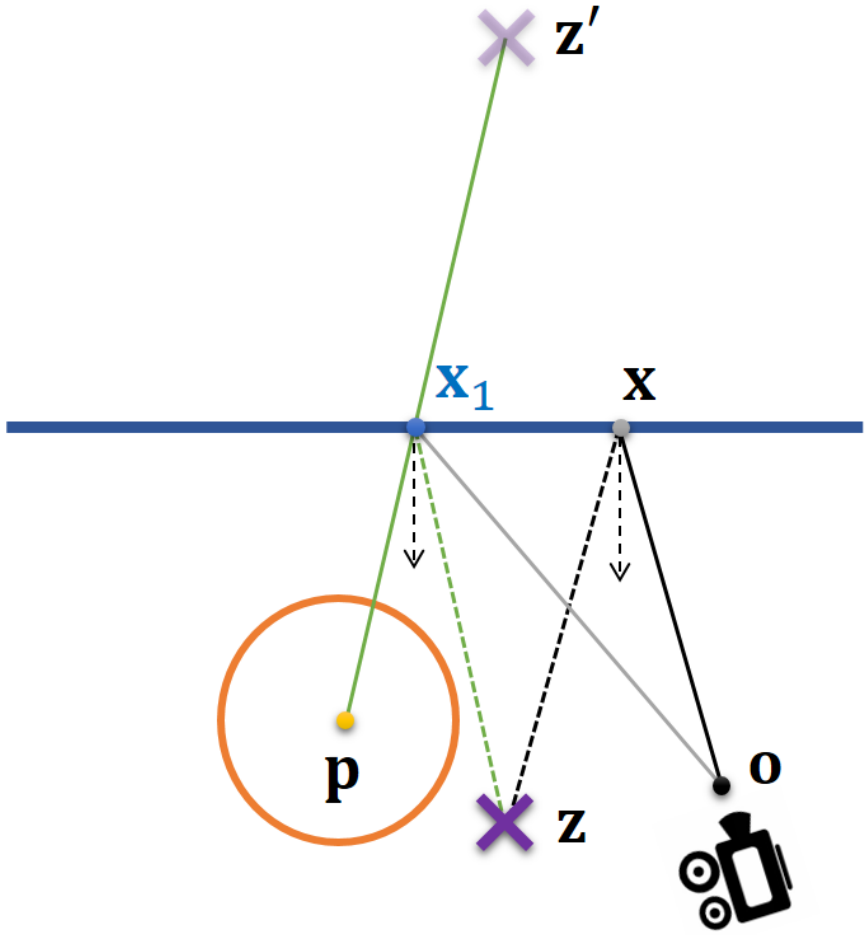
Probes Arranged on 3D Grid

Gradient-based Search Algorithm



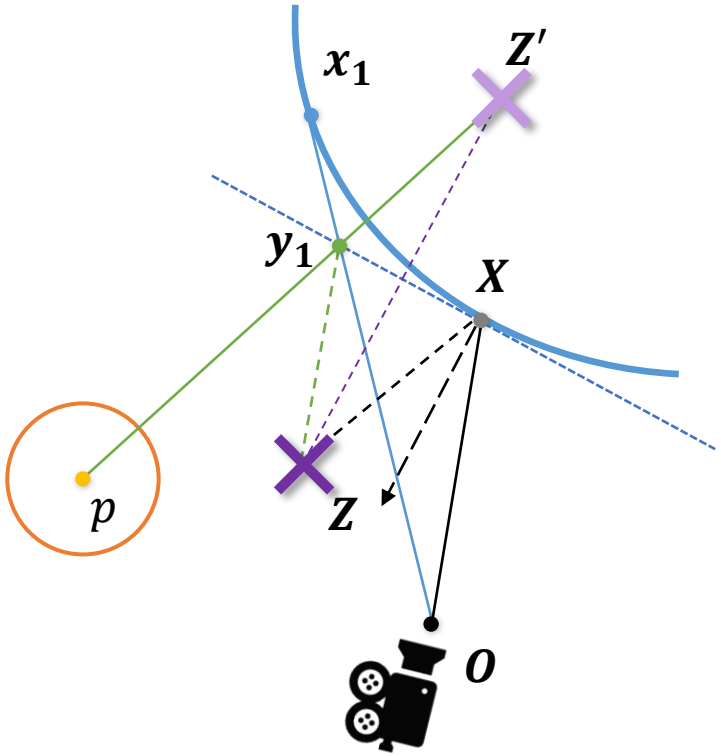
Panoramas Stored in Each Probe

Gradient-based Search Algorithm



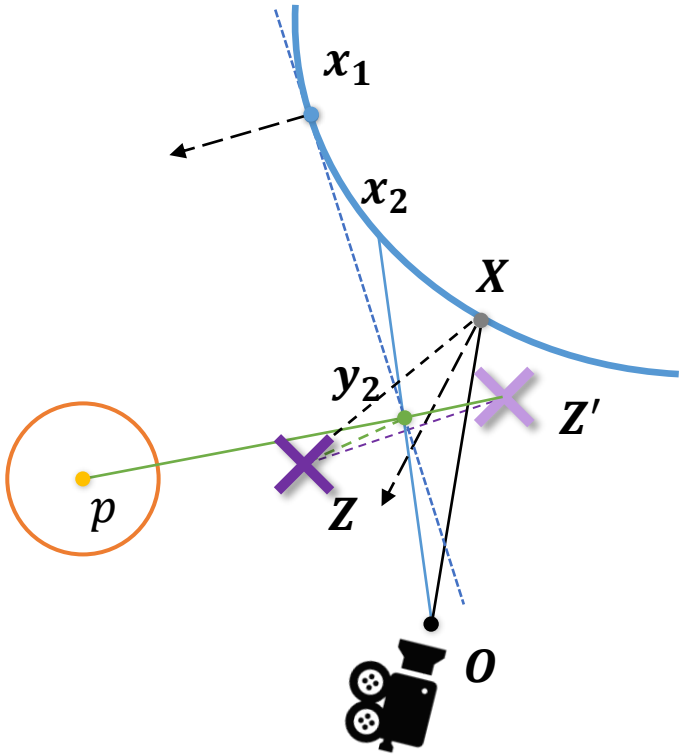
Simple Situation-A Planar Surface

Gradient-based Search Algorithm



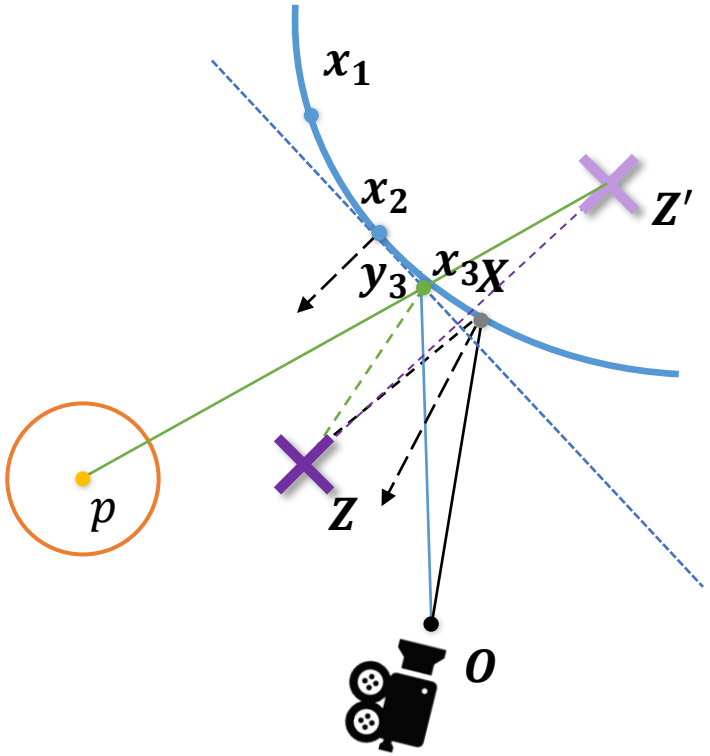
Sophisticated Curved Surface

Gradient-based Search Algorithm



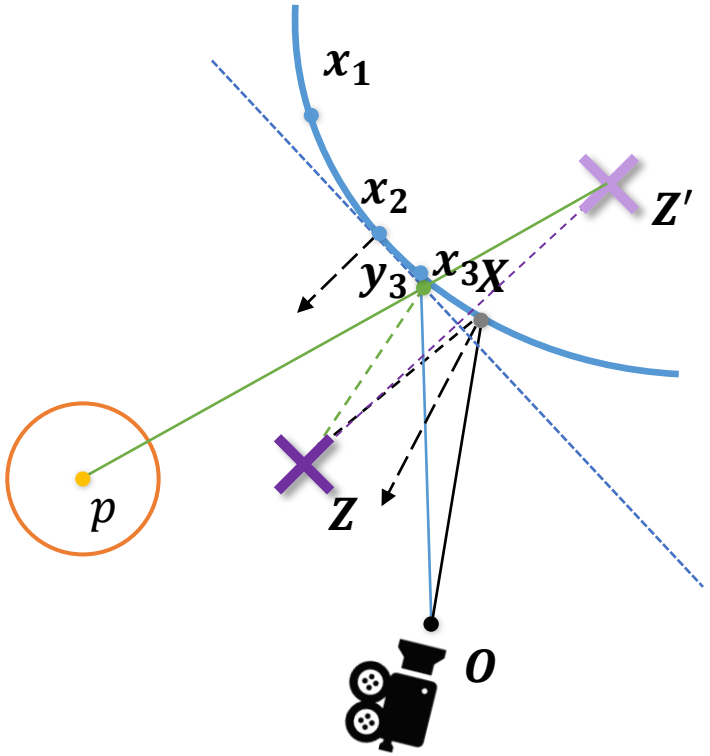
Sophisticated Curved Surface

Gradient-based Search Algorithm



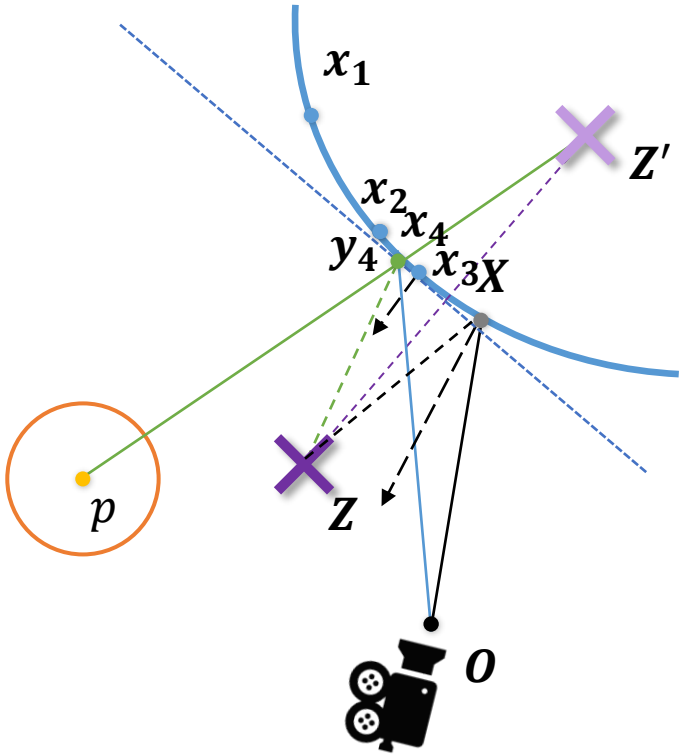
Sophisticated Curved Surface

Gradient-based Search Algorithm



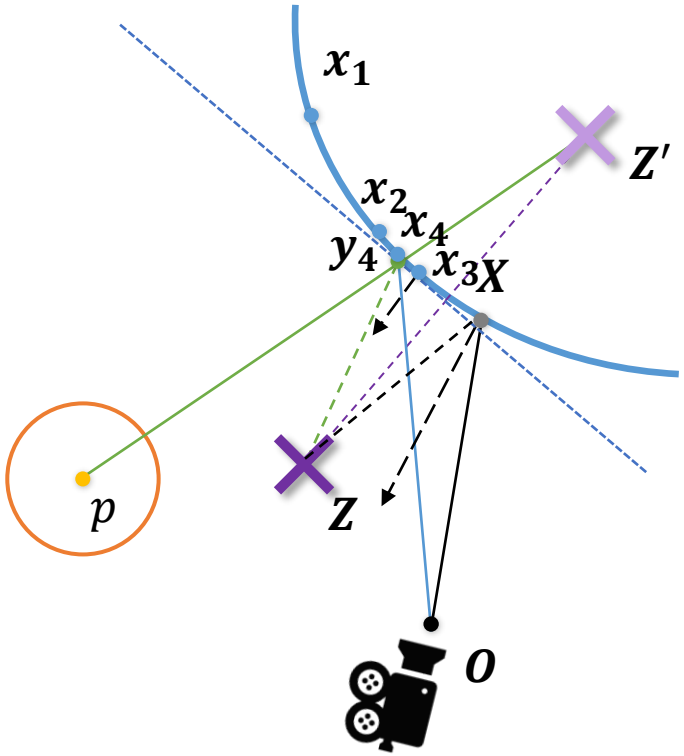
Sophisticated Curved Surface

Gradient-based Search Algorithm



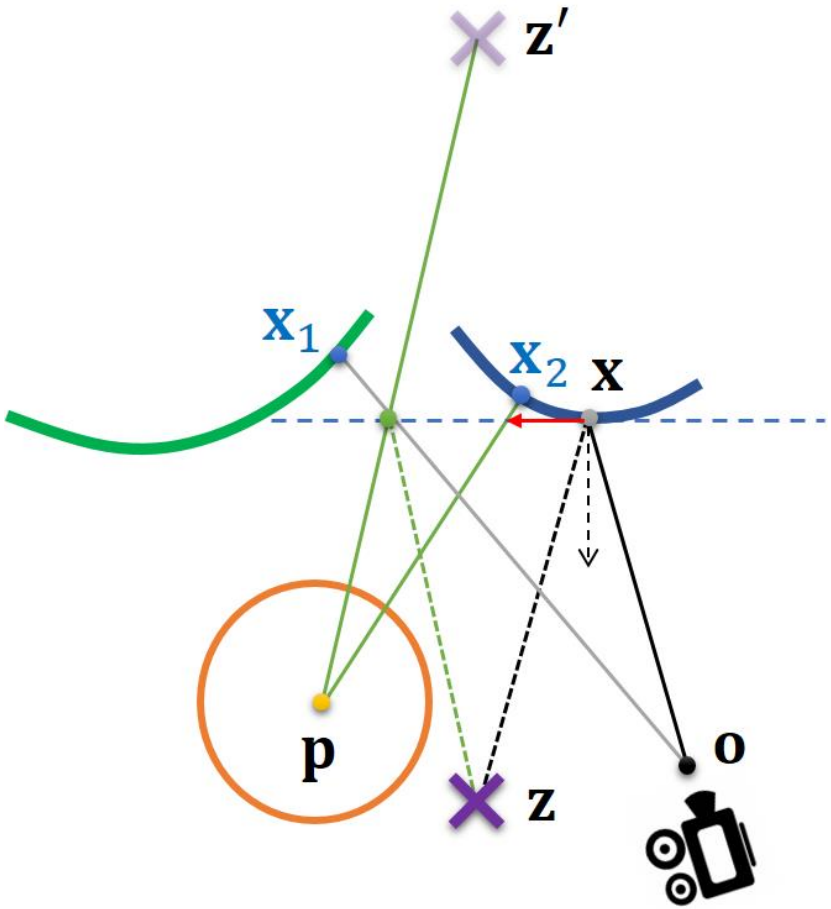
Sophisticated Curved Surface

Gradient-based Search Algorithm



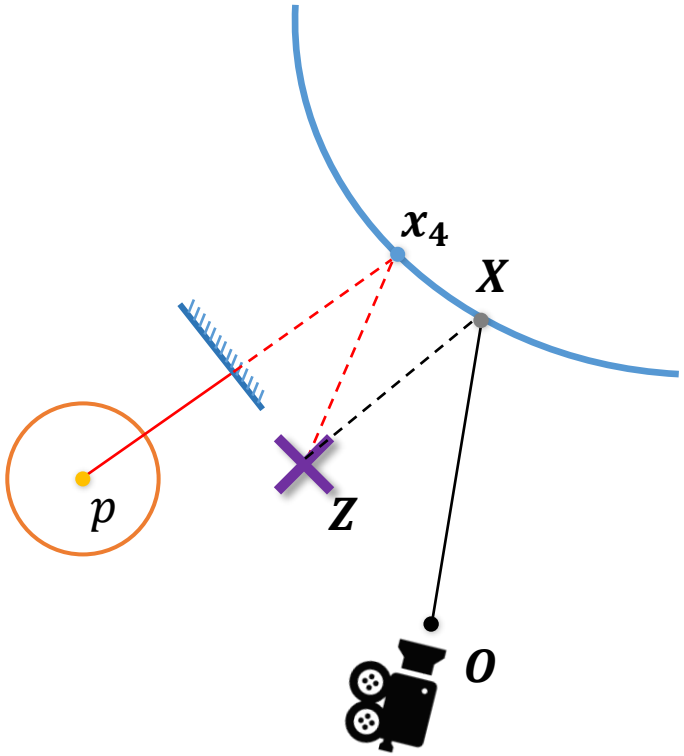
Sophisticated Curved Surface

Gradient-based Search Algorithm



Special Case-Search on Different Objects

Gradient-based Search Algorithm

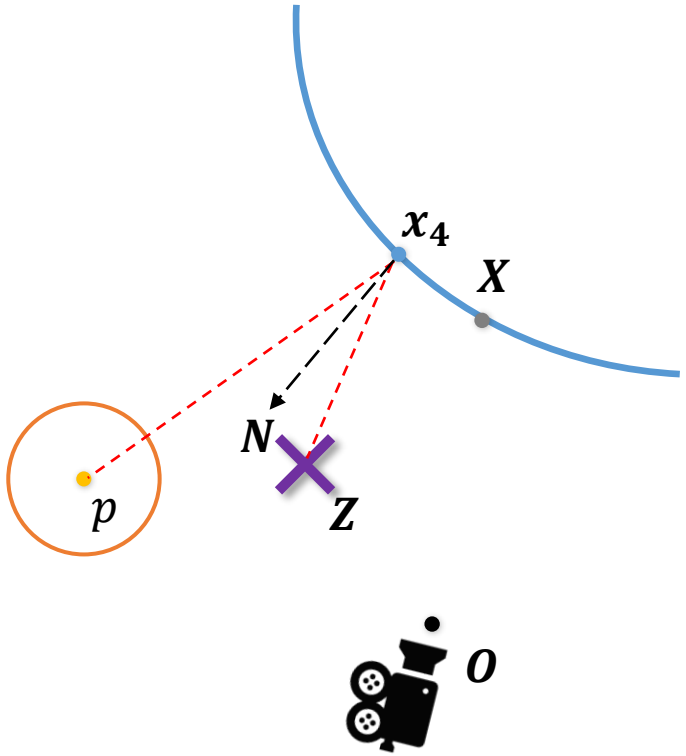


Special Case-Occluded Ray

Gradient-based Search Algorithm

Ablation on Visibility Check

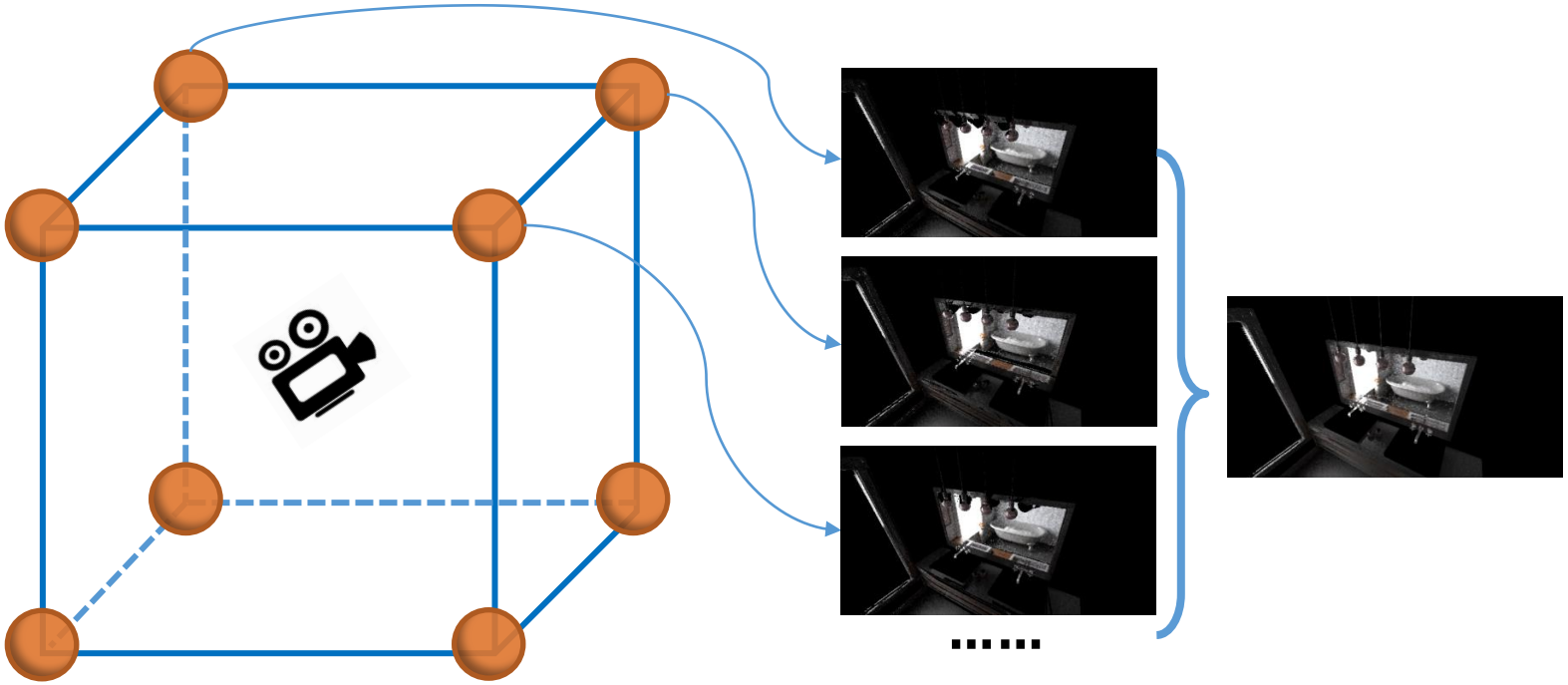
Gradient-based Search Algorithm



Confidence Value

$$\mathbb{C}(\mathbf{x}_k) = \frac{\mathbf{p}\mathbf{x}_k + \mathbf{z}\mathbf{x}_k}{\|\mathbf{p}\mathbf{x}_k + \mathbf{z}\mathbf{x}_k\|} \cdot \mathbf{N}(\mathbf{x}_k)$$

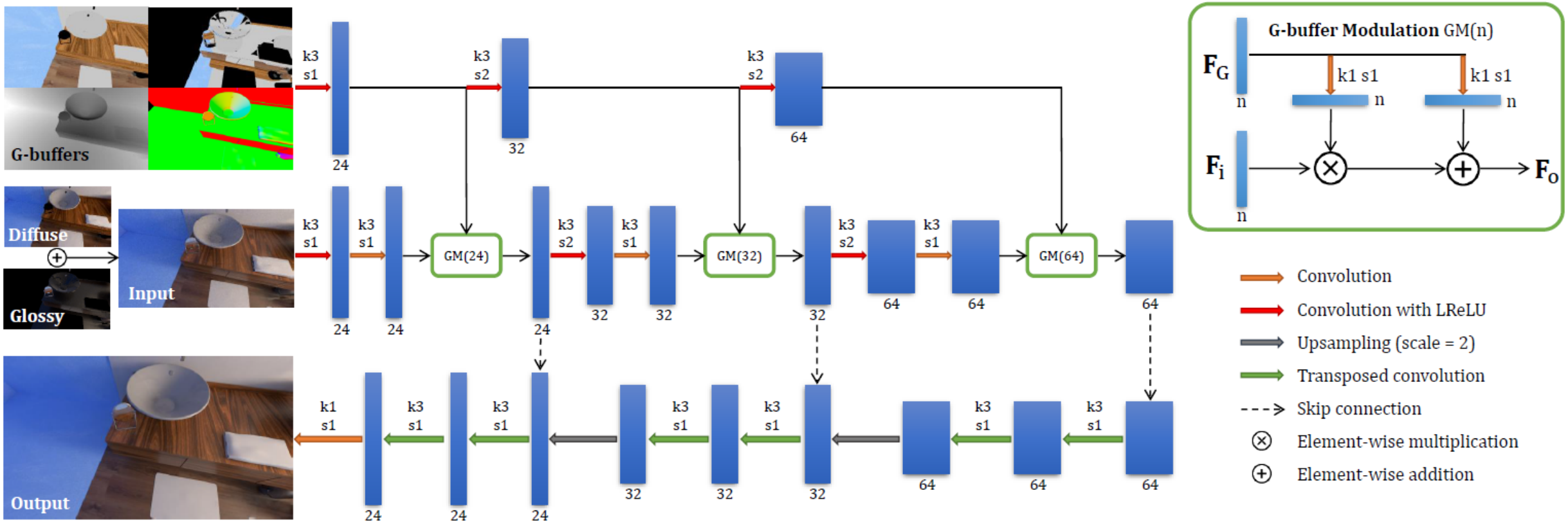
Gradient-based Search Algorithm



$$\mathbf{I}_g = \sum_{k=1}^{8} W_k \mathbf{I}_{g,k} \quad \text{with} \quad W_k = \frac{\exp[-\tau \mathbb{C}_k]}{\sum_{k=1}^{8} \exp[-\tau \mathbb{C}_k]}$$

Neural image reconstruction

Neural image reconstruction



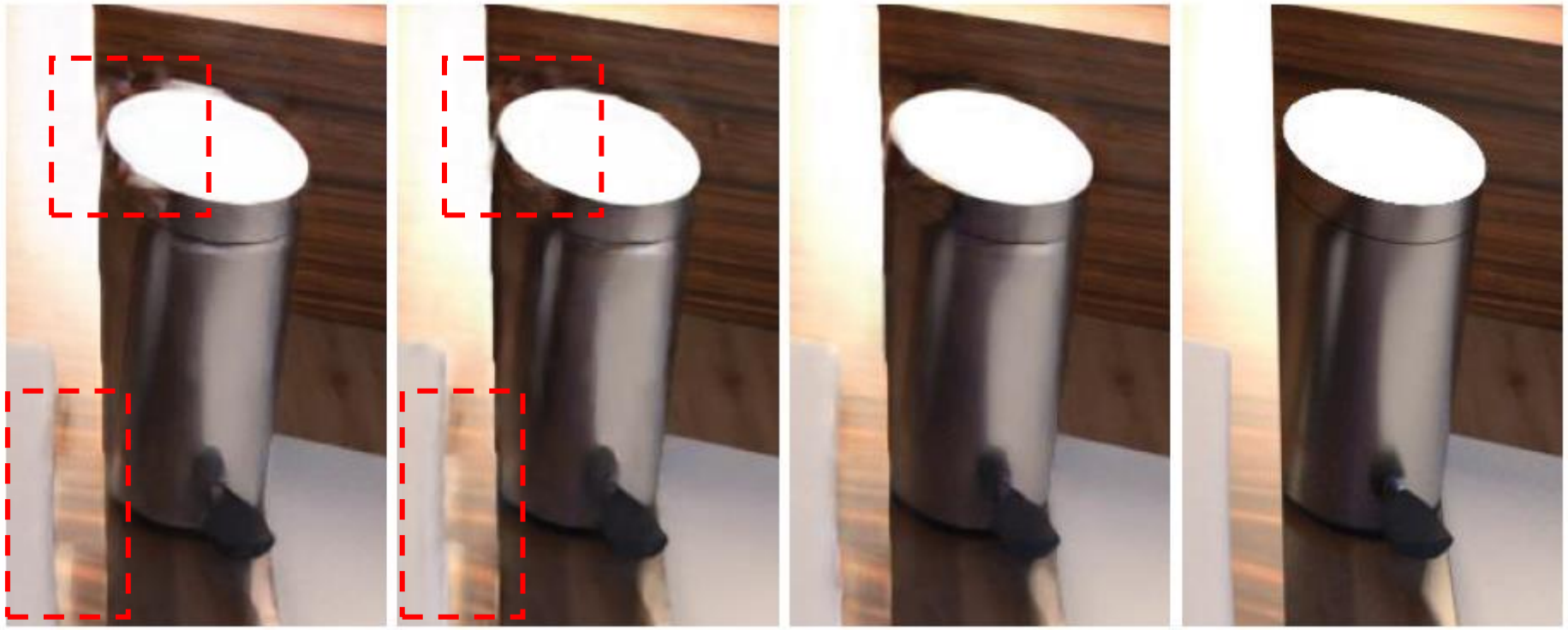
Loss Function

$$\mathcal{L} = \lambda_{L1}\mathcal{L}_{L1} + \lambda_{\mathrm{LPIPS}}\mathcal{L}_{\mathrm{LPIPS}} + \lambda_{\mathrm{T}}\mathcal{L}_{\mathrm{T}}$$

$$\mathcal{L}_{\mathrm{LPIPS}} = \sum_{l} ||\omega_l \odot (\mathbf{F}_l(\hat{\mathbf{I}}) - \mathbf{F}_l(\mathbf{I}_o))||_2^2$$

$$\mathcal{L}_{\mathrm{T}} = ||\mathbf{I}_o - \mathcal{W}(\mathbf{I}'_o, \mathbf{V})||_1$$

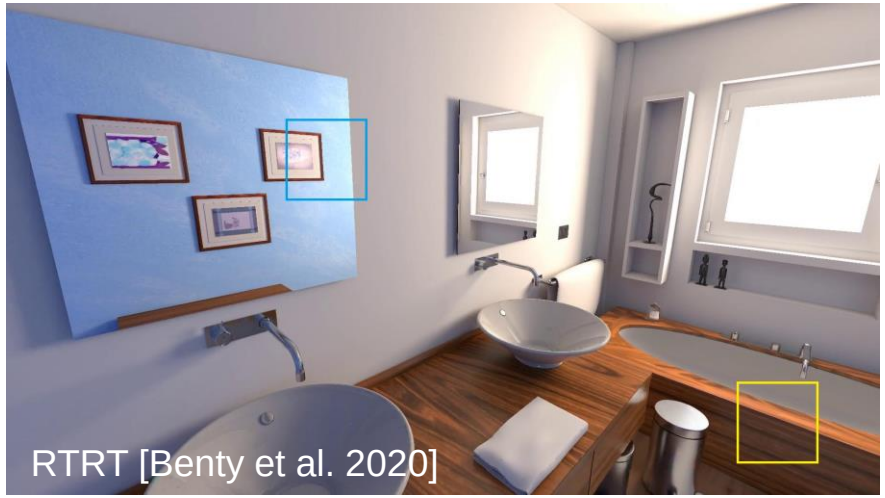
Network Validation

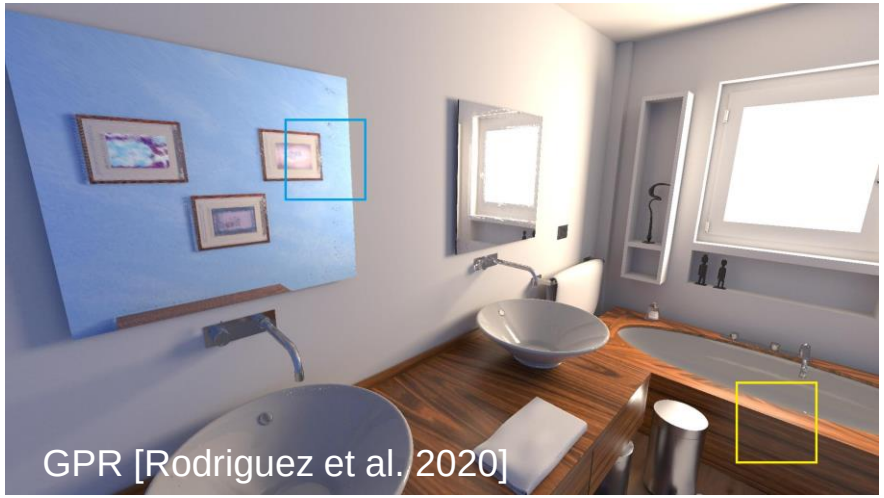


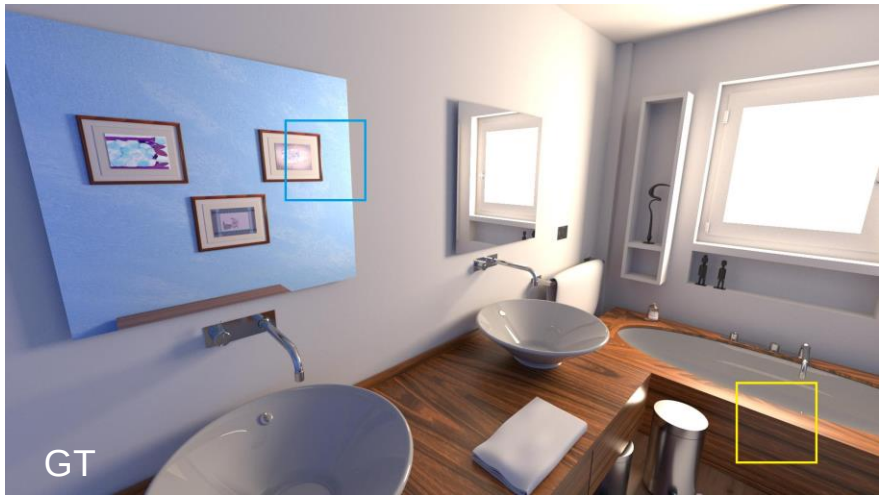
(a) Concate (b) w/o LPIPS (c) Ours (d) Ground truth

Quality Comparison

Bathroom

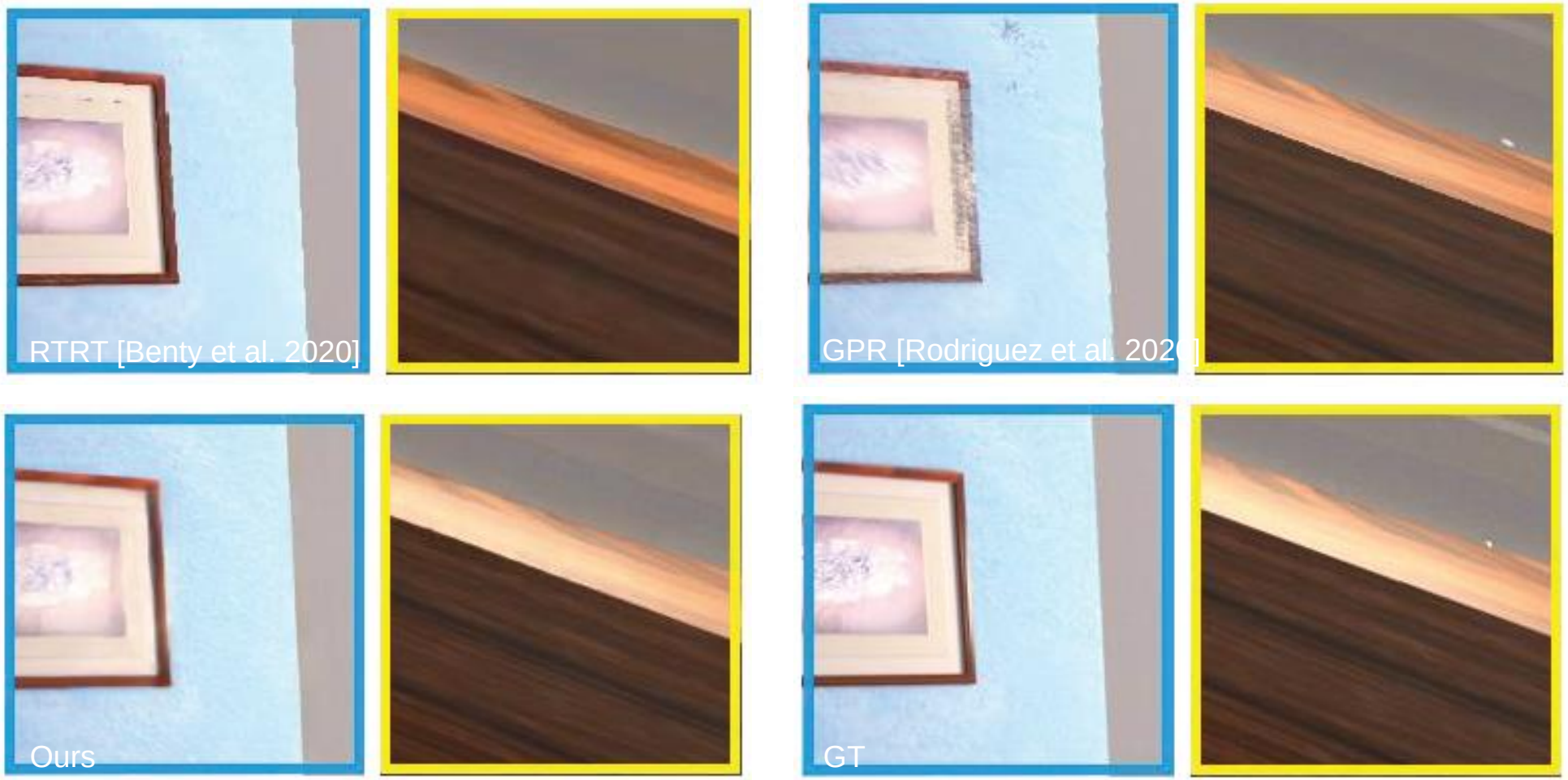






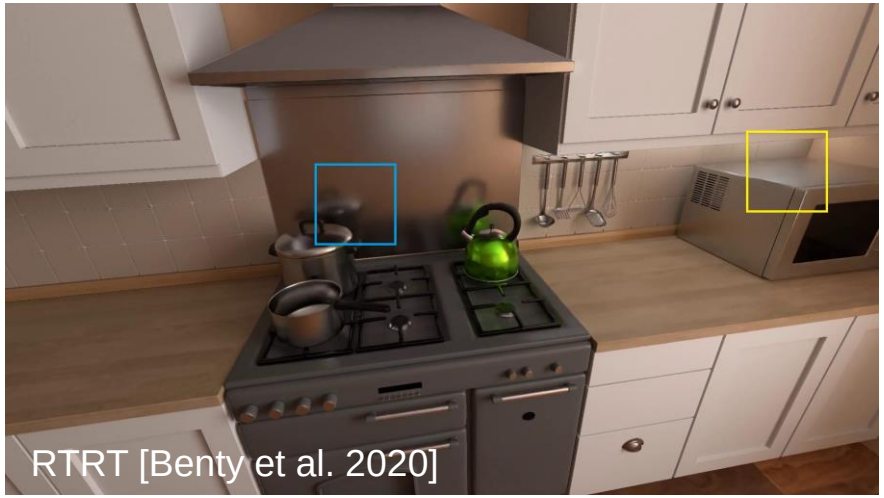
Quality Comparison

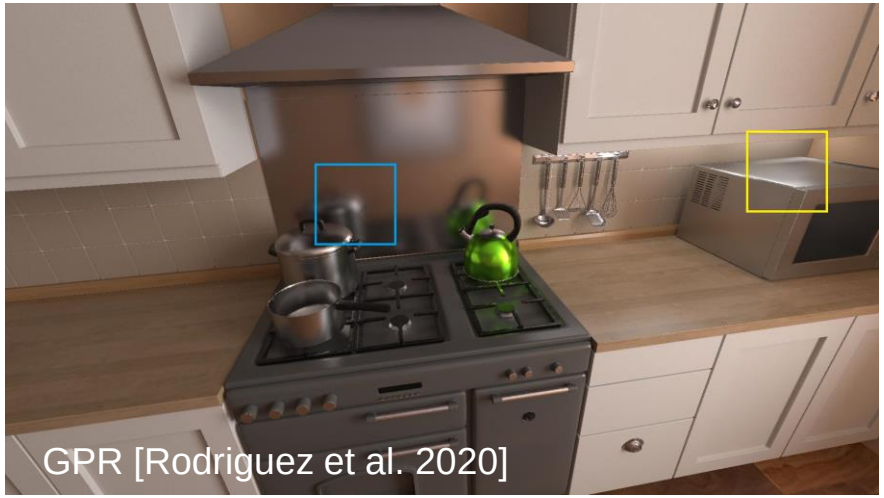
Bathroom

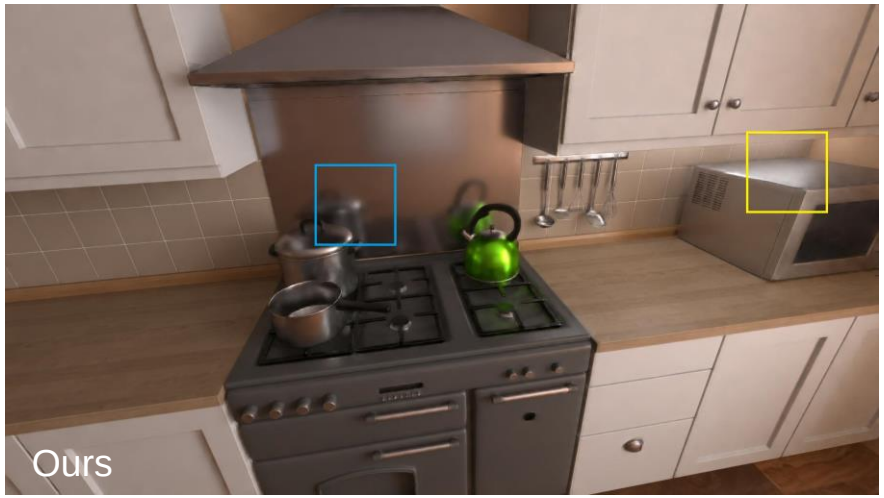


Quality Comparison

Kitchen

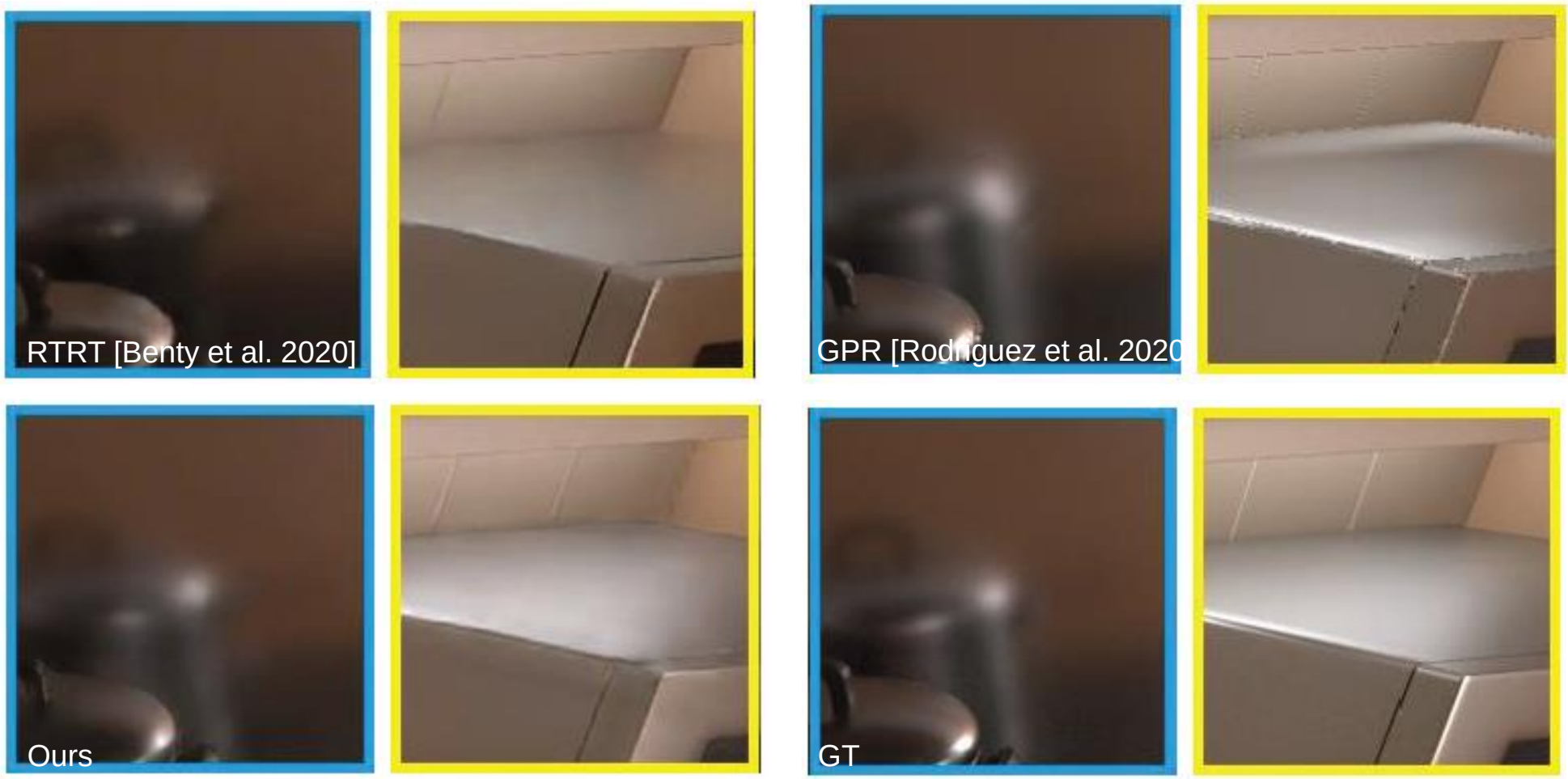






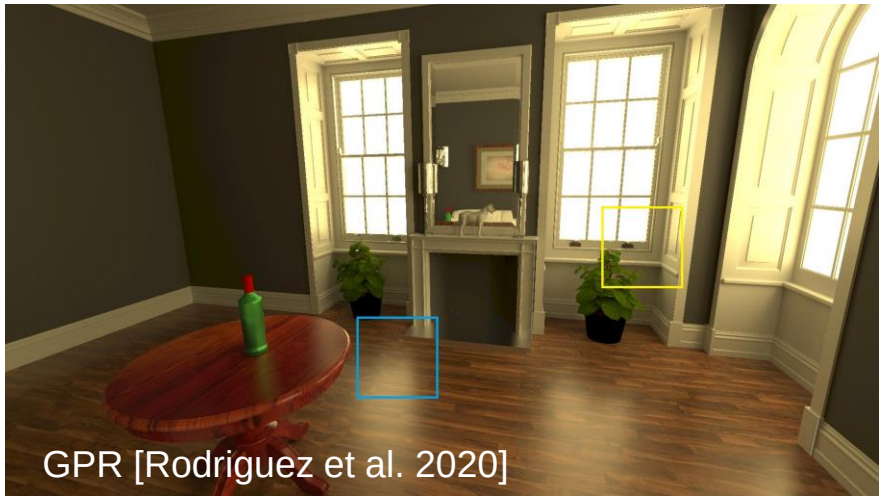
Quality Comparison

Kitchen



Quality Comparison

Livingroom

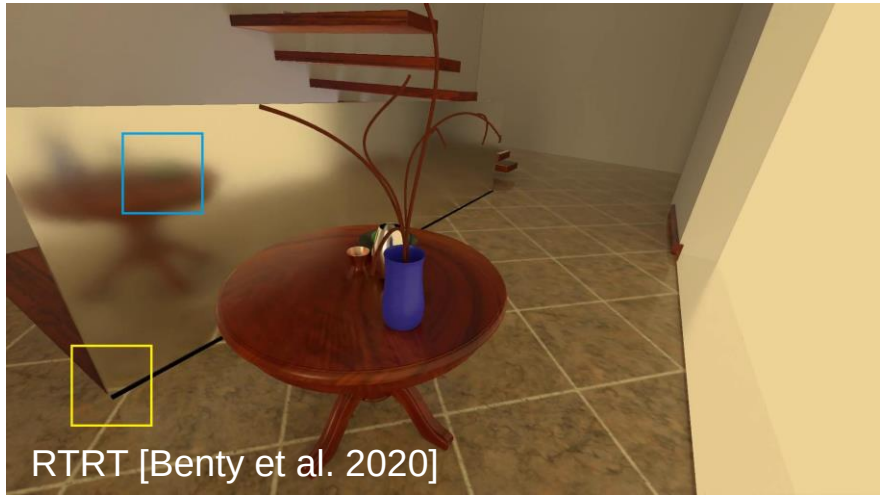


Quality Comparison

Livingroom

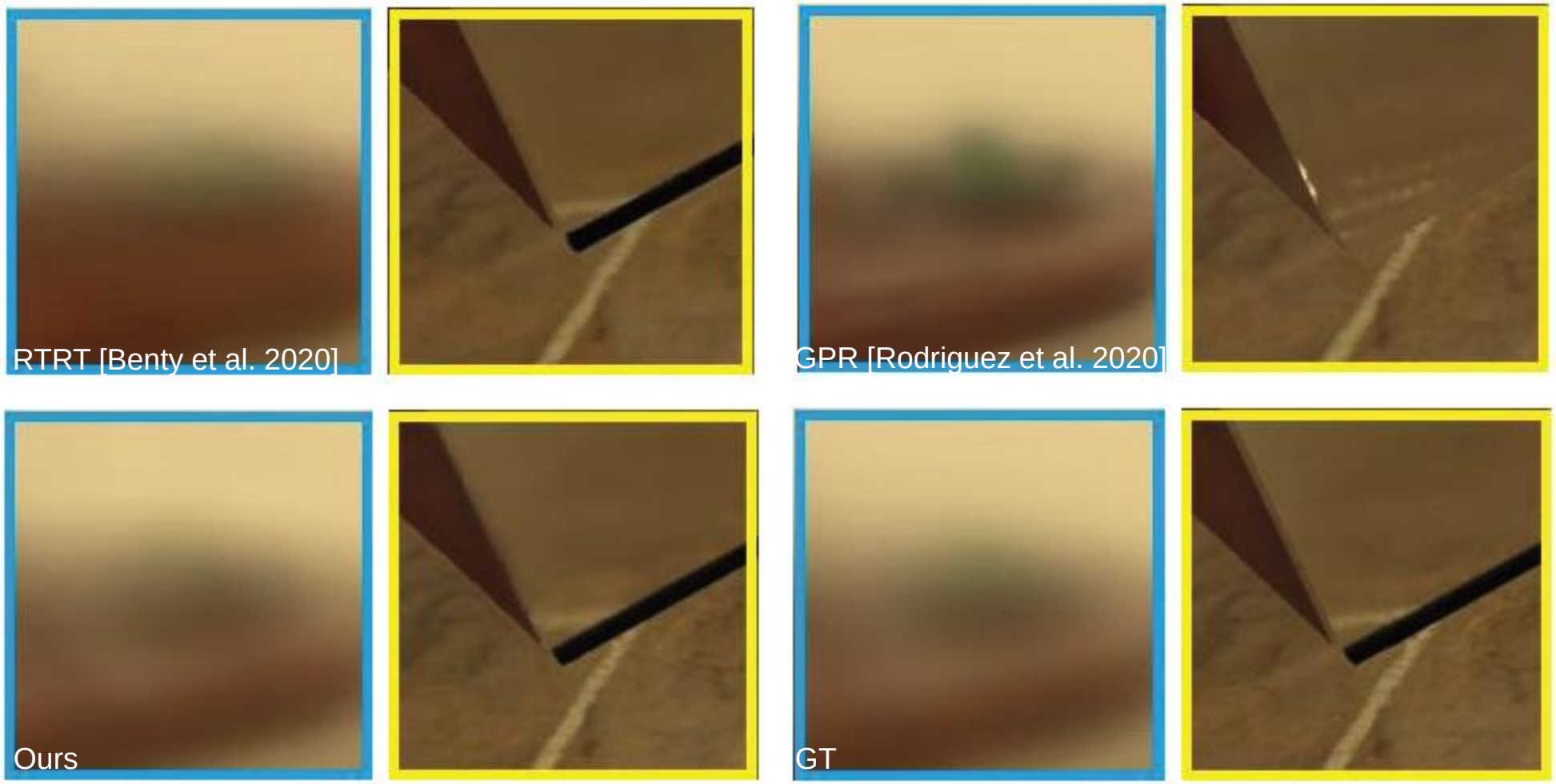
Quality Comparison

Staircase



Quality Comparison

Staircase



Quality Comparison

Quality Comparison

Bathroom

Method	RMSE	DSSIM	LPIPS
ISG	0.087	0.131	0.093
ULR	0.110	0.150	0.134
RTRT	0.057	0.068	0.055
GPR	0.033	0.041	0.044
Ours (Search)	0.043	0.093	0.139
Ours (Final)	**0.022**	**0.029**	**0.030**

Quality Comparison

Kitchen

Method	RMSE	DSSIM	LPIPS
ISG	0.078	0.132	0.092
ULR	0.060	0.117	0.103
RTRT	0.041	0.049	0.048
GPR	0.028	0.035	0.049
Ours (Search)	0.043	0.108	0.139
Ours (Final)	**0.024**	**0.031**	**0.032**

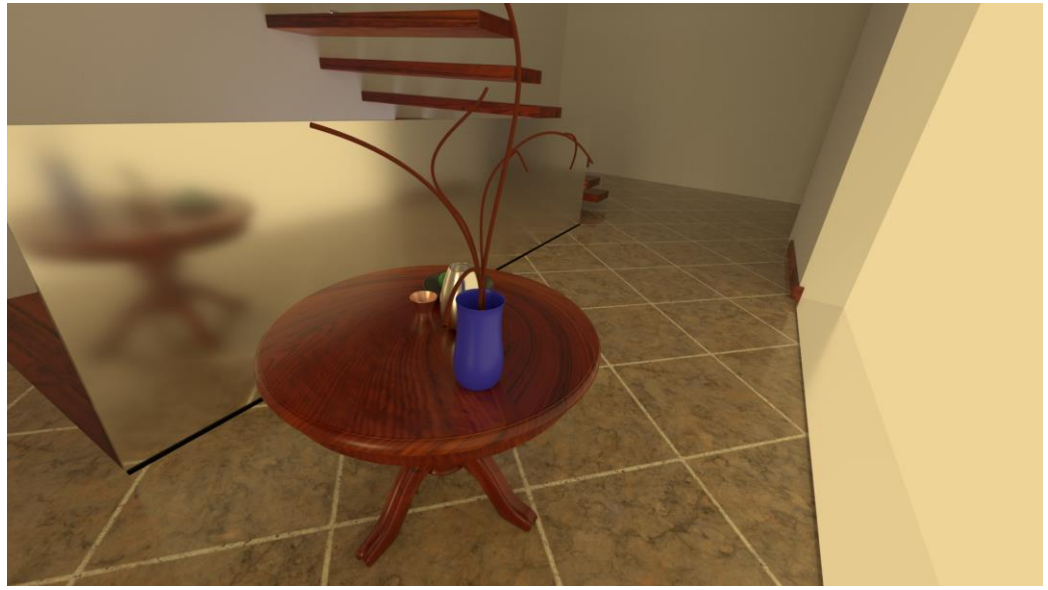
Quality Comparison

Livingroom

Method	RMSE	DSSIM	LPIPS
ISG	0.126	0.190	0.110
ULR	0.099	0.195	0.107
RTRT	0.055	0.081	0.062
GPR	0.034	0.044	0.047
Ours (Search)	0.044	0.078	0.110
Ours (Final)	**0.022**	**0.022**	**0.020**

Quality Comparison

Staircase



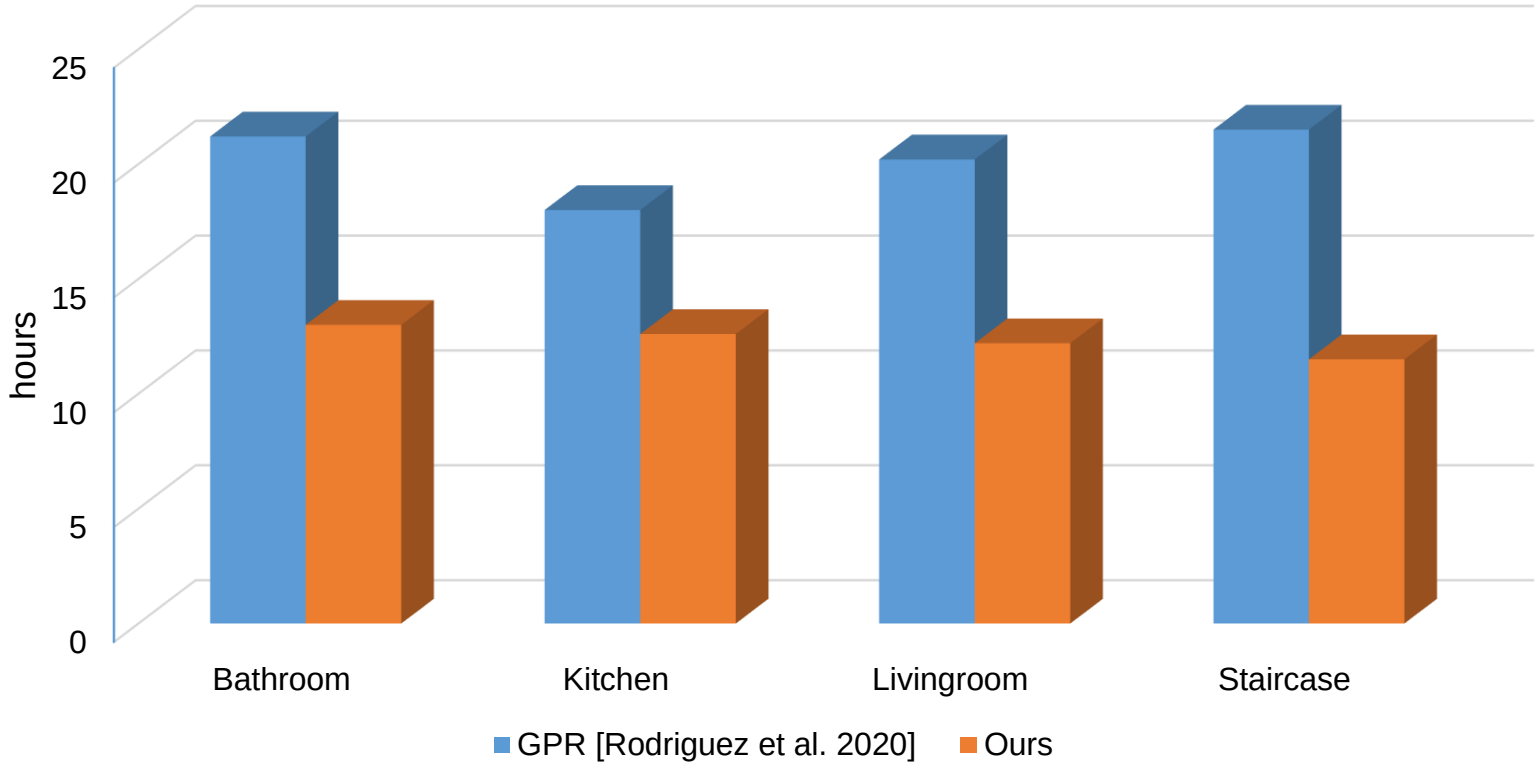
Method	RMSE	DSSIM	LPIPS
ISG	0.069	0.093	0.064
ULR	0.054	0.083	0.061
RTRT	0.053	0.074	0.051
GPR	0.020	0.021	0.030
Ours (Search)	0.030	0.060	0.100
Ours (Final)	**0.014**	**0.013**	**0.008**

Performance Analysis

Precomputation

Scene	Method	Lightmap	Probes	GT	Train	**Total**
Bat..	GPR	2.9 h	18.3 h	-	-	21.2 h
	Ours	0.08 h	0.8 h	8.2 h	3.9 h	13.0 h
Kit..	GPR	1.5 h	16.5 h	-	-	18.0 h
	Ours	0.04 h	0.6 h	8.1 h	3.9 h	12.6 h
Liv..	GPR	3.1 h	17.1 h	-	-	20.2 h
	Ours	0.09 h	0.9 h	7.3 h	3.9 h	12.2 h
Sta..	GPR	2.3 h	19.2 h	-	-	21.5 h
	Ours	0.06 h	0.8 h	6.7 h	3.9 h	11.5 h

Performance Analysis



Performance Analysis

Run-time

Scene	Method	Raster.	Raycast	Search	Infer.	**Total**
Bat..	GPR	0.5 ms	4 ms	20.5 ms	-	25.0 ms
	Ours	0.5 ms	4 ms	6 ms	14.6 ms	25.1 ms
Kit..	GPR	0.6 ms	4 ms	21.6 ms	-	26.2 ms
	Ours	0.6 ms	4 ms	6 ms	14.6 ms	25.2 ms
Liv..	GPR	0.5 ms	4 ms	21.6 ms	-	26.1 ms
	Ours	0.6 ms	4 ms	6 ms	14.6 ms	25.2 ms
Sta..	GPR	0.4 ms	4 ms	19.5 ms	-	23.9 ms
	Ours	0.6 ms	4 ms	4.4 ms	14.6 ms	23.6 ms

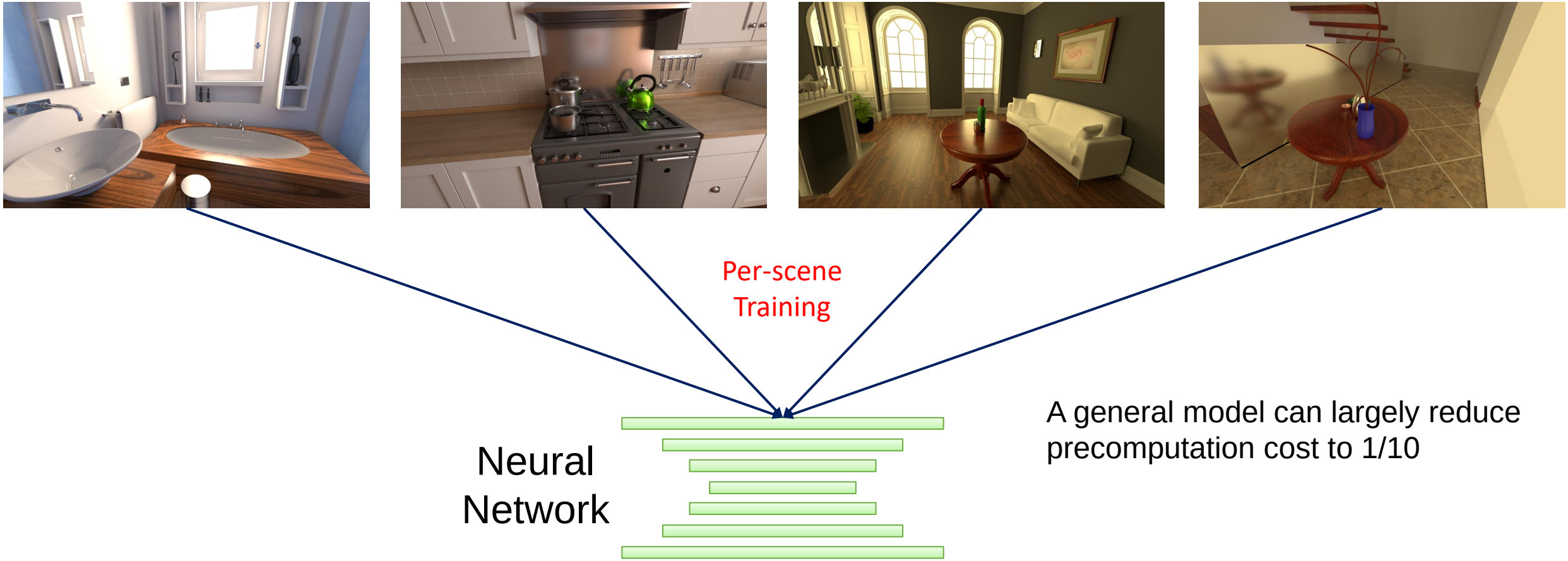
On run-time performance, Ours is similar to GPR, while achieving superior quality.

Limitations and Future Work

Highlights may be reduced

(a) Ours (Search) (b) Ours (Final) (c) Ground truth

Limitations and Future Work



A general model can largely reduce precomputation cost to 1/10

Limitations and Future Work

An adaptive probe placement method may further increase the rendering quality

Ours placed on 3D grid

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Thank You!

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