To Do

- Homework 4 (importance sampling) due May 17
- These lectures cover more advanced topics
  - May be relevant for your final project
  - Or curiosity in terms of frontiers of modern rendering
- This lecture on Monte Carlo denoising summary of whole CSE 274 class I taught last academic year
  - Topic of great current interest in both research and production offline and real-time (OptiX, RTX GPUs)
  - Good idea for final project, or simply leverage denoiser built into modern OptiX implementations
  - Can get down to 1-4 samples per pixel. Amazing!
- Lecture is high level, ask if need detailed pointers

Motivation

- Distribution effects (depth of field, motion blur, global illumination, soft shadows) are slow. Many dimensions sample
- Ray Tracing physically accurate but slow, not real-time
- Can we adaptively sample and filter for fast, real-time?

Sampling and Reconstruction

- Monte Carlo is noisy at low sample counts
- Can we reduce time/samples by smart adaptive sampling and smart filtering/reconstruction?
- General area of Monte Carlo denoising
- Long history [Mitchell 91, Guo 98]
Sample result

Adaptive sampling + reconstruction

- These algorithms use 2 kinds of noise reduction strategies, sometimes combined:
  1. Adaptive sampling algorithms
     - Use information from renderer to position new samples better to reduce noise
  2. Reconstruction (filtering) algorithms
     - Use information from renderer to remove MC noise directly
- Both methods have been explored in the past, but new algorithms make remarkable advances

History

- Adaptive sampling old technique Mitchell et al. 87, 91, ...
- But not very widely used... artifacts, can miss features
- After seminal papers in 87-91, not much follow on

Directional Coherence Maps

- Allocate samples to edges (Guo 98) Most of variance at those edges in the image

Directional Coherence Maps (Guo 98)

A Frequency Analysis of Light Transport

F. Durand, MIT CSAIL
N. Holzschuch, C. Soler, ARTIS/GRAVIR-IMAG INRIA
E. Chan, MIT CSAIL
F. Sillion, ARTIS/GRAVIR-IMAG INRIA
Fourier analysis 101

- Spectrum corresponds to blurriness:
  - Sharpest feature has size $\sim 1/F_{\text{max}}$
- Convolution theorem:
  - Multiplication of functions: spectrum is convolved
  - Convolution of functions: spectrum is multiplied
- Classical spectra:
  - Box becomes sinc
  - Dirac becomes constant

Transport

- Shear: $x' = x - v \cdot d$

Transport in Fourier space

- Shear in primal: $x' = x - v \cdot d$
- Shear in Fourier, along the other dimension

Transport becomes Shear

- This is consistent with light field spectra
  [Chai et al. 00, Isaksen et al. 00]

BRDF integration

- Ray-space: convolution
  - Outgoing light: convolution of incoming light and BRDF
  - For rotationally-invariant BRDFs
- Fourier domain: multiplication
  - Outgoing spectrum: multiplication of incoming spectrum and BRDF spectrum

Adaptive shading sampling

- Per-pixel prediction of max. frequency (bandwidth)
  - Based on curvature, BRDF, distance to occluder, etc.
  - No spectrum computed, just estimate max frequency

Per-pixel bandwidth criterion
Adaptive shading sampling

- Per-pixel prediction of max. frequency (bandwidth)
  - Based on curvature, BRDF, distance to occluder, etc.
  - No spectrum computed, just estimate max frequency

Uniform sampling

- 20,000 samples

Adaptive sampling

- 20,000 samples

Resurgence (2008 - )

- Eurographics 2015 STAR report by Zwicker et al. [former UCSD faculty]

Multi-Dimensional Adaptive Sampling

- Hachisuka, Jarosz, … Zwicker, Jensen [MDAS 2008]
- Scenes with motion blur, depth of field, soft shadows
- Involves high-dimensional integral, converges slowly
- Exploit high-dimensional info to sample adaptively
- Sampling in 2D image plane or other dims inadequate
- Need to consider full joint high-dimensional space
Multidimensional Adaptive Sampling

Figure 10: Visualizations of projected sample distributions using our method for the chess scene from Figure 8 and the pool scene from Figure 7. Our adaptive sampler places samples both around high-frequency image discontinuities (in focus chess piece and stationary pool ball) as well as in regions which exhibit significant motion blur or depth of field effects.

Multi-Dimensional Adaptive Sampling

Motion Blur and Depth of Field 32 samples per pixel

A-Priori Methods

- Egan et al. 2009: Frequency Analysis and Sheared Filtering for Motion Blur; first deep use frequency anal.

Fast Motion Blur Rendering

Garfield: A Tail of Two Kitties
Rhythm & Hues Studios
Twentieth Century-Fox Film Corporation

A Simple Approach

- For each pixel
- Sample many different moments in time
- Very expensive. Can we do better sampling, filtering?

Observation 1

- Motion-blurred images have low spatial frequency

Egan, Tseng, Holzschuch, Durand, Ramamoorthi 09
Observation 2

- Neighboring pixels sample correlated signals

\[
\begin{array}{c}
\text{TIME AXIS} \\
| 0.0 | 1.0 | 2.0 |
\end{array}
\]

Our Method

- Share samples across pixels
- Use wide filter sheared in space-time

\[
\begin{array}{c}
\text{TIME AXIS} \\
| 0.0 | 1.0 | 2.0 |
\end{array}
\]

Basic Example

- Low velocity, \( t = [0.0, 1.0] \)

\[
\begin{array}{c}
\text{x} \\
y \\
t
\end{array}
\]

Basic Example

- High velocity, \( t = [0.0, 1.0] \)

\[
\begin{array}{c}
\text{x} \\
y \\
t
\end{array}
\]

Shear in Space-Time

Object moving with low velocity

\[
\begin{array}{c}
\text{x} \\
y \\
t
\end{array}
\]

Basic Example – Fourier Domain

- Fourier spectrum, zero velocity

\[
\begin{array}{c}
\text{x} \\
y \\
t
\end{array}
\]
Basic Example – Fourier Domain

- Low velocity, small shear in both domains

\[ f(x, t) \rightarrow F(\Omega_x, \Omega_t) \]

slope = -speed

- Large shear

\[ f(x, t) \rightarrow F(\Omega_x, \Omega_t) \]

Standard Reconstruction Filter

- Standard anti-aliasing and reconstruction filter is axis-aligned

No aliasing!

Sheared Reconstruction Filter

- Our sheared filter allows for much tighter packing of replicas (ie sparse sampling)

Car Scene

Our Method, 4 samples per pixel

Static Render
Car Scene

Our Method, 4 samples per pixel

Ground Truth

Ballerina Video

Ballerina sequence (8 samples/pixel)

Note smooth motion-blur of dress and shadows

Frequency Analysis and Sheared Reconstruction for Rendering Motion Blur

ID: 0034

Fourier Analysis, Sheared Filtering

Previous Work
- Shinya 93: Spatio-temporal filtering of uniform velocity
- Chai et al. 00: Plenoptic Sampling: wedge spectra
- Hachisuka et al. 08: Multidimensional Adaptive Sampling

Our Subsequent Work
- Adaptive Wavelet Rendering [Overbeck et al 09]
- Area Light Soft Shadows [Egan et al 11a]
- Spherical Harmonic Directional Occlusion [Egan et al 11b]
- Fast (real-time) Sheared Filtering [Yan et al 15]

Real-Time Axis-Aligned Filtering
- Soft Shadows [Mehta Wang Ramamoorthi 12]
- Global Illumination [Mehta Wang Ramamoorthi Durand 13]
- Multiple Effects [Mehta Yao Ramamoorthi Durand 14]
- Multiple Axis-Aligned Filtering [Wu et al. 17]

Fast Sheared Filtering (FSF)

- Separable sheared filter

Fourier: sheared shape
Primal: separable filter, still hard to extend to higher dimensions (can be done by approximation)

Fourier: compact pack replicas
Primal: low sampling rate

Fast Sheared Filtering

Motivation: Cover the spectrum compactly

MAAF: Fourier

- Multiple Axis-Aligned Filter (MAAF)
### Video

![Video](image1.png)

### Sparse Sampling and Reconstruction

**A Priori Methods**
- Chai et al. 2000
- Egan et al. 2009
- Mehta et al. 2014
- Yan et al. 2015

**A Posteriori Methods**
- Hachisuka et al. 2008
- Rousselle et al. 2012
- Moon et al. 2016

### Adaptive Wavelet Rendering

Overbeck et al. 09

- General high-D effects
- Simple and fast (renders into wavelet dom)

### Feature-Space Methods

- General practical denoising (no frequency) [2012-]
- General effects (Sec 2.3 of EG STAR Report)
- General image-space denoising framework
- But use auxiliary features (depth, normals, etc.)
- Basis for methods deployed in industry today

### Random Parameter Filtering

- Sen Darabi 12, importance of each feature
  - Addresses noisy features (e.g. depth of field)
  - Notion of mutual information
- Weighted bilateral filter, very good at low samples
  - Parameters determined by feature importance
  - Auxiliary features are key to beat image denoising
  - Has led to newer methods, commercialization

![Random Parameter Filtering](image2.png)
Subsequent Work

- SURE (Stein’s unbiased risk estimator: general kernels, adaptive sampling, general effects)

Moon et al. local linear or polynomial models, treat as regression. Many other methods

- APR: Polynomial order chosen to minimize error
- Newest methods use deep learning instead

Impact: Offline

- Handle general effects. Sample and denoise (builds on AWR, AAF, FSF, MAAF. Predict general filter kernel)
- Many more sophisticated methods available now; used in almost every major production rendering software
- Based on Deep Learning for Monte Carlo Denoising

Impact: Real-Time

- Extend AAF, FSF, MAAF: Predict Filter based on Deep Learning (sample and AI-based denoising)
- NVIDIA software (OptiX 2017), hardware (RTX 2018)
- 40-year journey: ray tracing curiosity to every pixel