Sampling and Reconstruction of Visual Appearance

CSE 274 [Winter 2018], Lecture 10
Ravi Ramamoorthi
http://www.cs.ucsd.edu/~ravir

Applications
- Monte Carlo Rendering (biggest application)
- Light Transport Acquisition / Many Light Rendering
- Light Fields and Computational Photography
- Animation/Simulation (not covered in course)

- Introduce concepts of sparsity, coherence, compressive sensing for reconstruction

Acquiring Reflectance Field of Human Face [Debevec et al. SIGGRAPH 00]
Illuminate subject from many incident directions

Example Images

Motivation: Image-based Relighting
Sample Lighting Directions

Motivation: Image-based Relighting
Sample Lighting Directions
**Motivation: Image-based Relighting**

Sample Lighting Directions

Relight 256 Samples

Relight 4096 Samples

Relight +10000 Samples

Brute Force Capture Practically Impossible

Relighting as a Matrix-Vector Multiply

\[
\begin{bmatrix}
P_1 & P_2 & \ldots & P_N
\end{bmatrix}
\begin{bmatrix}
T_{11} & T_{12} & \ldots & T_{1M}
T_{21} & T_{22} & \ldots & T_{2M}
\vdots & \vdots & \ddots & \vdots
T_{N1} & T_{N2} & \ldots & T_{NM}
\end{bmatrix}
\begin{bmatrix}
L_1
L_2
\vdots
L_M
\end{bmatrix}
\]

Input Lighting (Cubemap Vector)

Output Image (Pixel Vector)

Precomputed Transport Matrix
Matrix Columns (Images)

\[
\begin{bmatrix}
T_{11} & T_{12} & \cdots & T_{1M} \\
T_{21} & T_{22} & \cdots & T_{2M} \\
T_{31} & T_{32} & \cdots & T_{3M} \\
\vdots & \vdots & \ddots & \vdots \\
T_{N1} & T_{N2} & \cdots & T_{NM}
\end{bmatrix}
\]

(Pre)compute: Ray-Trace Image Cols

\[
\begin{bmatrix}
T_{11} & T_{12} & \cdots & T_{1M} \\
T_{21} & T_{22} & \cdots & T_{2M} \\
T_{31} & T_{32} & \cdots & T_{3M} \\
\vdots & \vdots & \ddots & \vdots \\
T_{N1} & T_{N2} & \cdots & T_{NM}
\end{bmatrix}
\]

(Pre)compute 2: Rasterize Matrix Rows

\[
\begin{bmatrix}
T_{11} & T_{12} & \cdots & T_{1M} \\
T_{21} & T_{22} & \cdots & T_{2M} \\
T_{31} & T_{32} & \cdots & T_{3M} \\
\vdots & \vdots & \ddots & \vdots \\
T_{N1} & T_{N2} & \cdots & T_{NM}
\end{bmatrix}
\]

Outline

- Matrix Row-Column Sampling (Many Lights)
  (clustering for matrix completion of light transport)
- Compressive Sensing for Light Transport
- Matrix Completion

Complex Illumination: A Challenge

Conversion to Many Lights

- Area, indirect, sun/sky

Courtesy Walter et al., Lightcuts, SIGGRAPH 05/06

Hasan, Pellacini, Bala SIGGRAPH 07
A Matrix Interpretation

Pixels (2,000,000)
Lights (100,000)

Problem Statement

- Compute sum of columns

Note: We don’t have the matrix data

Image as a Weighted Column Sum

- The following is possible:
  - Compute very small subset of columns
  - Compute weighted sum

- Use rows to choose a good set of columns!

Exploration and Exploitation

- Compute rows (explore)
- Choose columns and weights?
- Compute columns (exploit)
- Weighted sum

Reduced Matrix

Reduced columns

Clustering Approach

Reduced columns
Choose k clusters
Choose representative columns
Reduced to Full

- Representative columns
- Use the same representatives for the full matrix
- Weighted sum

Full Algorithm

- Compute rows (GPU)
- Cluster reduced columns
- Choose representatives
- Compute columns (GPU)
- Weighted sum

Results

- We show 5 scenes:
- Kitchen, Temple, Trees, Bunny, Grand Central
- Show reference and 5x difference image
- All scenes have 100,000+ lights
- Timings
  - NVidia GeForce 8800 GTX
  - Light / surface sample creation not included

Results: Kitchen

- 388k polygons
- Mostly indirect illumination
- Glossy surfaces
- Indirect shadows
- Our result: 13.5 sec (432 rows + 864 columns)
- Reference: 13 min (using all 100k lights)

Results: Temple

- 2.1m polygons
- Mostly indirect & sky illumination
- Indirect shadows
- Our result: 16.9 sec (500 rows + 950 columns)
- Reference: 20 min (using all 100k lights)

Results: Trees

- 328k polygons
- Complex incoherent geometry
- Our result: 2.9 sec (100 rows + 200 columns)
- Reference: 14 min (using all 100k lights)
Results: Bunny
- 869k polygons
- Incoherent geometry
- High-frequency lighting
- Kajiya-Kay hair shader

Our result: 3.8 sec
(100 rows + 200 columns)
Reference: 10 min
(using all 100k lights)

Results: Grand Central
- 1.5m polygons
- Point lights between stone blocks

Our result: 24.2 sec
(588 rows + 1176 columns)
Reference: 44 min
(using all 100k lights)

Outline
- Matrix Row-Column Sampling (Many Lights)
  (clustering for matrix completion of light transport)
- Compressive Sensing for Light Transport
- Matrix Completion

Gu et al. ECCV 08
Peers et al. SIGGRAPH 09
Sen and Darabi EG 09 (reading)

Compressible / Sparseness
All Coefficients
65 Largest Coeff.

Motivation: Image-based Relighting
Brute Force Capture Practically Impossible
Sample Lighting Directions

Measurements
Measured Quanta
Compressive Sensing: A Brief Introduction

- Sparsity / Compressibility: Signals can be represented as a few non-zero coefficients in an appropriately-chosen basis, e.g., wavelet, gradient, PCA.

- For sparse signals, acquire measurements (condensed representations of the signals) with random projections.

$$A \begin{bmatrix} x \end{bmatrix} = b$$

where $A_{m \times n}$, $x_{n \times 1}$, and $b_{m \times 1}$.
Compressive Sensing

Sparse Signal: \( x \)

Measurement Ensemble: \( \Phi \)

\[ \text{Compressive Sensing} \]

\[ \text{Compressive Sensing} \]

\[ \text{Compressive Sensing} \]

\[ \text{Compressive Sensing} \]

\[ \text{Compressive Sensing} \]

\[ \text{Compressive Sensing} \]
Compressive Sensing

\[ x = \arg\min_x ||x||_1 \text{ s.t. } \Phi x = y \]

\[ M \sim K \log N \]

Brute Force: Result

Scene: Diffuse Sphere
Lighting Resolution: 128 x 128
Measurements: 1000 Normal Distributed Noise Light Conditions
Reconstruction: 100 Haar Wavelet Coefficients

Multi-resolution Approach
Multi-resolution Approach

Compressive Decoding

Init

Reflectance Func.

Results

Brute Force Algorithm Hierarchical Algorithm

Resolution

1000 Measurements
128 x 128 Lighting Resolution
128 Haar Wavelet Coefficients

Resolution

1000 Measurements
128 x 128 Lighting Resolution
128 Haar Wavelet Coefficients

Results

Reference

1000 Measurement
128 x 128 Lighting Resolution
128 Haar Wavelet Coefficients
Inhomogeneous Participating Media
Volume densities rather than boundary surfaces. Efficiency in acquisition is critical, especially for time-varying participating media.

Drifting Smoke of Incense (532fps Camera)
Mixing a Pink Drink with Water (1000fps Camera)

Video clips are from http://www.lucidmovement.com

Milk Dissolving: One Instance of time
- Milk drops dissolving in a water tank.

Photograph
Measurements (24 images of size 128x255)
Reconstructed Volume (128x128x255)

Compressive Structured Light
- Projector: DLP, 1024x768, 360 fps
- Camera: Dragonfly Express 8bit, 320x140 at 360 fps
- 24 measurements per time instance, and thus recover dynamic volumes up to 360/24 = 15 fps.

Gu, Nayar, Grinspun, Belhumeur, Ramamoorthi 08, 13

Milk Dissolving: Time-varying Volume
- Milk drops dissolving in a water tank.

Video (15fps)
Reconstructed Volume (128x128x255)
Outline

- Matrix Row-Column Sampling (Many Lights) (clustering for matrix completion of light transport)
- Compressive Sensing for Light Transport
- Matrix Completion
  - Extension to compressive sensing: Low rank matrices
  - Minimize matrix norm (rank), given some entries
  - Combine many ideas seen previously

Huo et al. SIGGRAPH Asia 16

Outline

- Matrix Completion
  - Extension to compressive sensing: Low rank matrices
  - Minimize matrix norm (rank), given some entries
  - Combine many ideas seen previously

Huo et al. SIGGRAPH Asia 16

Results (Participating Media)

Summary

- Light Transport for Acquisition, Many Light Rendering
- Compressive Sensing for projected patterns
- Matrix Completion for many light rendering
- Leverages popular ideas in applied math
- Consider all forms of coherence