Denoising Monte Carlo Sequences

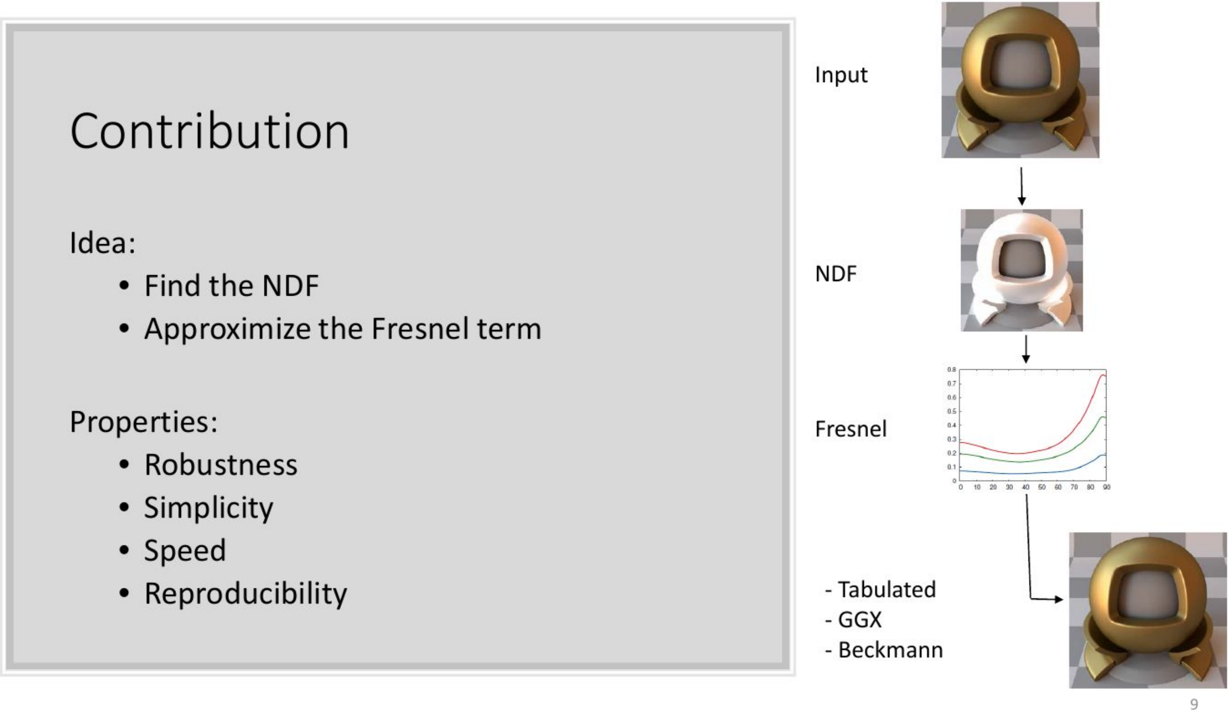
This time with: Recurrent Auto-Encoders and Temporal Gradient Estimation

Speaker: Nick Heppert - 20186505

Microfacet model and Microfacet-based BRDF

- Extracting Microfacet-based BRDF Parameters from Arbitrary Materials with Power Iterations
- Fast Global Illumination with Discrete Stochastic Microfacets Using a Filterable Model

Extracting Microfacet-based BRDF Parameters from Arbitrary Materials with Power Iterations



Contribution

Idea:

- Find the NDF
- Approximize the Fresnel term

Properties:

- Robustness
- Simplicity
- Speed
- Reproducibility

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Fast Global Illumination with Discrete Stochastic Microfacets Using a Filterable Model

Idea:

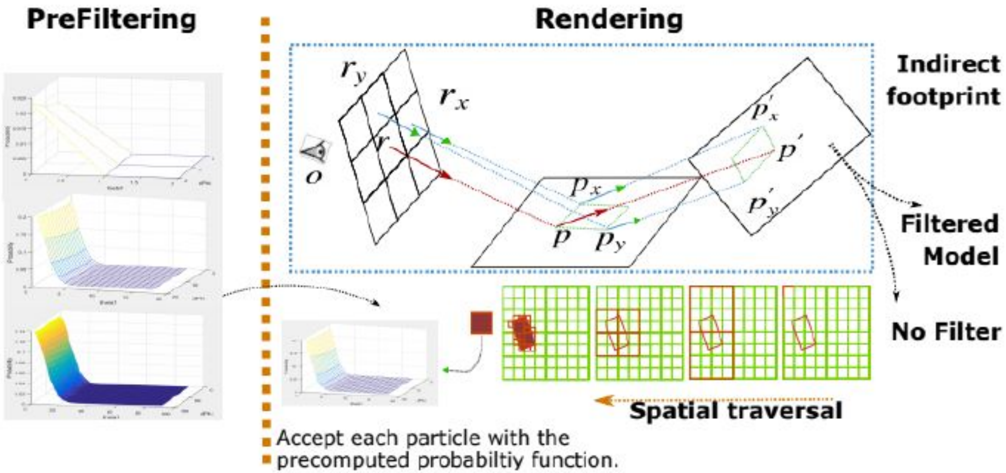
If a footprint cover a large surface,

- individual glint are not noticeable;
- average contribution

In practice:

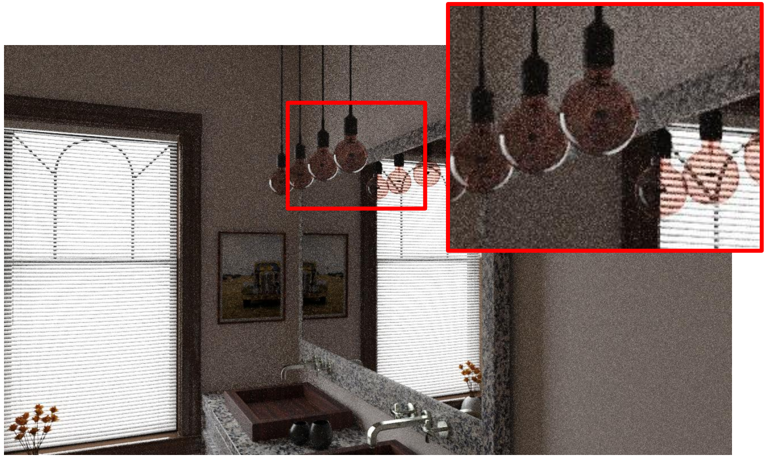
Filterable model preafer for

- material far from camera;
- Several bounce in global illumination

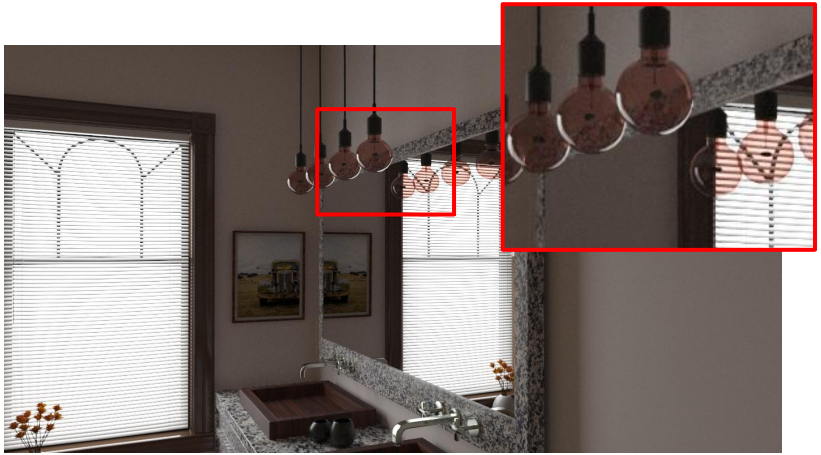


Motivation

- High samples per pixels (spp) → A lot of time
- Cut down time by creating low samples images → Noisy
- Desired: Same Performance
- + Sequences: Consistent through time



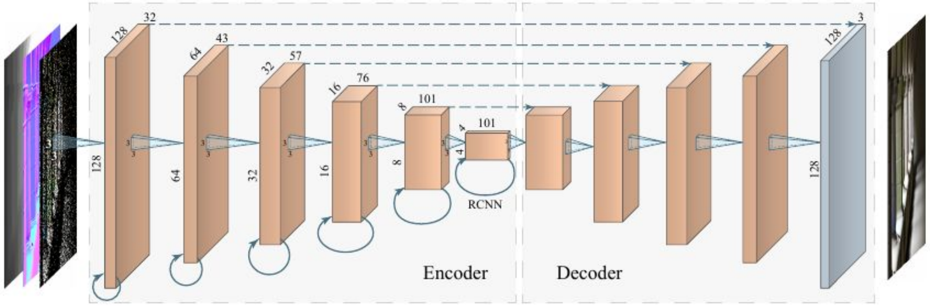
128spp



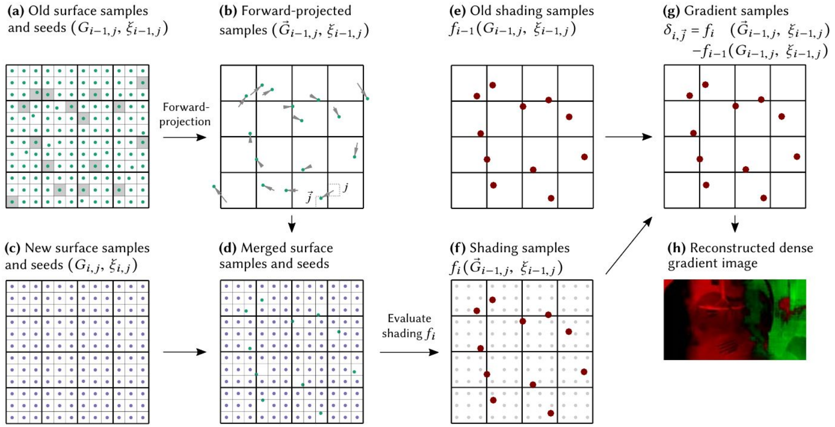
8192spp

Papers

- Interactive Reconstruction of Monte Carlo Image Sequences using a Recurrent Denoising Autoencoder



- Gradient Estimation for Real-Time Adaptive Temporal Filtering


(a) Old surface samples and seeds $(G_{i-1,j},\ \xi_{i-1,j})$
Forward-projection
(b) Forward-projected samples $(\vec{G}_{i-1,j},\ \xi_{i-1,j})$
$\vec{j}$
j
(e) Old shading samples $f_{i-1}(G_{i-1,j},\ \xi_{i-1,j})$
(g) Gradient samples $\delta_{i,\vec{j}} = f_i\ (\vec{G}_{i-1,j},\ \xi_{i-1,j}) - f_{i-1}(G_{i-1,j},\ \xi_{i-1,j})$
(c) New surface samples and seeds $(G_{i,j},\ \xi_{i,j})$
(d) Merged surface samples and seeds
Evaluate shading f_i
(f) Shading samples $f_i(\vec{G}_{i-1,j},\ \xi_{i-1,j})$
(h) Reconstructed dense gradient image

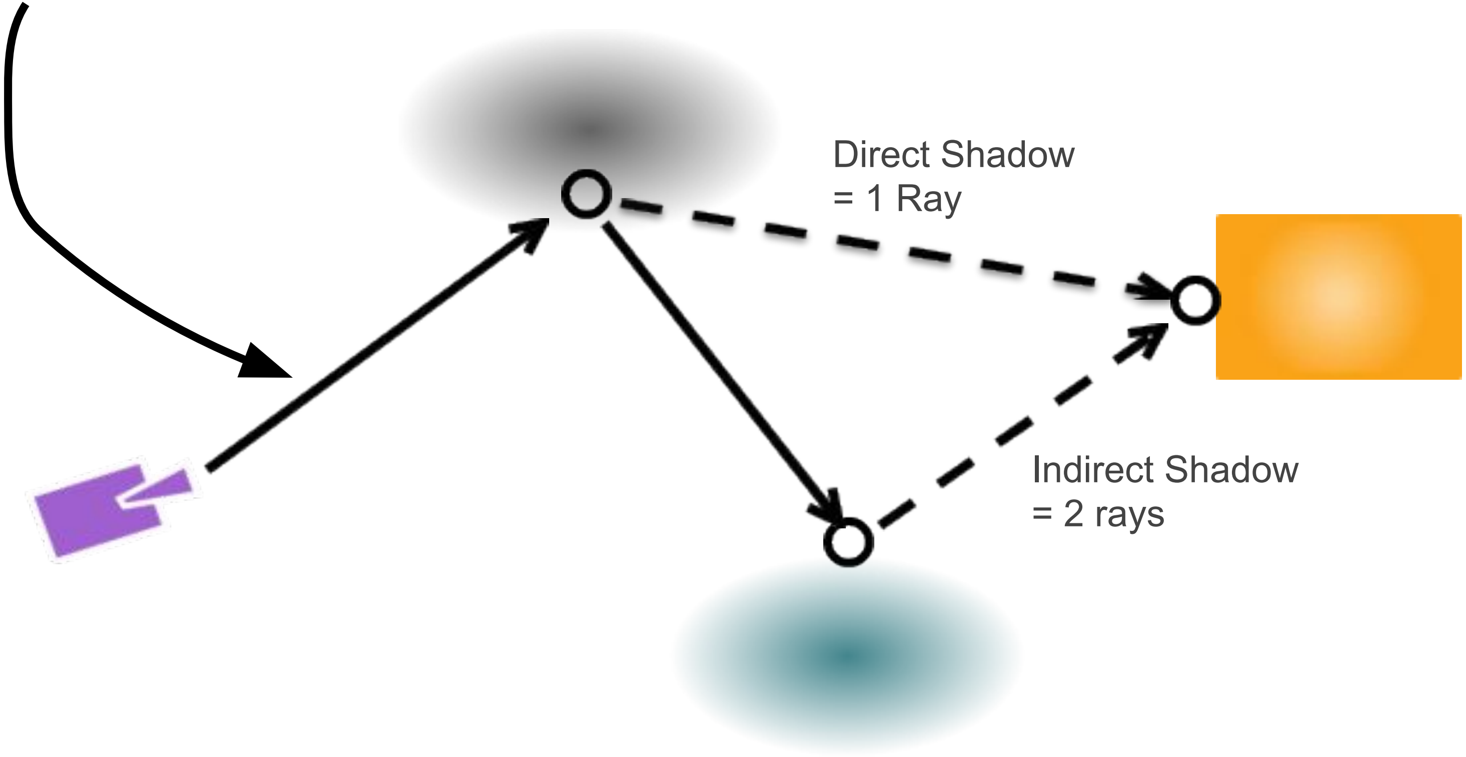
Interactive Reconstruction of Monte Carlo Image Sequences using a Recurrent Denoising Autoencoder

C. R. A. Chaitanya et al.

Environment

- Interactive Path Tracer
  - 1spp (!) for 1080p@30FPS
  - Next event estimation
  - Use rasterization to store shading attributes in G-Buffer
  - OptiX
- No depth of field or motion blur
- Rasterization to generate G-Buffer: 4 scalar values per pixel
  - View-space shading normals (2D)
  - Linearized depth (1D)
  - Material roughness (1D)
- + RGB (3D) → 7 scalar values per pixel

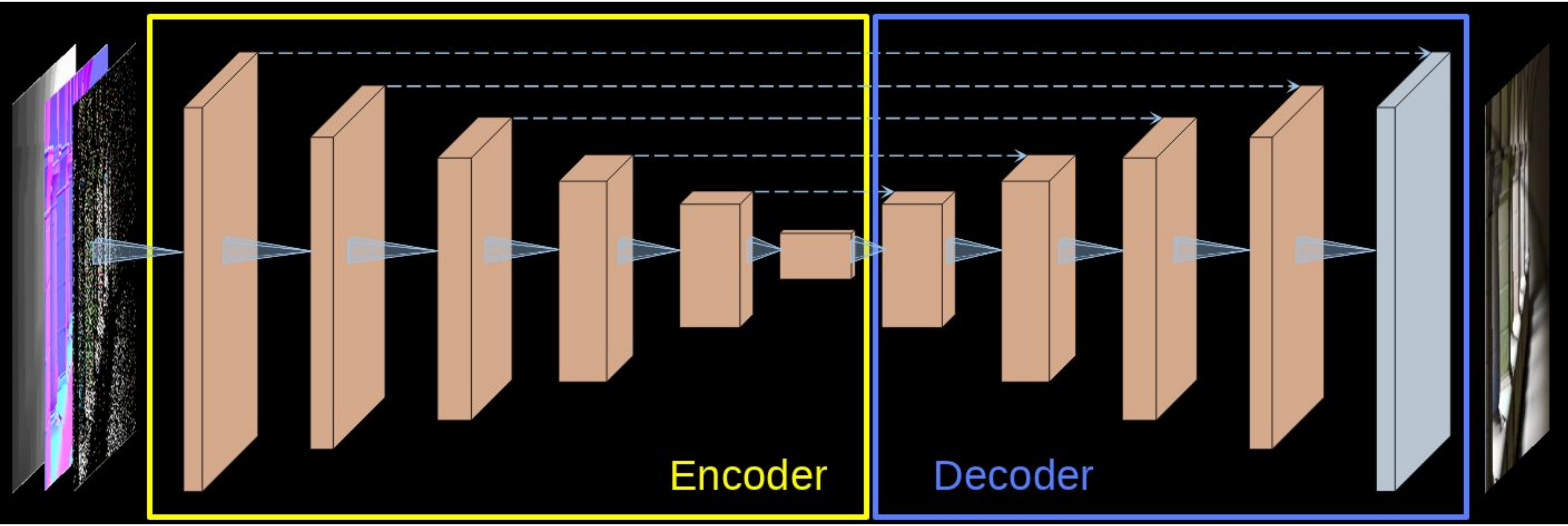
1spp



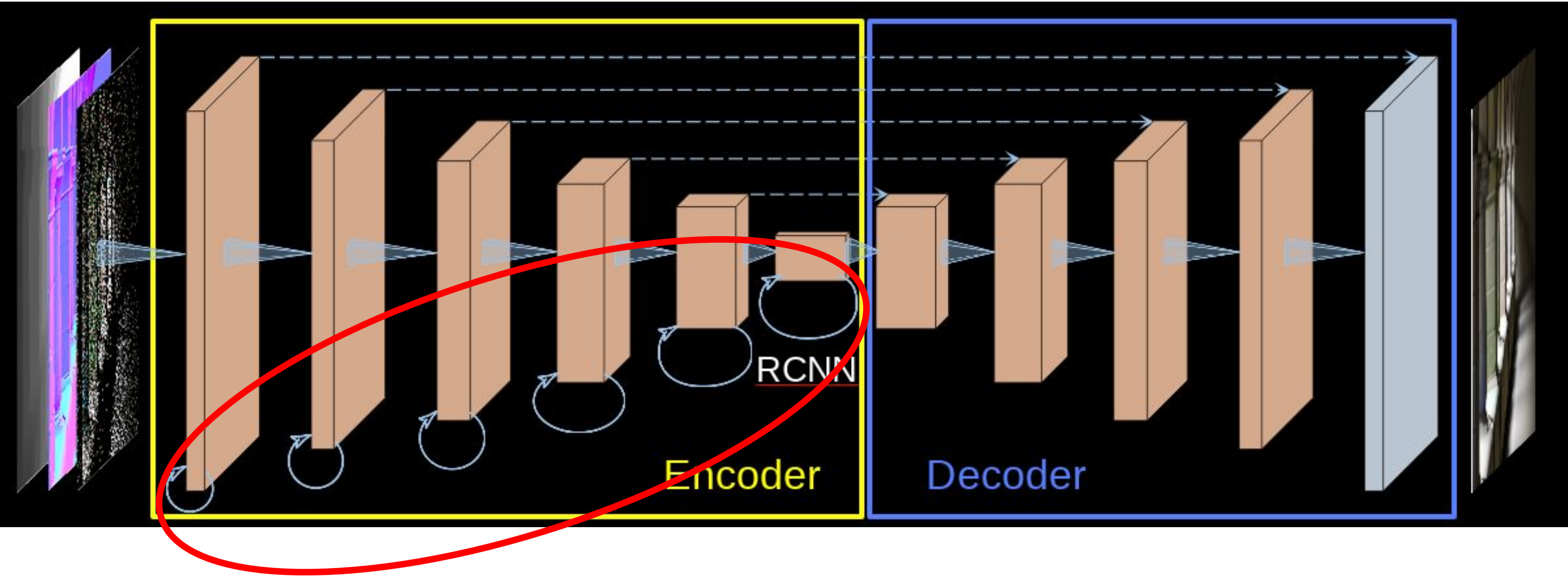
Direct Shadow
= 1 Ray

Indirect Shadow
= 2 rays

Denoising Autoencoder (DAE)

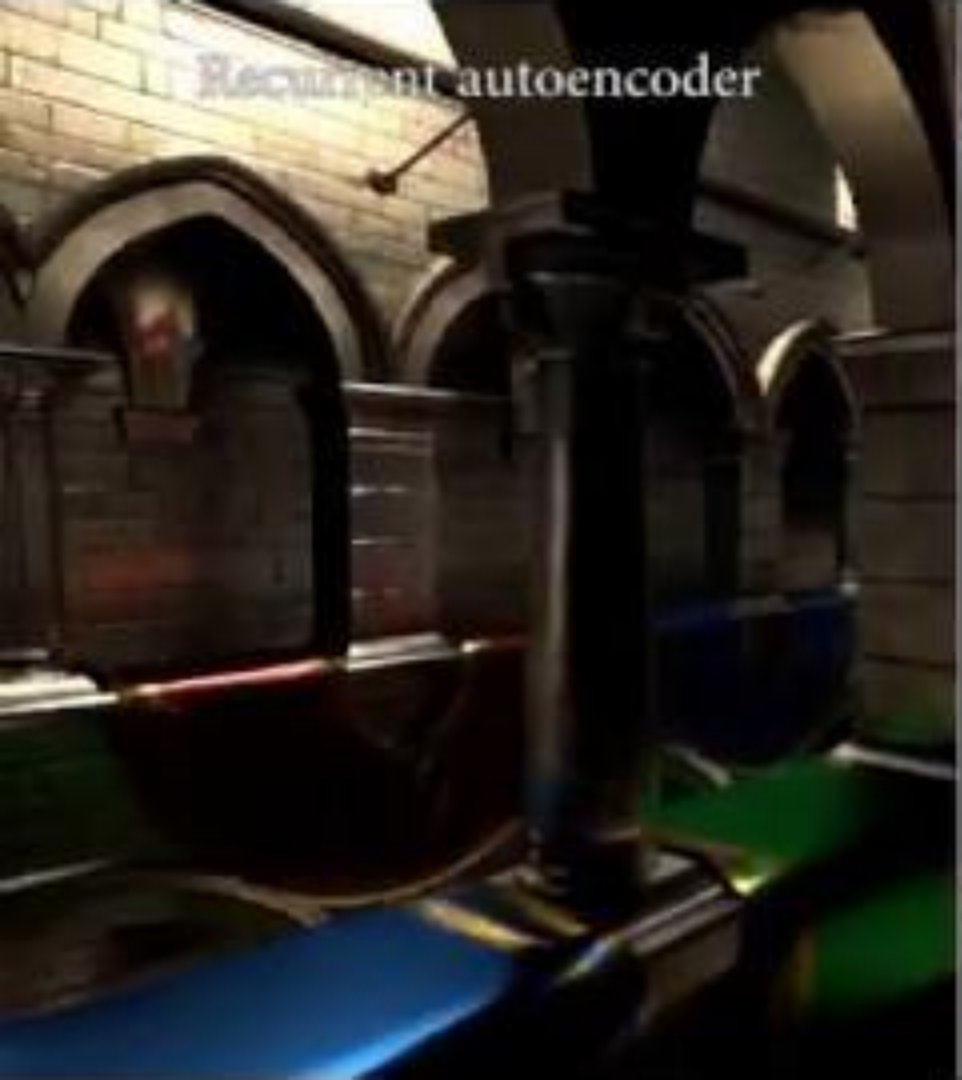


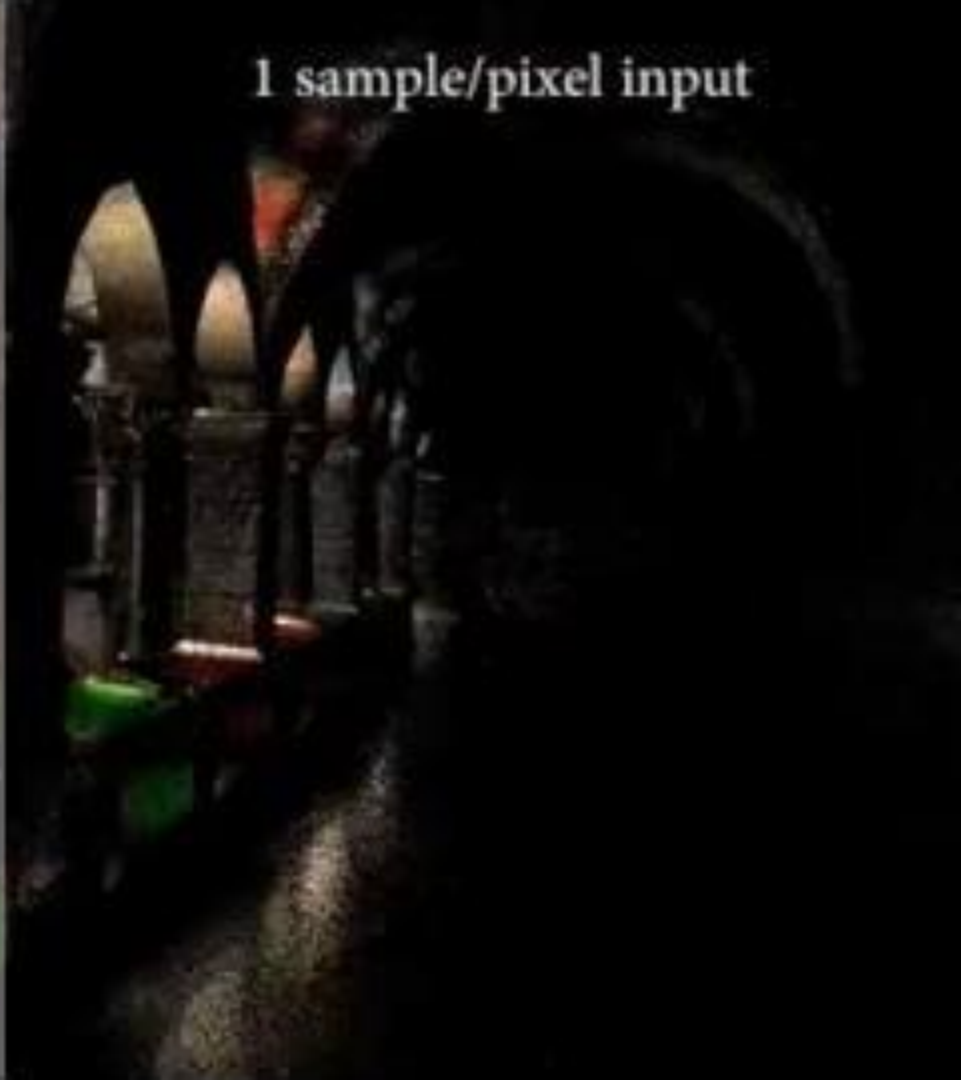
Recurrent Denoising Autoencoder (RAE)

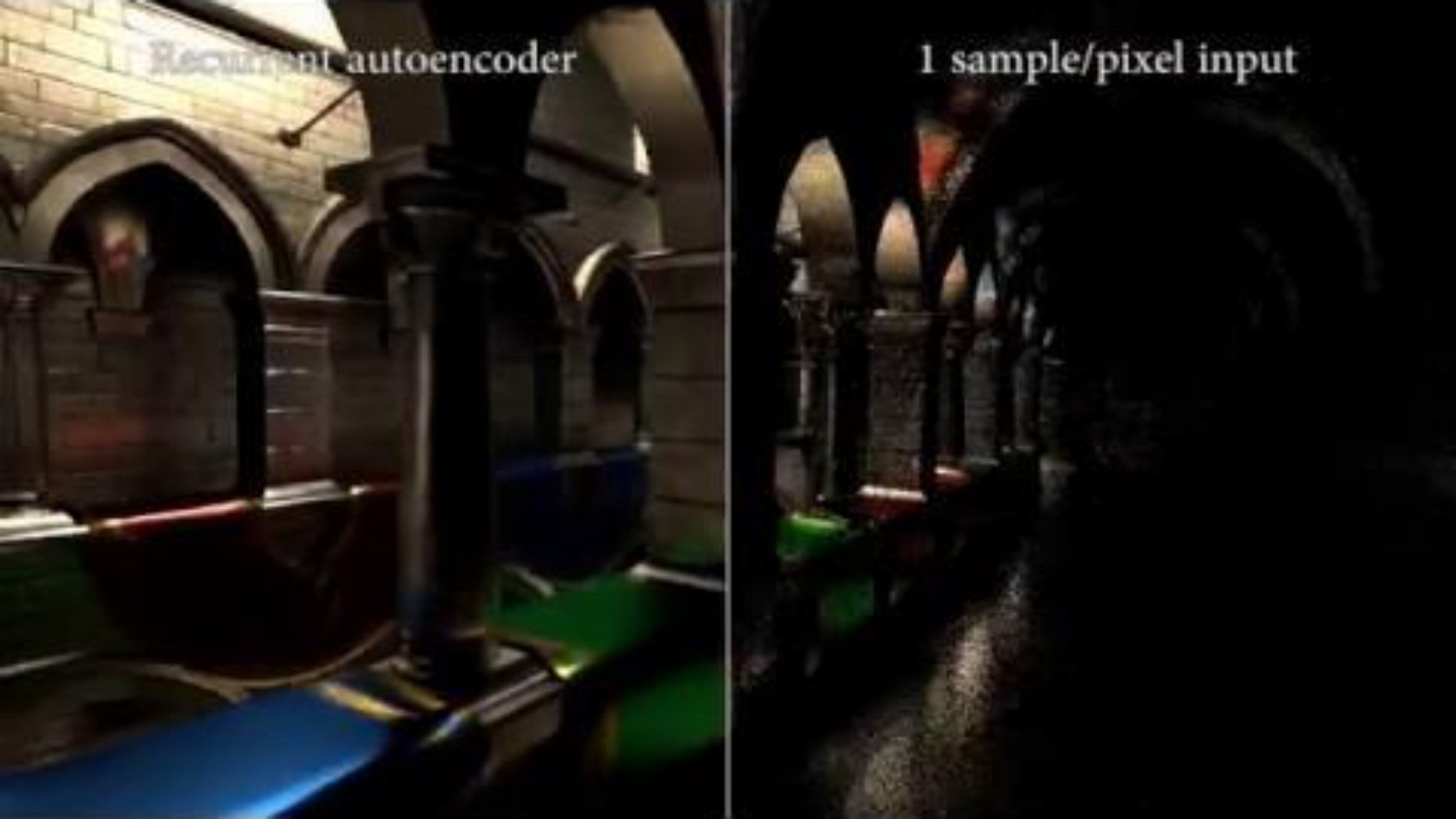


Training Setup

- Data augmentation for sequence
  - 1024 x 1024 → 128 x 128 randomly sampled
  - Random beginning of sequence
  - Forward and backward replay
  - Random stop
  - Random rotation
- Loss L1:
  - pixel-wise →Single images
    $\mathcal{L}_t = \frac{1}{N} \sum_i^N \left(|\nabla P_i - \nabla T_i| \right)$
  - pixel-wise gradient → Edges
    $\mathcal{L}_t = \frac{1}{N} \sum_i^N \left(|P_i - T_i| \right)$
  - pixel-wise time derivative → Coherent over time
    $\mathcal{L}_t = \frac{1}{N} \sum_i^N \left(\left| \frac{\partial P_i}{\partial t} - \frac{\partial T_i}{\partial t} \right| \right)$


Recurrent autoencoder


1 sample/pixel input


Recurrent autoencoder
1 sample/pixel input

Gradient Estimation for Real-Time Adaptive Temporal Filtering

C. Schied et al.

Problem

- Static scenes
- Moving scenes: ghosting & temporal lagging
    - Constant temporal accumulation factor α
    - Shading samples from previous frame re-used
    - Sudden change → not relevant anymore

→ Solution:

- Adaptively change temporal accumulation factor per frame per pixel
    - Fast response time for sudden changes
    - Aggressive re-use for static regions

Back-Propagation

$$\hat{c}_i(x) = \alpha \cdot c_i(x) + (1 - \alpha) \cdot \hat{c}_{i-1}(\overleftarrow{x})$$

where

$\hat{c}_i$	new temporally filtered frame
i	current timestep
x	pixel position in current frame
c_i	current frame
$\hat{c}_{i-1}$	previously temporally filtered frame
$\overleftarrow{x}$	pixel position in previous frame

Back-Propagation

$$\hat{c}_i(x) = \alpha \cdot c_i(x) + (1 - \alpha) \cdot \hat{c}_{i-1}(\overleftarrow{x})$$

Big α → Current Frame
Small α → Previous Frame

Temporal Gradient

Basic Version:

Shading Function

Shading Function

$$\delta_{i,\vec{j}} := f_i(\overrightarrow{G}_{i-1,j}) - f_{i-1}(G_{i-1,j})$$

Forward Projected Sample

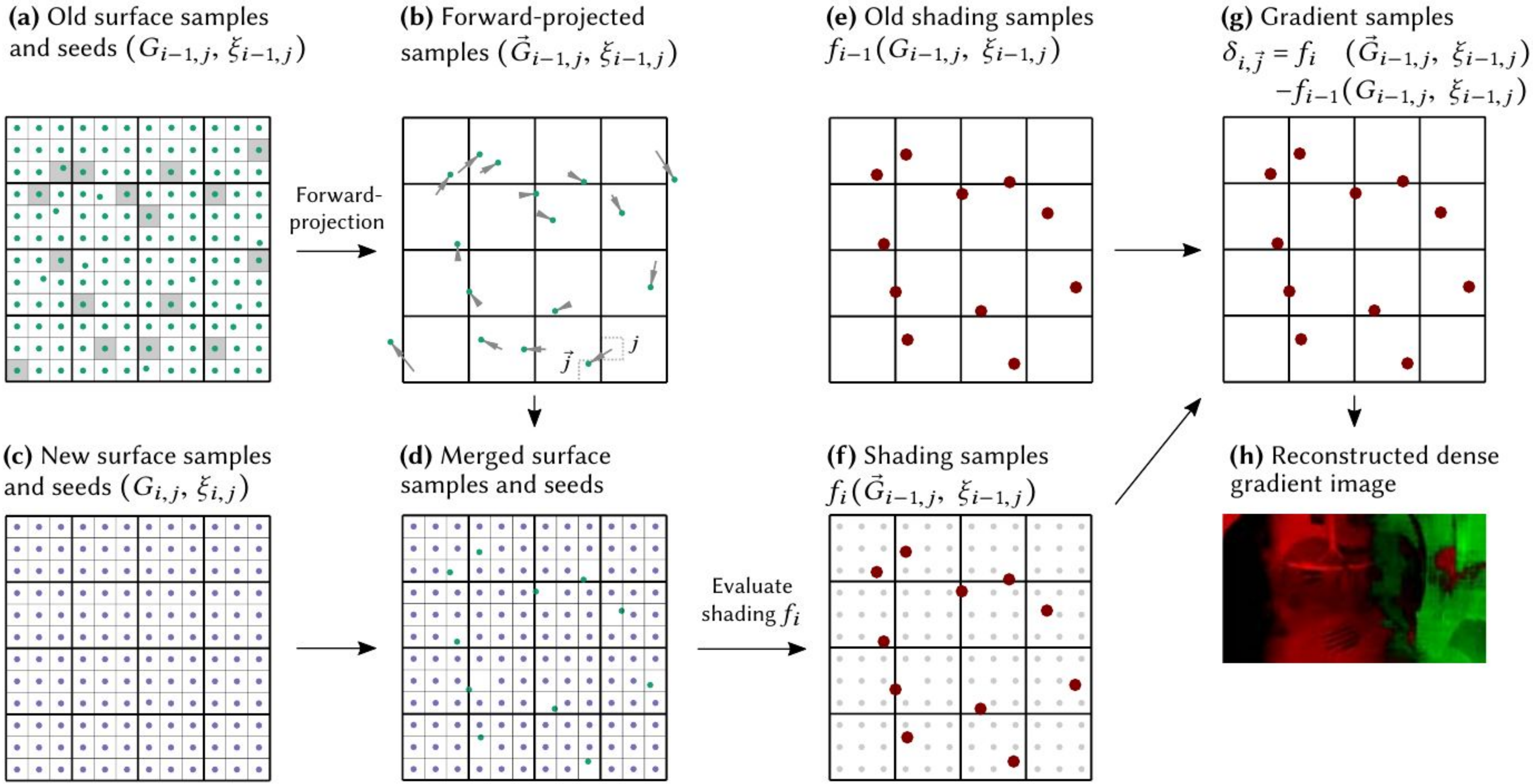
Previous Sample

Extended Version:

$$\delta_{i,\vec{j}} := f_i(\overrightarrow{G}_{i-1,j}, \xi_{i,\vec{j}}) - f_{i-1}(G_{i-1,j}, \xi_{i-1,\vec{j}})$$

Random Number

Random Number



(a) Old surface samples and seeds $(G_{i-1,j},\ \xi_{i-1,j})$

(b) Forward-projected samples $(\vec{G}_{i-1,j},\ \xi_{i-1,j})$

(c) New surface samples and seeds $(G_{i,j},\ \xi_{i,j})$

(d) Merged surface samples and seeds

(e) Old shading samples $f_{i-1}(G_{i-1,j},\ \xi_{i-1,j})$

(f) Shading samples $f_i(\vec{G}_{i-1,j},\ \xi_{i-1,j})$

(g) Gradient samples $\delta_{i,\vec{j}} = f_i\quad(\vec{G}_{i-1,j},\ \xi_{i-1,j})$ $-f_{i-1}(G_{i-1,j},\ \xi_{i-1,j})$

(h) Reconstructed dense gradient image

Controlling the Temporal Accumulation Factor

Normalized History Weight:

$$\lambda(p) := \min\left(1, \frac{|\hat{\delta}_i(p)|}{\hat{\Delta}_{i,\vec{j}}(p)}\right)$$

p: Subset

Normalizer:

$$\Delta_{i,\vec{j}} := \max\left(f_i(\overrightarrow{G}_{i-1}, j, \xi_{i-1,j}), f_{i-1}(\overrightarrow{G}_{i-1}, j, \xi_{i-1,j})\right)$$

Adaptive Temporal Accumulation Factor:

$$\alpha_i(p) := (1 - \lambda(p)) \cdot \alpha + \lambda(p)$$

$$\hat{c}_i(x) = \alpha \cdot c_i(x) + (1 - \alpha) \cdot \hat{c}_{i-1}(\overleftarrow{x})$$

Evaluation: RAE vs. A-RAE

- RAE
  - no temporal accumulation
- A-RAE
  - Adaptive temporal accumulation
- Trade-Off
  - Image Quality
  - Temporal ghosting & lagging
- Inference Time RAE: 191ms
  - Adaptive temporal accumulation: 2ms
  - Negligible

A-SVGF (ours, slowed)

A-SVGF (ours, slowed)

Summary

- Baseline auto-encoder network
- + Skip connections
- + Recurrent blocks
- + Adaptive temporal accumulation
- → 1spp real-time
  - Quake 2
  - http://brechpunkt.de/q2vkpt/ (open source)
  - https://youtu.be/vY0W3MkZFs4 (closed source)

Quiz

1. Which buffer is not used to train the recurrent auto-encoder (RAE)?
   a. View-space shading normals (2D)
   b. Raw texture color (3D)
   c. Material roughness (1D)
   d. Linearized depth (1D)
2. When the temporal gradient δ increases which is frame is getting preferred?
   a. previous frame
   b. current frame
3. When increasing the temporal accumulation factor α which frame is getting preferred?
   a. previous frame
   b. current frame