Analysis of Sample Correlations for Monte Carlo Rendering

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Rendering = Geometry + Radiometry

Geometry / Projection
for pin-hole model is known since 400BC
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Radiometrically accurate simulation
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Radiometrically accurate simulation
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OpenGL
[Stachowiak 2010]

Raytracing
[Whitted 1980]
Radiometric fidelity improves photorealism

Papas et al. [2013]
Radiometric fidelity improves photorealism

Krivanek et al. [2014]
Reconstruction: Estimate image samples
Naive method: sample image at grid locations
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Ground truth (high-res) image

Reconstruct on (low-res) pixel grid

Average
Antialiasing using general reconstruction filters

Weighted Average
Naive method: sample image at grid locations
Rendering: reconstructing integrals
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Each path has an associated radiance value
Global Illumination: Participating media

Each path has an associated radiance value.
s-dimensional path space

Pixel sensor
s-dimensional path space

Pixel sensor
Path-space integration

(projection)

s-dimensional path space

Pixel sensor
Rendering = integration + reconstruction
Frequency analysis of light fields in rendering

Local variation of the integrand

Reconstruction filter

s-dimensional path space

Pixel sensor

Pixel radiance value

Pixel sensor
A Frequency Analysis of Light Transport
Frédéric Durand, Nicolas Holzschuch, Cyril Soler, Eric Chan, François X. Sillion
MIT-CSAIL, ARTIS GRAVIR/IMAG-INRIA

Abstract
We present a signal-processing framework for light transport. We study the frequency content of radiance and how it is altered by...

Practical Filtering for Efficient Ray-Traced Directional Occlusion
Kevin Egan*, Yu-Ting Tseng, Nicolas Holzschuch, Frédéric Durand, Ravi Ramamoorthi
Columbia University, MIT-CSAIL, UC Berkeley

(a) Our Method
32 rays/shading p0, 1 hr 48 min
(b) Monte Carlo
40 rays, 1 hr 42 min
Equal Time
(c) Our Method
32 rays, 1 hr 48 min
(d) Monte Carlo
256 rays, 7 hrs 4 min
Equal Quality
(e) Relighting output from (a)
30 seconds each

Temporal Light Field Reconstruction for Rendering Distribution Effects
Jaakko Lehtinen, Timo Aila, Juwen Chen, Samuel Laine, Frédéric Durand
NVIDIA Research, MIT-CSAIL, NVIDIA Research, MIT-CSAIL

Our result: 16 spp, 403 ± 10 s (+2.5%)

PBRT, 16 spp, 403 s
PBRT, 256 spp, 6426 s

Figure 1: A scene with complex occlusion rendered with depth of field. Left: Images rendered by PBRT [Pharr and Humphrey 2010] using 16 and 256 low-discrepancy samples per pixel (top) and traditional anti-aliased filtering. Right: Image reconstructed by our algorithm in 10 seconds from the same 16 samples per pixel. We obtain defocus quality similar to the 256 spp result in approximately 1/66 of the time.

Abstract
Traditionally, effects that require evaluating multidimensional integrals for each pixel, such as motion blur, depth of field, and dramatic reductions in sampling rate, rely on fairly simple re-

4D Frequency Analysis of Computational Cameras for Depth of Field Extension
Anat Levin1, Samuel W. Hasinoff1, Paul Green1, Frédéric Durand1, William T. Freeman1
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Standard lens image
Our lattice-focal lens: input
Lattice-focal lens: all-focused output

Figure 1: Left: Image from a standard lens showing limited depth of field, with only the rightmost subject in focus. Center: Input from our lattice-focal lens. The defocus kernel of this lens is designed to preserve high frequencies over a wide depth range. Right: An all-focused image reconstructed from the lattice-focal lens image. Since the defocus kernel emphasizes high frequencies, we achieve a good reconstruction over the whole image.
This STAR: Analyze sample correlations for MC sampling

Assessing MSE, bias, variance and convergence of Monte Carlo estimators using spatial and spectral tools
This STAR: Analyze sample correlations for MC sampling

- Fredo Durand [2011]
- Subr and Kautz [2013]
- Pilleboue et al. Georgiev & Fajardo [2015]
- Singh & Jarosz [2017a]
- Singh et al. [2017b]
- Ramamoorthi et al. [2012]
- Subr et al. [2014]
- Cengiz Oztireli [2016]
- Singh et al. [2019]
Sample correlations affect light transport / appearance

Jarabo et al. [2018]  
Non-exponential media

Guo et al. [2019]  
Spatially-correlated media

Bitterli et al. [2018]  
Traditional exponential media

Non-exponential media

Uncorrelated media
Theoretical Tools

Point Processes

Fourier transform / Series

Samples Quality Assessment

Pair Correlation Function

Fourier Transform / Series

Error Formulations

Spatial Domain Formulations

Fourier Domain Formulations

Error Analysis

Stratification Strategies

Low Discrepancy Samplers

Stochastic Samplers