

Sampling and Reconstruction of Visual Appearance: From Denoising to View Synthesis

CSE 274 [Fall 2022], Lecture 5

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Applications: Sampling/Reconstruction

- Monte Carlo Rendering
- Light Transport Acquisition
- Light Fields and Computational Photography
- View synthesis
- Animation/Simulation (not covered in course)

- Brief overview of these applications today, and opportunities/history for sampling/reconstruction

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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?

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Monte Carlo Path Tracing



1000 paths/pixel

Jensen

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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]

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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

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Directional Coherence Maps

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

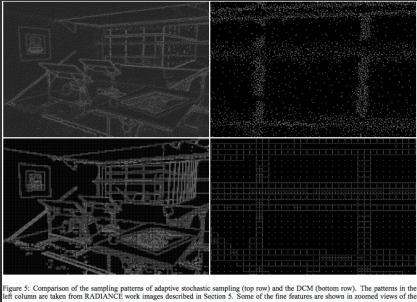
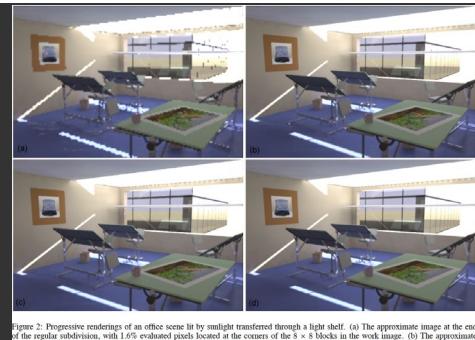


Figure 5: Comparison of the sampling patterns of adaptive stochastic sampling (top row) and the DCM (bottom row). The patterns in the left column are taken from RADIANCE work images described in Section 5. Some of the fine features are shown in zoomed views of the lamppost features in the right column. These zoomed views correspond to the same region as the zoomed views in Fig. 4.

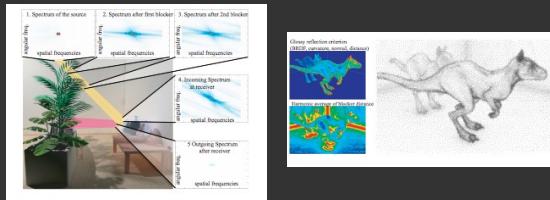
Directional Coherence Maps (Guo 98)



Guo 98

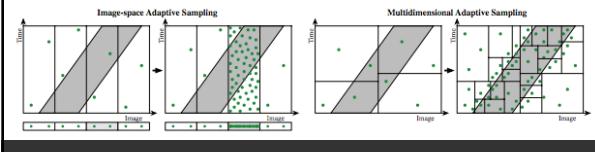
Resurgence (2008 -)

- Eurographics 2015 STAR report by Zwicker et al. [former UCSD faculty, now at Maryland]
- [Durand et al. 2005] Frequency analysis light transport. Proposed use for adaptive sampling. Not very practical



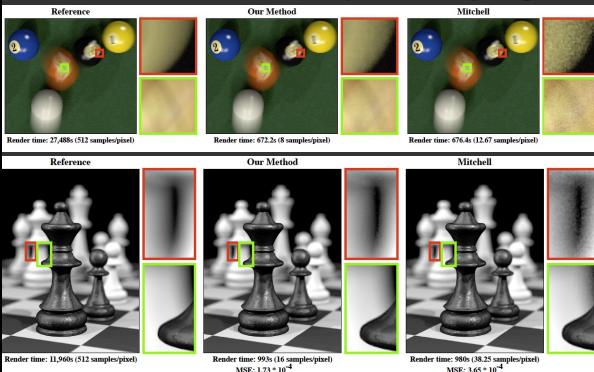
Multi-Dimensional Adaptive Sampling

- 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



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Multidimensional Adaptive Sampling



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Multidimensional Adaptive Sampling

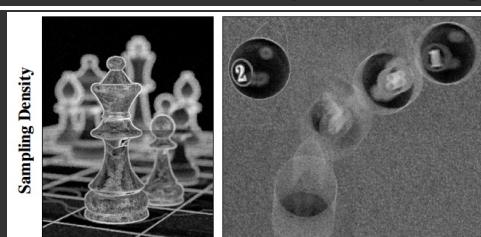


Figure 10: Visualizations of projected sample distributions using our method for the chess scene from Figure 8 and the pool scene from Figure 7. Our adaptive sampler places samples both around high frequency image discontinuities (in-focus chess piece and stationary pool ball) as well as in regions which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

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Multi-Dimensional Adaptive Sampling



Motion Blur and Depth of Field 32 samples per pixel

A-Priori Methods

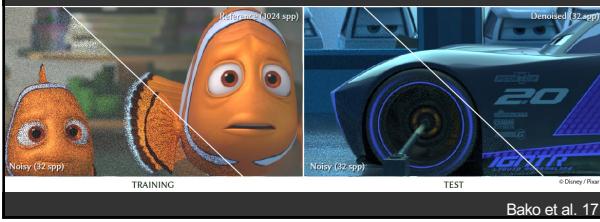
- Egan et al. 2009: Frequency Analysis and Sheared Filtering for Motion Blur; first deep use frequency anal.



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A-Posteriori Methods

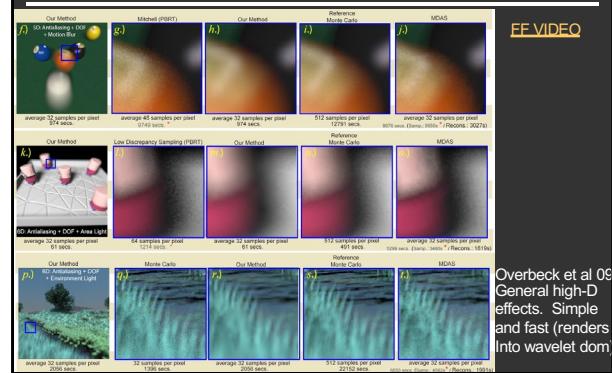
- Adaptive Wavelet Rendering (Overbeck et al. 2009)
- Handle general effects. Sample and denoise
- Many more sophisticated methods available now; used in almost every major production rendering software



Bako et al. 17

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Adaptive Wavelet Rendering



EE VIDEO

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Real-Time

- Axis-Aligned Filtering (Mehta et al. 12, 13, 14)
- Optix plus image-space filtering
- Newer extensions to sheared filtering
- Most recent work (NVIDIA) is fully general, 1 sample per pixel, using modern machine learning methods (similar ideas relevant in offline rendering as well)
- Huge impact in real-time, video games, essential in modern real-time rendering based on deep learning

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Real-Time MAAF Video

Multiple Axis-Aligned Filters for Rendering of Combined Distribution Effects

Online submission ID: 1000

NO AUDIO

Recurrent Autoencoder Video (Chaitanya et al. 17)

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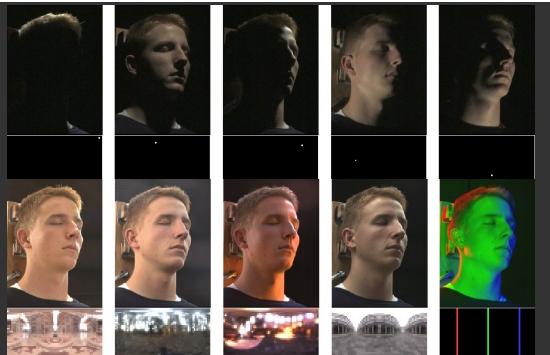
Acquiring Reflectance Field of Human Face [Debevec et al. SIGGRAPH 00]

Illuminate subject from many incident directions



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Example Images



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Motivation: Image-based Relighting



Sample Lighting Directions

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Motivation: Image-based Relighting



Sample Lighting Directions

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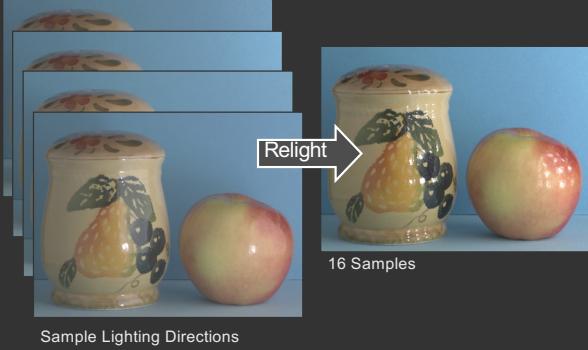
Motivation: Image-based Relighting



Sample Lighting Directions

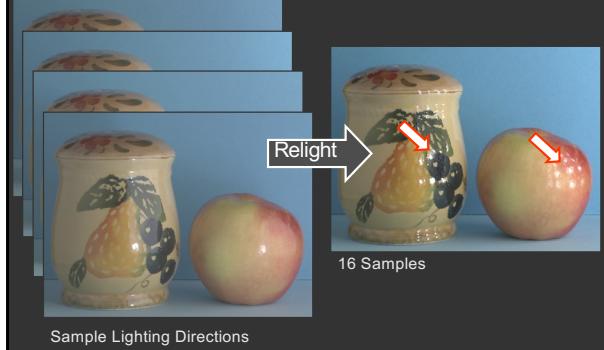
24

Motivation: Image-based Relighting



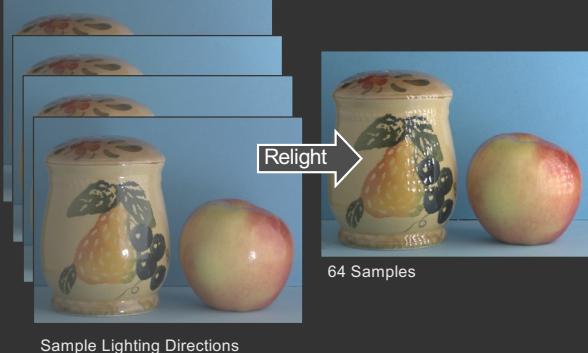
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Motivation: Image-based Relighting



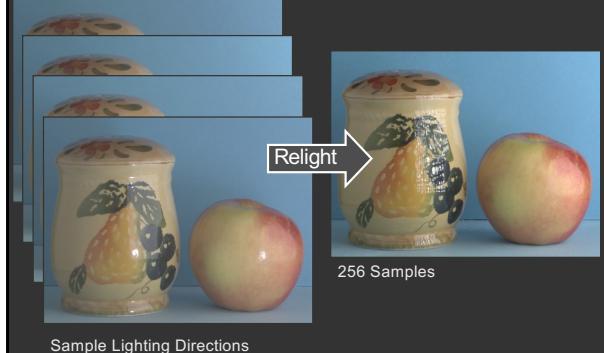
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Motivation: Image-based Relighting



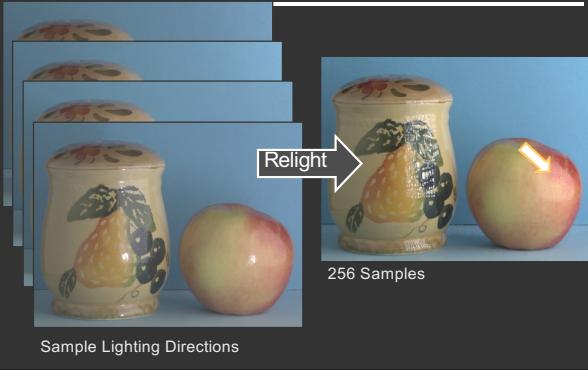
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Motivation: Image-based Relighting



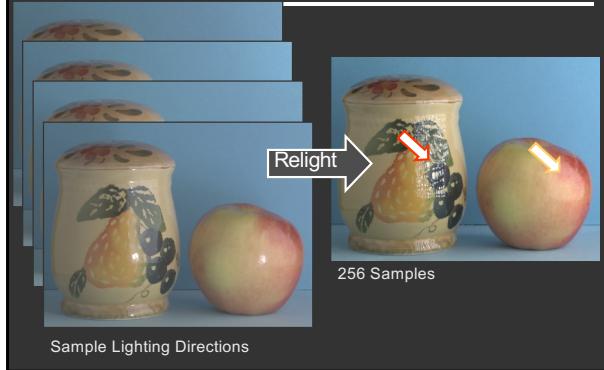
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Motivation: Image-based Relighting



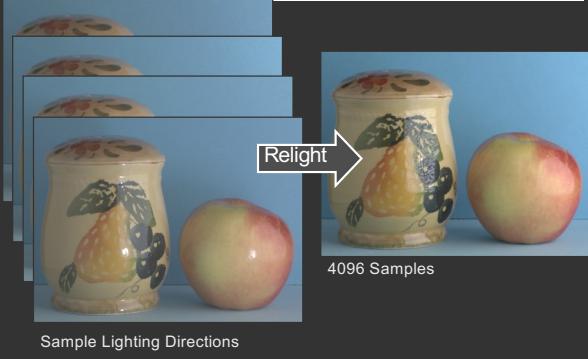
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Motivation: Image-based Relighting



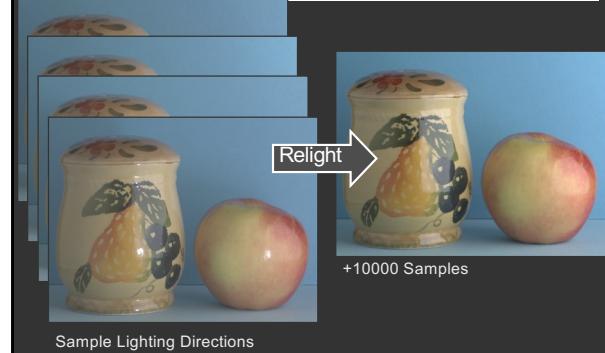
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Motivation: Image-based Relighting



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Motivation: Image-based Relighting



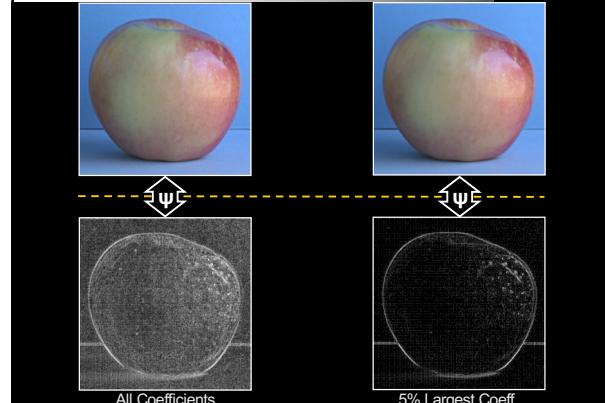
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Motivation: Image-based Relighting



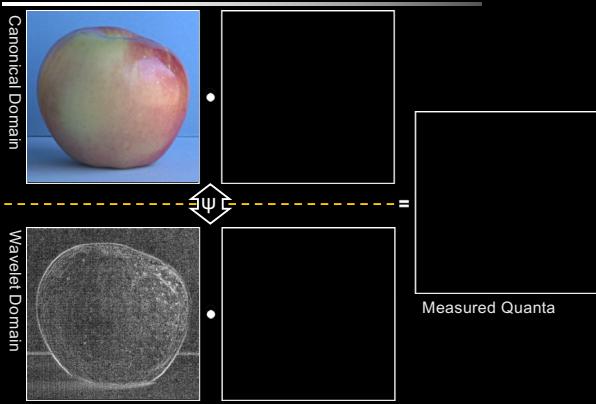
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Compressible / Sparseness



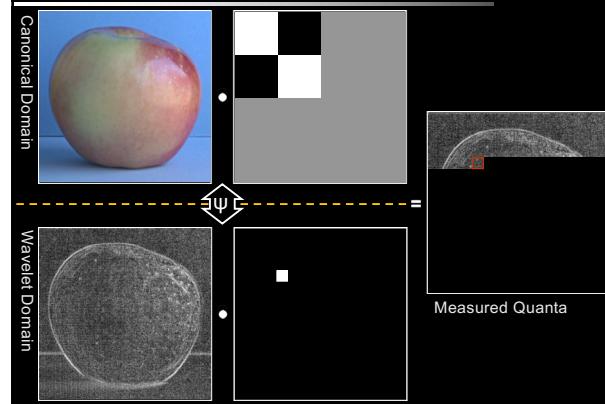
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Measurements



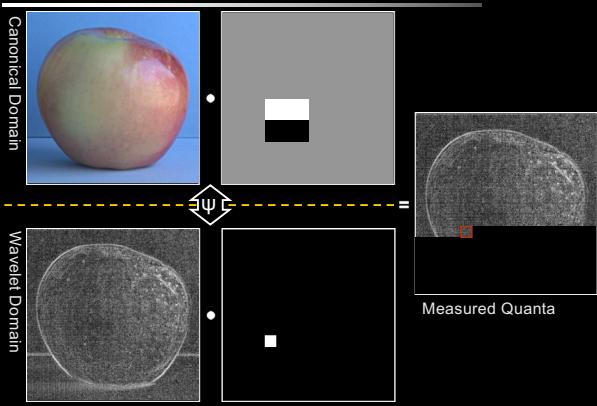
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Measurements



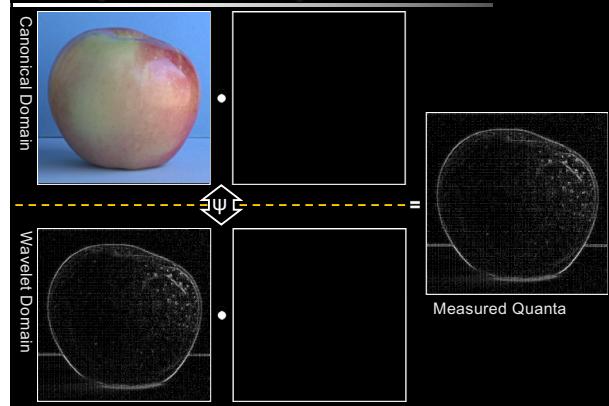
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Measurements



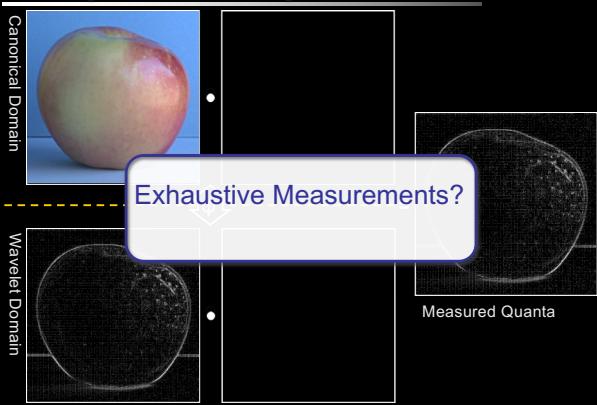
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Compressible / Sparseness



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Compressive / Sparseness



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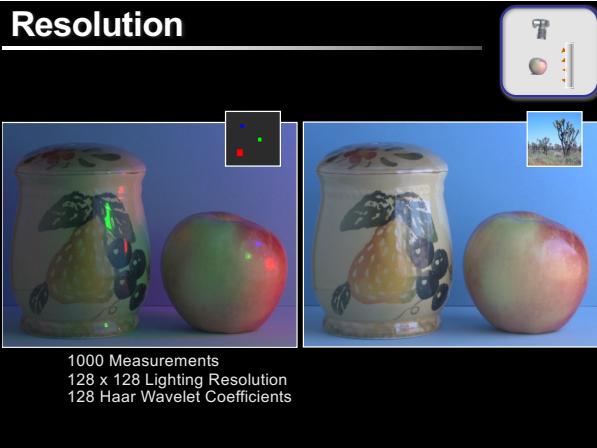
Compressive Sensing: A Brief Introduction

- 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**.

$$\mathbf{A} \begin{pmatrix} \text{Measurement Ensemble} \\ m \times n, \text{ where } m < n \end{pmatrix} \begin{pmatrix} \text{Signal} \\ n \times 1 \end{pmatrix} = \begin{pmatrix} \text{Measurements} \\ m \times 1 \end{pmatrix} \mathbf{b}$$

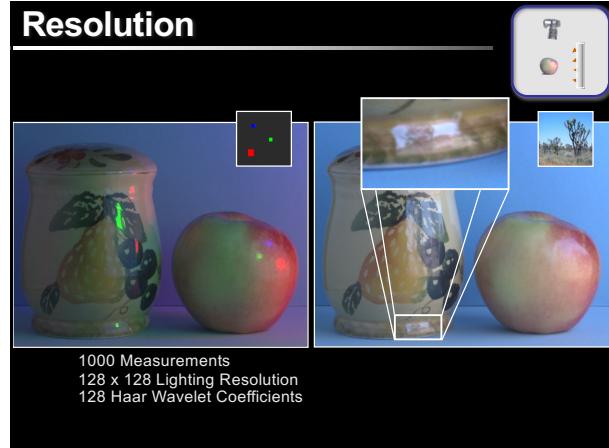
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Resolution



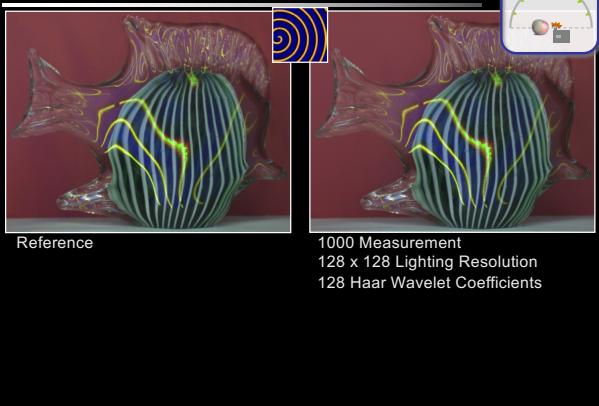
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Resolution



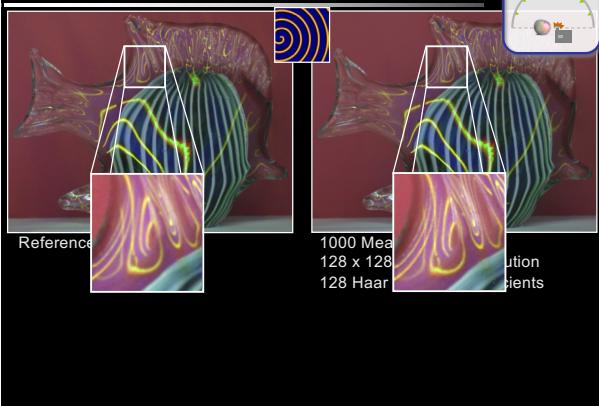
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Results



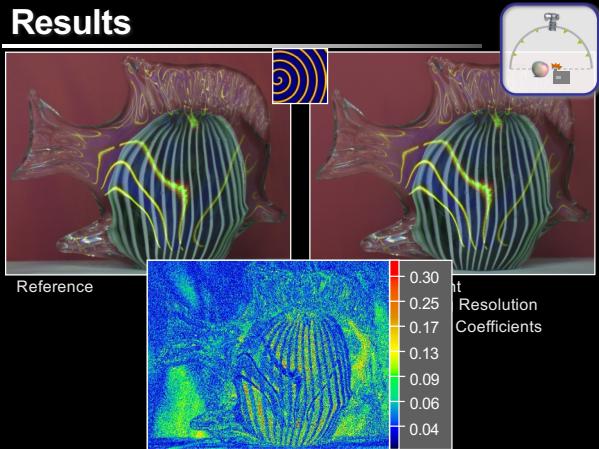
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Results



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Results



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Light Field Rendering

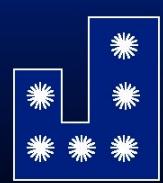
Marc Levoy Pat Hanrahan



Computer Science Department
Stanford University

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Apple's QuickTime VR



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Generating New Views

Problem: fixed vantage point/center

One Solution: view interpolation

- Interpolating between range images (Chen and Willams, 1993)
- Correspondences and epipolar analysis (McMillan and Bishop, 1995)
- Requires depths or correspondences:
must be extracted from acquired imagery
relatively expensive and error-prone morph

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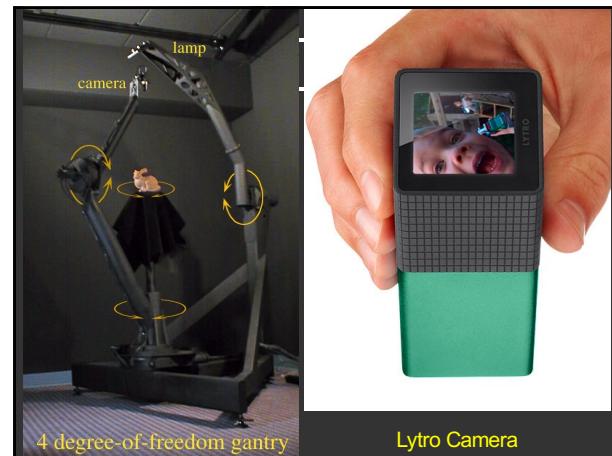
Light Fields

Gershun's and Moon's idea of a light field: 
Radiance as a function of a ray or line: $L(x, y, z, \theta, \phi)$

- In "free space" (no occluders) 5D reduces to 4D
 - Exterior of the convex hull of an object
 - Interior of an environment
- Images are 2D slices
 - Insert acquired imagery
 - Extract image from a given viewpoint

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4D Light Field



4 degree-of-freedom gantry

Lytro Camera

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Light Field as a 2D Array of Images

Camera Array



$$L(r) = L(u, v, s, t)$$

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Dual Interpretation of Light Field

Plenoptic Light Field
Field radiance



UV Array of ST Images

Surface Light Field
Surface radiance



ST Array of UV Images

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Compression Example



Original



Compressed 120:1

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Light fields



Refocusing



Viewpoint Change

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Recent Light Field Cameras



Google VR light field camera



Pelican



Light



RayTrix



Lytro Illum

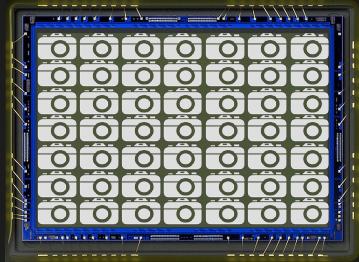
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Recent Light Field Cameras



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Resolution trade-off



UC San Diego Kalantari et al.



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Solution: angular super-resolution



UC San Diego Kalantari et al.

Straightforward solution

- Model the process with a single CNN



UC San Diego

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Single CNN's result



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High-level idea

- Follow the pipeline of existing techniques and break the process into two components
Goesele et al. [2010]; Chaurasia et al. [2013]
 - Disparity estimator
 - Color predictor
- Model the components using learning
- Train both models simultaneously



UC San Diego

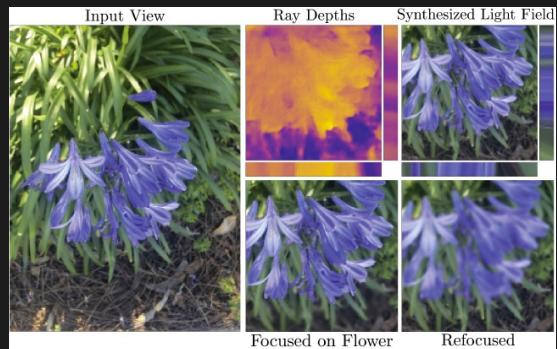
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Our result



UC San Diego Kalantari et al.

4D RGBD Light Fields from 2D Image



UC San Diego

Srinivasan et al. ICCV 17

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Light Fields with 4000x fewer views



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NEURAL RADIANCE FIELDS

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Summary

- Brief overview of applications, some algorithms
- Will cover in greater detail in rest of course
- Biggest practical progress in Monte Carlo rendering: order of magnitude speedups
- Widely used in production, also in real-time
- Very relevant in light transport acquisition
- Sampling/Reconstruction key for light fields
- View Synthesis other major focus, huge explosion
- Many other applications: PRT, Animation, etc.

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