

Real-time Path-Tracing Denoising

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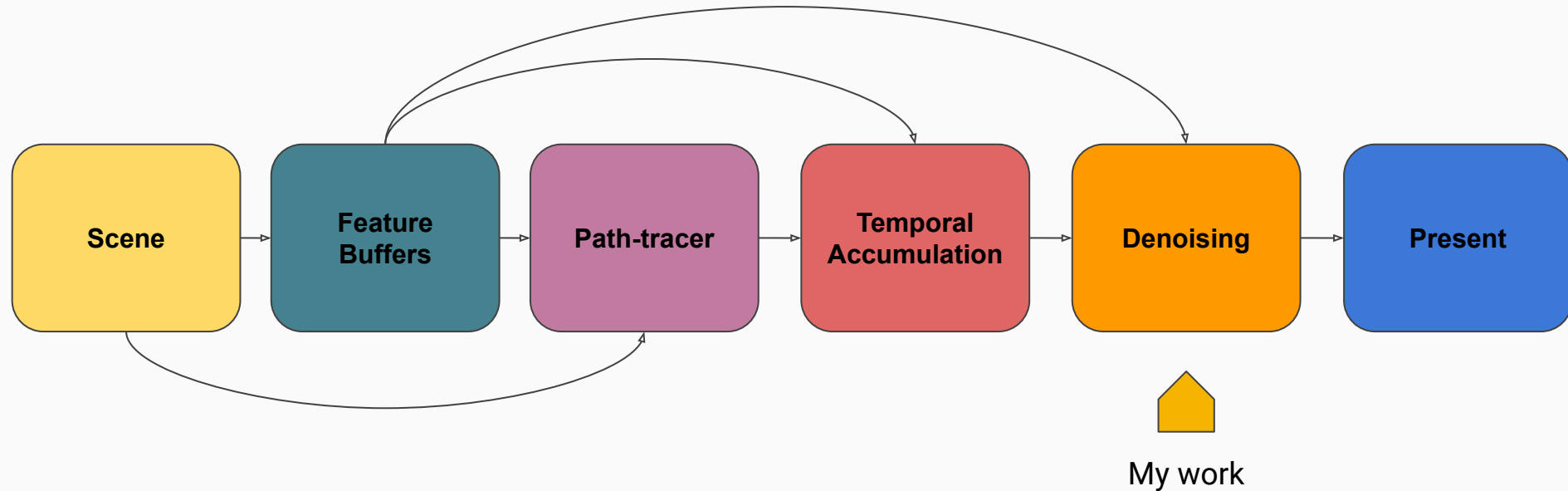
Objectives

Physically based path-tracing benefits from a versatile, and powerful pipeline

We want to leverage it in a real-time renderer by

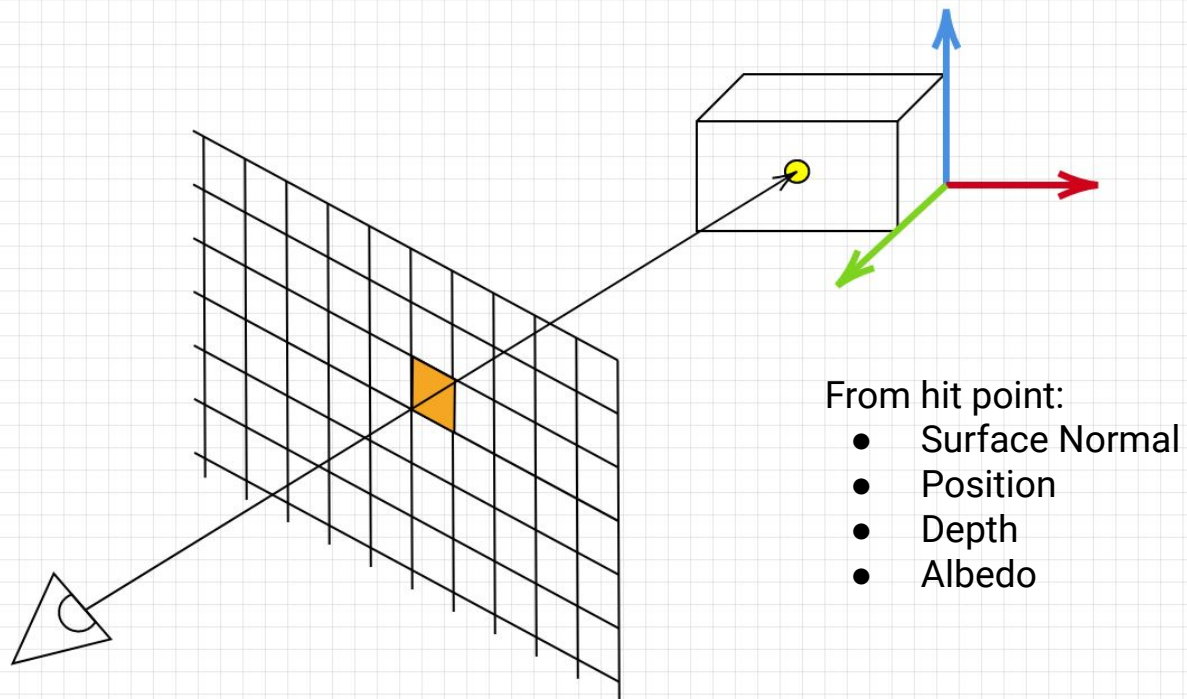
- Applying specific constraints
- Adding new ***reconstruction filters*** (purpose of this master thesis)

Rendering Pipeline

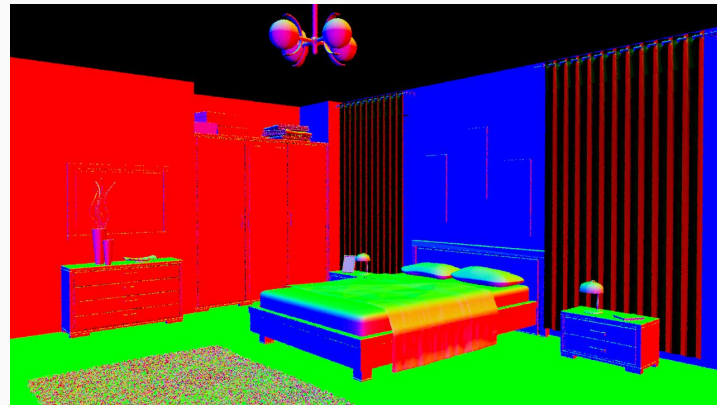


Feature buffers

Feature buffers—Origin



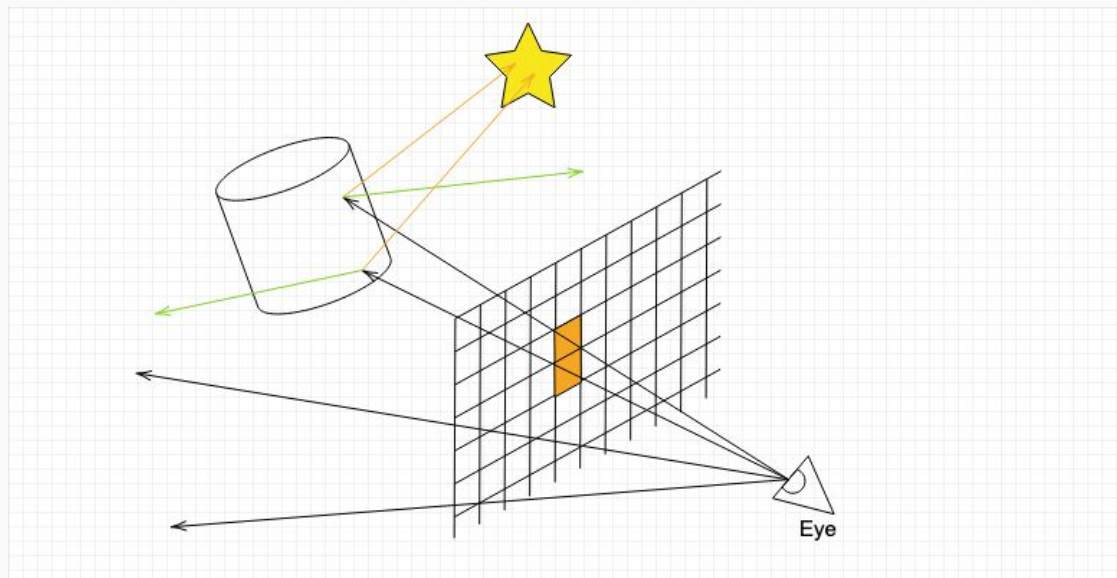
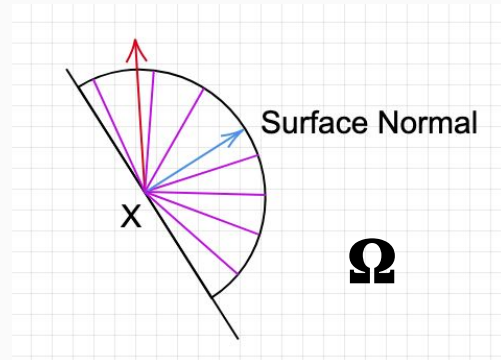
Feature buffers—Data



Path-Tracer

$$L_0(X, \hat{\omega}_0) = L_e(X, \hat{\omega}_0) + \left[\int_{\Omega} L_i(X, \hat{\omega}_i) f(X, \hat{\omega}_i, \hat{\omega}_0) |\hat{\omega}_i \cdot \hat{n}| d\hat{\omega}_i \right]$$

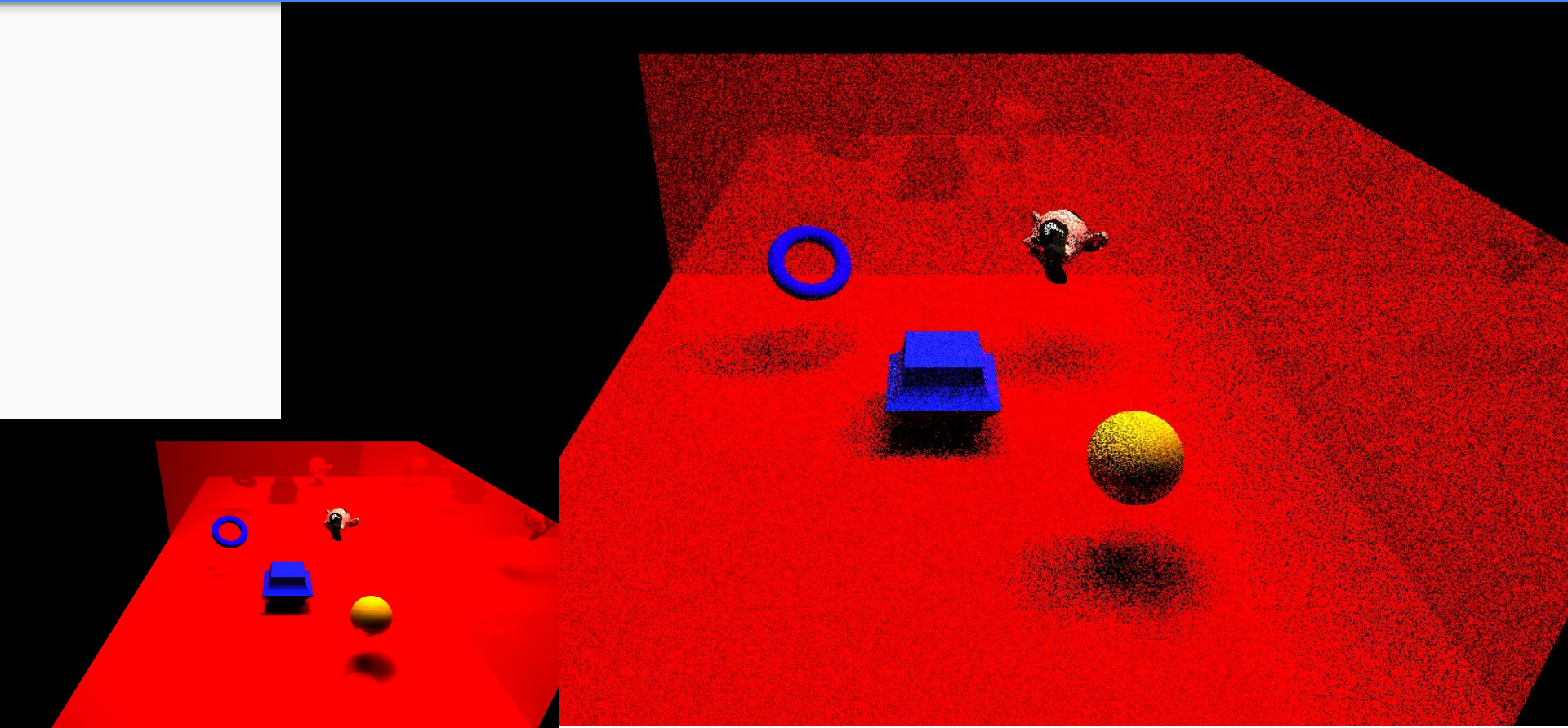
Rendering Equation - Kajiya 1986



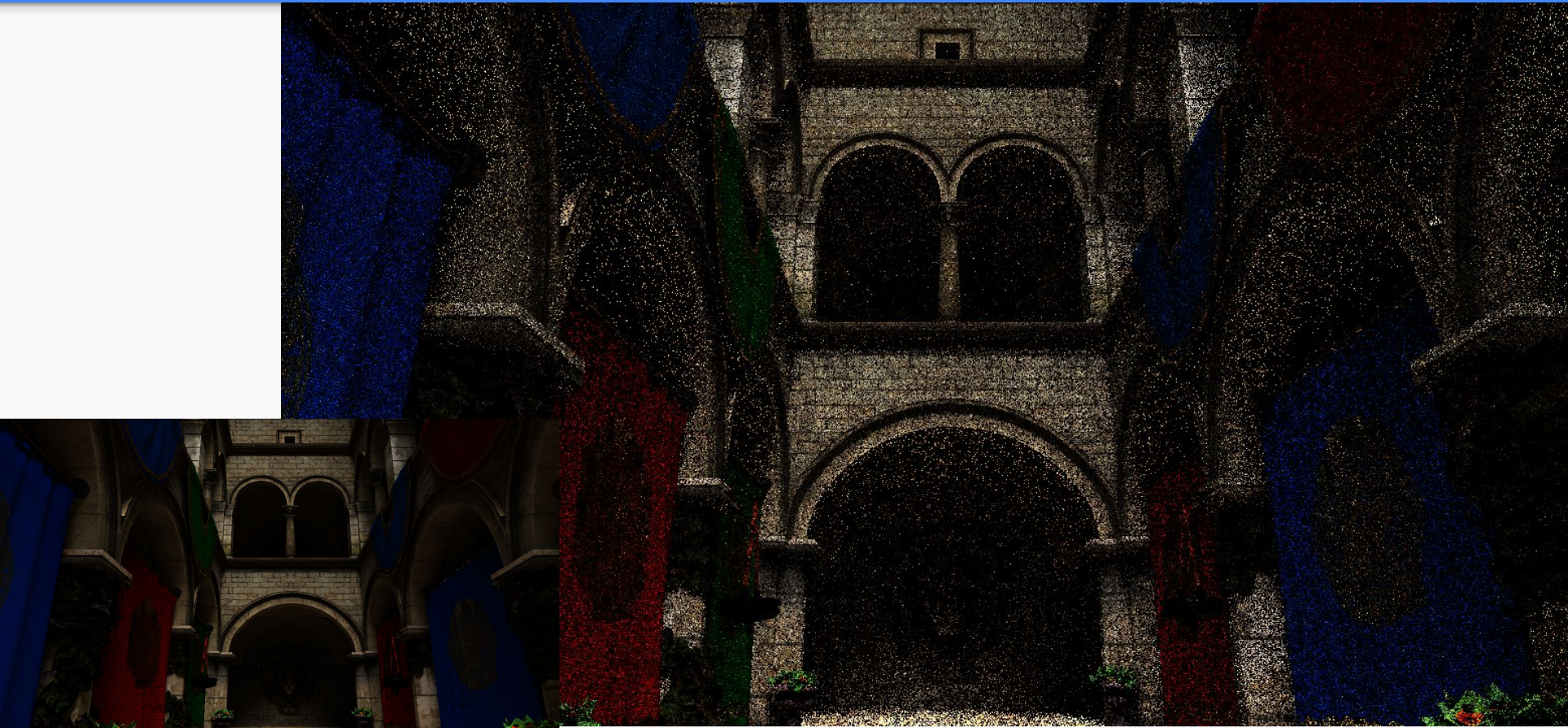
- Recursive
- Possibly infinite (depth, Ω)

“Approximation” → Monte Carlo
When to stop?

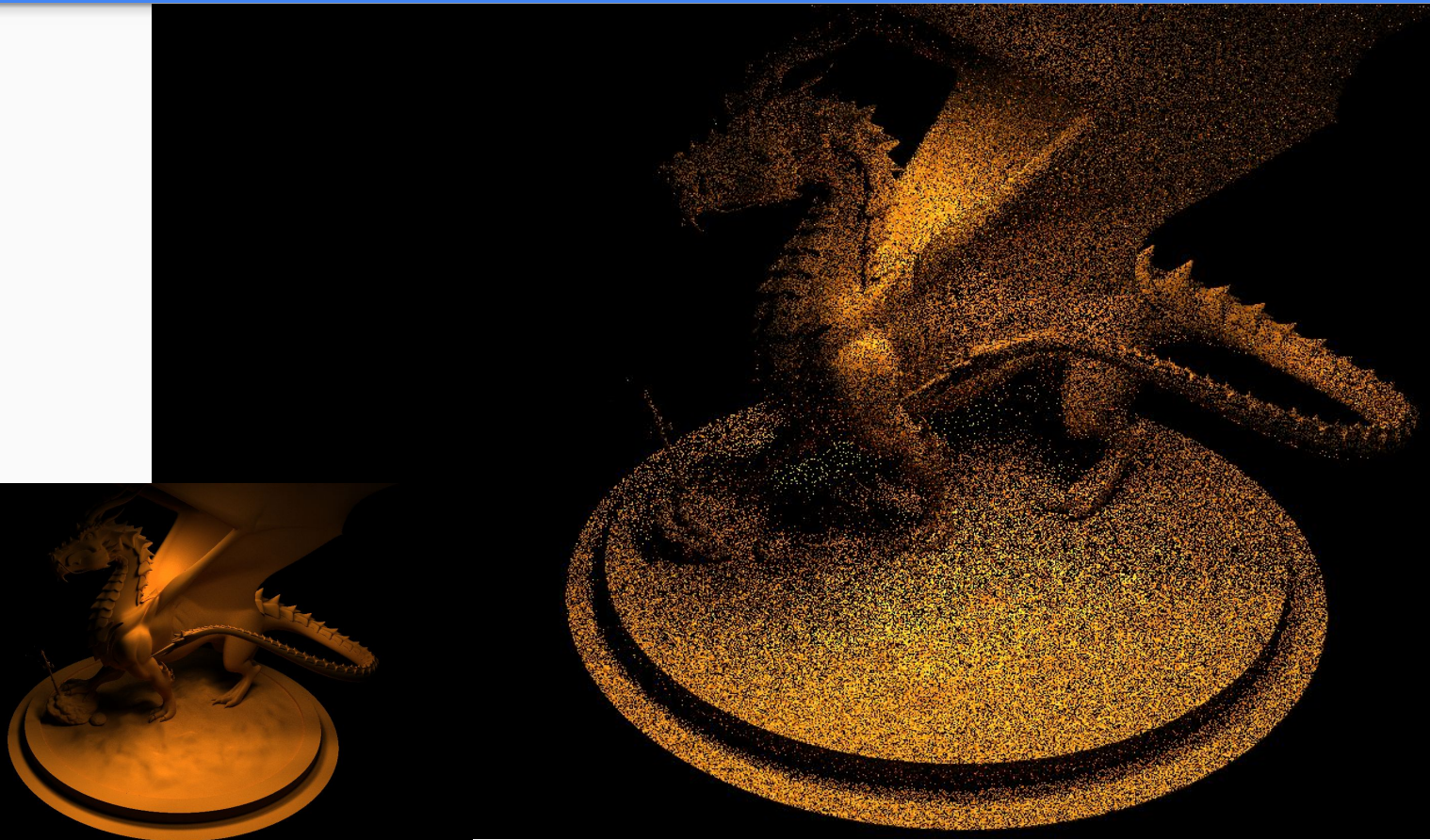
Path-Tracer—Results with applied constraints



Path-Tracer—Results with applied constraints



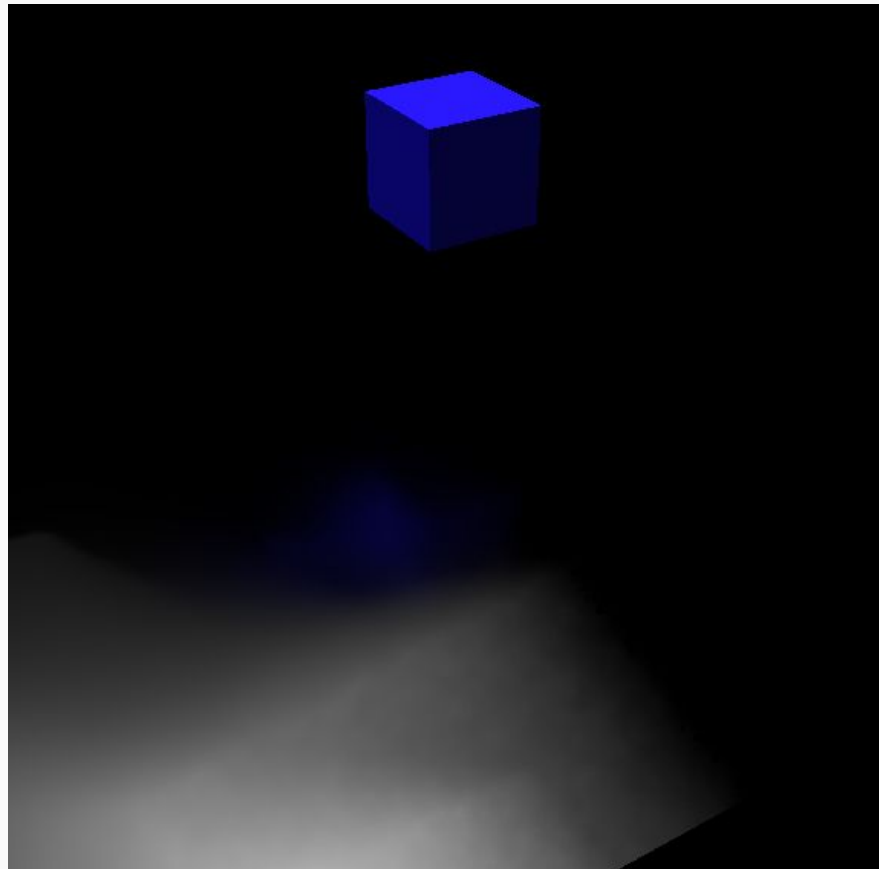
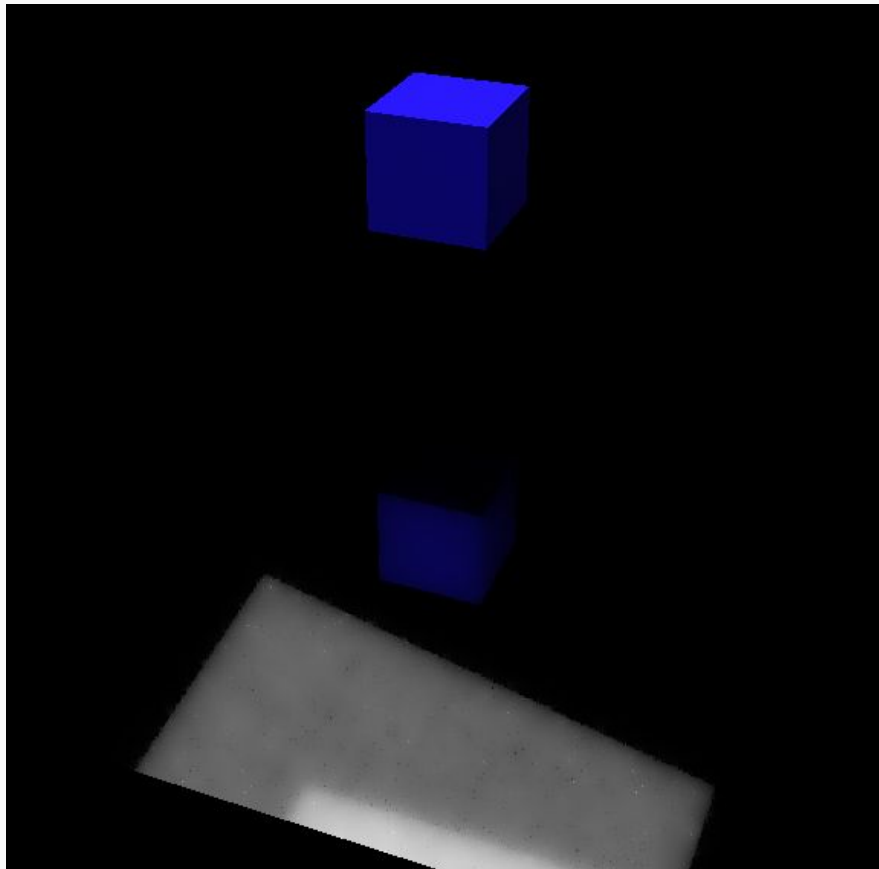
Path-Tracer—Results with applied constraints



$$C'_i(p) = \alpha \times C_i(p) + (1 - \alpha) \times C'_{i-1}(\overleftarrow{p})$$



Temporal Accumulation—Problems



Denoising Methods

Blockwise Multi-Order Feature Regression for Real-Time Path Tracing Reconstruction

Special form of the least square problem

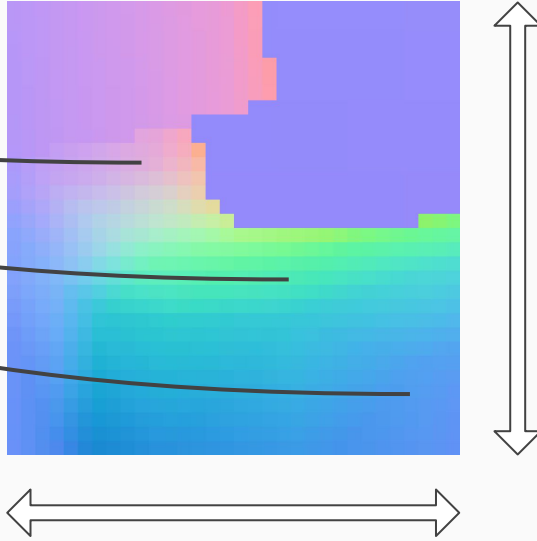
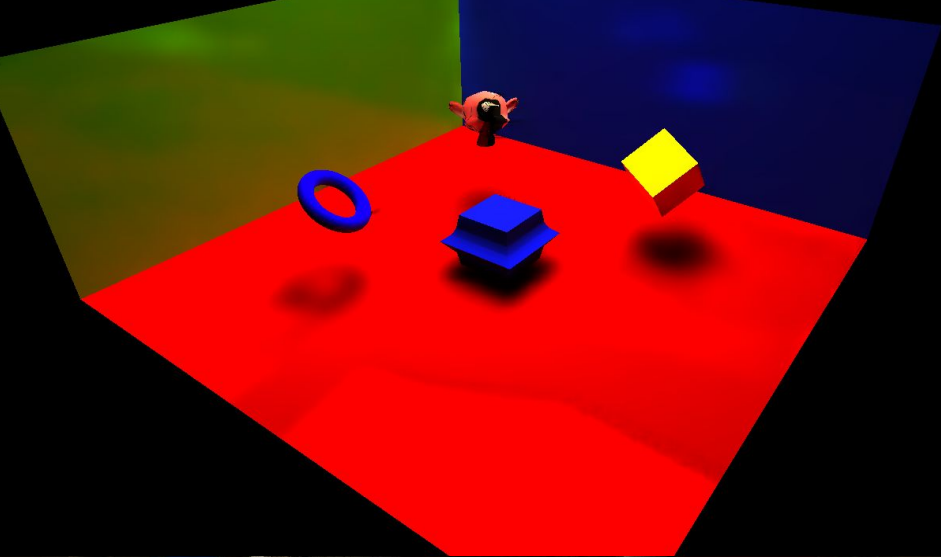
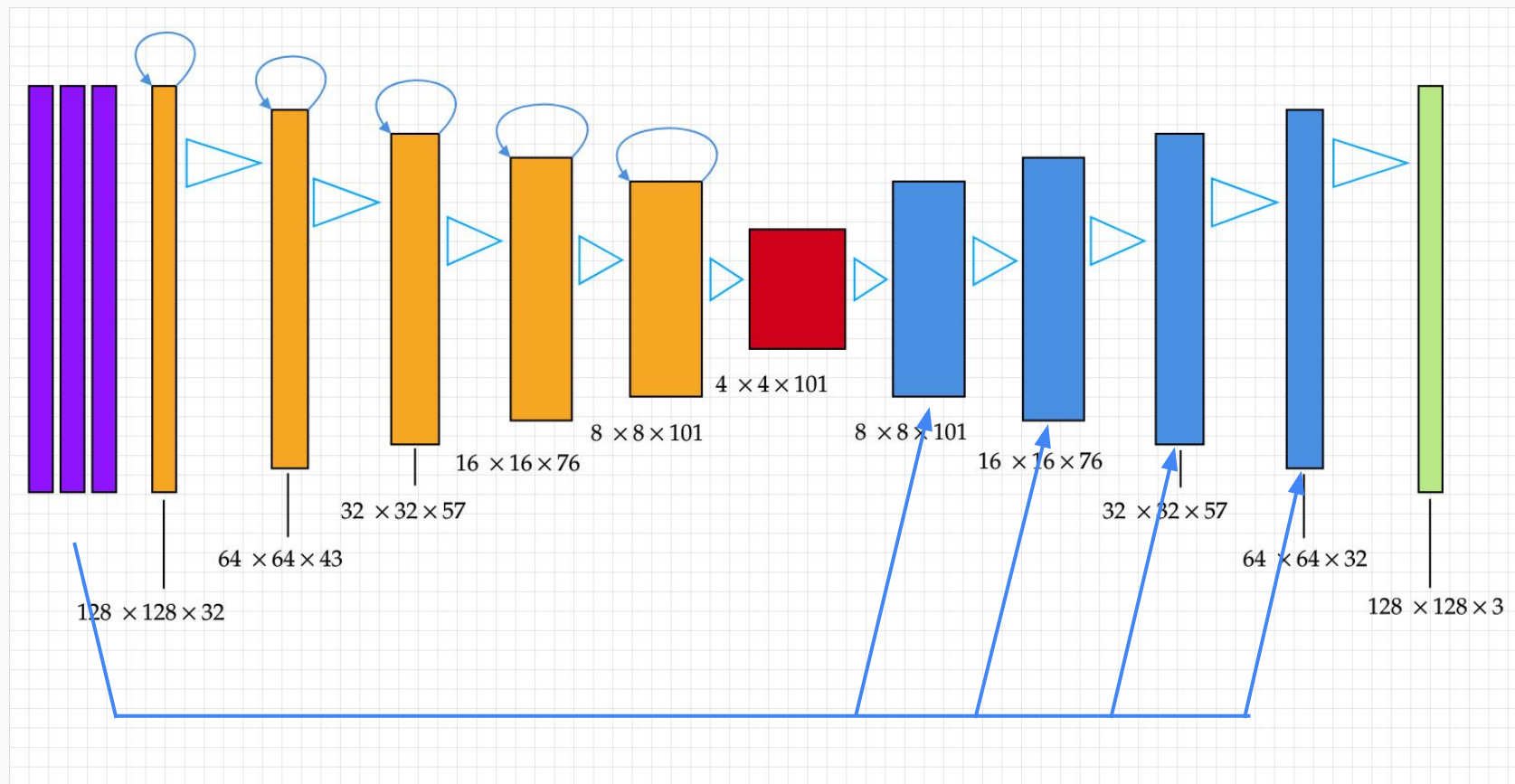
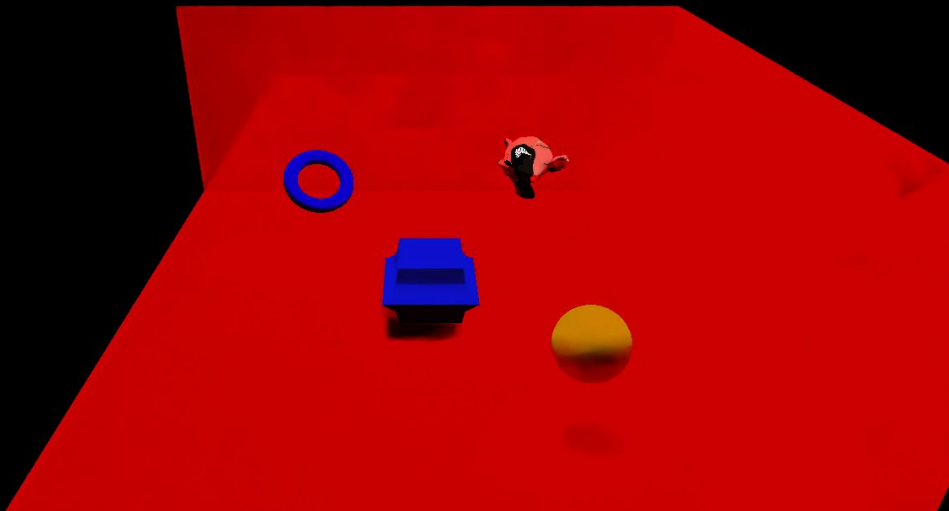
$$\tilde{I} T = \begin{bmatrix} N_x(p_1) & N_y(p_1) & N_z(p_1) & \dots & r^{(c)}(p_1) \\ N_x(p_2) & N_y(p_2) & N_z(p_2) & \dots & r^{(c)}(p_2) \\ N_x(p_3) & N_y(p_3) & N_z(p_3) & \dots & r^{(c)}(p_3) \\ \dots & \dots & \dots & \dots & \dots \end{bmatrix}$$


Diagram illustrating the blockwise multi-order feature regression for real-time path tracing reconstruction. The matrix equation shows features $N_x(p_i)$, $N_y(p_i)$, $N_z(p_i)$, and a target $r^{(c)}(p_i)$ for points p_1, p_2, p_3 . The first column of features is highlighted with a red box. Lines connect these features to a corresponding region in a 2D color map. Below the matrix, the equation $R \hat{\alpha}^{(c)} = r^{(c)}$ is shown, with $\hat{\alpha}^{(c)}$ highlighted by an orange box. To the right of the color map, there are two double-headed arrows indicating dimensions.

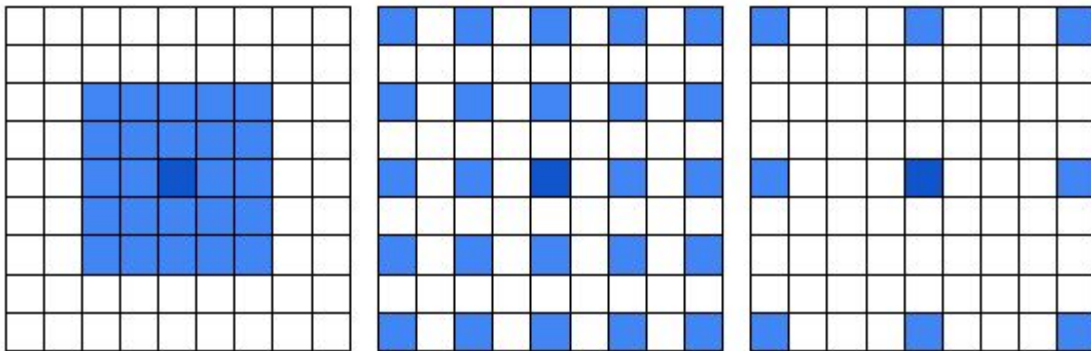


Machine-Learning with a Recurrent Auto-Encoder





(Adaptive) Spatio-temporal Variance Guided Filtering



*Weights computation with
edge-avoiding functions*

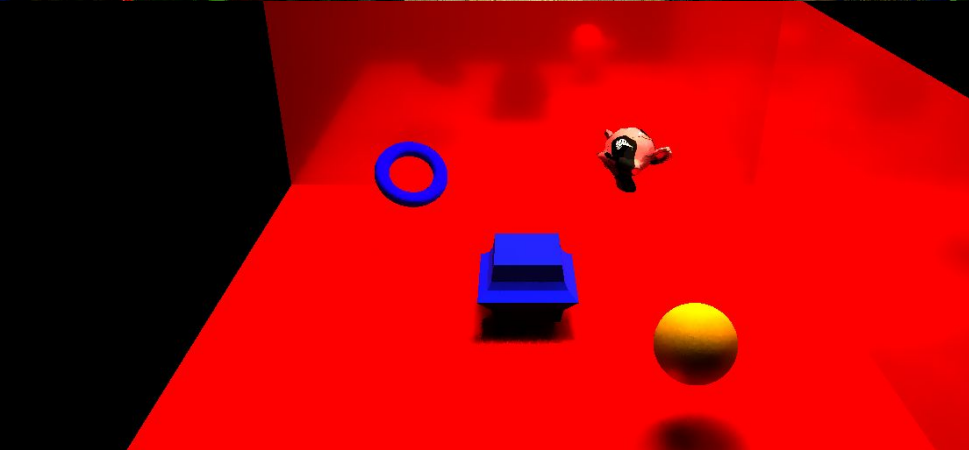
Related samples: 0.0

Unrelated samples: 1.0

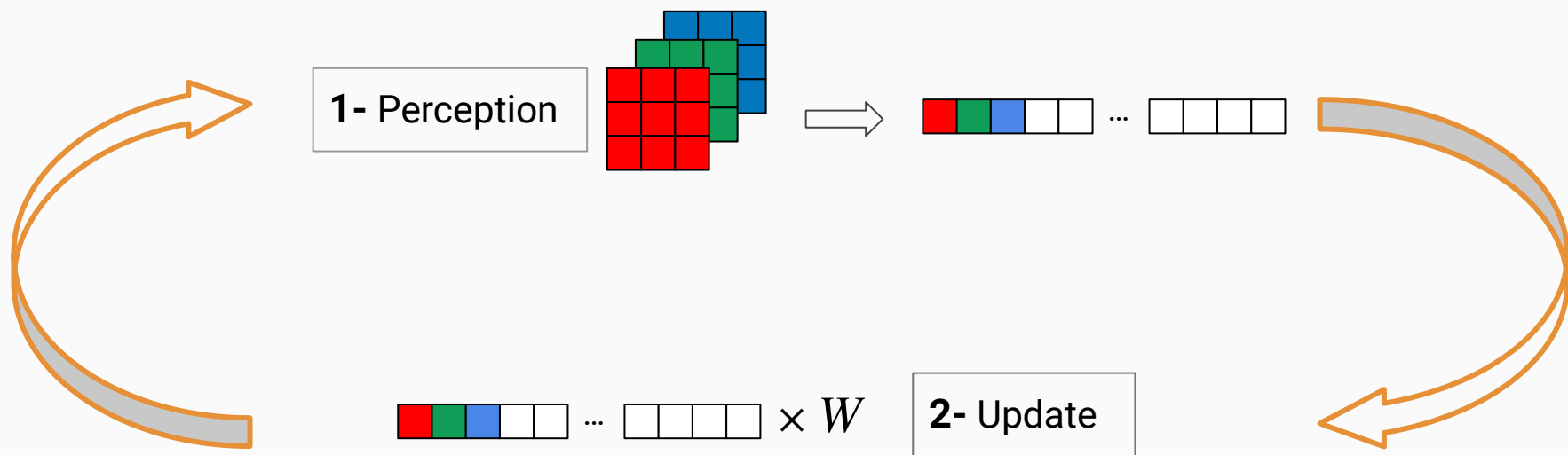


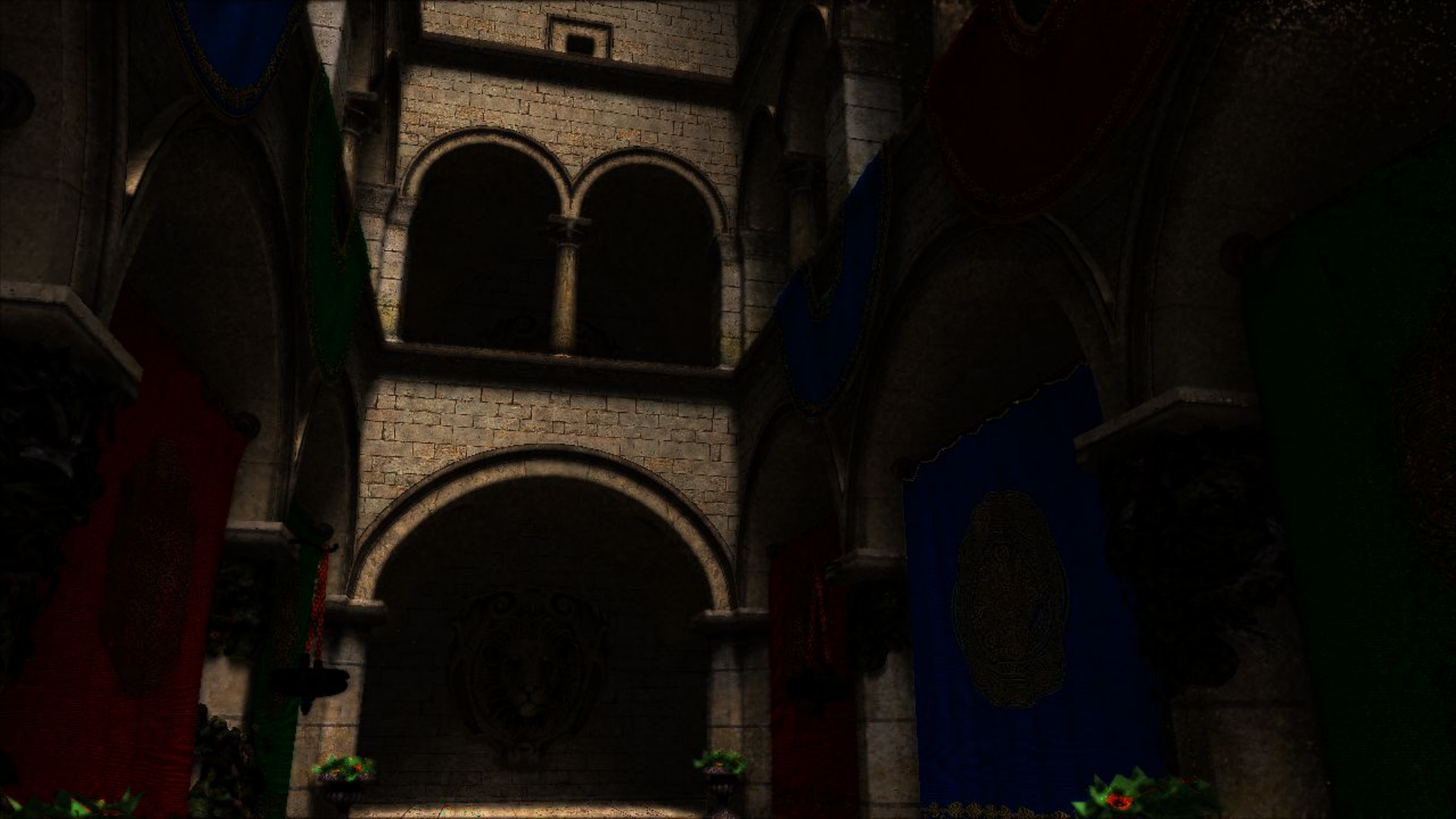
$$C'_i(p) = \alpha \times C_i(p) + (1 - \alpha) \times C'_{i-1}(\overleftarrow{p})$$

Was fixed, now *variable* per pixel
Based on the luminance variation



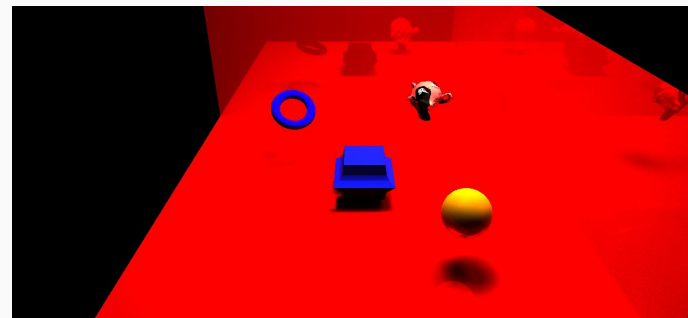
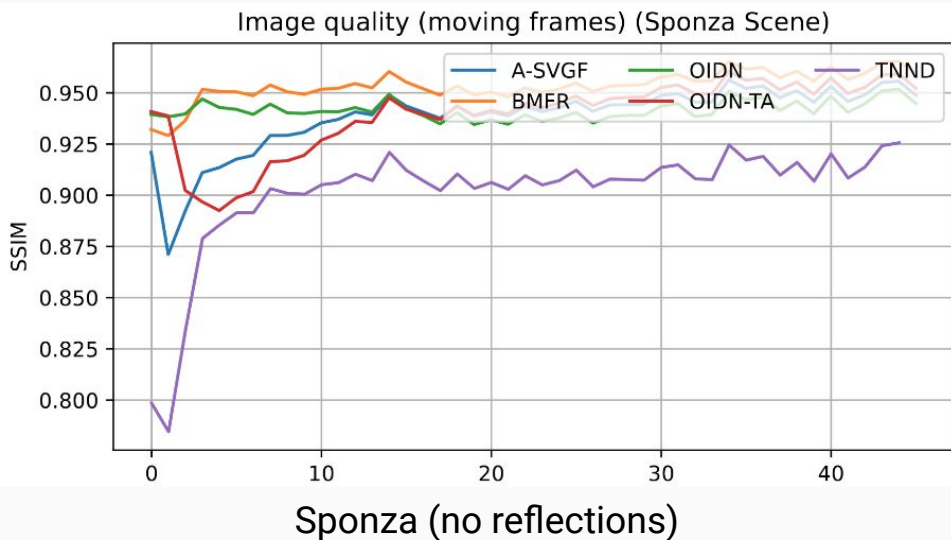
Tiny Neural Network Denoiser - Cellular Automata



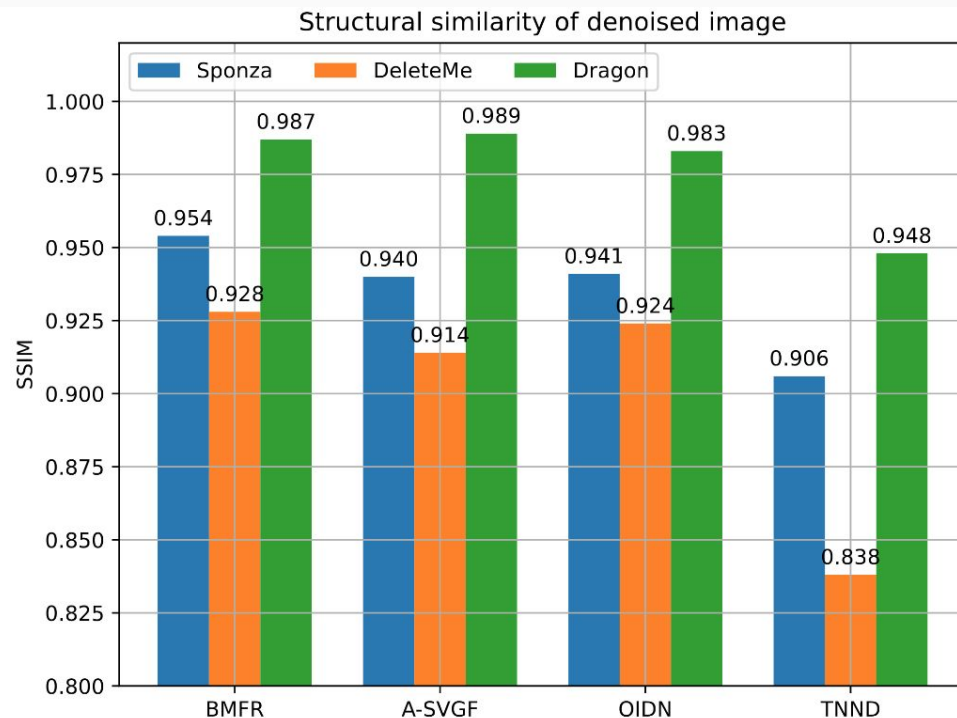


Comparison & Results

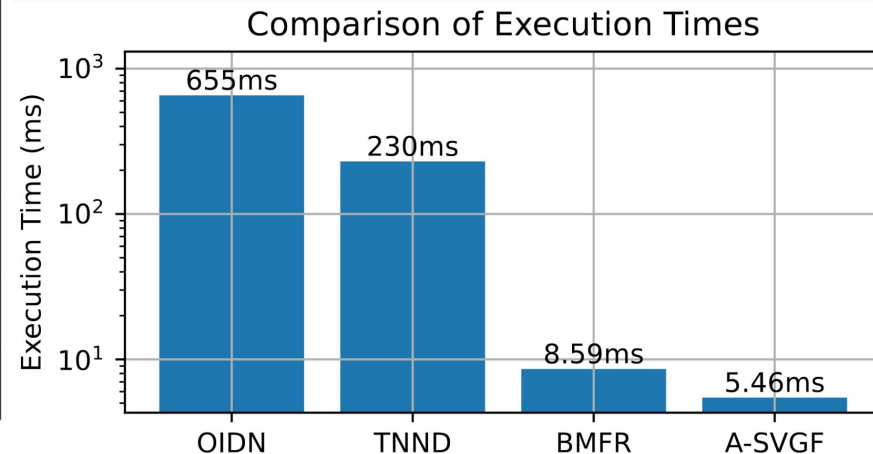
Comparison & Results



Comparison & Results



- Overall results very similar
- But computational complexity is not



- TNND needs more work (GPU implementation, more diverse dataset, ...)
- Some other techniques suggest moving the denoising further up in the pipeline
- Moving the whole pipeline on the GPU
- Implement compressed G-Buffer

Thank you!

BMFR

