Computational Imaging for Self-Driving Vehicles

Jan Kautz  Ramesh Raskar  Achuta Kadambi  Guy Satat
Computational Imaging for Self-Driving Vehicles

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Computational Imaging  
Self Driving Cars  
Novel Sensors  
LIDAR

Challenging Weather  
Open Problems  
Deep Learning
Sample Slides for Module 1:

Introduction to Computational Imaging and Implications for Self-Driving Cars
Bit Hacking

Photon Hacking

Optics
Displays
Sensors
Illumination

Computational Light Transport

Computational Photography

Signal Processing
Computer Vision
Machine Learning

Bit Hacking
Plenoptic Light Transport

\[ I(x, y, \theta_1, \theta_2, \lambda, \rho, t, n) \]
Plenoptic Light Transport

Viewpoint Diversity
(Light Field Cam)

$I(x, y, \theta_1, \theta_2, \lambda, \rho, t, n)$

Plenoptic Light Transport

$I(x, y, \theta_1, \theta_2, \lambda, \rho, t, n)$

Viewpoint Diversity
(Light Field Cam)

Wavelength Diversity
(Hyperspectral Cam)

Plenoptic Light Transport

$I(x, y, \theta_1, \theta_2, \lambda, \rho, t, n)$

Viewpoint Diversity
(Light Field Cam)

Wavelength Diversity
(Hyperspectral Cam)

Polarization Diversity
(Photos, Shape, Scatter)

Plenoptic Light Transport

$I(x, y, \theta_1, \theta_2, \lambda, \rho, t, n)$

- Viewpoint Diversity
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- Wavelength Diversity
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- Polarization Diversity
  (Photos, Shape, Scatter)

- Time of Flight
  (3D, Scattering)

Plenoptic Light Transport

\[ I(x, y, \theta_1, \theta_2, \lambda, \rho, t, n) \]

- **Viewpoint Diversity**
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  (3D, Scattering)

Plenoptic Light Transport

\[ \Sigma_n I(x, y, \theta_1, \theta_2, \lambda, \rho, t, n) \]

- **Viewpoint Diversity** (Light Field Cam)
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- **Bounce Index** (Scattering)
- **Time of Flight** (3D, Scattering)

Plenoptic Light Transport

\[ \int \sum_n I(x, y, \theta_1, \theta_2, \lambda, \rho, t, n) \]

Viewpoint Diversity
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Plenoptic Light Transport

\[ \int_\lambda \int_\rho \int_t \sum_n I(x, y, \theta_1, \theta_2, \lambda, \rho, t, n) \]

- **Viewpoint Diversity** (Light Field Cam)
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Plenoptic Light Transport

\[ \int_{\theta_1} \int_{\theta_2} \int_{\lambda} \int_{\rho} \int_{t} \sum_{n} I(x, y, \theta_1, \theta_2, \lambda, \rho, t, n) \]

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(3D, Scattering)

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Plenoptic Light Transport

\[ I(x, y) = \int_{\theta_1} \int_{\theta_2} \int_{\lambda} \int_{\rho} \int_{t} \sum_n I(x, y, \theta_1, \theta_2, \lambda, \rho, t, n) \]

Viewpoint Diversity
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Time of Flight
(3D, Scattering)

Three lidar systems

A forward facing camera

Radar sensors

Self-driving sensors
<table>
<thead>
<tr>
<th></th>
<th>Classification</th>
<th>Resolution</th>
<th>Localization</th>
<th>Availability</th>
<th>Any Weather</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Radar</strong></td>
<td>✓</td>
<td>×</td>
<td>×</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td><strong>Ultrasonic</strong></td>
<td>×</td>
<td>×</td>
<td>×</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td><strong>Camera</strong></td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>×</td>
</tr>
<tr>
<td><strong>LiDAR</strong></td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>×</td>
<td>×</td>
</tr>
</tbody>
</table>
- Resolution
- Optical Contrast
- Non ionizing
- Availability of fluorophores
Optical Contrast

Visible light

X-Ray

Wildlife Rehabilitation Center of Minnesota
Light and Matter in a Nutshell

Object → Lens

Absorption

Scattering
Seeing Around Corners

Vetlen 2012
Single Photon Sensitive Imaging

Time-of-Flight Imaging Sensors

Time-of-Flight Sensors: Computes depth based on speed of light (aka SONAR with light.)

Time-of-Flight Principle: Distance of object is proportional to time traveled by light

Continuous Wave ToF

Phase $\propto \frac{2d}{c}$

Pixel
Light source
Distance
Object

Pulsed/Impulse Based ToF

Time-of-Flight $\propto \frac{2d}{c}$

Example: Femto-photography

Distance
Object
Nanophotography

[Kadambi et al 2013]
Real-time Localization

Figure 9: Imaging around the corner. (left) We use the same scene from Figure 12a but replace the moving ping pong ball with a “T” shaped object. (right) Using pseudoinverse beamforming, we are able to recover the image shown on the right.

Kadambi, Zhao, Shi, Raskar. "Occluded Imaging with Time of Flight Sensors." ACM ToG 2016 (Pres. at SIGGRAPH)
Wavelength vs Shininess

\[ \text{FWHM}^{\ell} = d \arcsin \left( \frac{\lambda \gamma}{\lambda + D \gamma} \right) \]
Multi-Dimensional Light Transport
Sample Slides for Module 3:
Emerging Vision Sensors for Self-Driving Cars
What’s next for 3D imaging?
Microsoft Kinect v2
Microsoft Kinect v2
Multistripe Laser Scan
Multistripe Laser Scan

NextEngine 3D

$3000 USD

Raster
Multistripe Laser Scan

NextEngine 3D

$3000 USD

Raster
Polarized 3D

3D Photo w.

$30 Pol. Filter
Polarized 3D

3D Photo w.

$30 Pol. Filter
Polarized 3D

3D Photo w.

$30 Pol. Filter
\[ I(x, y) = \int_{\theta_1} \int_{\theta_2} \int_{\lambda} \int_{\rho} \int_{t} \sum_n I(x, y, \theta_1, \theta_2, \lambda, \rho, t, n) \]

**Viewpoint Diversity**  
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(Photos, Shape, Scatter)

**Bounce Index**  
(Scattering)

**Time of Flight**  
(3D, Scattering)

Polarization of Light
Polarization of Light
Polarization of Light

Plane of Polarization
Polarization of Light

Plane of Polarization

Plane of Polarization
Cool 2D Photos

Photo Credit: Bob Atkins
Cool 2D Photos

Photo Credit: Bob Atkins
Polarization used in 2D photography...

... But what about Polarizers for 3D Cams?
Shape from Polarization
Shape from Polarization

Diagram showing a vector $\vec{n}$ pointing towards an object.
Shape from Polarization
Shape from Polarization

\[ \theta \]

Object

\[ \theta' \]
Shape from Polarization

\[ \theta \]

\[ \theta' \]

Object

\[ \vec{n} \]
Shape from Polarization

Old Principle [Fresnel 1819]

\[ r_\perp = \frac{\cos \theta_i - n \cos \theta_t}{\cos \theta_i + n \cos \theta_t} \]
\[ r_\parallel = \frac{\cos \theta_i - n \cos \theta_t}{\cos \theta_t + n \cos \theta_i} \]

SfP crux: Solve for theta
Old Principle [Fresnel 1819]

\[
\begin{align*}
    r_\perp &= \frac{\cos \theta_i - n \cos \theta_t}{\cos \theta_i + n \cos \theta_t} \\
    r_\parallel &= \frac{\cos \theta_i - n \cos \theta_t}{\cos \theta_t + n \cos \theta_i}
\end{align*}
\]

SfP crux: Solve for theta

⚠️ Need to know refractive index
Image Formation Model

\[ \varphi \]

\[ I_{\text{max}} \]

\[ I_{\text{min}} \]

Intensity

Polarizer Angle (Radians)

0 1 2 3 4 5 6
Image Formation Model

\[ I(\phi_{\text{pol}}) = \frac{I_{\text{max}} + I_{\text{min}}}{2} + \frac{I_{\text{max}} - I_{\text{min}}}{2} \cos\left(2\left(\phi_{\text{pol}} - \phi\right)\right) \]
Image Formation Model

\[ I(\phi_{pol}) = \frac{I_{\max} + I_{\min}}{2} + \frac{I_{\max} - I_{\min}}{2} \cos\left(2(\phi_{pol} - \phi)\right) \]

Suppose \( \exists \phi \) and \( \phi' = \phi + \pi \)
Image Formation Model

\[ I(\phi_{pol}) = \frac{I_{\text{max}} + I_{\text{min}}}{2} + \frac{I_{\text{max}} - I_{\text{min}}}{2} \cos\left(2\left(\phi_{pol} - \phi\right)\right) \]

Suppose \( \exists \phi \) and \( \phi' = \phi + \pi \)

\( \text{Azimuthal Ambiguity problem with} \ 2^P \ \text{solutions} \)
Why is Shape from Polarization Unpopular?

1. $\pi$ Ambiguity in Surface Normal
Why is Shape from Polarization Unpopular?

1. $\pi$ Ambiguity in Surface Normal
Why is Shape from Polarization Unpopular?

1. $\pi$ Ambiguity in Surface Normal

2. Refractive Distortion
Why is Shape from Polarization Unpopular?

1. $\pi$ Ambiguity in Surface Normal

2. Refractive Distortion
Why is Shape from Polarization Unpopular?

1. $\pi$ Ambiguity in Surface Normal

2. Refractive Distortion

3. Low SNR for some geometries

4. Usual challenges of integrating surface normals...
Shape from Polarization in the Lab

Polarization Inverse Rendering

Real Image

Synthesized Image

Miyazaki ICCV 2003

Shape from Diffuse Polarization

Atkinson TIP 2006
Shape from Polarization in the Lab

Polarization Inverse Rendering

Real Image  Synthesized Image

Shade from Diffuse Polarization

Miyazaki ICCV 2003  Atkinson TIP 2006

SfP never as popular as shading or photometric stereo
Frequency Analysis

3D Shape  Depth Map

Ground Truth
Frequency Analysis

3D Shape | Depth Map | Slice | 1D FFT

Ground Truth
Frequency Analysis

- 3D Shape
- Depth Map
- Slice
- 1D FFT

Ground Truth

Coarse Depth
Frequency Analysis

3D Shape | Depth Map | Slice | 1D FFT
--- | --- | --- | ---
Ground Truth | ![3D Shape](image1.png) | ![Slice](image2.png) | ![1D FFT](image3.png)
Coarse Depth | ![3D Shape](image4.png) | ![Slice](image5.png) | ![1D FFT](image6.png)
Frequency Analysis

3D Shape  Depth Map  Slice  1D FFT

Ground Truth

Coarse Depth

Polarization

ωLPF
Frequency Analysis

3D Shape  Depth Map  Slice  1D FFT

Ground Truth

Coarse Depth

Polarization

ωLPF
Frequency Analysis

3D Shape

Depth Map

Slice

1D FFT

Ground Truth

Coarse Depth

Polarization

ω_{LPF}
Spanning Tree Integration

Full Gradients
Polarized 3D Fuses Depth and Polarization

Spanning Tree Integration

Full Gradients
Polarized 3D Fuses Depth and Polarization

Spanning Tree Integration

Full Gradients

Minimum Spanning Tree
Polarized 3D Fuses Depth and Polarization

Spanning Tree Integration

\[
\begin{bmatrix}
\lambda \mathbf{M} \otimes \mathbf{I} \\
\nabla^2_S
\end{bmatrix}
\mathbf{VEC}(\widehat{\mathbf{D}}) =
\begin{bmatrix}
\lambda \mathbf{VEC}(\mathbf{M} \otimes \mathbf{D}) \\
\nabla^T_S(\mathbf{N}_{corr})
\end{bmatrix}
\]

Full Gradients
Minimum Spanning Tree

Ground Truth Surface
Full Integration
Spanning Tree Integration
Assumptions

Unpolarized World Assumption

Dielectric or Low-frequency Material Transition

No specular interreflections

Diffuse-dominant or Specular-dominant surfaces with slack
Challenging Materials
Challenging Materials

Kinect
Challenging Materials

Kinect

Shading [Wu 14]
Challenging Materials

Kinect  
Shading [Wu 14]  
Polarized 3D
Challenging Materials

Kinect

Shading [Wu 14]

Polarized 3D
Break Lighting Assumptions

Kinect
Break Lighting Assumptions

Kinect

Shading [Wu 14]

Polarized 3D
Break Lighting Assumptions

Kinect

Shading [Wu 14]

Polarized 3D
Sensing with Compressive Sampling
Single Pixel Camera – Pros and Cons

- **Hardware complexity**: Regular Camera vs. Single Pixel Camera
- **Software complexity**: FemtoPixel Camera
- **Acquisition Time**: Regular Camera vs. Single Pixel Camera
Lensless Imaging with a Femto-Pixel

Satat, Tancik, Raskar IEEE Trans. Computational Imaging 2017
Lensless Imaging with a Femto-Pixel

Traditional  Our approach

50  50

Regular pixel  Femto-pixel
Framework for Imaging with a Femto-Pixel
Sample Slides for Module 4:

Imaging in Challenging Weather Conditions
Light Scatters
How to Overcome Scattering

- Hardware
- Computational imaging
- Image processing
Lessons learned from seeing into the body
Optics Based Solutions

Photon gating:
• Angle
• Time
• Polarization

Not enough photons
Optics Based Solutions
Optics Based Solutions

Long iterative process
Use All Photons!

Computationally Invert Scattering

Satat, Heshmat, Raviv, Raskar Nature Scientific Reports 2016
• Estimate target
• Estimate scattering
10,000,000,000 Slower

Time
A scene is multiplied by a scatterer to produce a measurement. The equation is given by:

\[ s(x, y) \ast K(x, y, t) = m(x, y, t) \]
Estimating the Scattering - $K(x, y, t)$

- Point Spread Function
- Probabilistic interpretation:
  - Probability to measure photon at specific location and time
  - Bayes rule

\[
K(x, y, t) = f_T(t) W(x, y|t)
\]

- Probability to measure a photon at time $t$
- Given the time, probability to measure a photon at location $x, y$
Estimating the Scattering - $K(x, y, t)$

$$K(x, y, t) = f_T(t) \ W(x, y|t)$$

• $f_T(t), \ W(x, y|t) \ – \ Easier \ to \ estimate$

• Assumptions:
  • Enough samples to satisfy law of large numbers
We illuminate the entire object simultaneously with a pulse of light.
Light scatters as it propagates through the tissue.
Recovery of Slits

Time-Averaged

Ballistic

All Photon

Distance [cm]
## Results

<table>
<thead>
<tr>
<th>Mask</th>
<th>Time Averaged</th>
<th>Ballistic</th>
<th>All Photons</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1.png" alt="A" /></td>
<td><img src="image2.png" alt="Time Averaged A" /></td>
<td><img src="image3.png" alt="Ballistic A" /></td>
<td><img src="image4.png" alt="All Photons A" /></td>
</tr>
<tr>
<td><img src="image5.png" alt="5mm" /></td>
<td><img src="image6.png" alt="24.25 mm" /></td>
<td><img src="image7.png" alt="13.25 mm" /></td>
<td><img src="image8.png" alt="5.95 mm" /></td>
</tr>
<tr>
<td><img src="image9.png" alt="PSNR: 10.30 dB, SSIm: 0.19" /></td>
<td><img src="image10.png" alt="PSNR: 14.74 dB, SSIm: 0.17" /></td>
<td><img src="image11.png" alt="PSNR: 14.30 dB, SSIm: 0.27" /></td>
<td><img src="image12.png" alt="PSNR: 18.64 dB, SSIm: 0.79" /></td>
</tr>
</tbody>
</table>
# Invariant to Layered Material

<table>
<thead>
<tr>
<th>Ground truth</th>
<th>Material 1</th>
<th>Material 2</th>
<th>Material 3</th>
<th>Material 4</th>
</tr>
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<tbody>
<tr>
<td><img src="image1.png" alt="Ground truth" /></td>
<td><img src="image2.png" alt="Material 1" /></td>
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<td><img src="image9.png" alt="Material 3" /></td>
<td><img src="image10.png" alt="Material 4" /></td>
</tr>
</tbody>
</table>
Properties of All Photons Imaging

• Recovers scatterer and target
  • Calibration free

• Minimal assumptions

• Works with layered materials

• Doesn't require raster scan
Challenges
Computational Imaging for Autonomous Vehicles

Sample Slides for Module 5:

Data Driven Computational Imaging