Gradient-Domain Photon Density Estimation

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Summary of Previous Presentation

Interactive Sound Propagation and Rendering for Large Multi-Source Scenes

- A paper for rendering **large number of sounds** in a **complex scene** at an **interactive rate** using:

1. Acoustic Reciprocity for Spherical Sources

   - Backwards Ray Tracing : Rays from listener to sound sources

   - Spherical sound source : Allows smooth interpolation

2. Source Clustering

   - Clustered when sound sources are far away from the listener

   - Clustered when sound sources are close to each other with no obstacles

3. Hybrid Convolution Rendering

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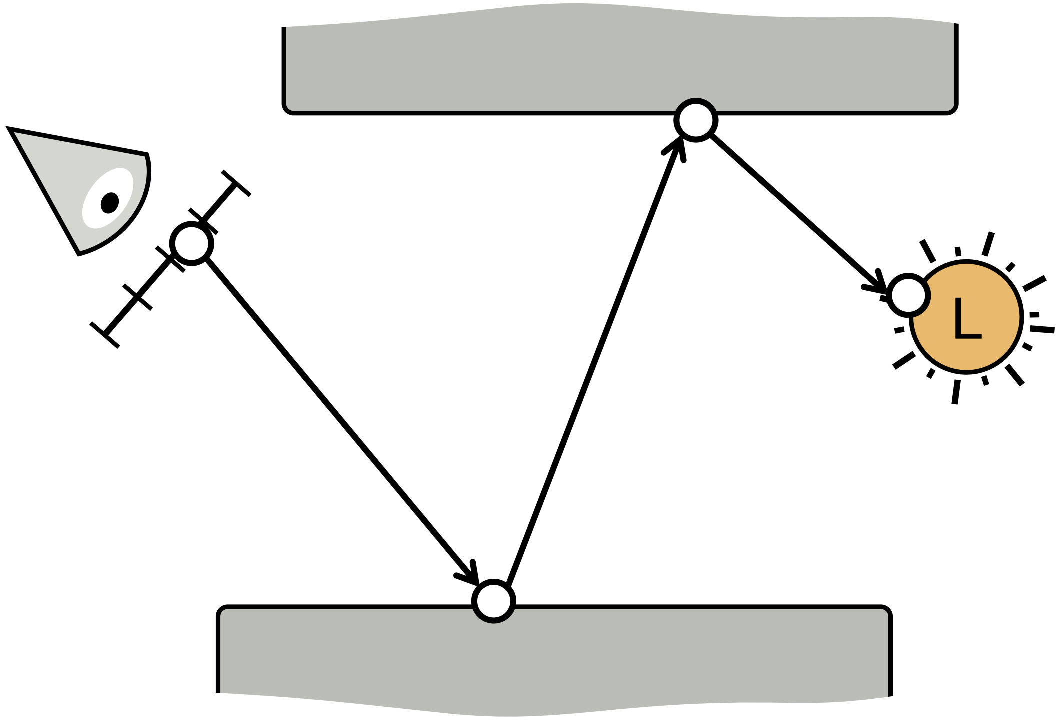
Backgrounds

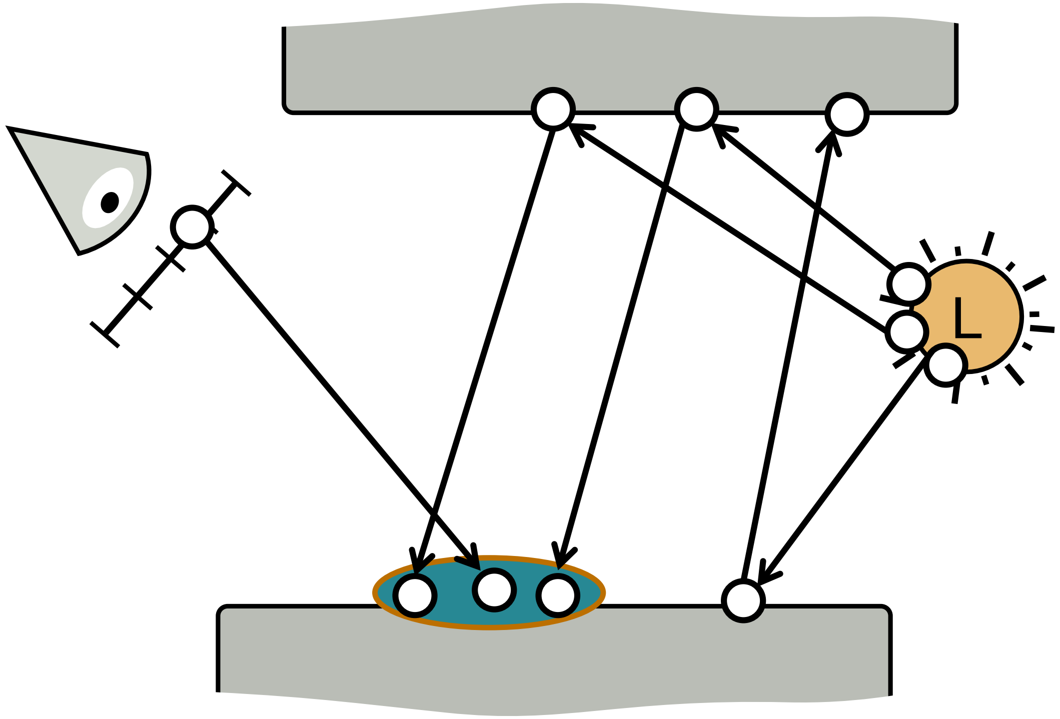
Classical Rendering

Classical Rendering

Path-based rendering techniques
(i.e Path tracing …)

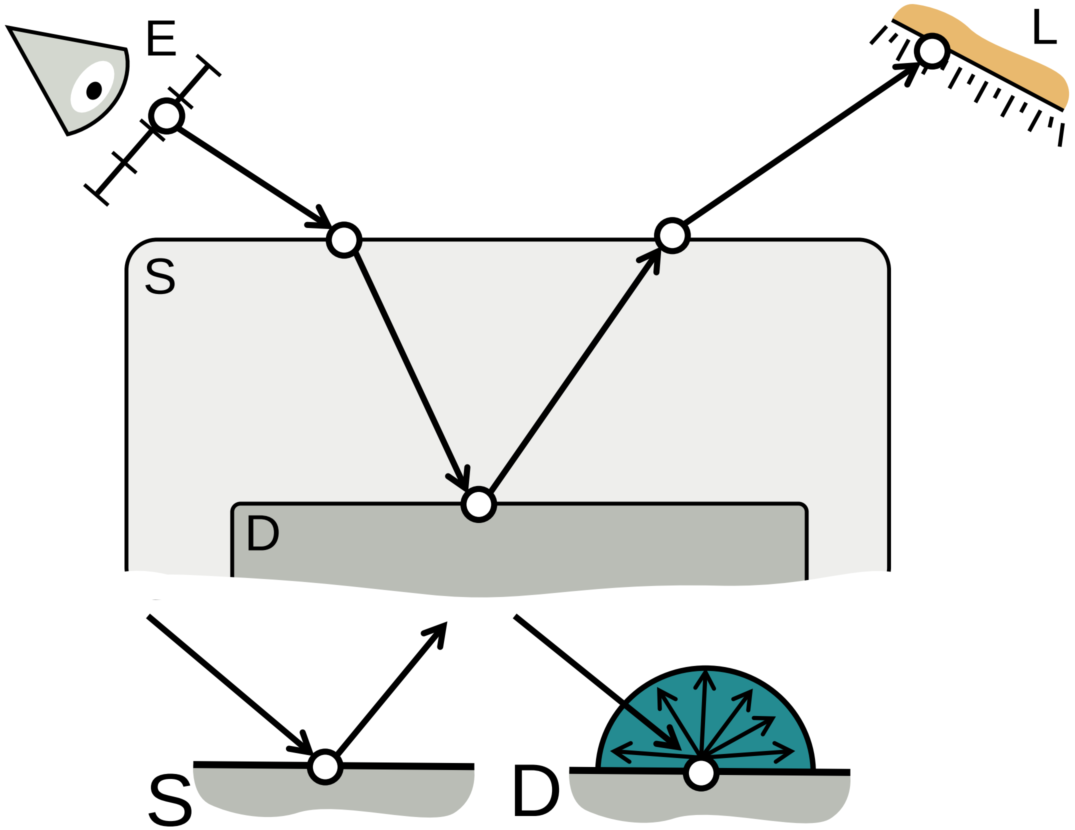


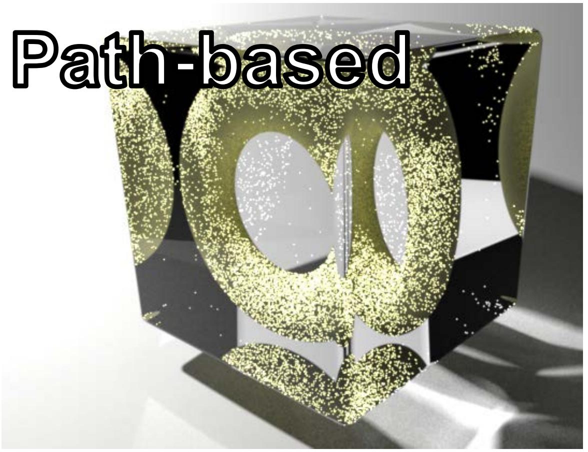
Density-based rendering techniques
(i.e SPPM [Hachisuka et al. 2008]…)

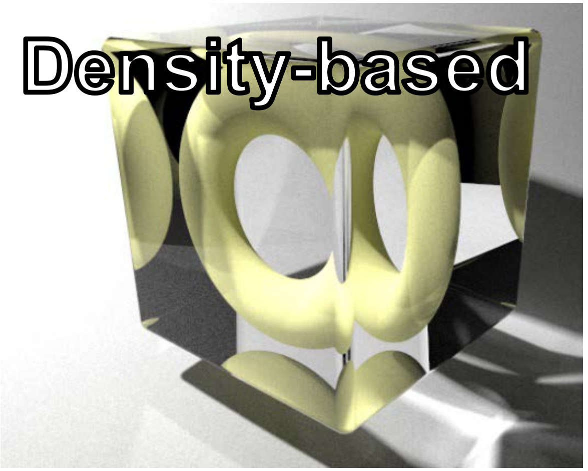


Classical Rendering

Path-based techniques are not robust to SDS Light Tranport







Gradient-domain Rendering

An Idea of Gradient-domain Rendering

- Several Monte Carlo light transport techniques aim to adaptively sample light transport **“Where it matters”**

- We focus on **the finite differences of path throughput between pixels.**

An Idea of Gradient-domain Rendering

Horizontal Difference

Vertical Difference

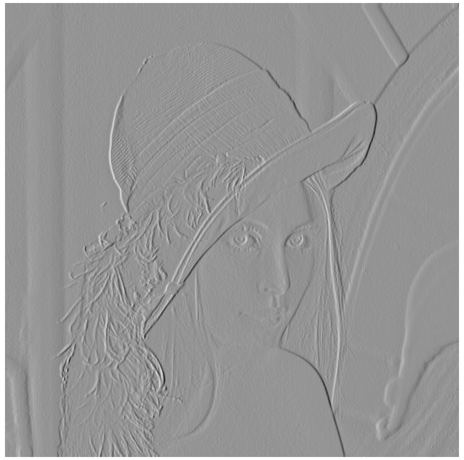
Poisson Solver

Final Image

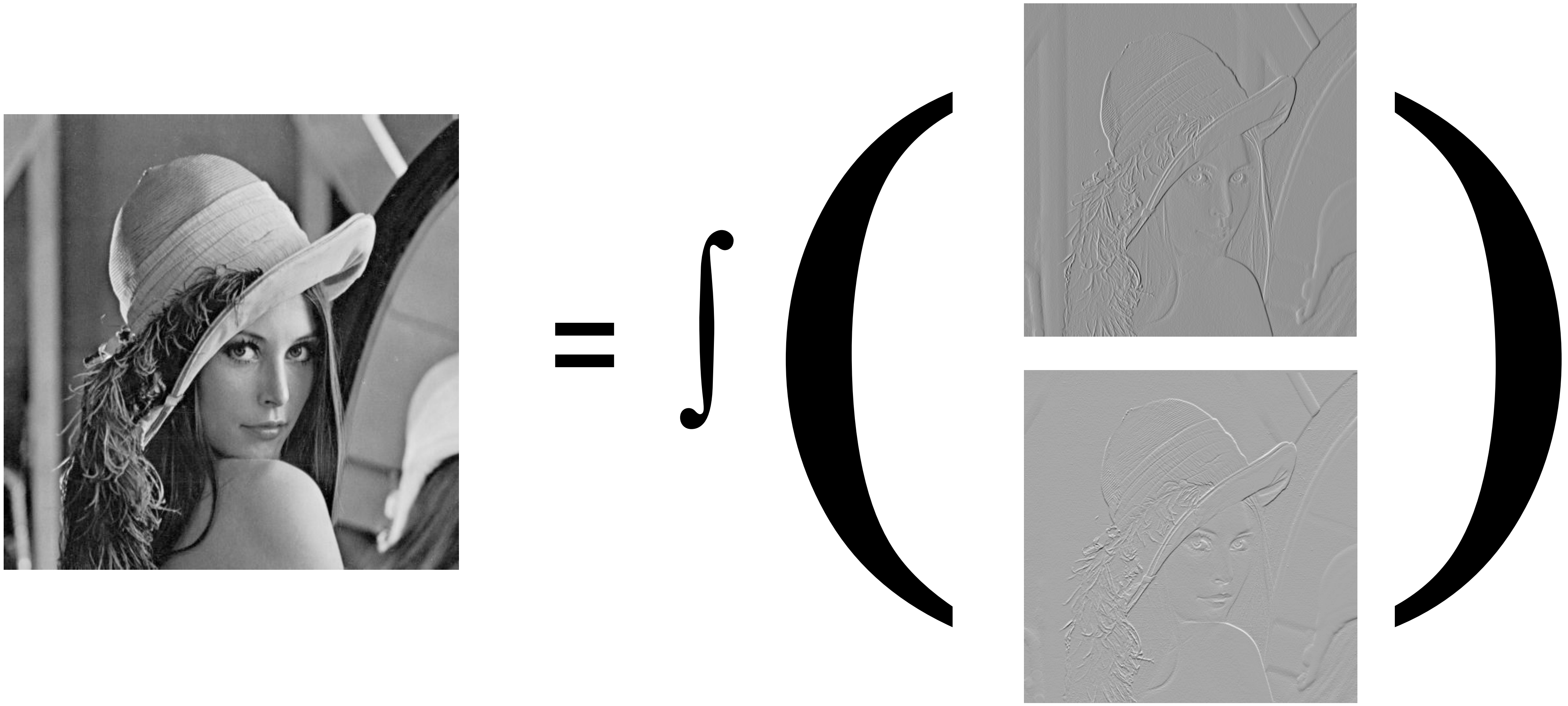
$$I = \arg\min \|D_x I - G_x\|_p + \|D_y I - G_y\|_p + \lambda \|I - I_0\|_p$$

I : final image
Gx, Gy : horizontal and vertical gradients
Dx, Dy : 1D convolution operators that compute finite differences along axes

An Idea of Gradient-domain Rendering

∇  $=$ $\left(\right.$   $\left. \right)$

An Idea of Gradient-domain Rendering

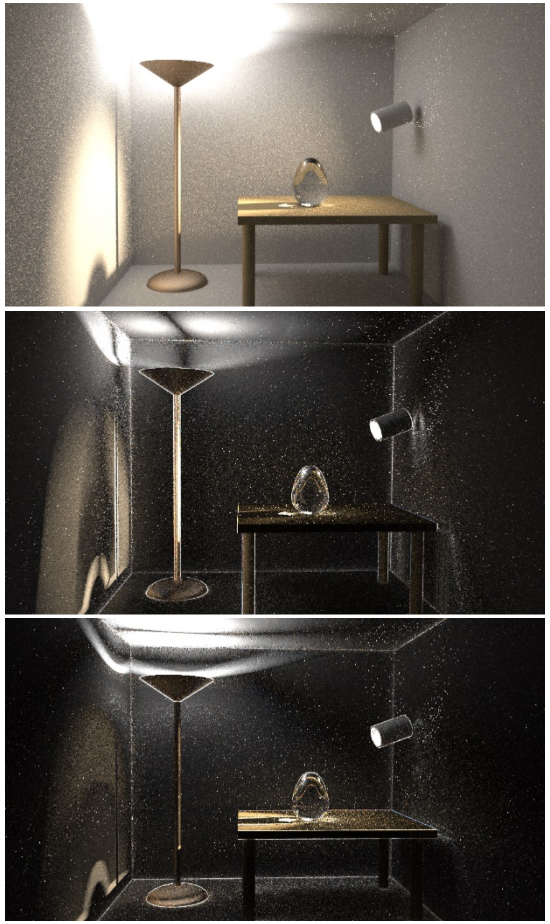


Gradient-domain Rendering

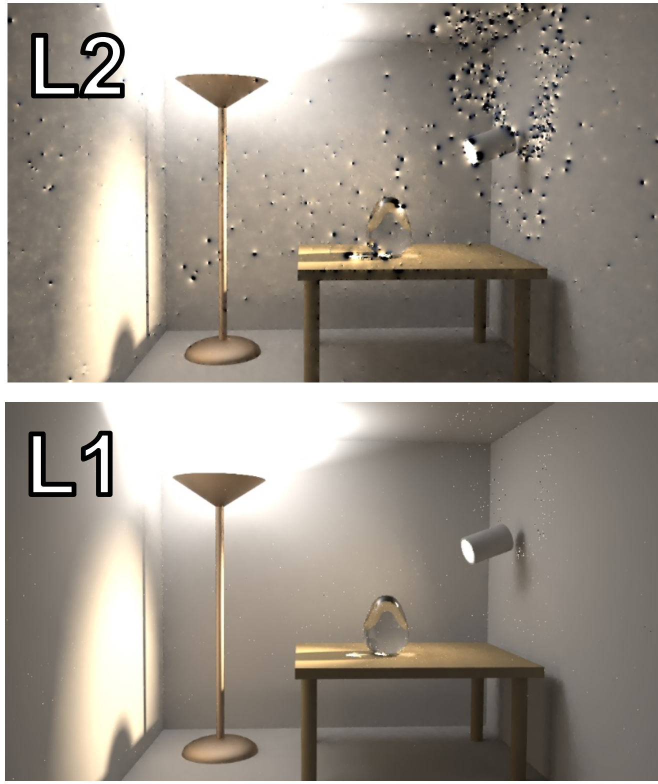
Classical rendering

Primal-domain
(i.e Path tracing)

Gradients
Horizontal
Vertical



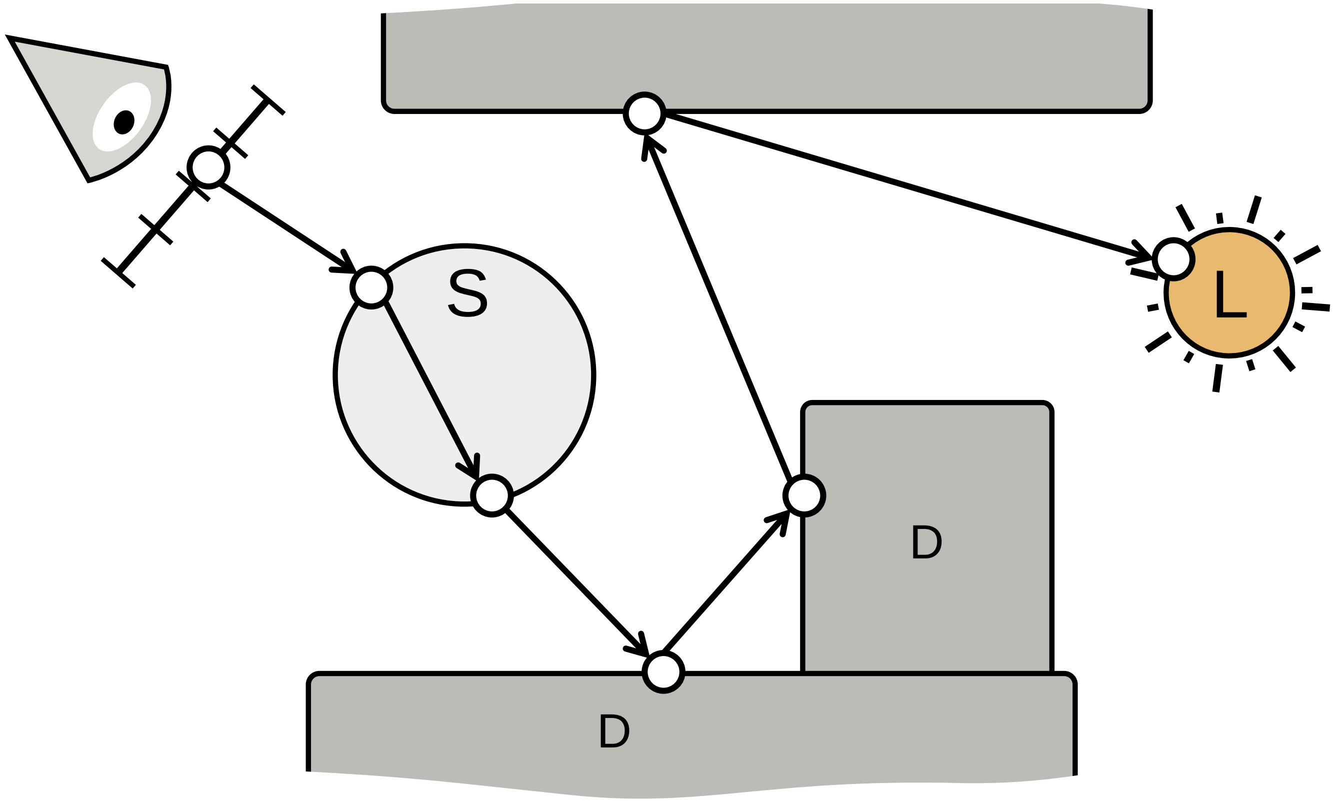
Poisson
reconstruction



Gradient-domain Rendering

Shift mapping: exploit coherency to reduce noise in gradients

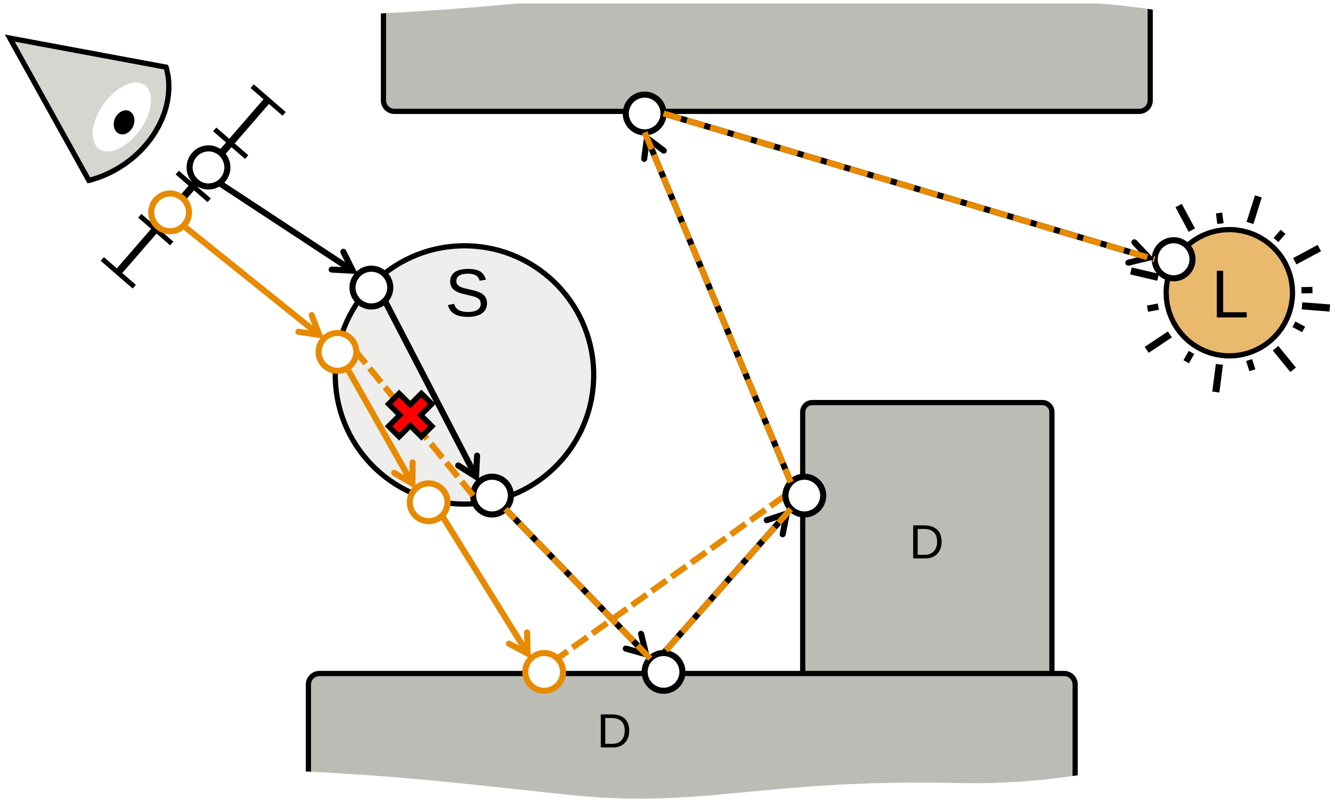
1) Generate the **base path**



Gradient-domain Rendering

Shift mapping: exploit coherency to reduce noise in gradients

2) Generate the **shift paths** through neighbor pixel



Problem & Goal

Problem & Goal

- Gradient-domain Metropolis light transport [Lehtinen et al. 2013]:
  (+) Adaptive density (-) Markov chain MC
- Gradient-domain path tracing, [Kettunen et al. 2015]
  (+) Simple (-) No adaptive sampling
- Gradient-domain bi-directional path tracing [Manzi et al. 2015]
  (+) More robust (-) More costly

- They are all path-based methods!

Problem & Goal

- Current gradient-domain rendering is path-based

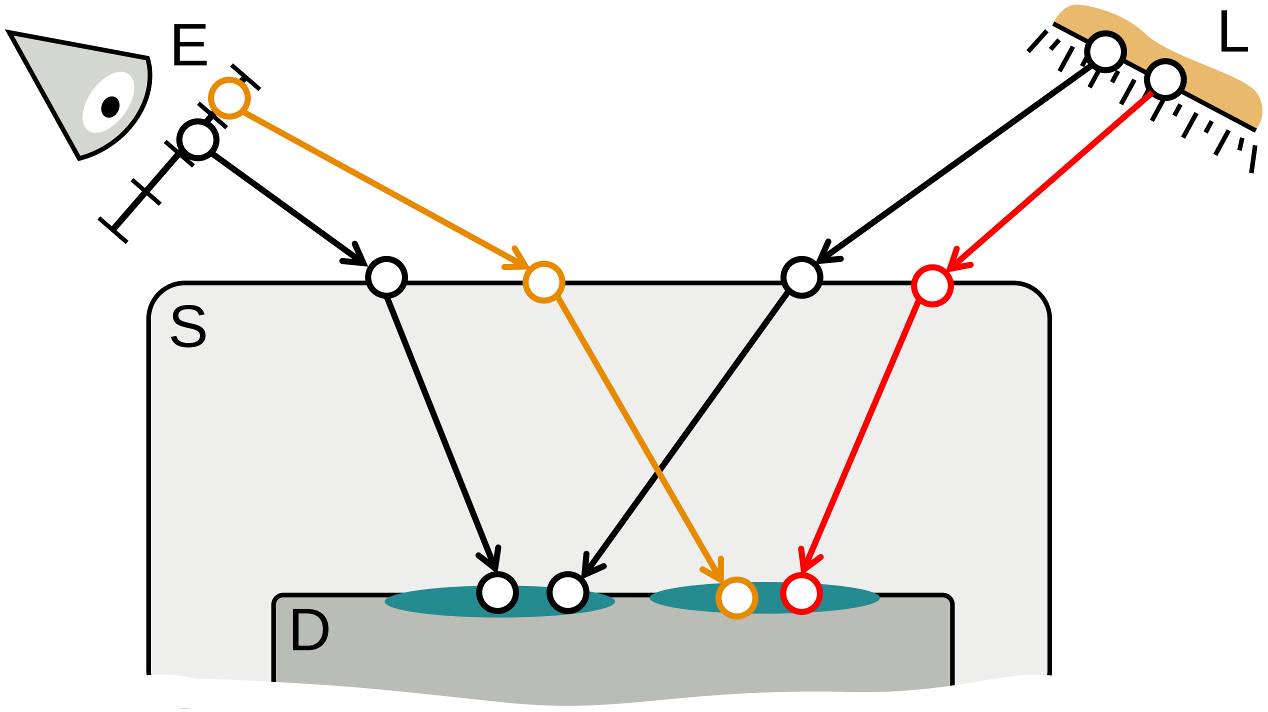
  = Problems with SDS paths

- Our goal : is to use photon density estimation as the primal technique and compute gradient information

Hybrid shift mapping

Photon density estimation:

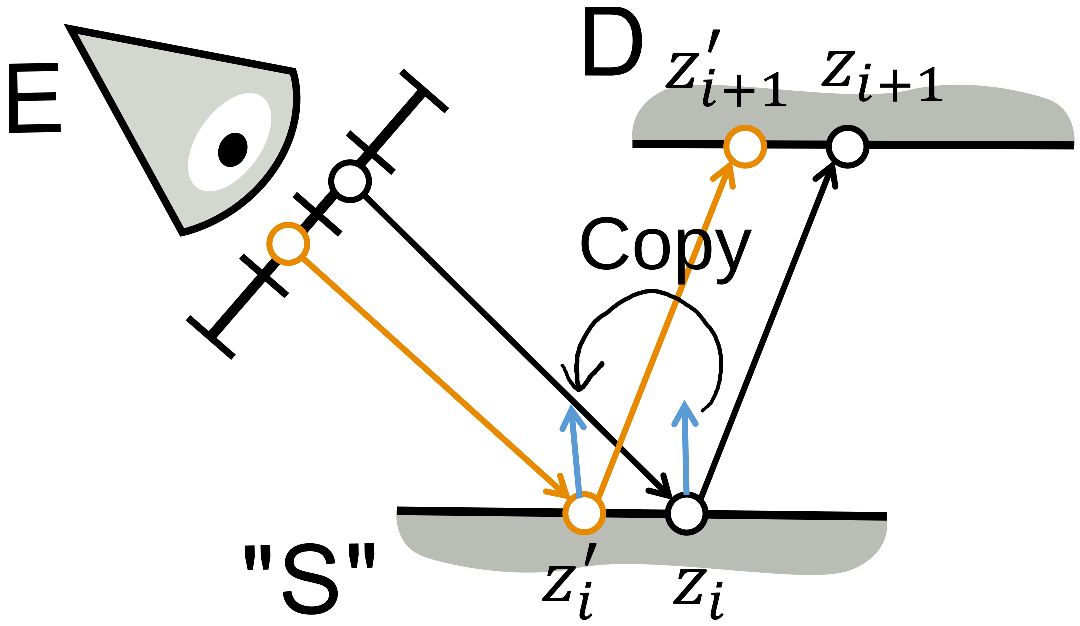
Two **independent** paths that compose the base path

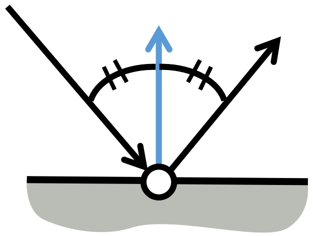


How to define a proper shift operator?

Gradient-domain Photon Density Estimation

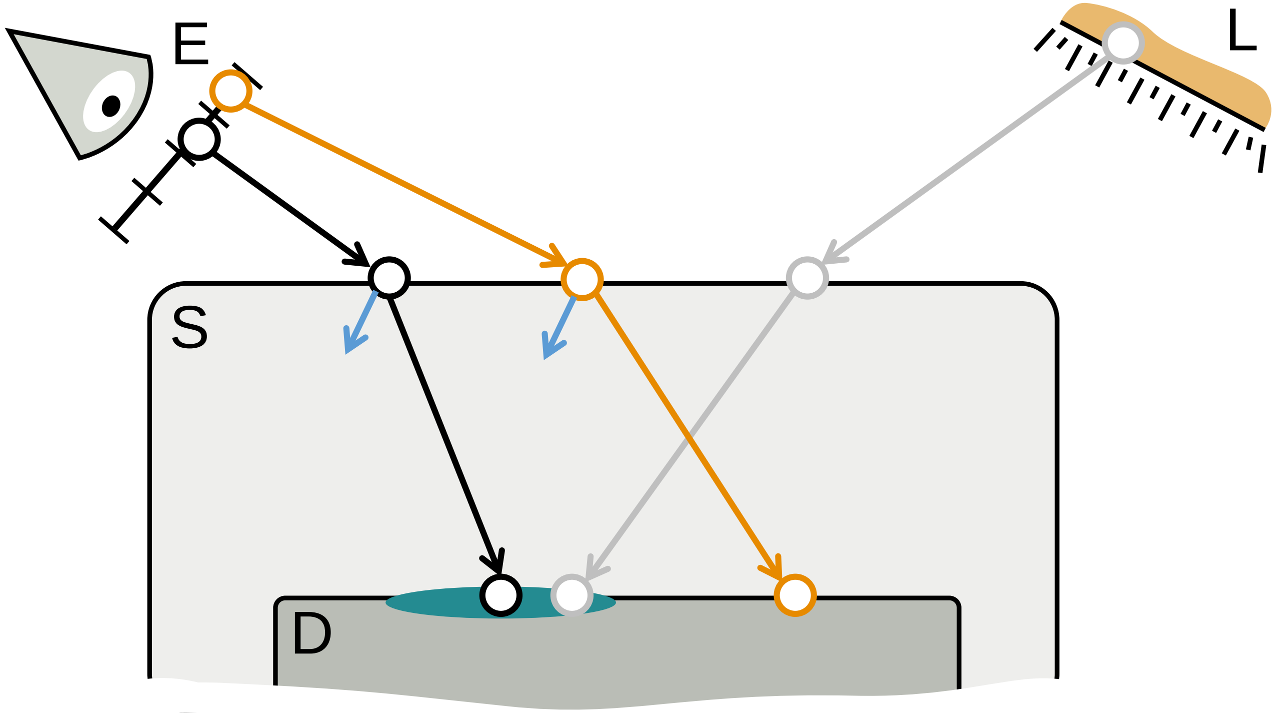
Step 1: Shift sensor path



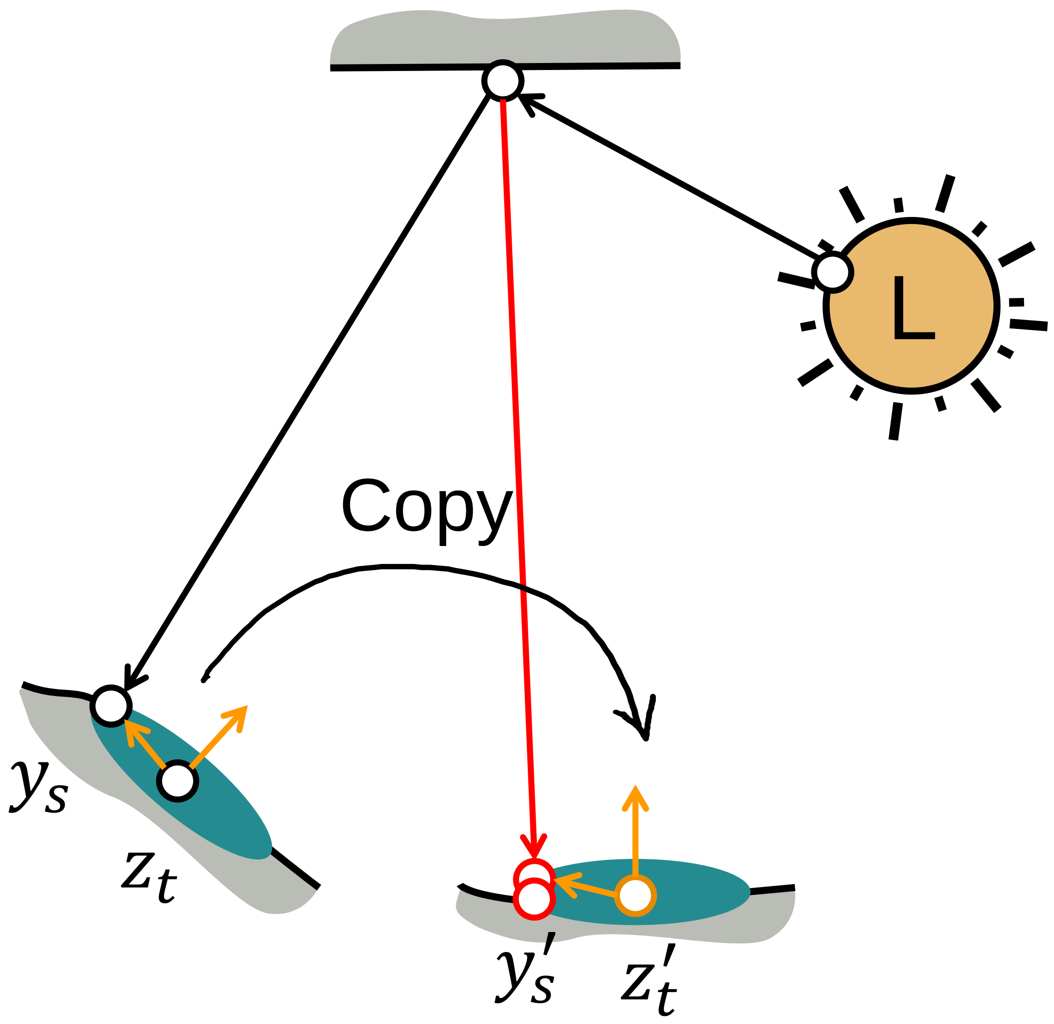


Half vector

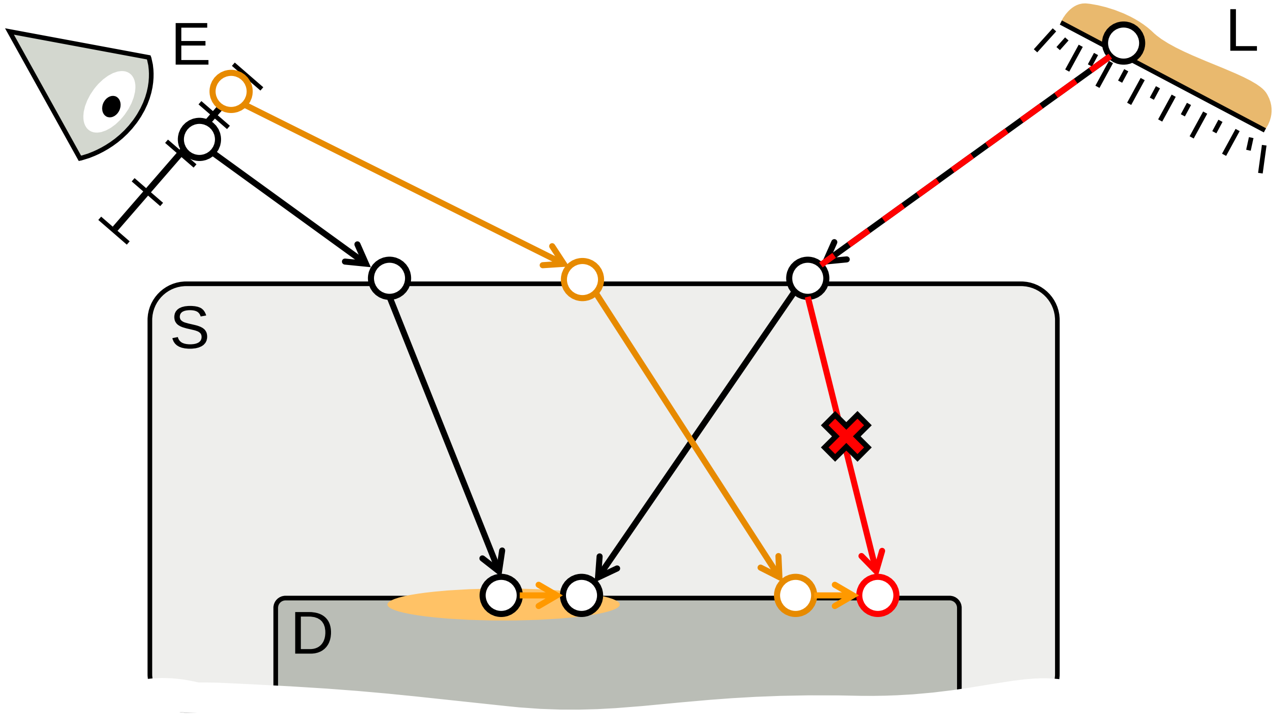
Half vector copy [Manzi et al. 2015]



Step 2: Shift photon location

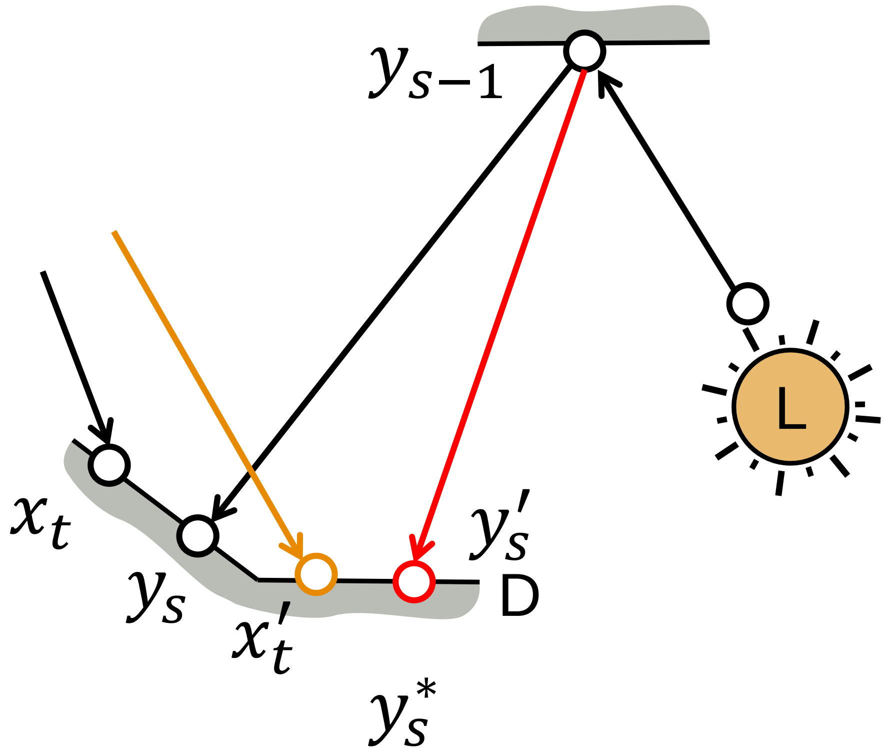


Step 3: Shift the rest of the light path

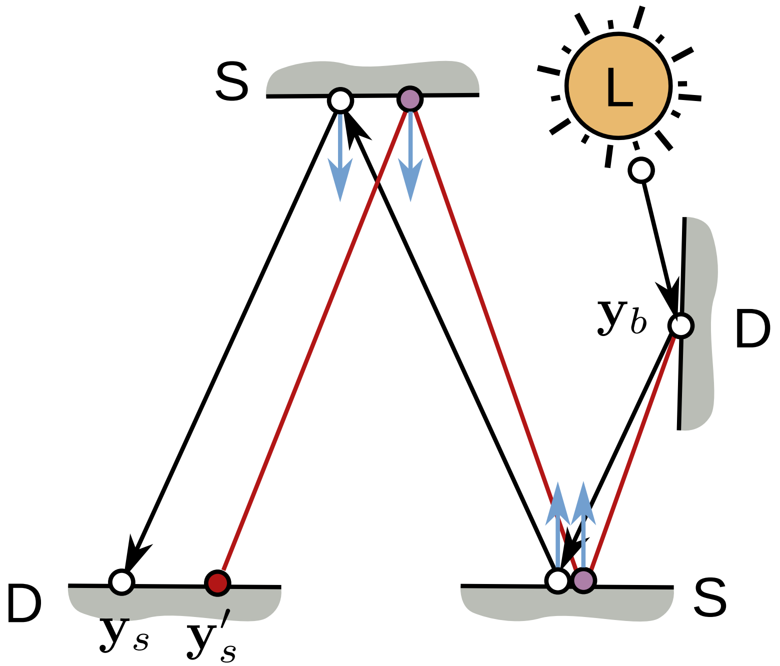


Step 3: Shift the rest of the light path

<u>Case 1:</u> Diffuse parent

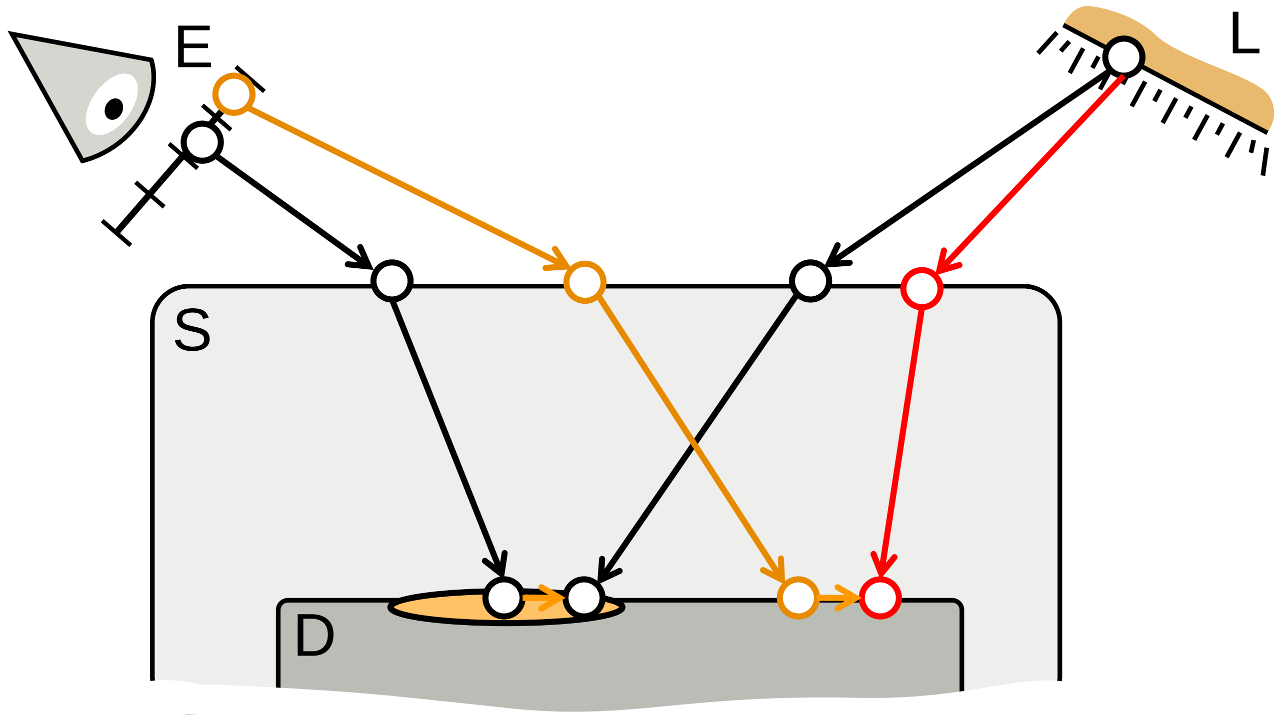


<u>Case 2:</u> "Specular" parent



Find a valid light path using Manifold Exploration [Jakob et al. 2012].

Finish



Jacobian : See the paper

$$I_j^i = \int_{\mathcal{P}} h_i(\mathbf{x}) f(T(\mathbf{x})) \left| \frac{dT(\mathbf{x})}{d\mathbf{x}} \right| d\mathbf{x},$$

$$J = J_\omega \left[\frac{G(\mathbf{z}_i, \mathbf{z}_{i+1})}{G(\mathbf{z}'_i, \mathbf{z}'_{i+1})} \right] \left[\frac{\cos(\mathbf{n}'_i, \mathbf{z}'_i \to \mathbf{z}'_{i+1})}{\cos(\mathbf{n}_i, \mathbf{z}_i \to \mathbf{z}_{i+1})} \right],$$

$$J = \left| \frac{\partial \mathbf{y}'_{b+1}}{\partial \mathbf{y}_{b+1}} \right| = \left| \frac{\partial \mathbf{y}'_{b+1}}{\partial \mathbf{y}'_s} \right| \left| \frac{\partial \mathbf{y}'_s}{\partial \mathbf{y}_s} \right| \left| \frac{\partial \mathbf{y}_s}{\partial \mathbf{y}_{b+1}} \right|,$$

$$\left| \frac{\partial \mathbf{y}'_s}{\partial \mathbf{y}_s} \right| = \left| \frac{\partial \mathbf{y}'_s}{\partial \mathbf{y}^*_s} \right| \left| \frac{\partial \mathbf{y}^*_s}{\partial \mathbf{y}_s} \right| = \frac{G(\mathbf{y}_{s-1}, \mathbf{y}^*_s)}{G(\mathbf{y}_{s-1}, \mathbf{y}'_s)},$$

$$\left| \frac{\partial \mathbf{y}_{b+1}}{\partial \mathbf{y}_s} \right| = \frac{G(\mathbf{y}_b, \mathbf{y}_{b+1}, \ldots, \mathbf{y}_s)}{G(\mathbf{y}_b, \mathbf{y}_{b+1})},$$

$$J = \left| \frac{\partial[\mathbf{y}'_{b+1} \ldots \mathbf{y}'_s]}{\partial[\mathbf{y}_{b+1} \ldots \mathbf{y}_s]} \right| = \left| \frac{\partial[\mathbf{y}'_{b+1} \ldots \mathbf{y}'_s]}{\partial[\mathbf{o}'_{b+1} \ldots \mathbf{y}'_s]} \right| \left| \frac{\partial[\mathbf{o}'_{b+1} \ldots \mathbf{y}'_s]}{\partial[\mathbf{o}_{b+1} \ldots \mathbf{y}_s]} \right| \left| \frac{\partial[\mathbf{o}_{b+1} \ldots \mathbf{y}_s]}{\partial[\mathbf{y}_{b+1} \ldots \mathbf{y}_s]} \right|$$

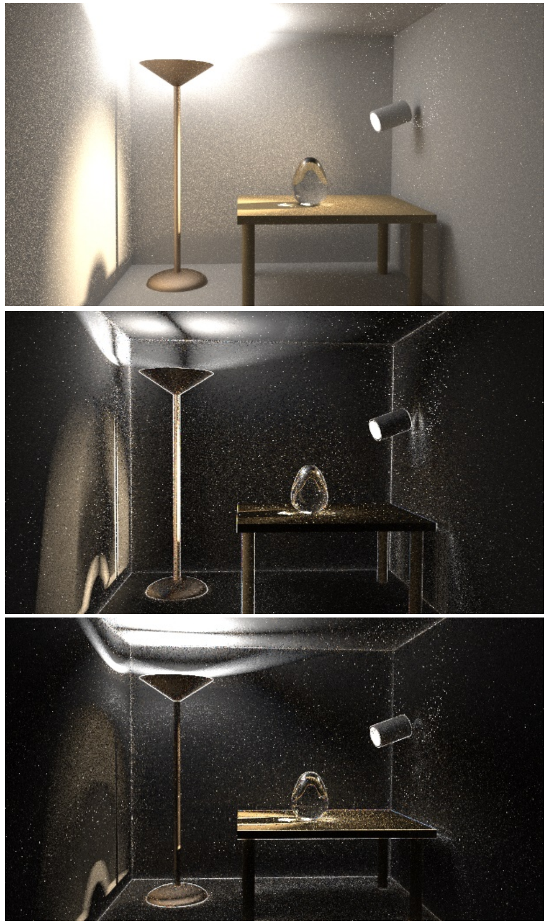
$$w(\mathbf{x}) = \frac{p(\mathbf{y})p(\mathbf{z})}{p(\mathbf{y})p(\mathbf{z}) + p(T(\mathbf{y}))p(T(\mathbf{z}))\,|T'(\mathbf{y})T'(\mathbf{z})|},$$

Gradient-domain density estimation

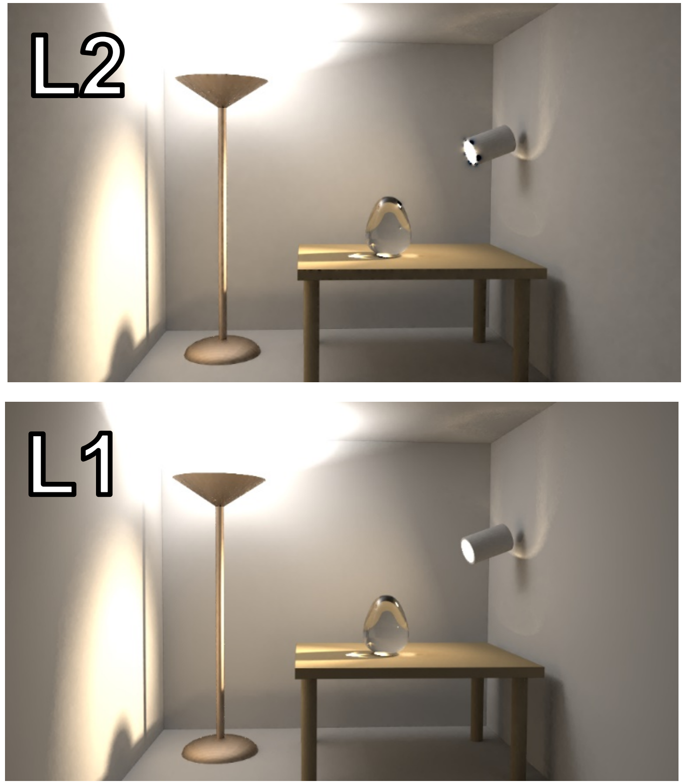
Consistent: Use same reduction scheme as SPPM

Primal-domain
SPPM

Gradients
Our shift mapping



Poisson reconstruction



Results

G-BDPT L1 – 5 min

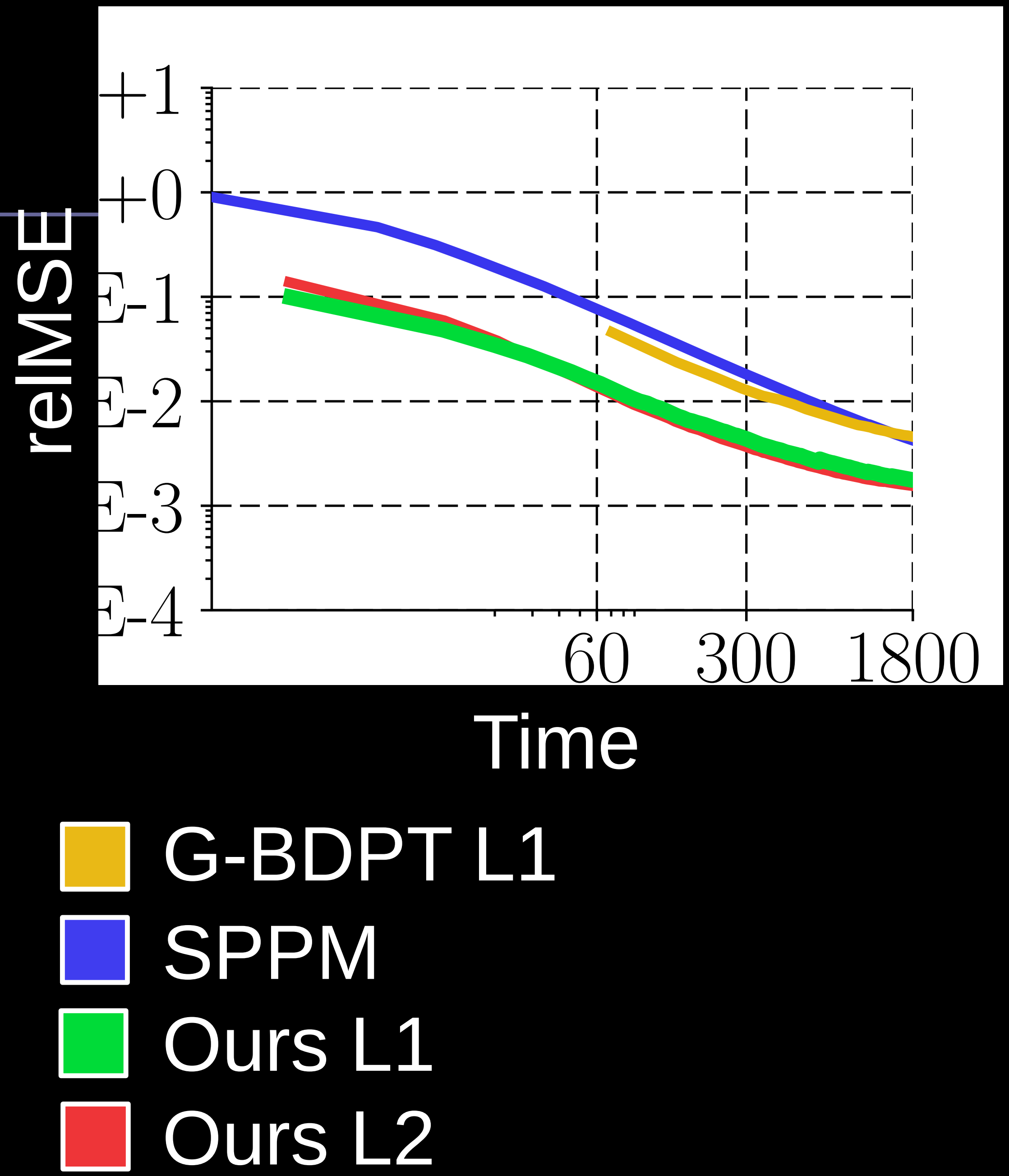
G-BDPT L1

G-BDPT L

SPPM

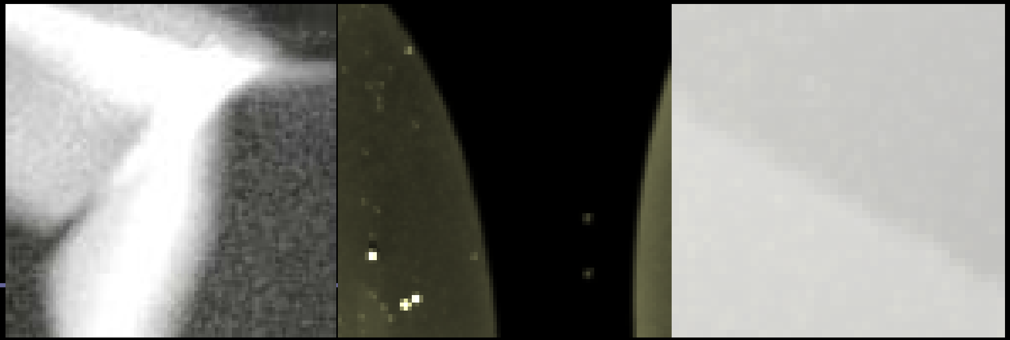

Ours L2 – 5 min
G-BDPT L
SPPM
Ours L2

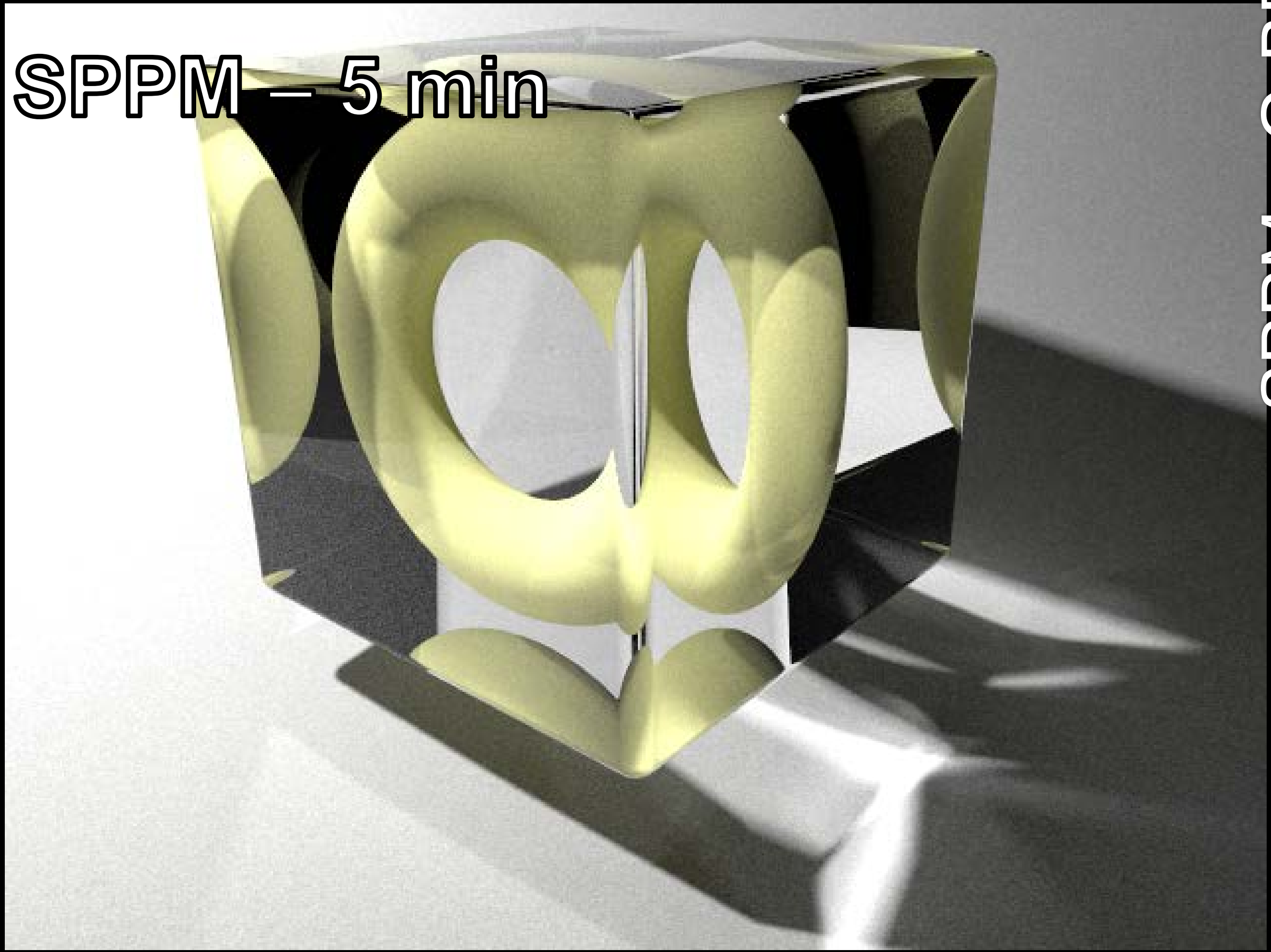

Reference
G-BDPT L
SPPM
Ours L2
Ref.

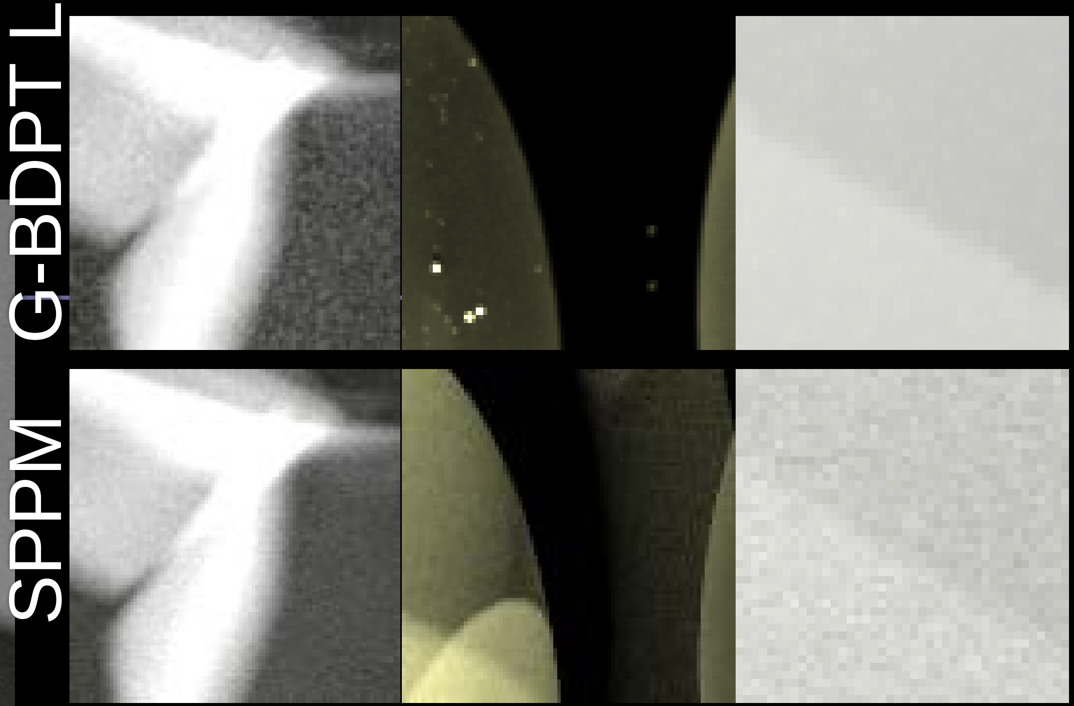


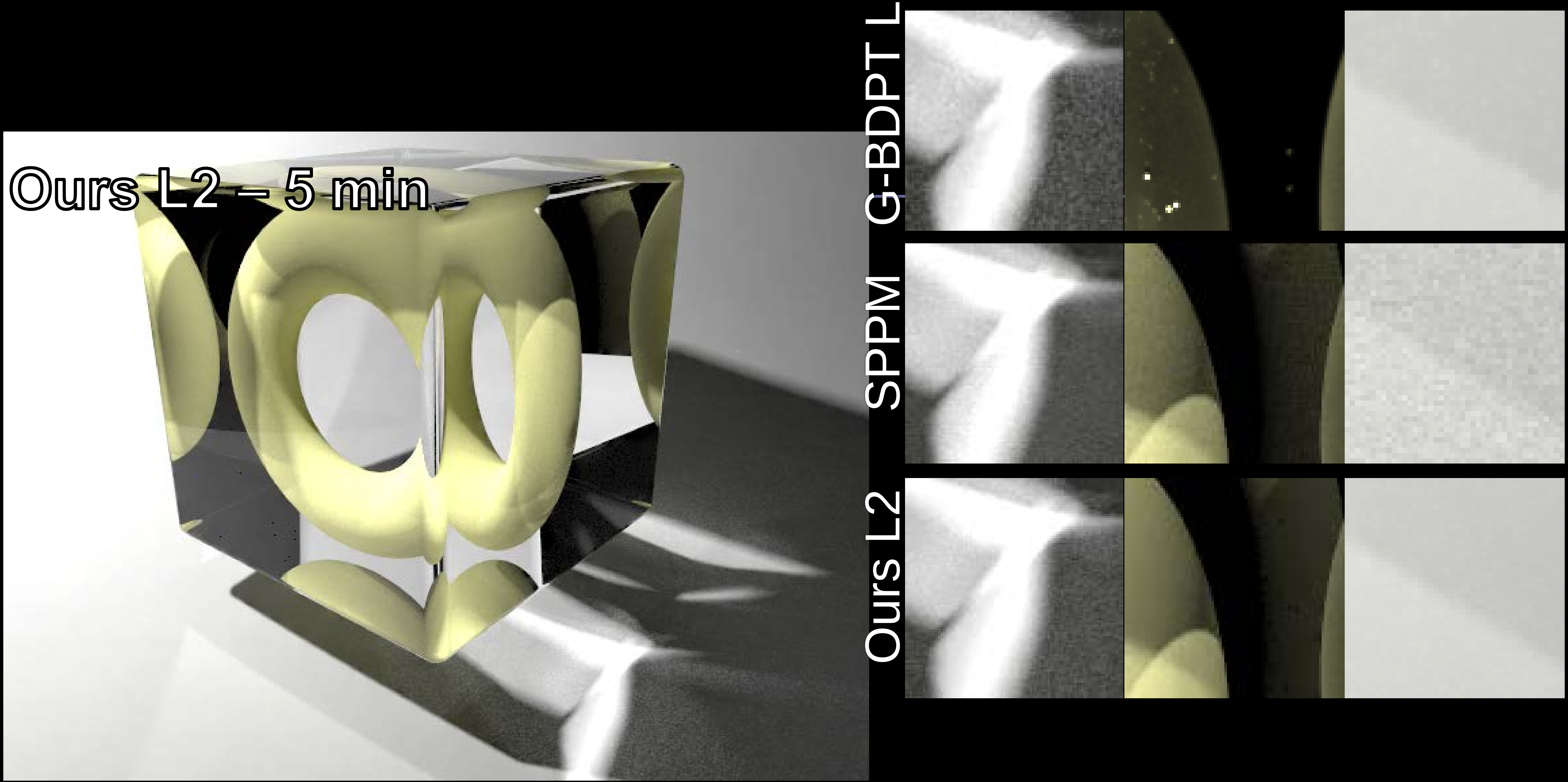
relMSE
+1
+0
E-1
E-2
E-3
E-4
60
300
1800
Time
G-BDPT L1
SPPM
Ours L1
Ours L2

G-BDPT L

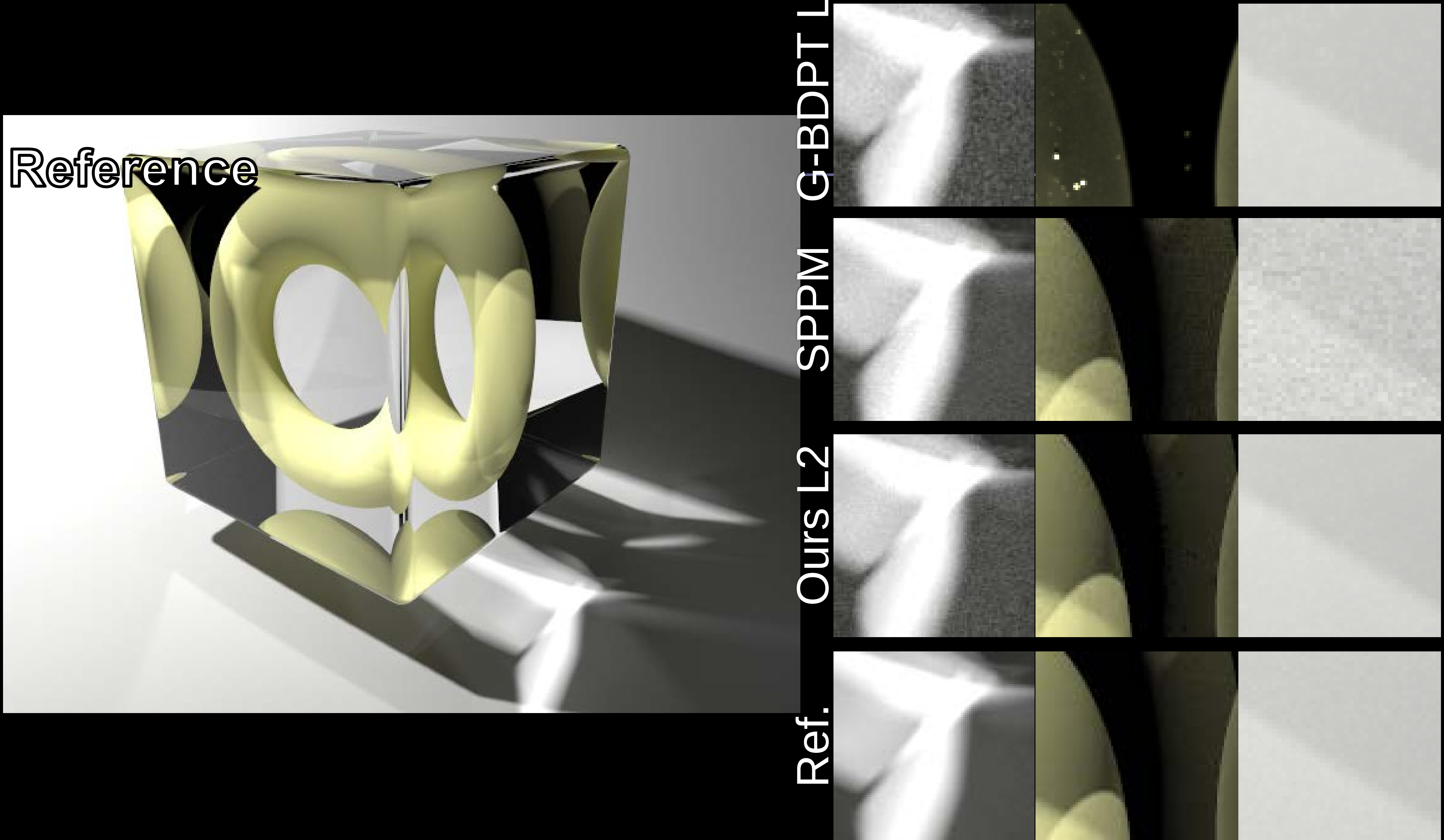


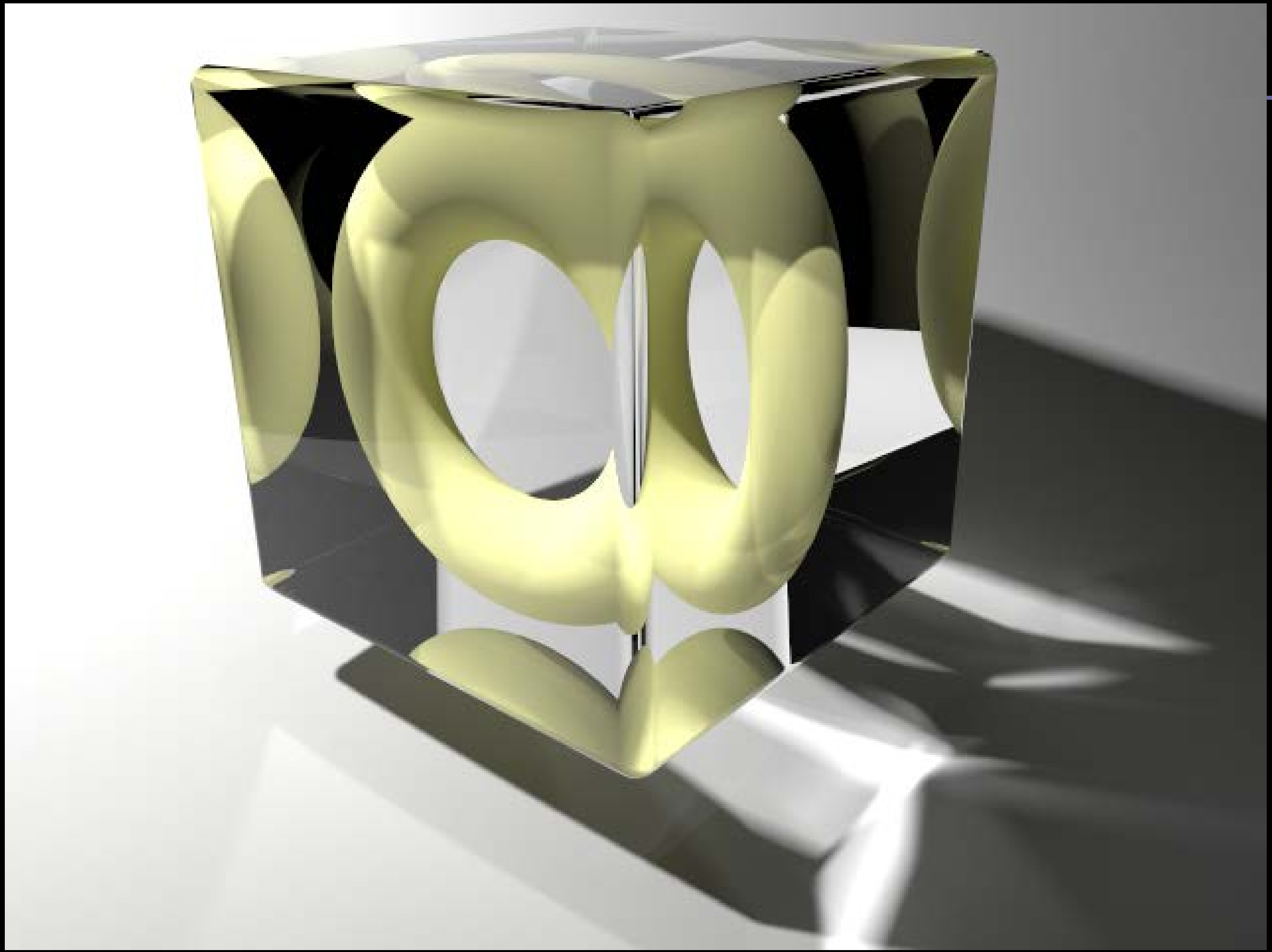

SPPM – 5 min

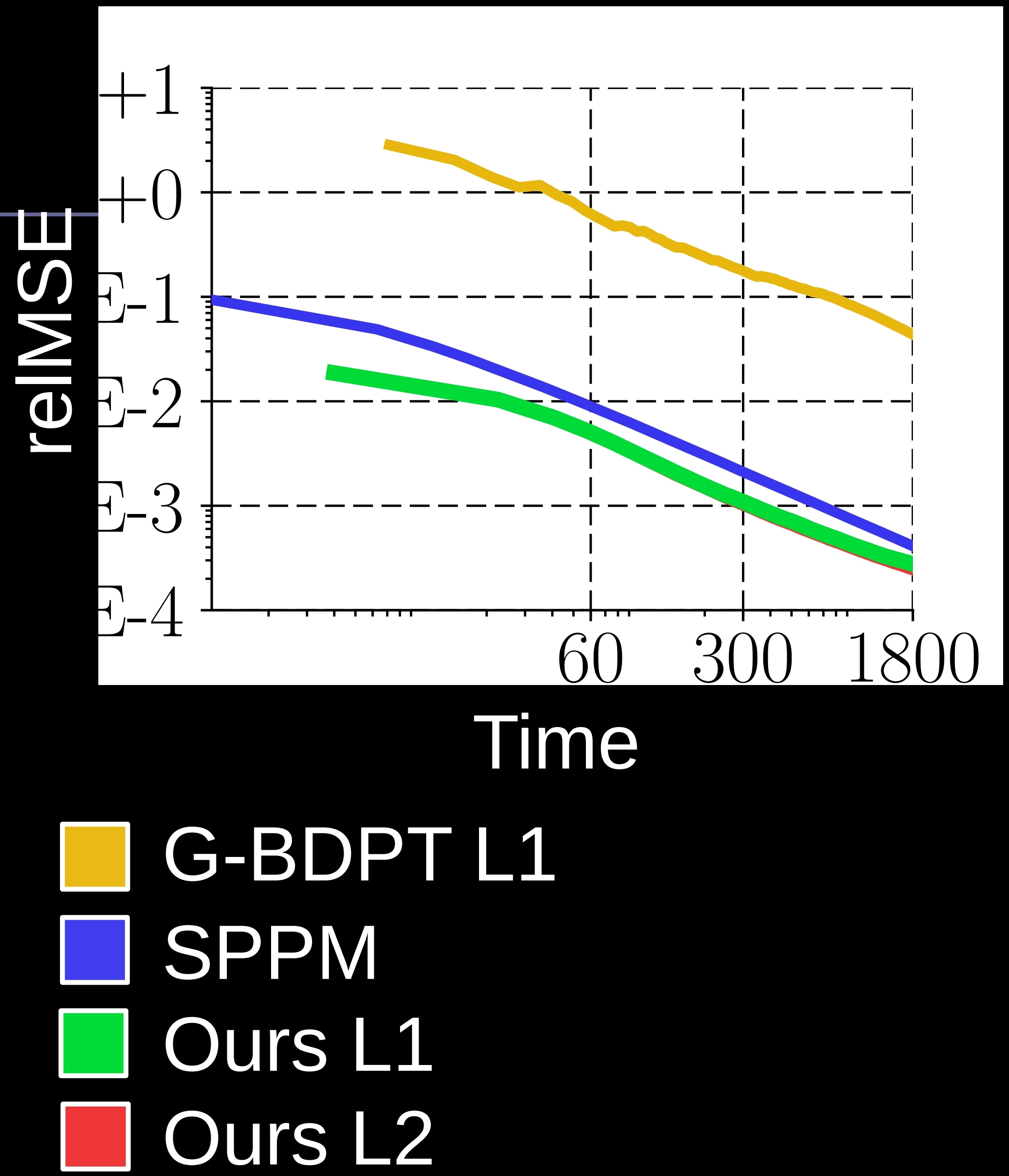

G-BDPT L
SPPM



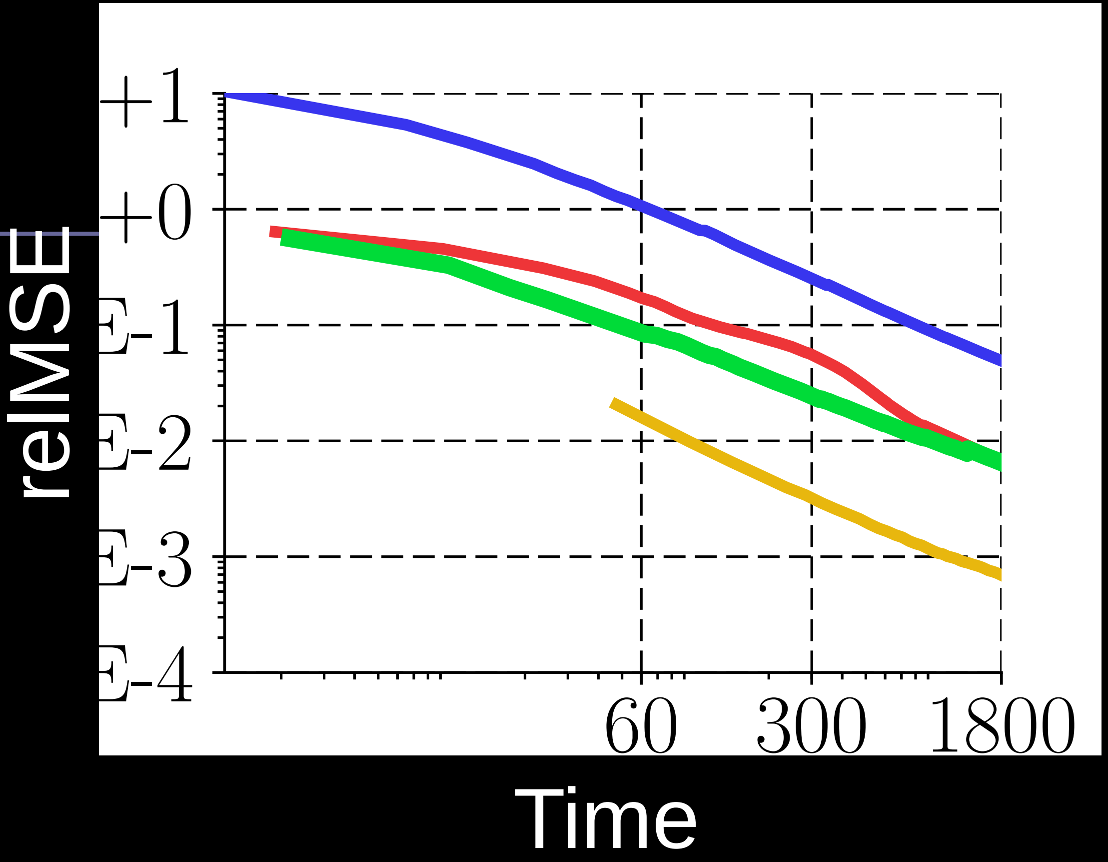
Ours L2 – 5 min
G-BDPT L
SPPM
Ours L2


Reference
G-BDPT L
SPPM
Ours L2
Ref.




relMSE
E+1
E+0
E-1
E-2
E-3
E-4
60
300
1800
Time
G-BDPT L1
SPPM
Ours L1
Ours L2

Sponza


+1
+0
E-1
E-2
E-3
E-4
60
300
1800
relMSE
Time
G-BDPT L1
SPPM
Ours L1
Ours L2

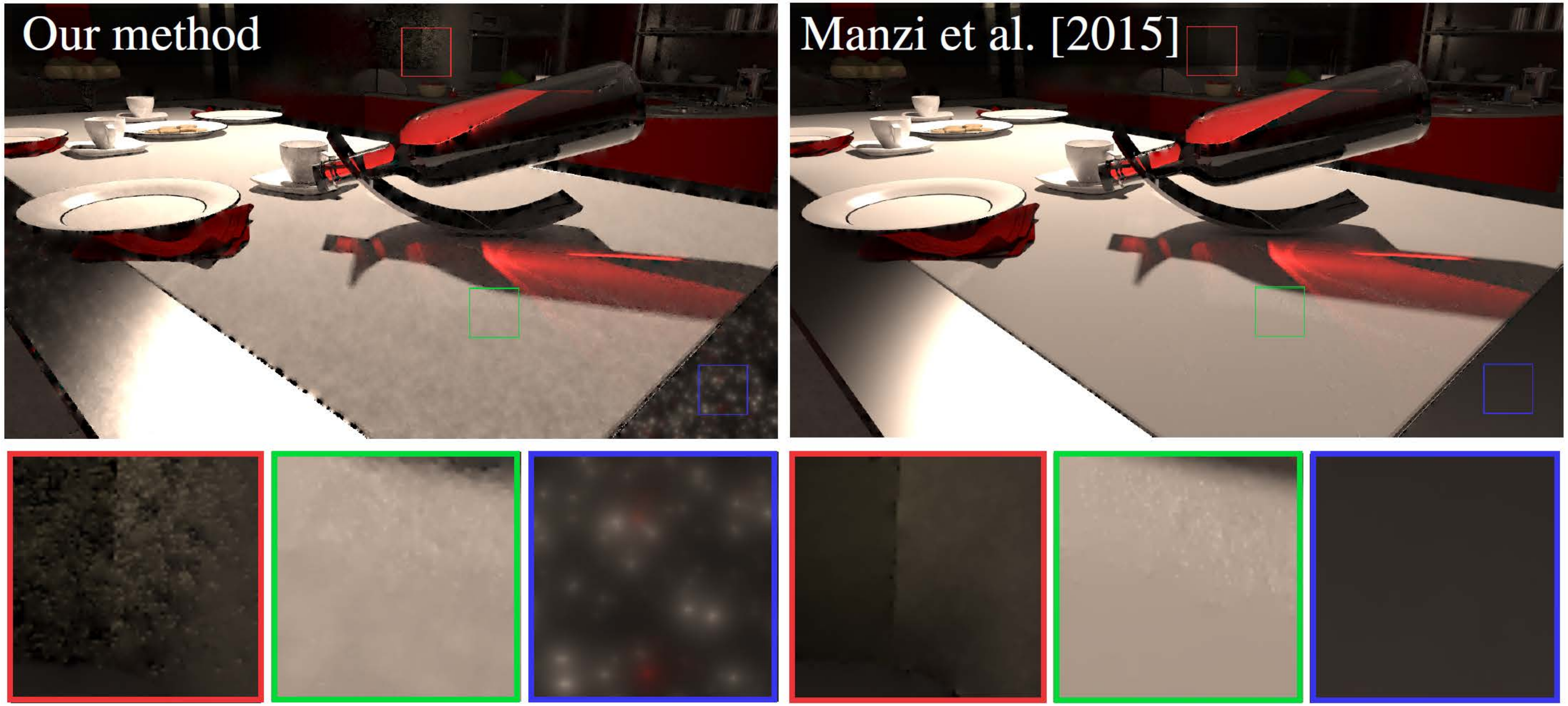
Limitations

Limitations

1) Gather photon on glossy surfaces

Limitations

2) Non uniform photon distribution



Conclusion

Conclusion

- The first gradient-domain photon density estimation technique.
  - New hybrid shift mapping
    - shifting sensor path
    - shifting photon path

  - calculate gradient -> poisson problem -> get final image

  - treat SDS path well

References

1. The slides of Gradient-Domain Photon Density Estimation
2. The slides of State of the Art in Photon Density Estimation, SIGGRAPH Asia 2013 Course

   http://users-cs.au.dk/toshiya/starpm2013a/

Thank you for Listening