

Team 1

Mid-term Project Presentation

Adding indirect lighting to ReSTIR DR

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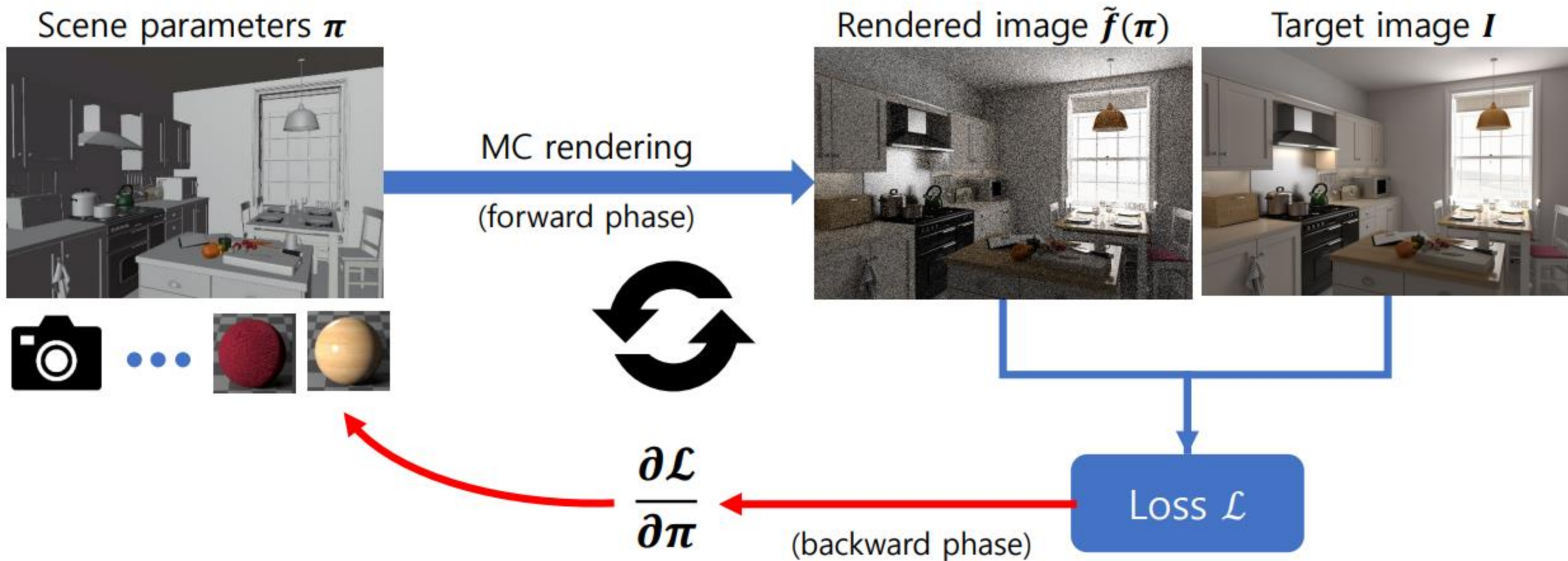
THE PREMIER CONFERENCE & EXHIBITION ON COMPUTER
GRAPHICS & INTERACTIVE TECHNIQUES

Parameter-space ReSTIR for Differentiable and Inverse Rendering

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Forward and Inverse Rendering



Target-Aware Image Denoising for Inverse Monte Carlo Rendering, Bochang Moon

Inverse rendering (materials)

Initial

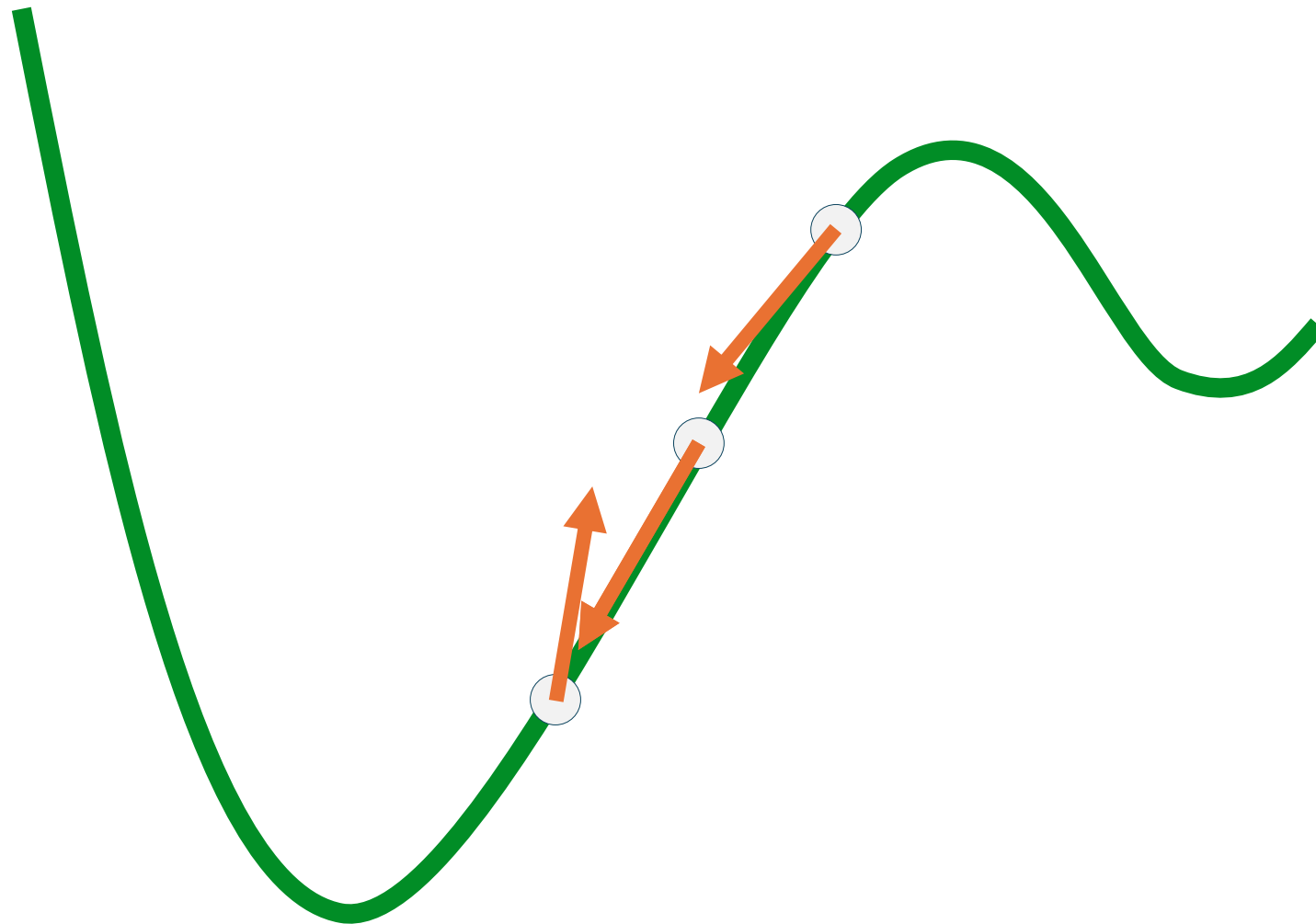


Target

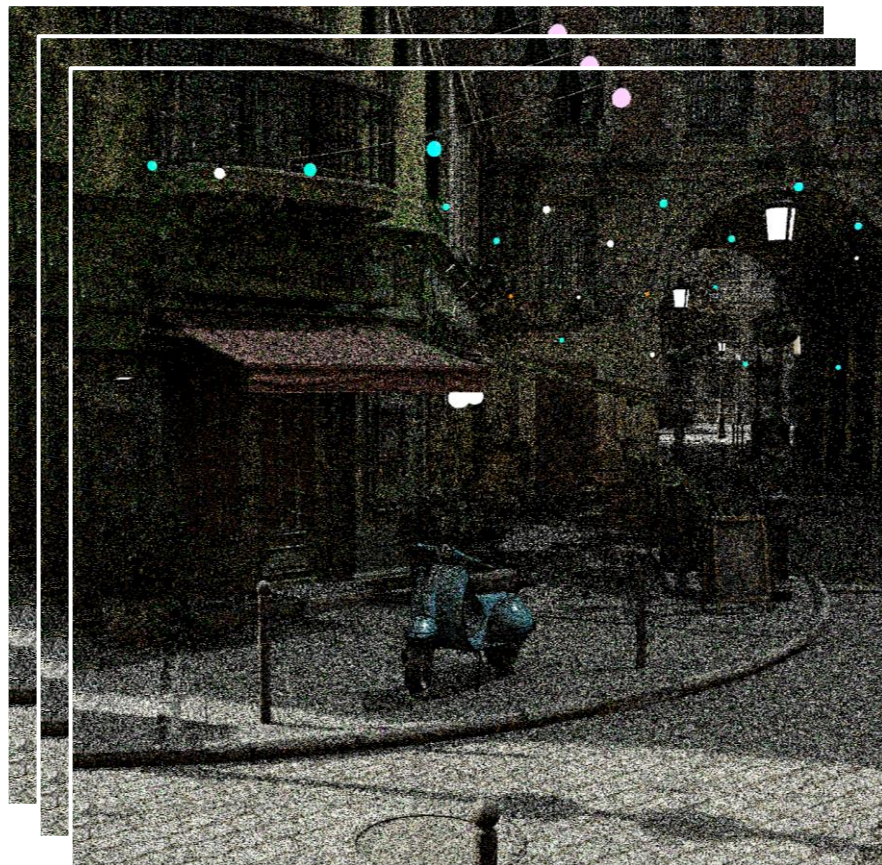




Noisy gradients



ReSTIR (unbiased spatiotemporal reuse)



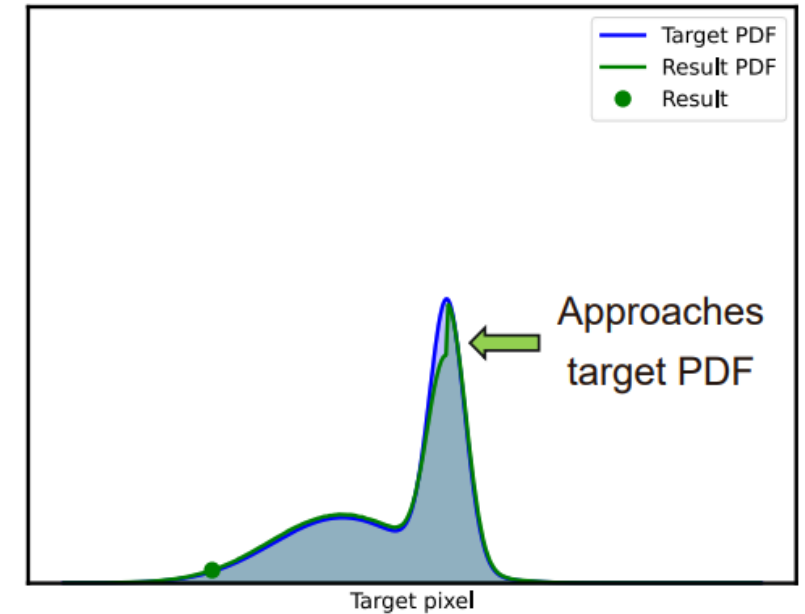
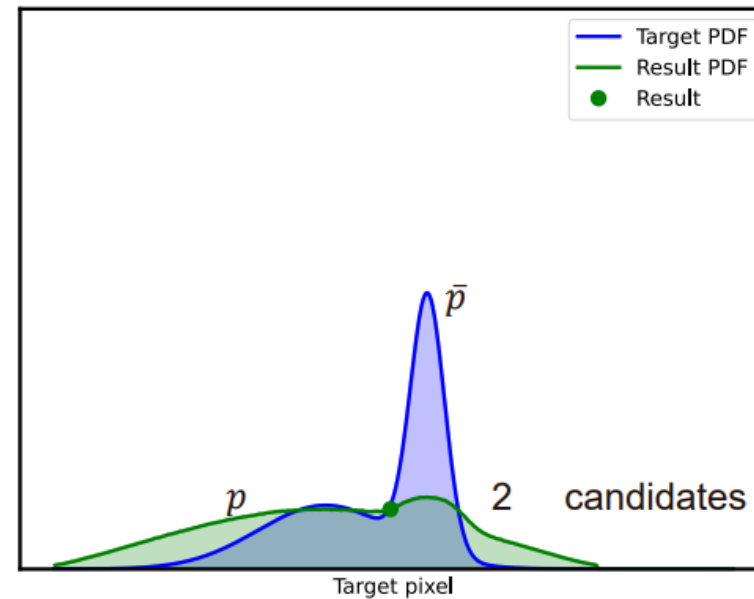
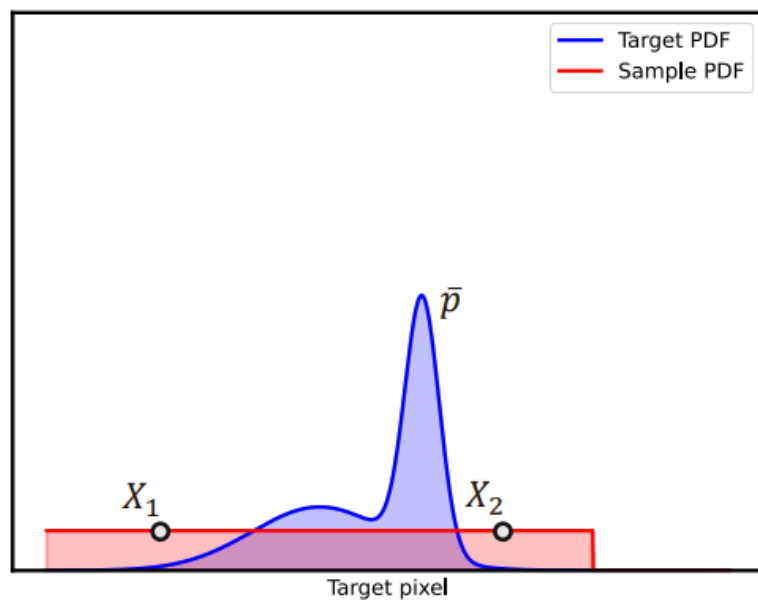
Sequence of
similar noisy frames



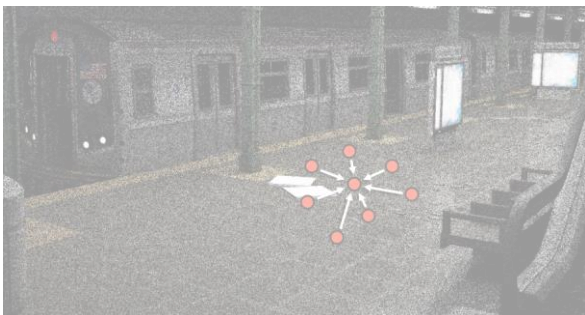
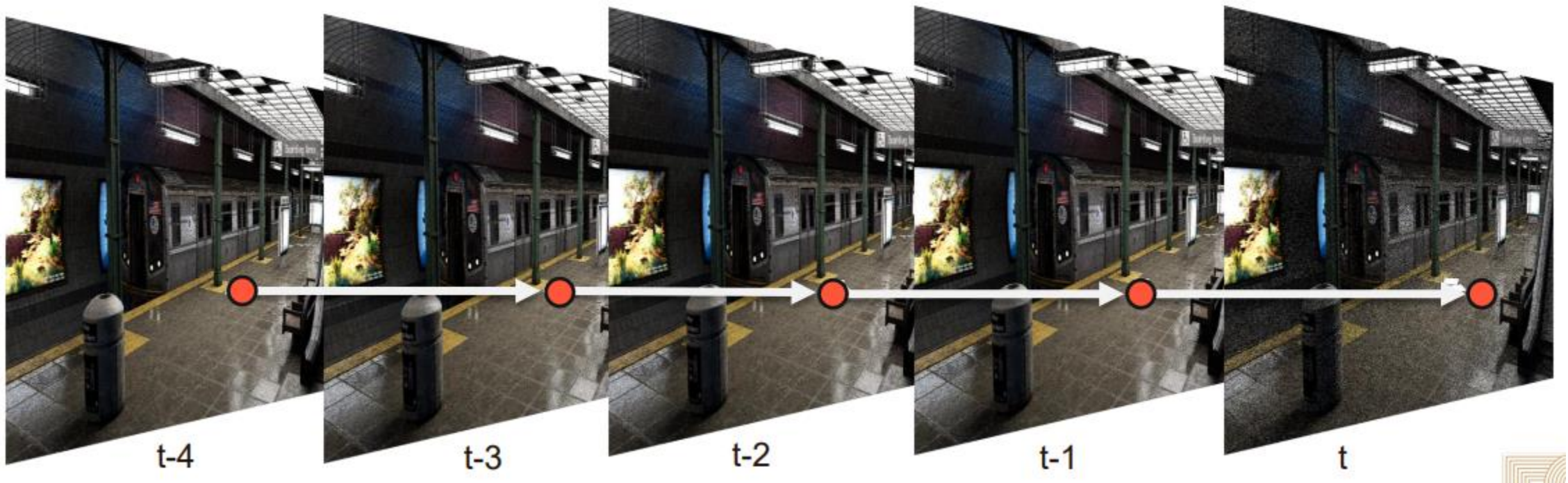
Reuse of
previous frames

Resampled Importance Sampling (RIS)

- Generate points $X_i \sim q$
- Pick one with probability proportional to $f(X_i)$



ReSTIR temporal reuse



(spatial reuse is not used in ReSTIR DR)

Theoretical contributions of the paper

- Parameter-Space Differentiable Rendering
- Resampling with Positive and Negative Functions
 - Positivization

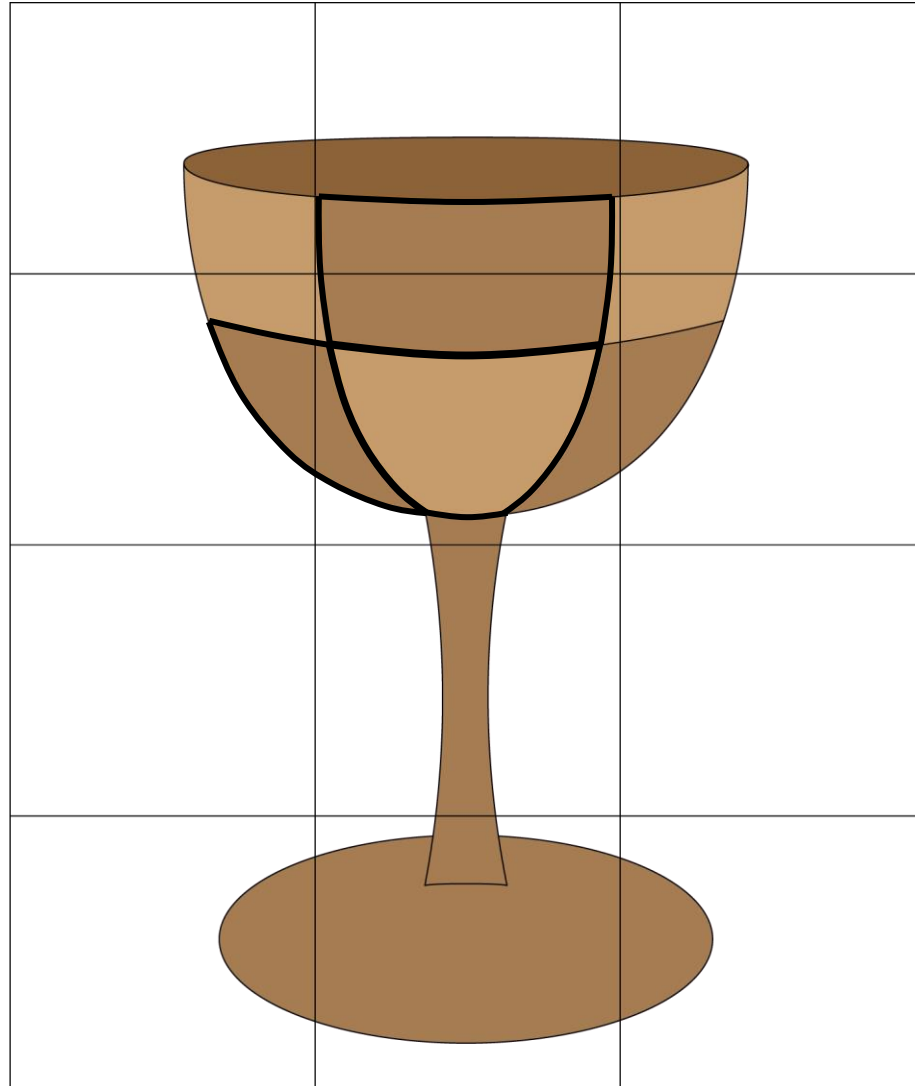
- This will not be modified in our project

The Problem with Pixel-centric Differentiable Rendering

Rendering

Forward
Rendering

Single
intensity I
for each of
N pixels
=
N samples



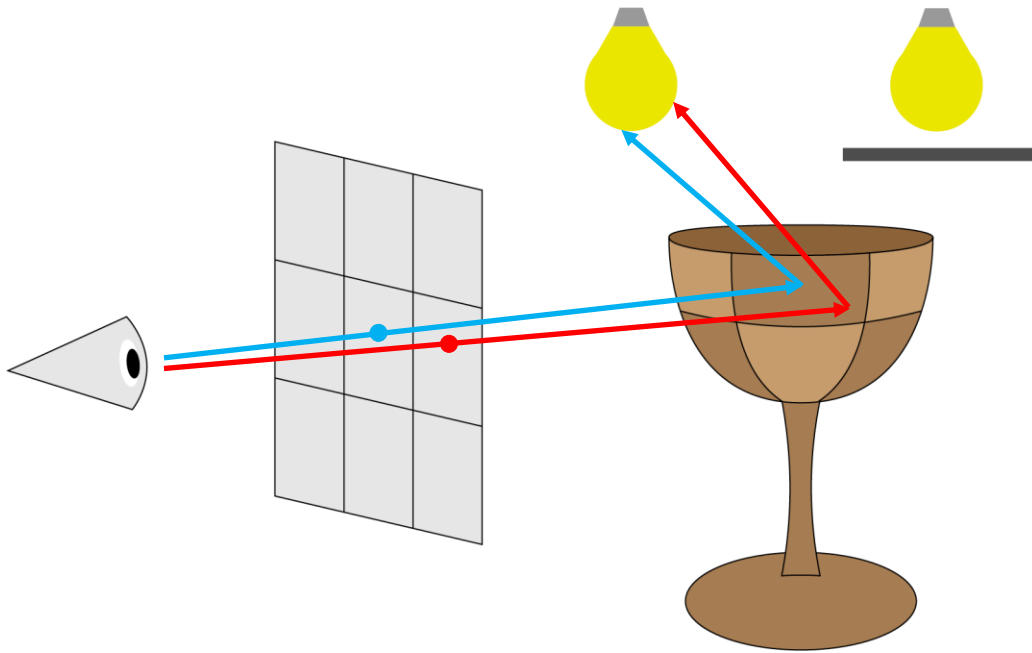
Differentiable
Rendering

One derivative for
each texel π_i in
each pixel

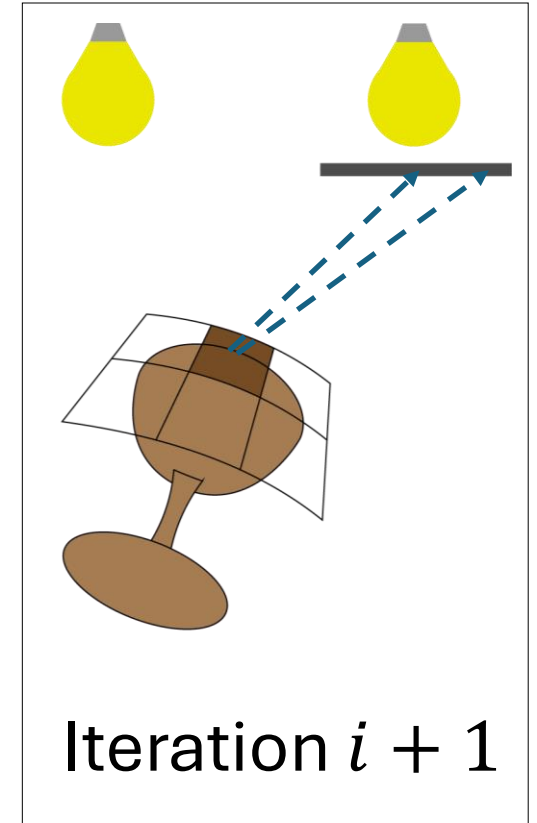
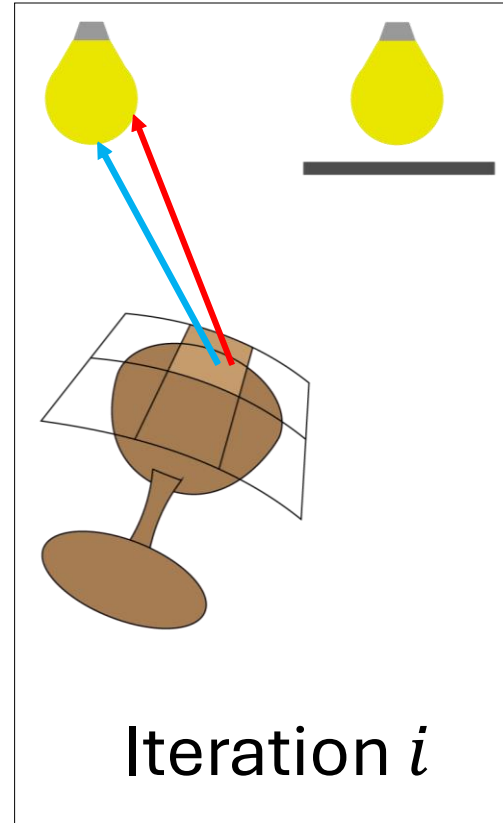
$$\frac{\partial I}{\partial \pi_0} \quad \frac{\partial I}{\partial \pi_1} \quad \frac{\partial I}{\partial \pi_2} \dots$$

M texels =
N · M samples

Texture Optimization Algorithm



Store
1 **positive**, 1 **negative**
sample per texel



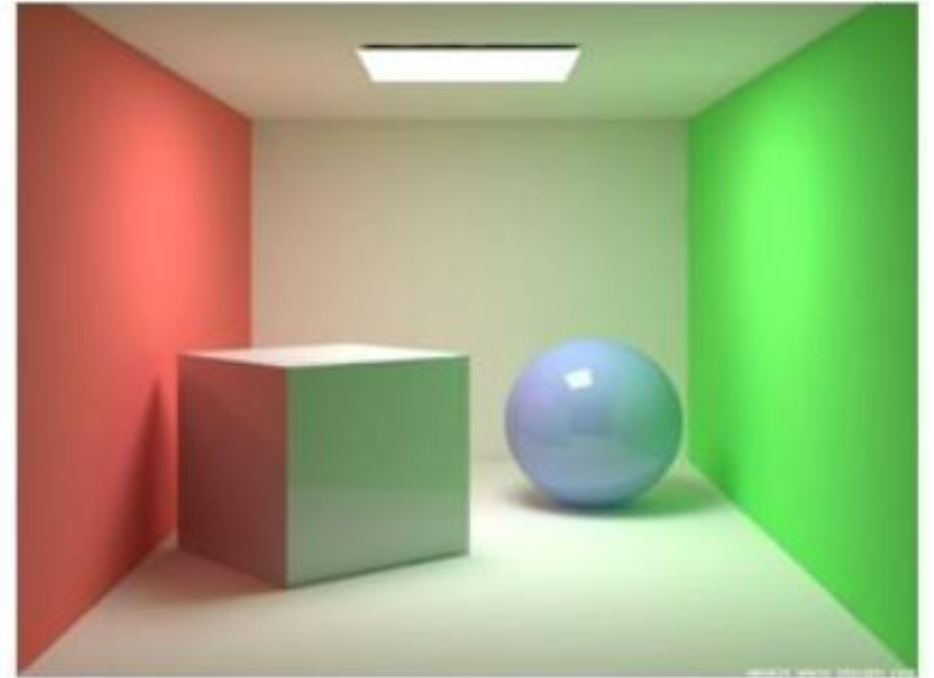
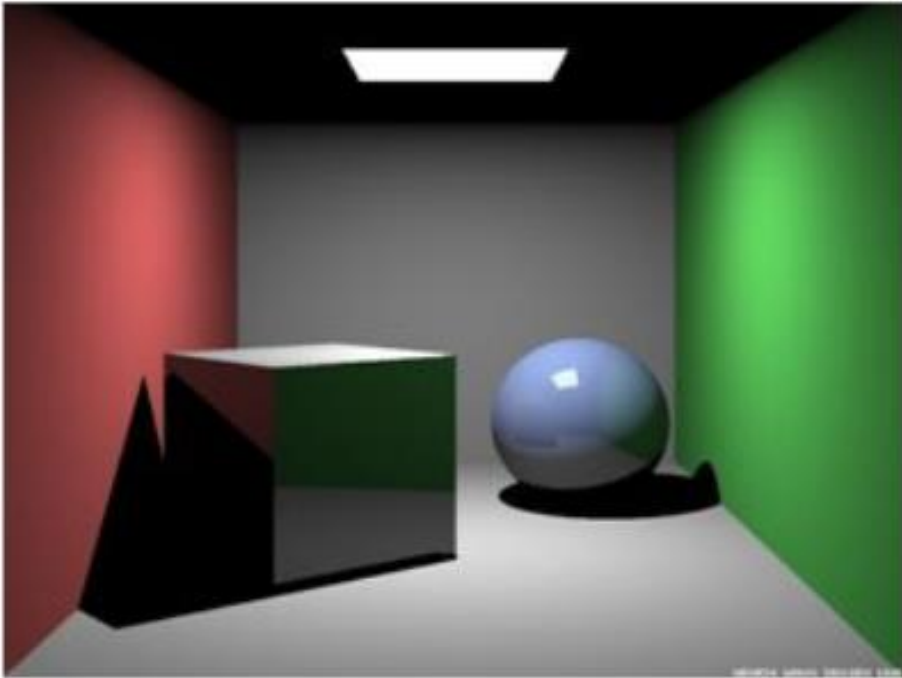
Summary

- **Parameter-space differentiable rendering** enables efficient derivative reuse.
- **Positivized RIS** extends RIS to real-valued functions to achieve theoretical zero-variance convergence of resampled derivative estimates.
- **Reusing samples** from previous gradient descent iterations results in faster inverse rendering.
- **Limitation:**
 - Assumes gradient correlation, which may fail at high learning rates.
 - Impact of gradient errors on convergence speed is unclear.

Project

Future work. Reuse across parameters, analogous to spatial reuse in ReSTIR, is possible with our parameter-space formulation. A potential challenge lies in efficiently selecting neighboring parameters to reuse. Reuse introduces correlation in sample estimates [Sawhney et al. 2022], and the exact effect of correlated gradients in inverse optimization is an interesting avenue to be investigated. While we have focused on differentiable and inverse rendering for BRDF textures under complex direct lighting, our theory and methods are general and can be extended to other rendering methods and scenarios involving general light transport, discontinuities, and other parameters, such as in volumetric or neural representations. Finally, our PGRIS estimator is immediately applicable to Monte Carlo integral estimation in contexts broader than rendering, where integrands can be both positive and negative.

| Motivation



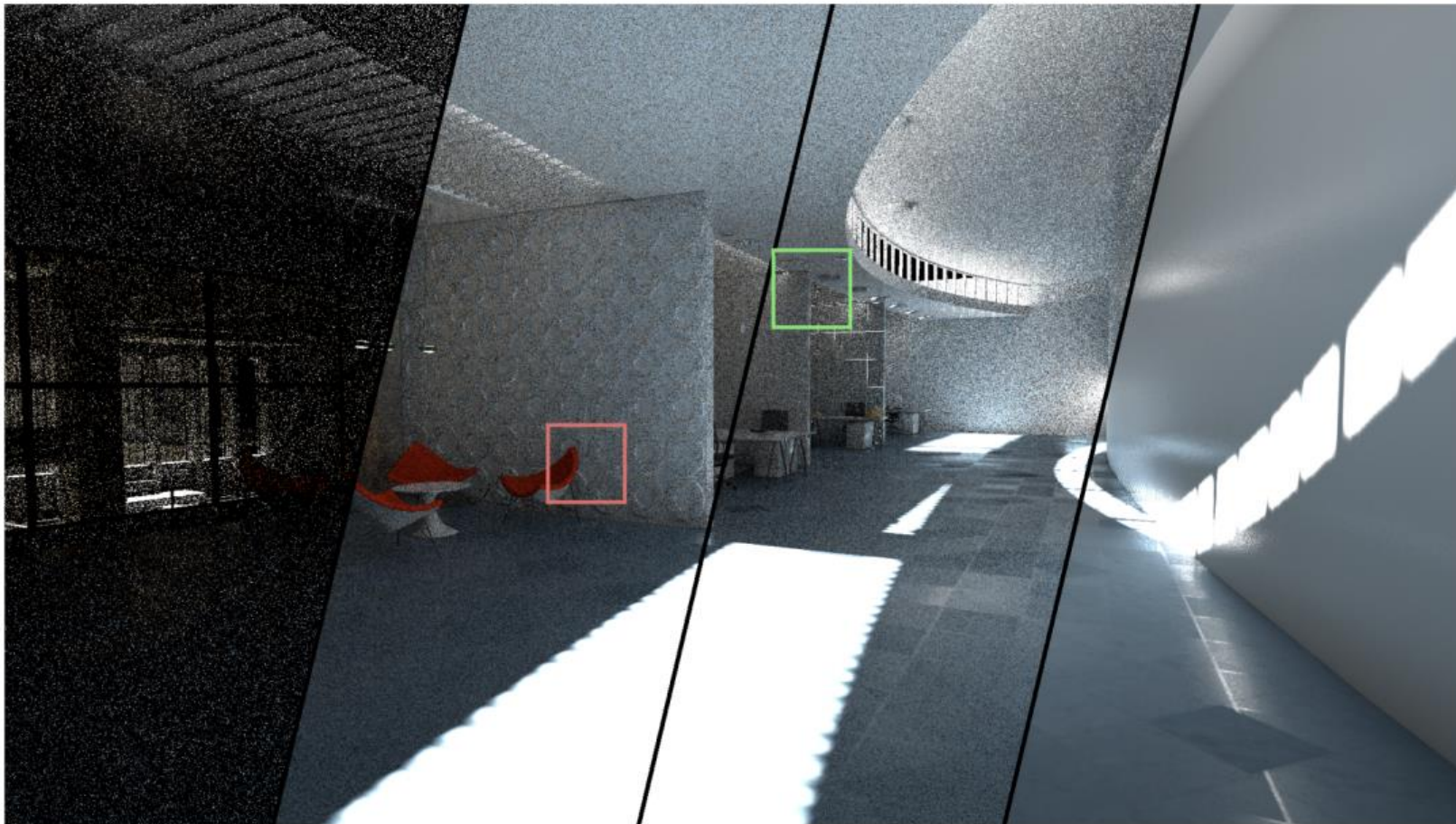
ReSTIR GI

Path Traced
(1spp) 8.0 ms
0.265 MSE

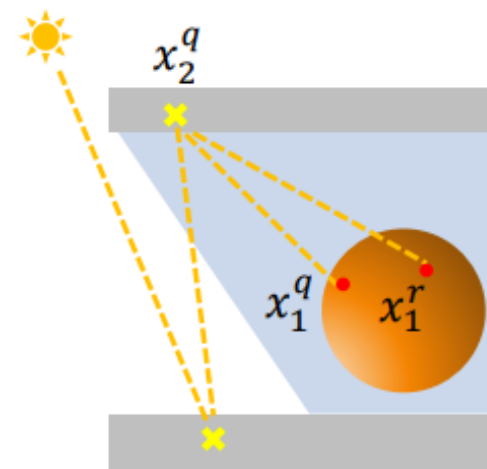
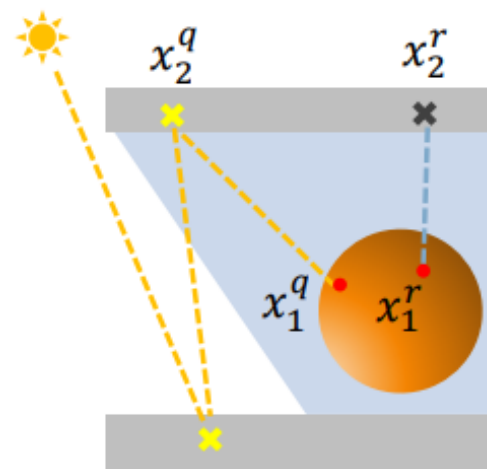
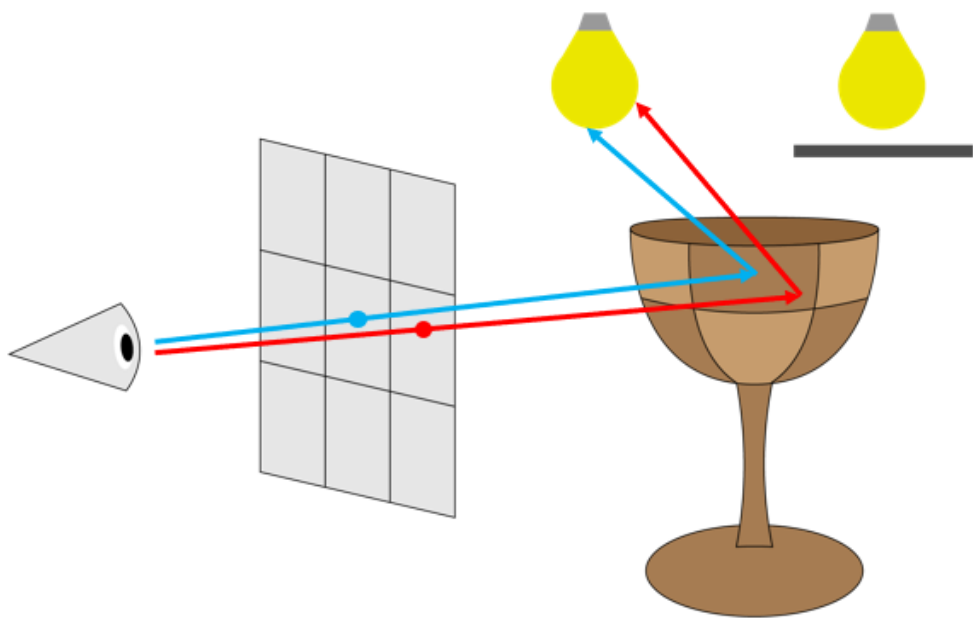
ReSTIR GI
(biased) 8.9 ms
0.0175 MSE (15.1x)

ReSTIR GI
(unbiased) 9.6 ms
0.0224 MSE (11.8x)

Reference



Multiple bounces



TODO

- Mitsuba 3
- Implement ReSTIR GI
- Test scenes/experiments

Roles

- Niklas Sanden
 - Try to compile Mitsuba
 - Extend ReSTIR DR with GI
- Tan Chao
 - Try compile Mitsuba
 - Try to find different scenes for indirect illumination
 - Set the experiments up in Mitsuba