CVPR 2018

Computational Imaging for Self-Driving Vehicles

Jan Kautz Ramesh Raskar Achuta Kadambi Guy Satat

Computational Imaging for Self-Driving Vehicles

Jan Kautz

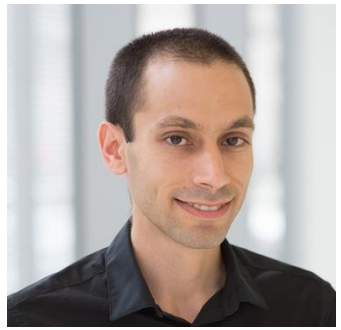
NVIDIA

Ramesh Raskar

MIT

Achuta Kadambi

MIT



Guy Satat

MIT

Computational Imaging

Self Driving Cars

Novel Sensors

LIDAR

Challenging Weather

Open Problems

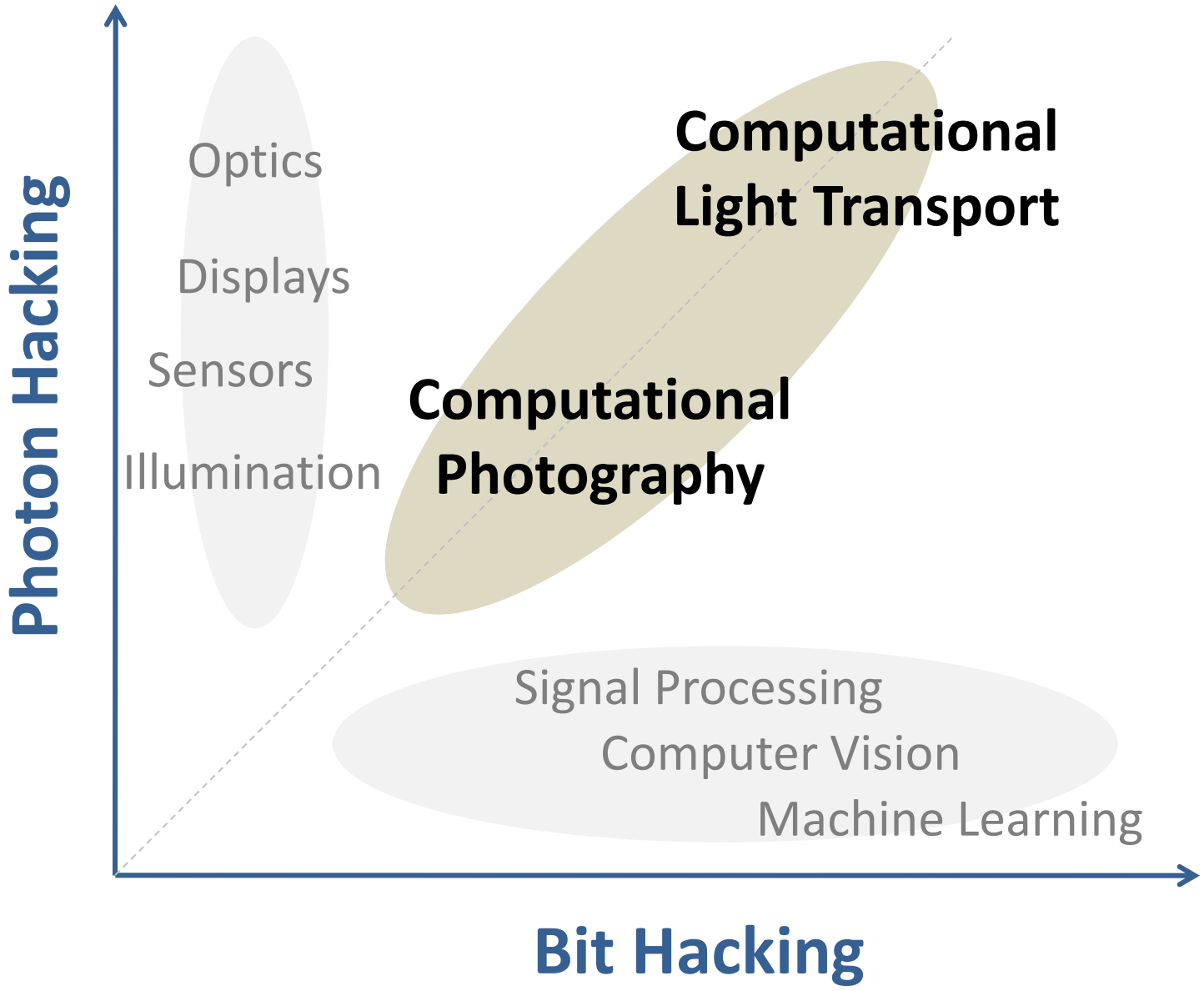
Deep Learning

CVPR 2018

Computational Imaging for Self-Driving Vehicles

Sample Slides for Module 1:

Introduction to Computational Imaging
and
Implications for Self-Driving Cars


Photon Hacking
Optics
Displays
Sensors
Illumination
Computational
Light Transport
Computational
Photography
Signal Processing
Computer Vision
Machine Learning
Bit Hacking

Plenoptic Light Transport

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

Adelson and Bergen “The Plenoptic Function…” MIT Press 1991

Plenoptic Light Transport

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

Viewpoint Diversity
(Light Field Cam)

Adelson and Bergen "The Plenoptic Function…" MIT Press 1991

Plenoptic Light Transport

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

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Wavelength Diversity
(Hyperspectral Cam)

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Plenoptic Light Transport

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(Light Field Cam)

Wavelength Diversity
(Hyperspectral Cam)

Polarization Diversity
(Photos, Shape, Scatter)

Adelson and Bergen "The Plenoptic Function…" MIT Press 1991

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Wavelength Diversity
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Polarization Diversity
(Photos, Shape, Scatter)

Time of Flight
(3D, Scattering)

Adelson and Bergen "The Plenoptic Function…" MIT Press 1991

Plenoptic Light Transport

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Wavelength Diversity
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Polarization Diversity
(Photos, Shape, Scatter)

Time of Flight
(3D, Scattering)

Bounce Index
(Scattering)

Adelson and Bergen "The Plenoptic Function…" MIT Press 1991

Plenoptic Light Transport

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

Viewpoint Diversity
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Wavelength Diversity
(Hyperspectral Cam)

Polarization Diversity
(Photos, Shape, Scatter)

Time of Flight
(3D, Scattering)

Bounce Index
(Scattering)

Adelson and Bergen "The Plenoptic Function…" MIT Press 1991

Plenoptic Light Transport

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

Viewpoint Diversity
(Light Field Cam)

Wavelength Diversity
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Polarization Diversity
(Photos, Shape, Scatter)

Time of Flight
(3D, Scattering)

Bounce Index
(Scattering)

Adelson and Bergen "The Plenoptic Function…" MIT Press 1991

Plenoptic Light Transport

$$\int_{\rho}\int_{t}\Sigma_n I(x, y, \theta_1, \theta_2, \lambda, \rho, t, n)$$

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Adelson and Bergen "The Plenoptic Function…" MIT Press 1991

Plenoptic Light Transport

$$\int_{\lambda}\int_{\rho}\int_{t}\Sigma_n I(x, y, \theta_1, \theta_2, \lambda, \rho, t, n)$$

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Plenoptic Light Transport

$$I(x,y) = \int_{\theta_1}\int_{\theta_2}\int_{\lambda}\int_{\rho}\int_{t} \Sigma_n I(x,y,\theta_1,\theta_2,\lambda,\rho,t,n)$$

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

Time of Flight
(3D, Scattering)

Bounce Index
(Scattering)

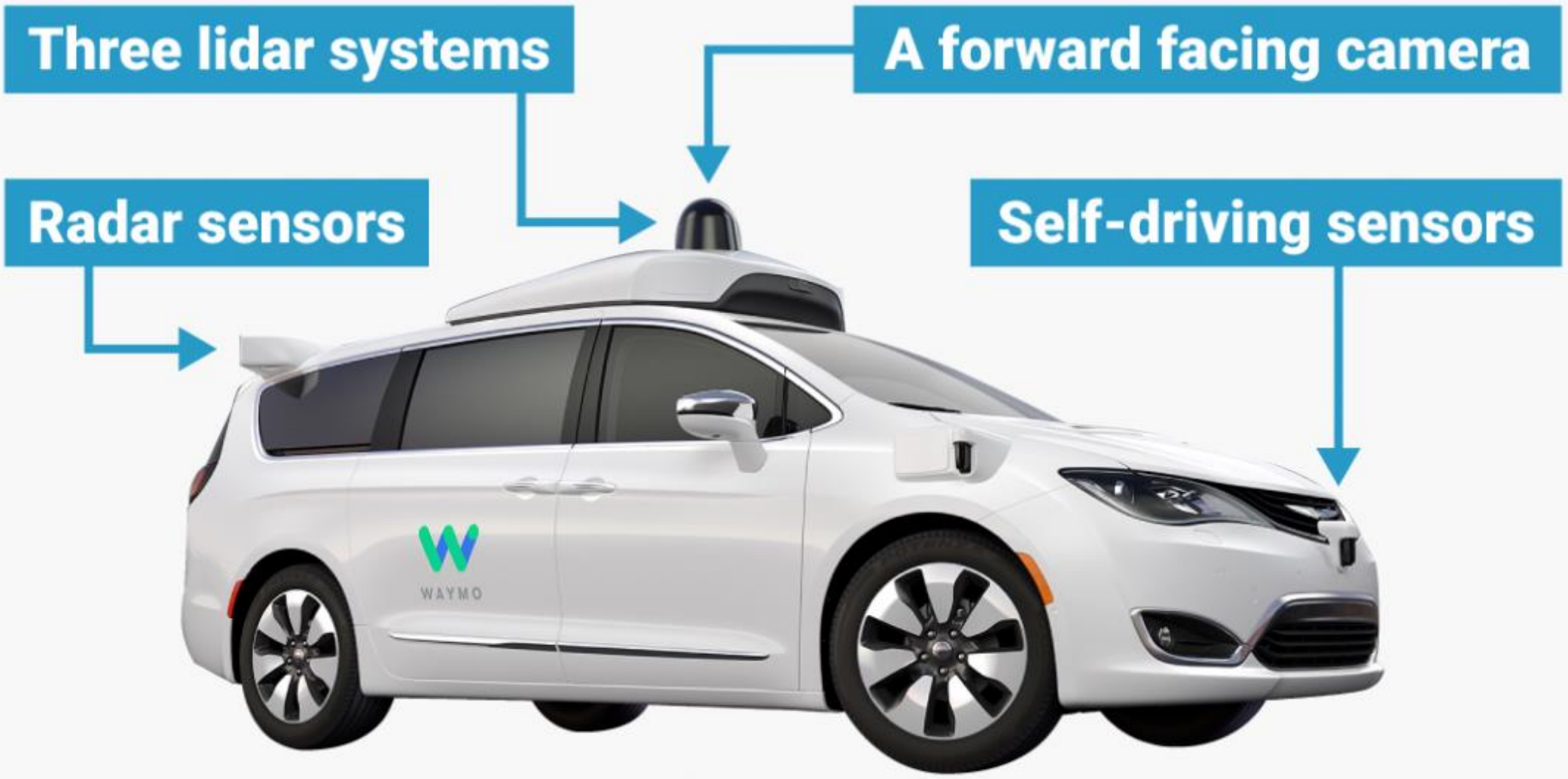
Adelson and Bergen "The Plenoptic Function…" MIT Press 1991

Shower Curtain: Diffuser

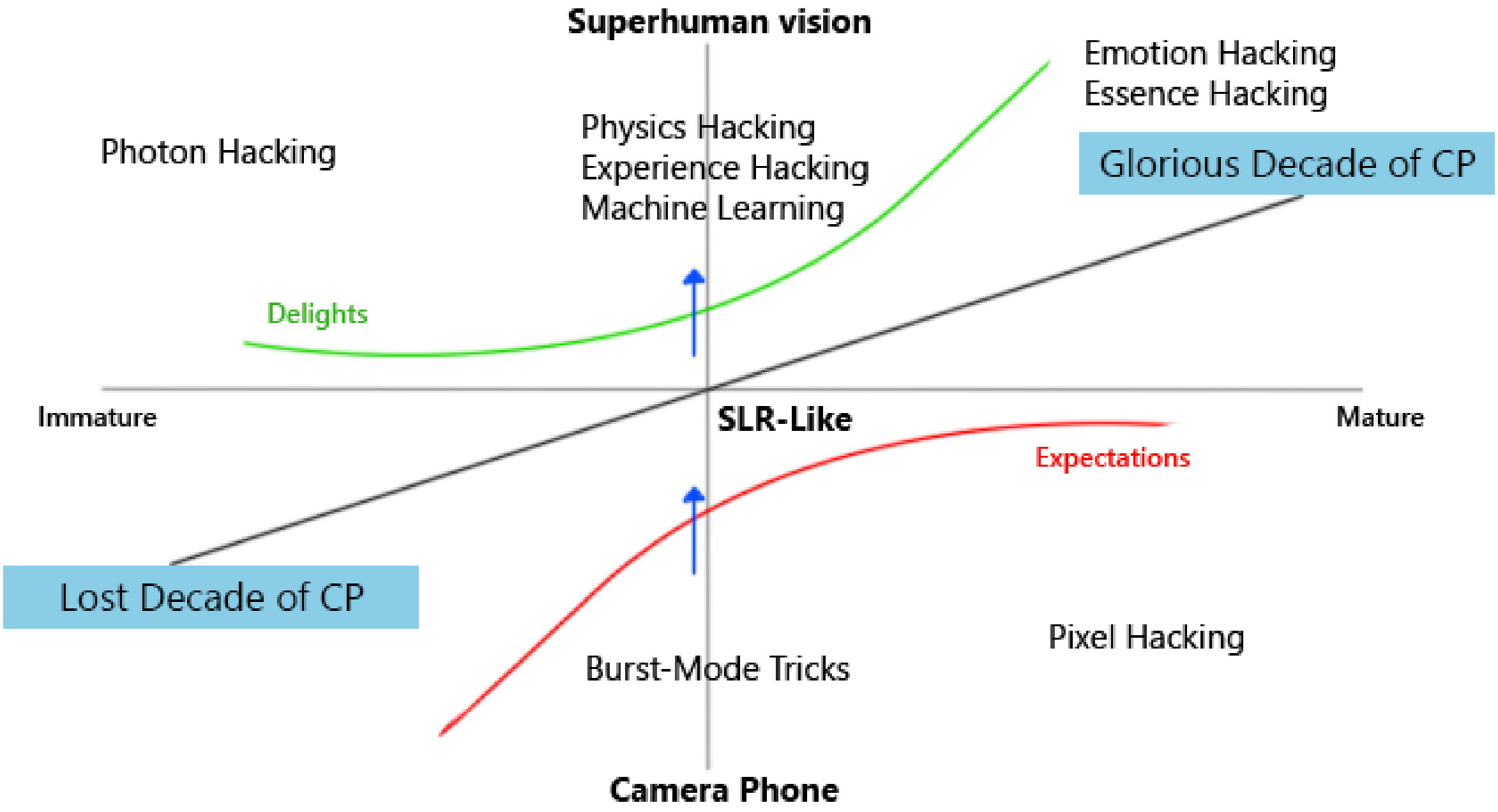
Courtesy of Shree Nayar. Used with permission.
Source: http://www1.cs.columbia.edu/CAVE/projects/separation/occluders_gallery.php

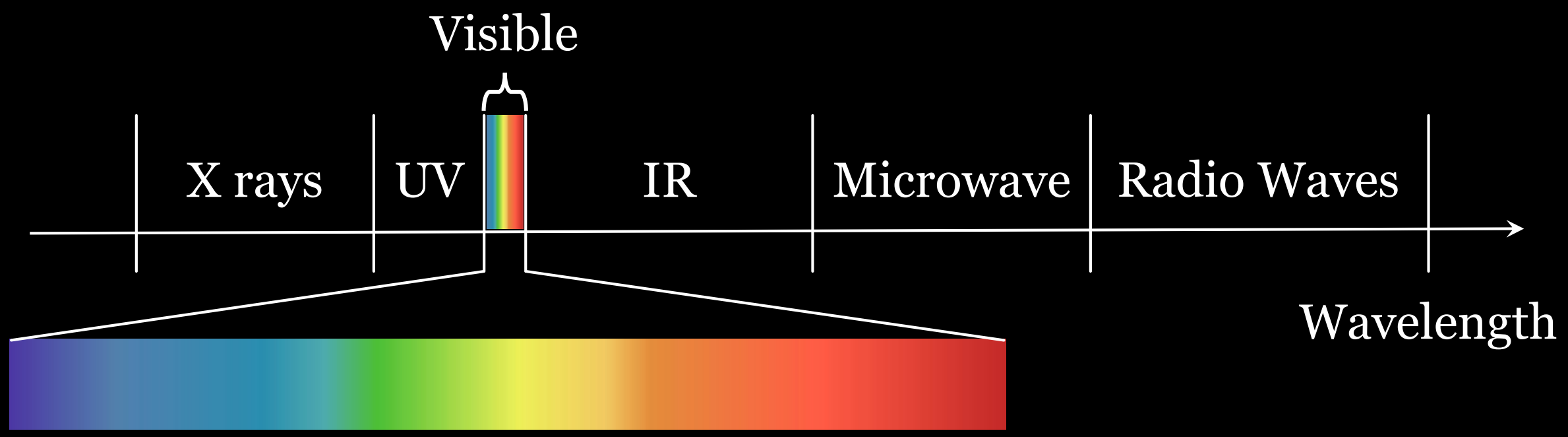
Direct

Global


Three lidar systems
A forward facing camera
Radar sensors
Self-driving sensors
WAYMO

	Classification	Resolution	Localization	Availability	Any Weather
Radar	✓	✗	✗	✓	✓
Ultrasonic	✗	✗	✗	✓	✓
Camera	✓	✓	✓	✓	✗
LiDAR	✓	✓	✓	✗	✗


Superhuman vision
Emotion Hacking
Essence Hacking
Physics Hacking
Experience Hacking
Machine Learning
Photon Hacking
Glorious Decade of CP
Delights
Immature
SLR-Like
Mature
Expectations
Lost Decade of CP
Pixel Hacking
Burst-Mode Tricks
Camera Phone

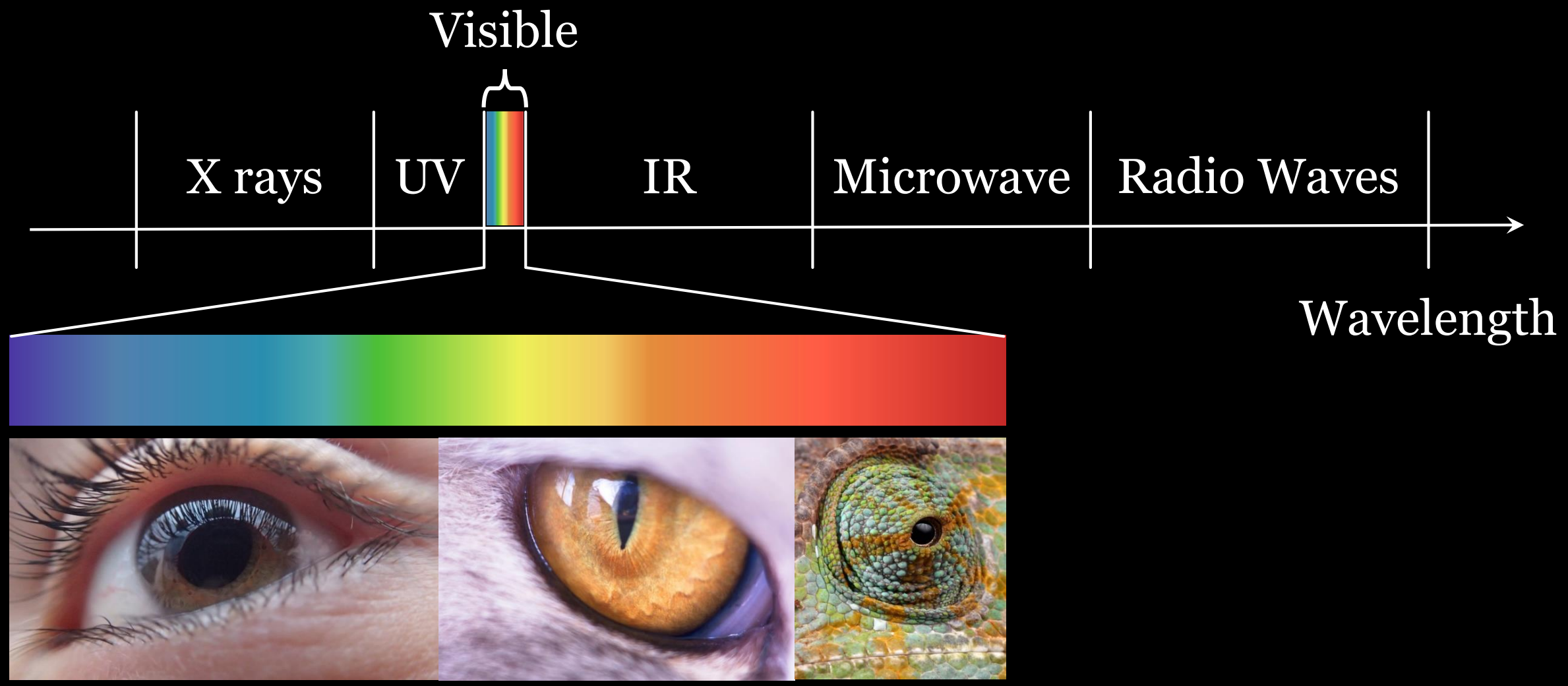


- Resolution
- Optical Contrast
- Non ionizing
- Availability of fluorophores

Optical Contrast

Visible light

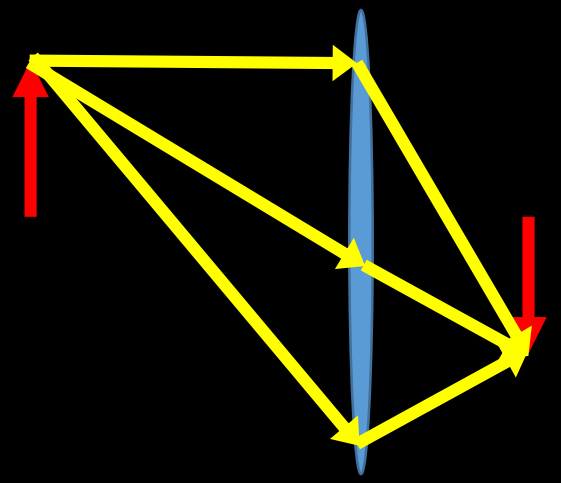
X-Ray

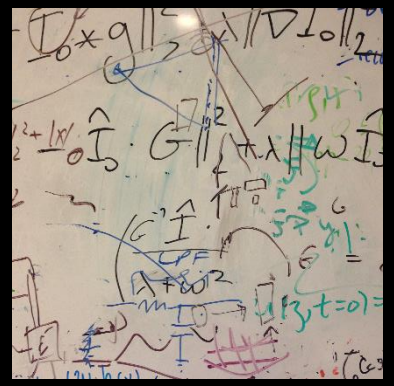

Visible
X rays
UV
IR
Microwave
Radio Waves
Wavelength

Light and Matter in a Nutshell

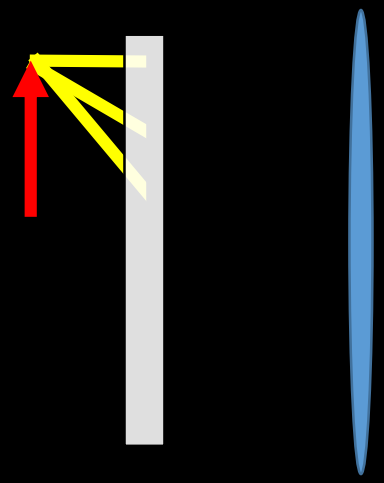
Object

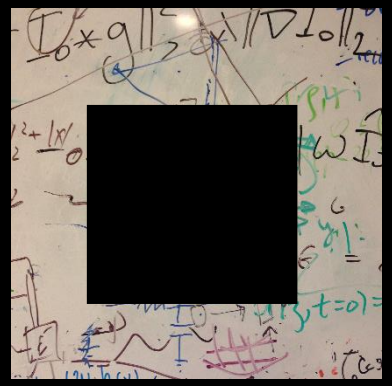
Lens



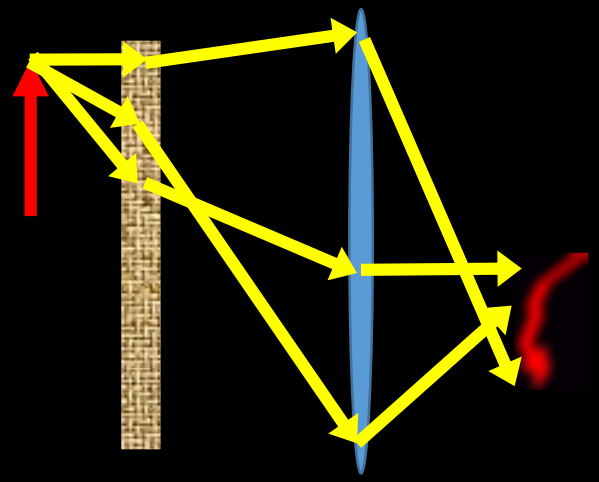


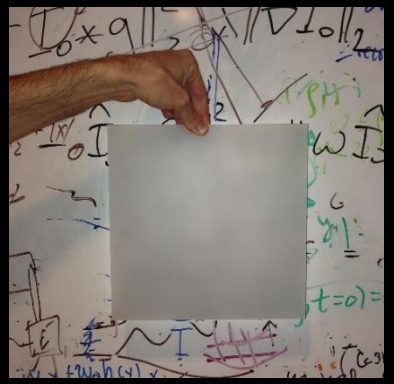
Absorption





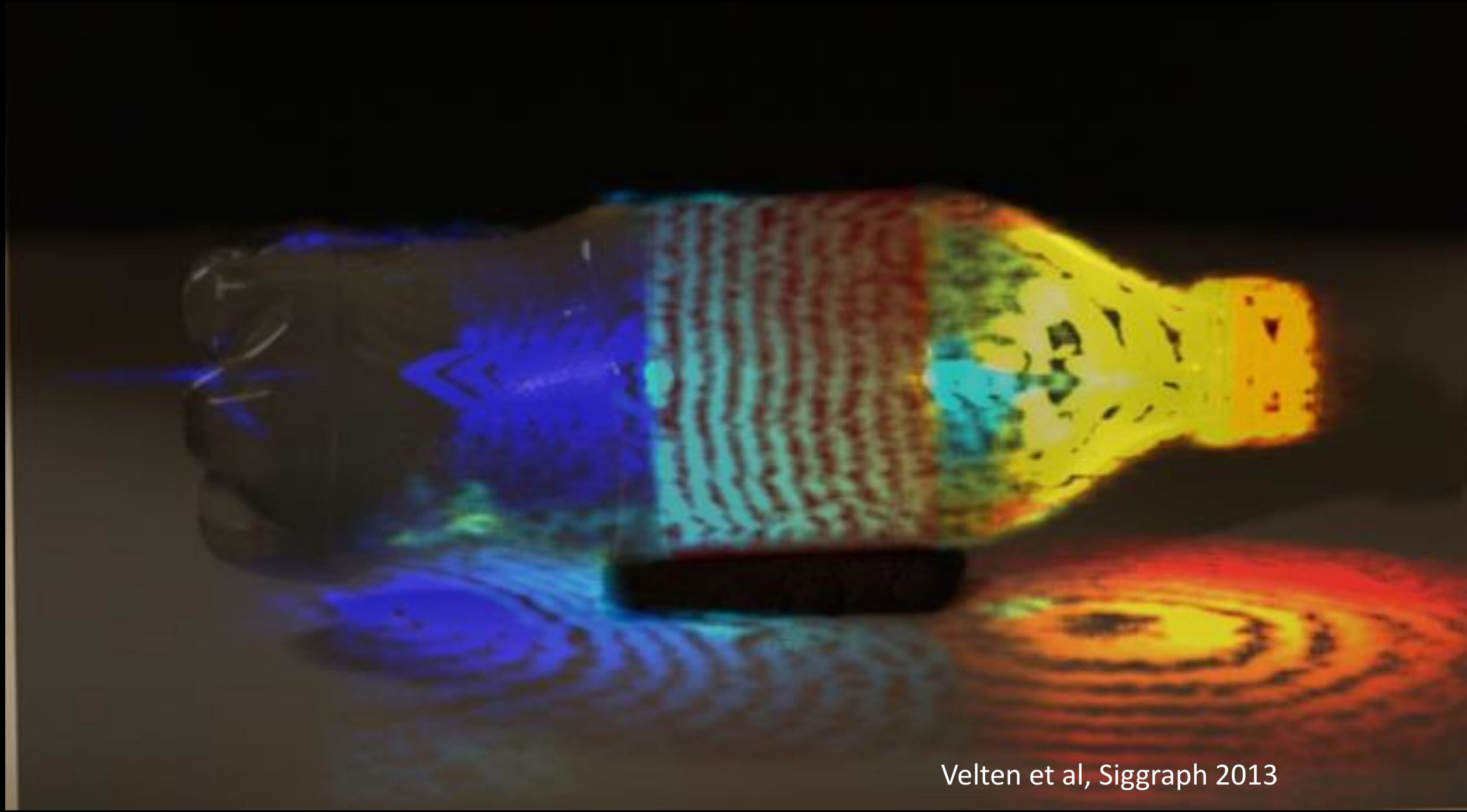
Scattering





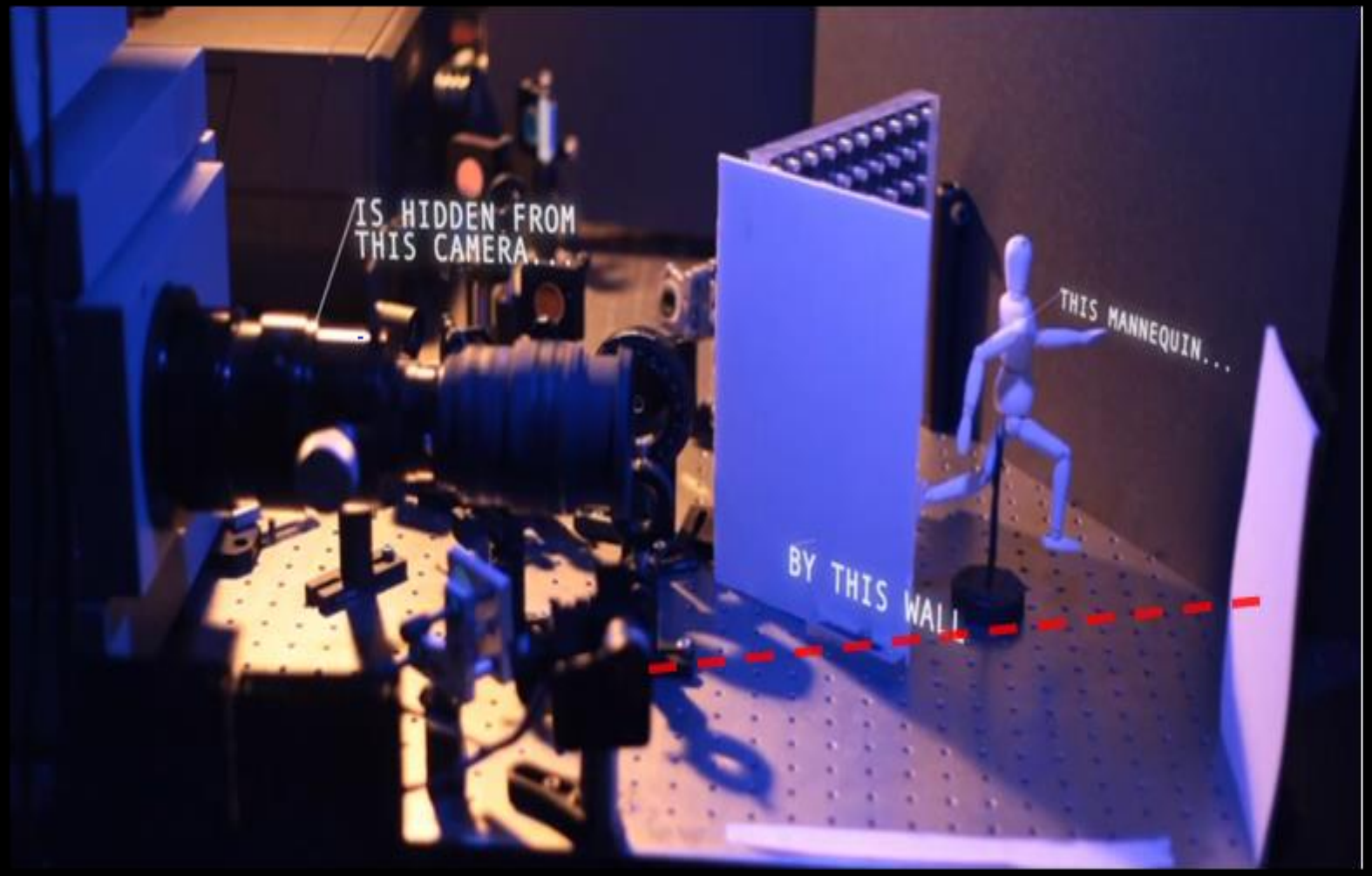
Light in Flight

Velten 2011



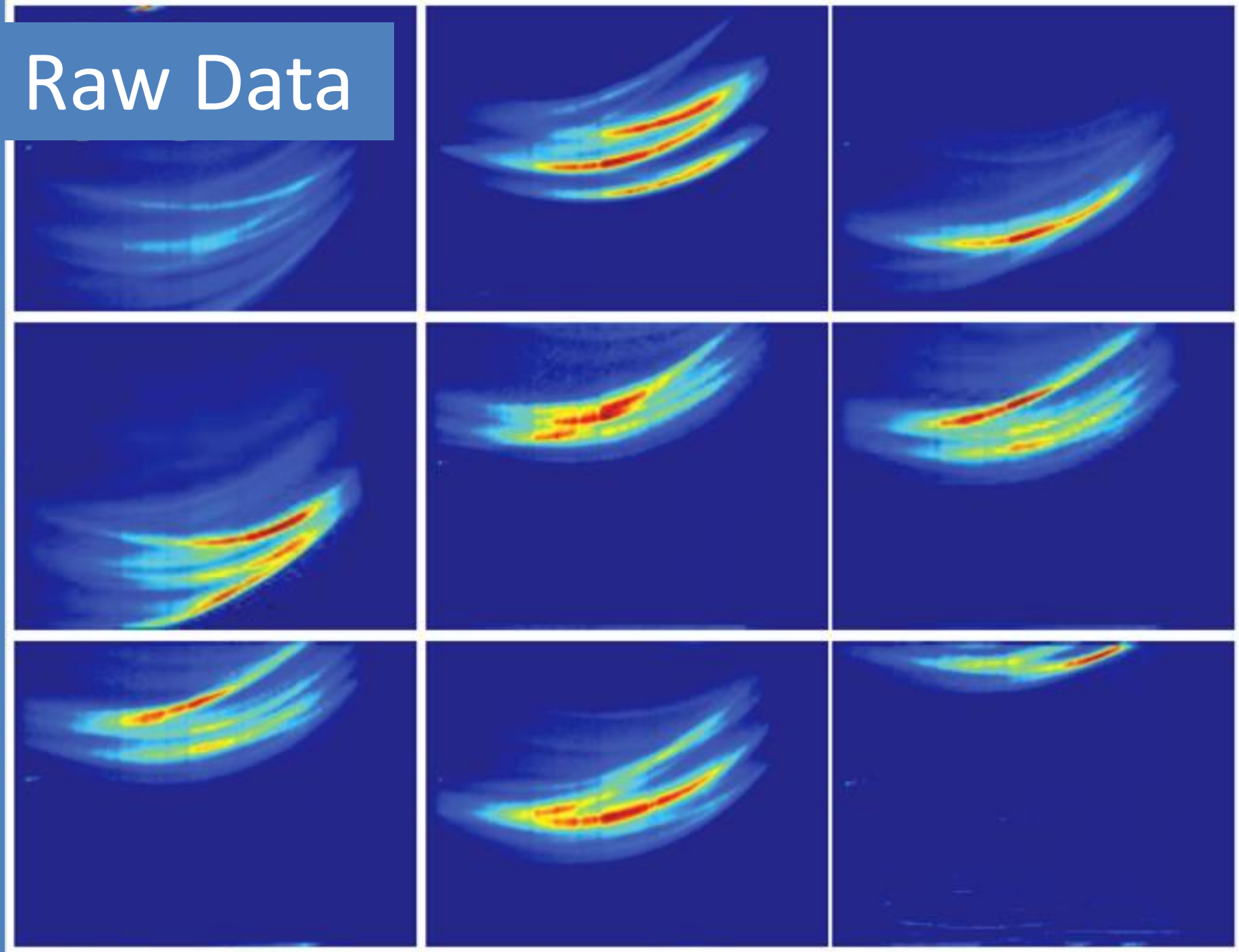
Velten et al, Siggraph 2013

Seeing Around Corners

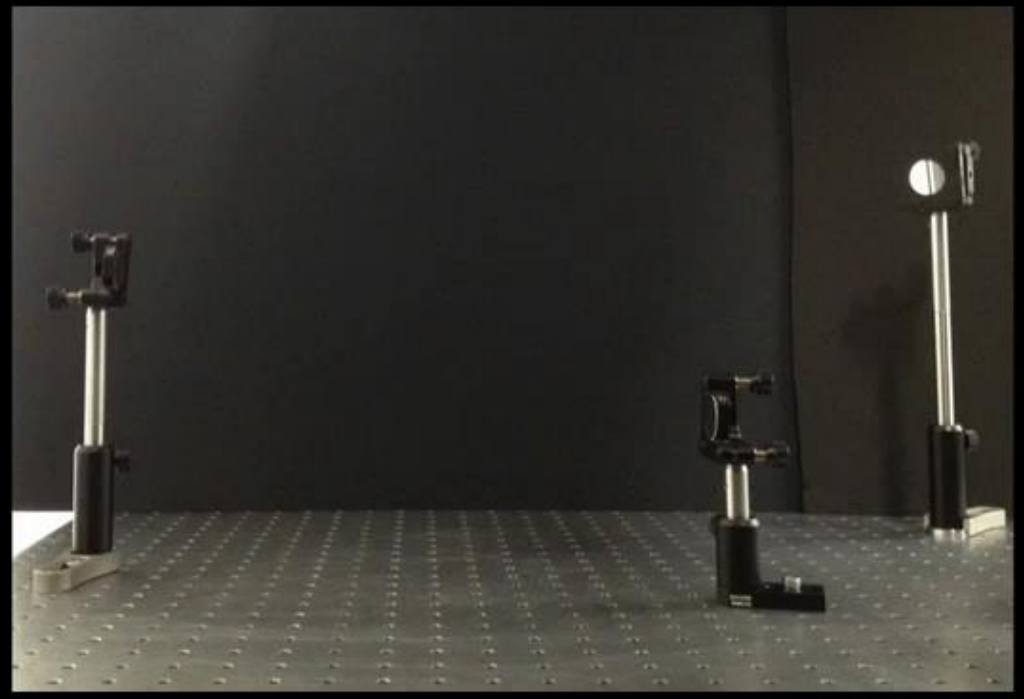


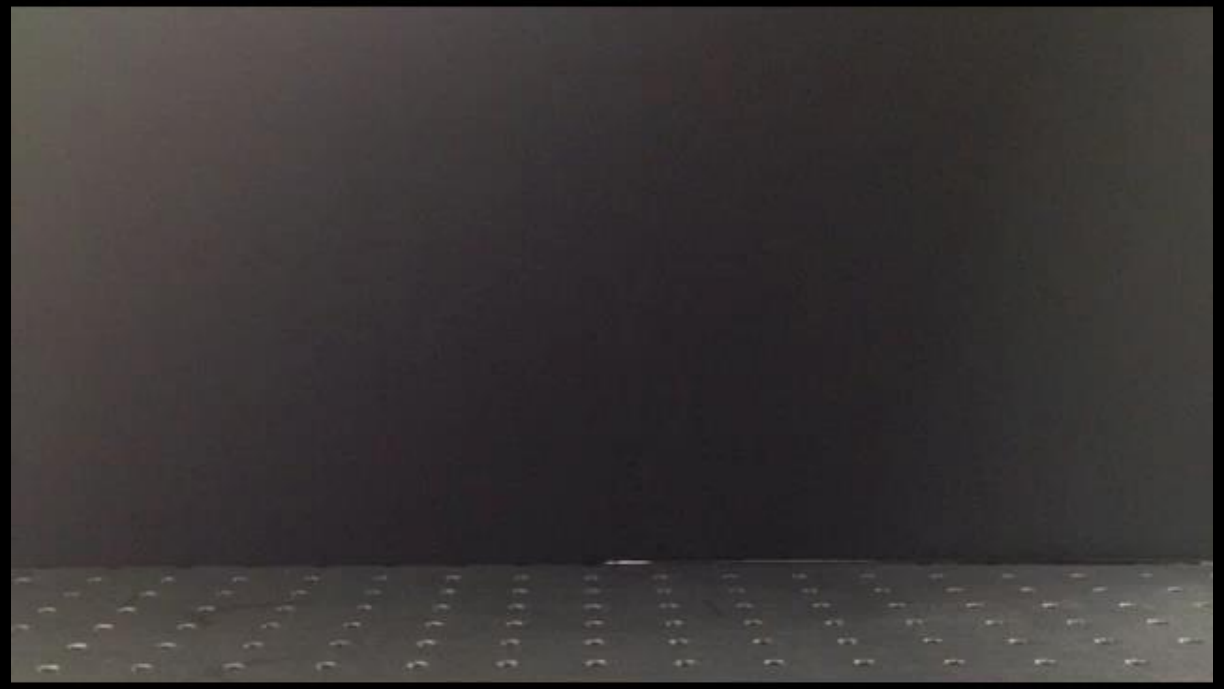
Vetlen 2012

Raw Data



Single Photon Sensitive Imaging



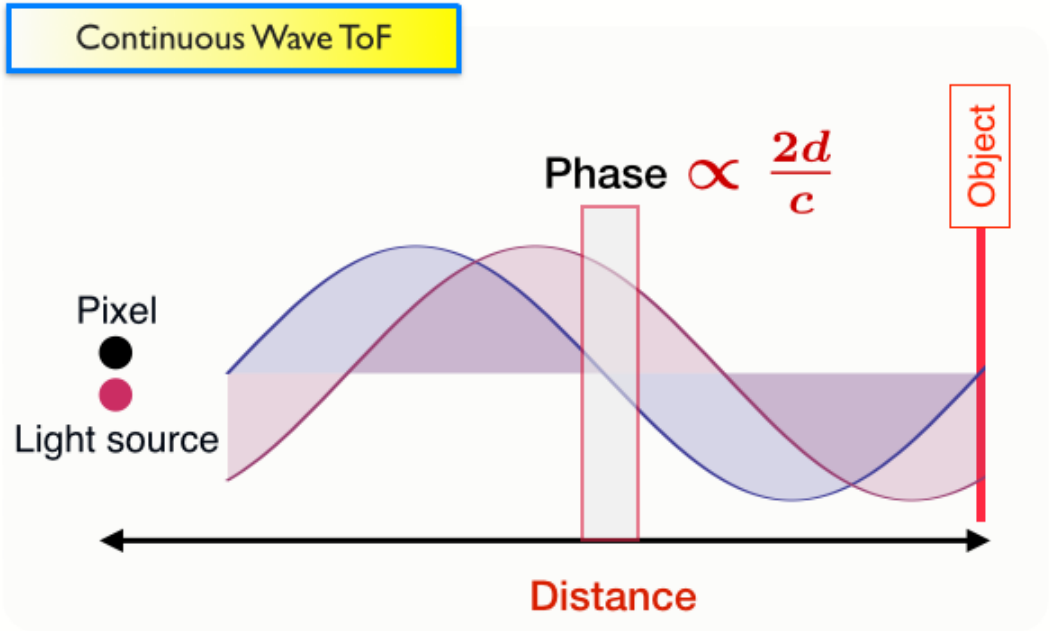


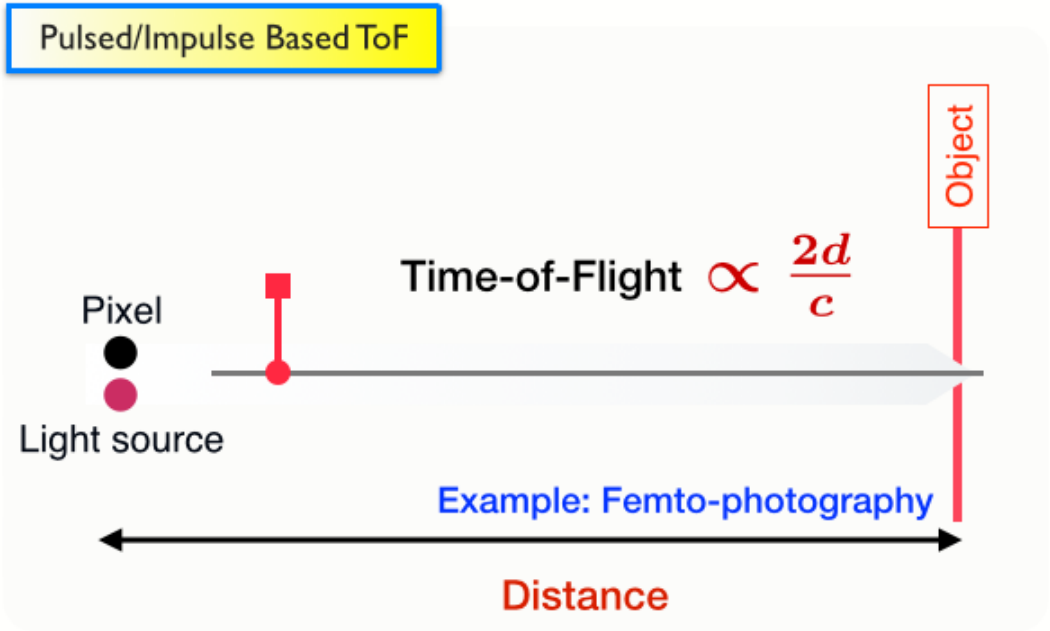
Gariepy et al. Nature Comm (2015)

Time-of-Flight Imaging Sensors

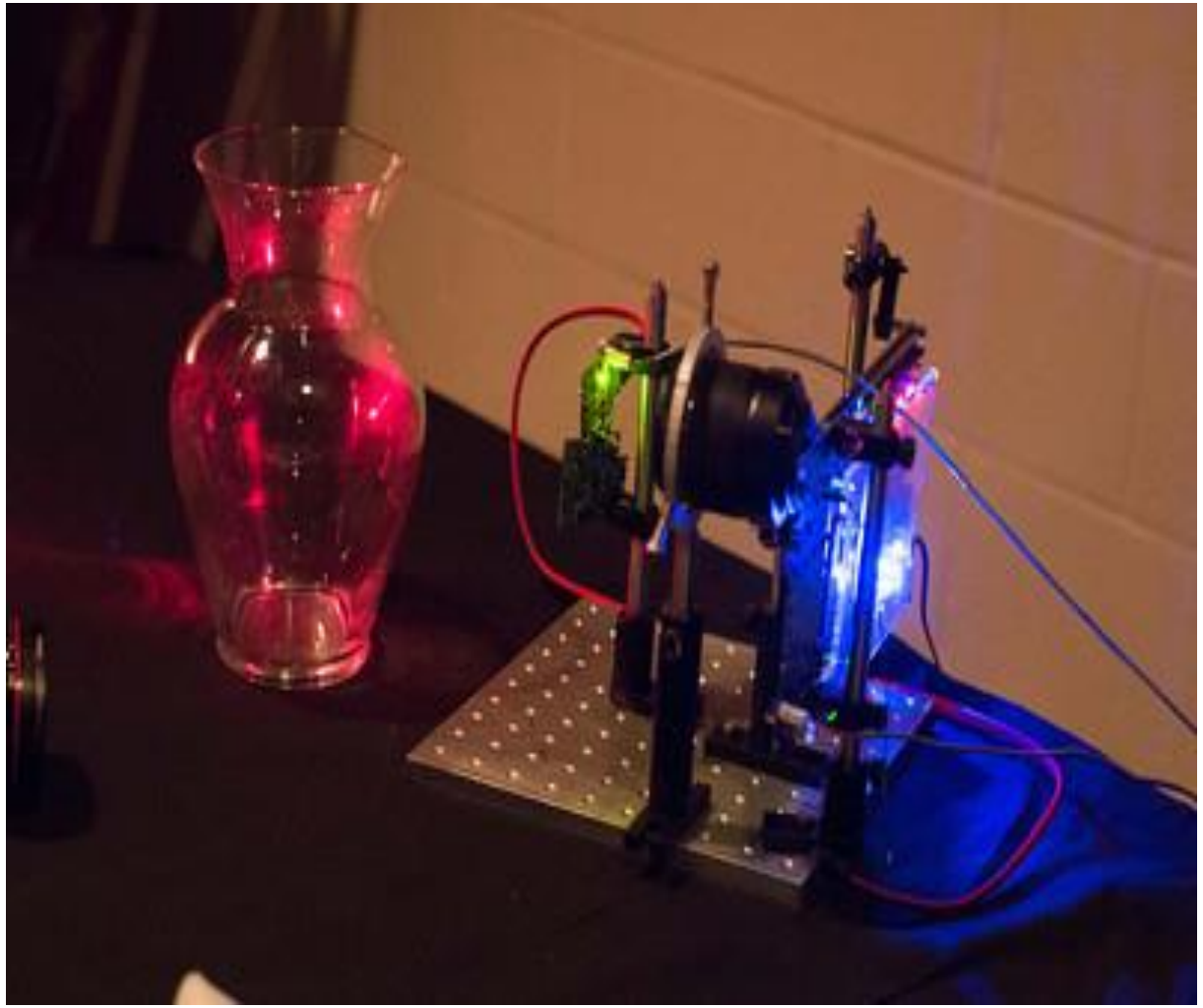
Time-of-Flight Sensors: Computes depth based on speed of light (aka SONAR with light.)

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





Nanophotography



[Kadambi et al 2013]

Real-time Localization

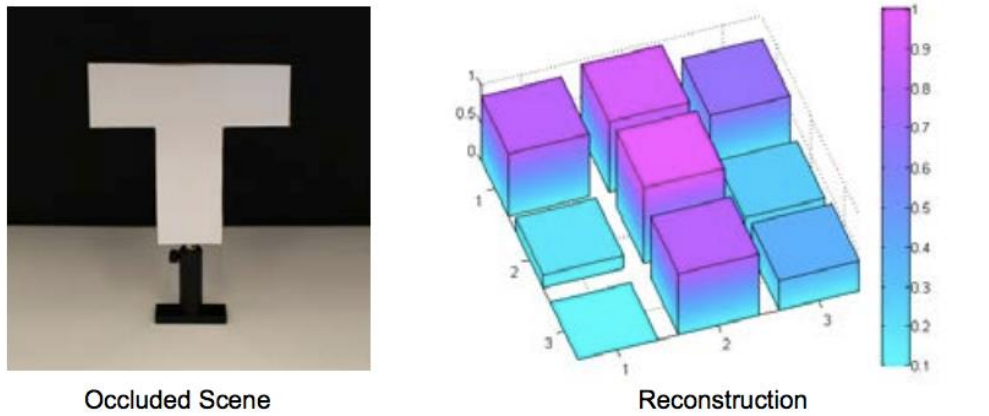
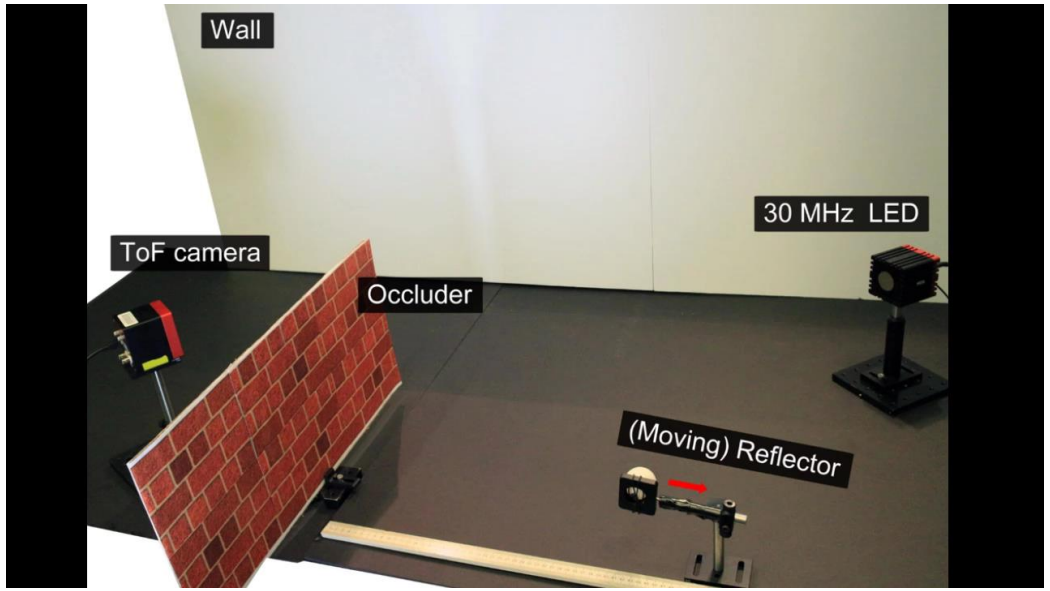


Figure 9: *Imaging around the corner. (left) We use the same scene from Figure 12a but replace the moving ping pong ball with a "T" shaped object. (right) Using pseudoinverse beamforming, we are able to recover the image shown on the right.*

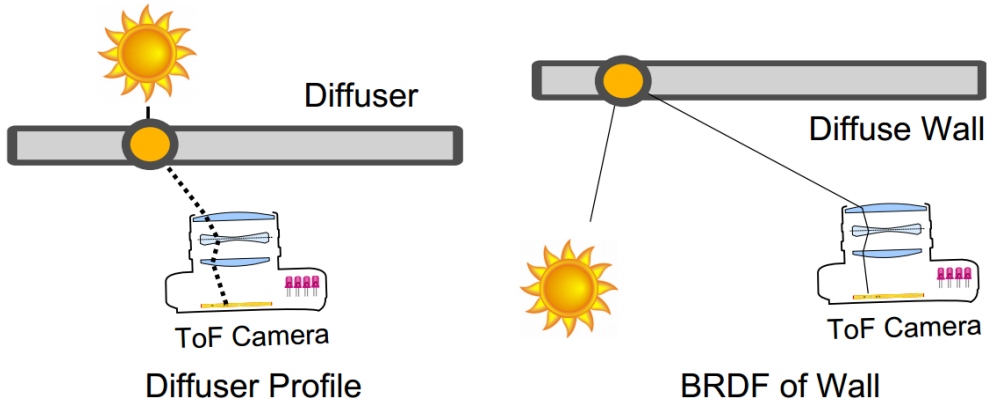
Imaging

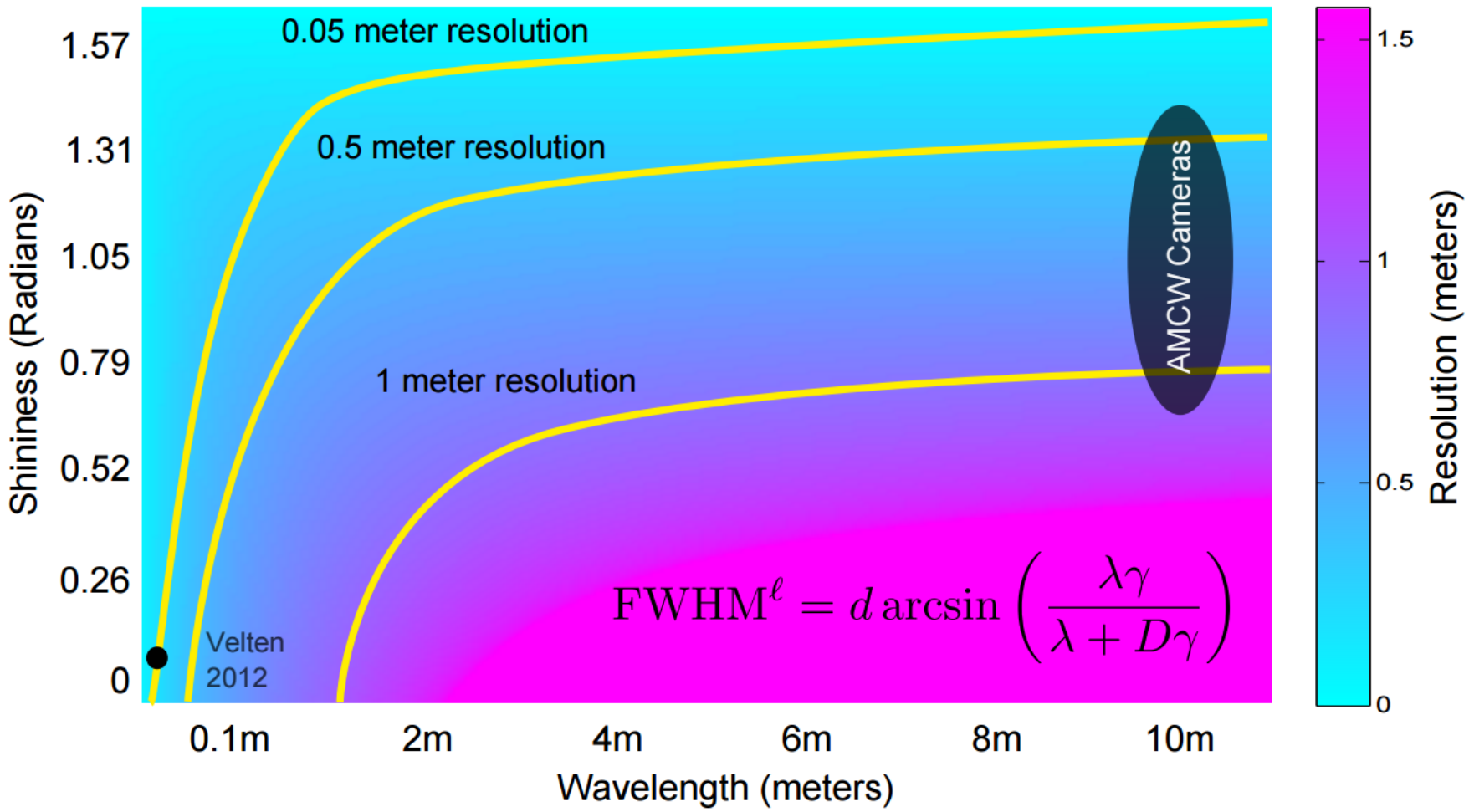


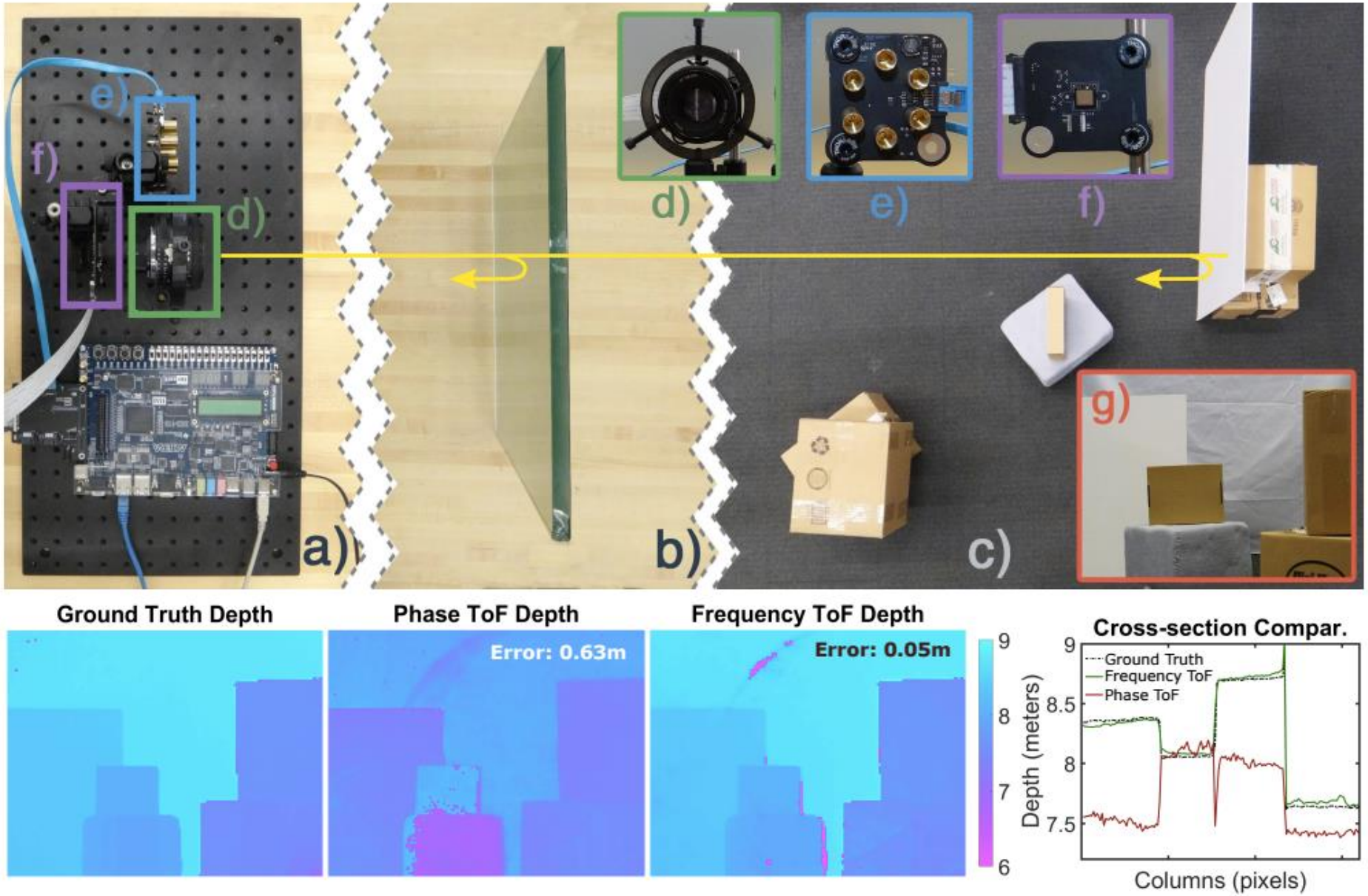
Real Time Localization

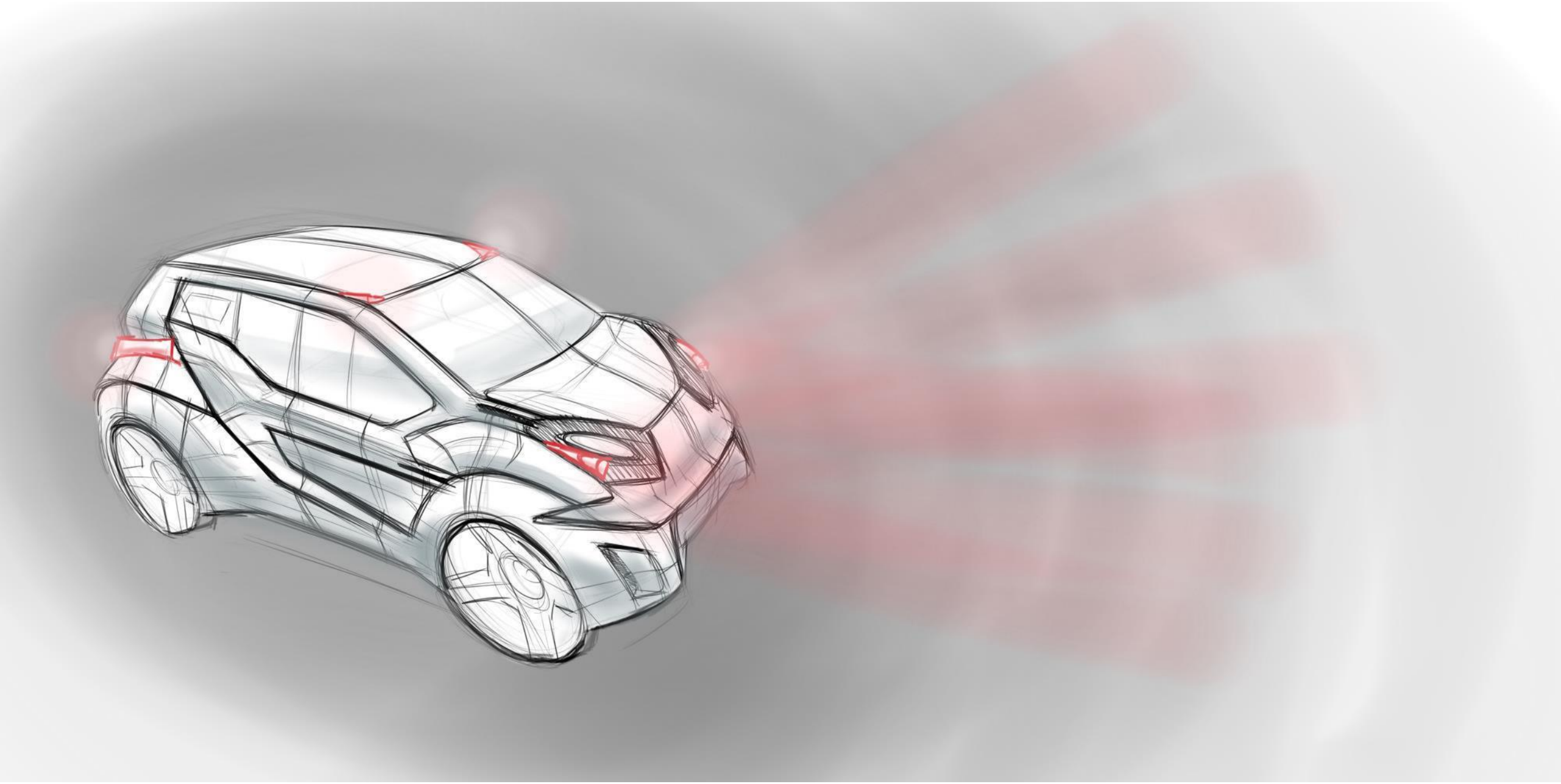
Kadambi, Zhao, Shi, Raskar. "Occluded Imaging with Time of Flight Sensors." ACM ToG 2016 (Pres. at SIGGRAPH)

Wavelength vs Shininess

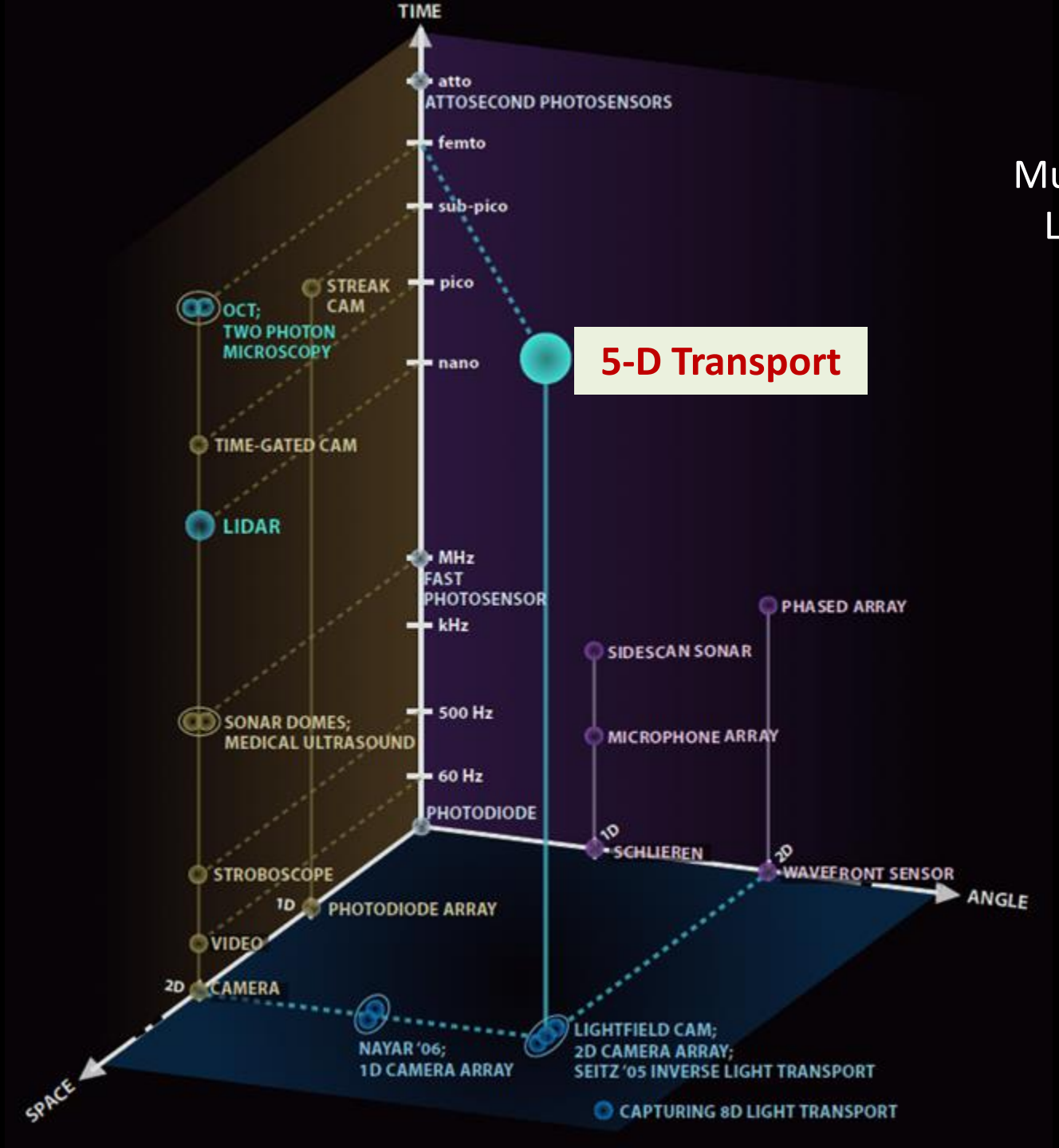





a)
b)
c)
d)
e)
f)
g)
Ground Truth Depth
Phase ToF Depth
Error: 0.63m
Frequency ToF Depth
Error: 0.05m
9
8
7
6
Cross-section Compar.
Ground Truth
Frequency ToF
Phase ToF
Depth (meters)
9
8.5
8
7.5
Columns (pixels)



Multi-Dimensional Light Transport



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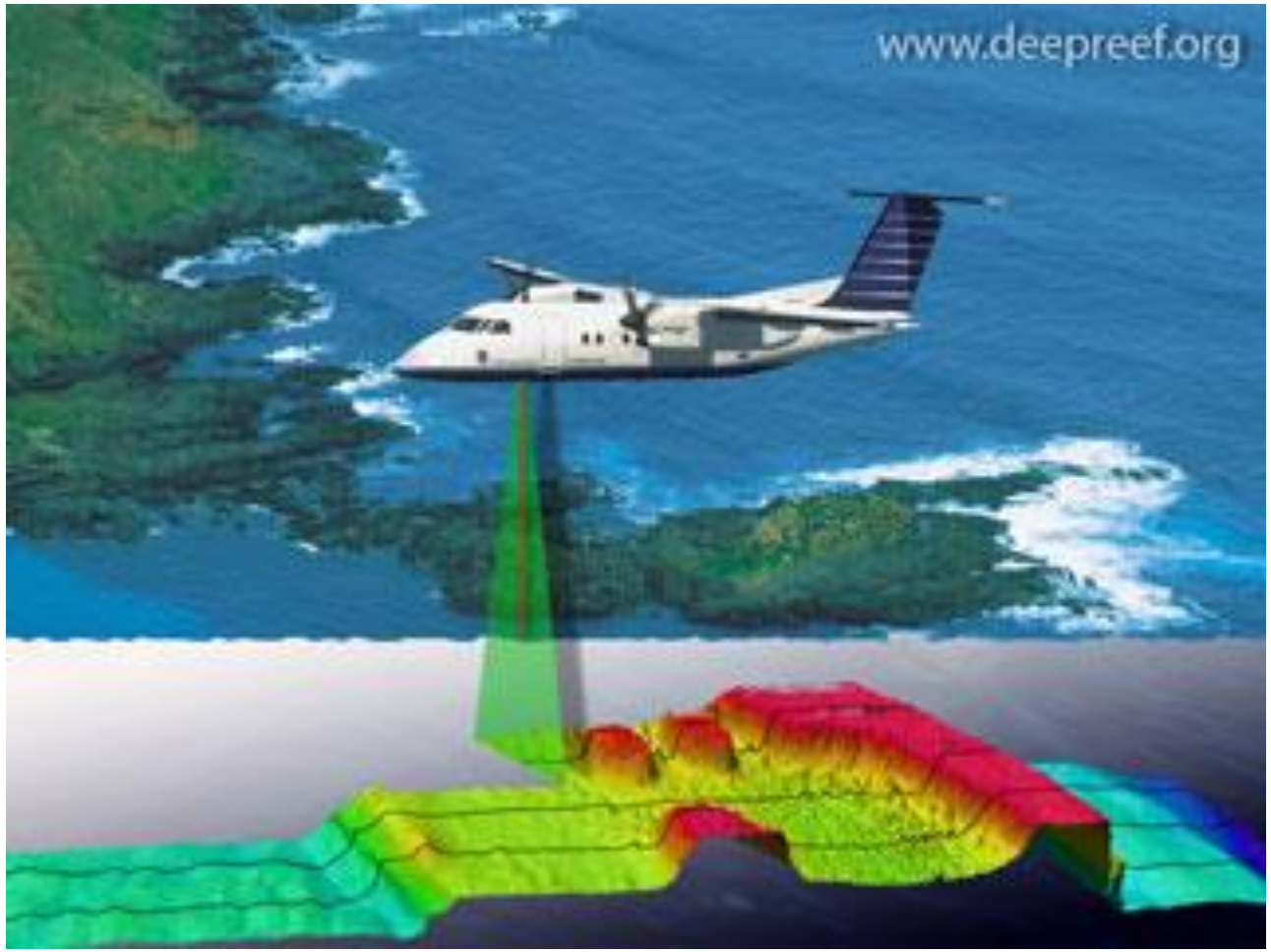
Computational Imaging for Autonomous Vehicles

Sample Slides for Module 3:

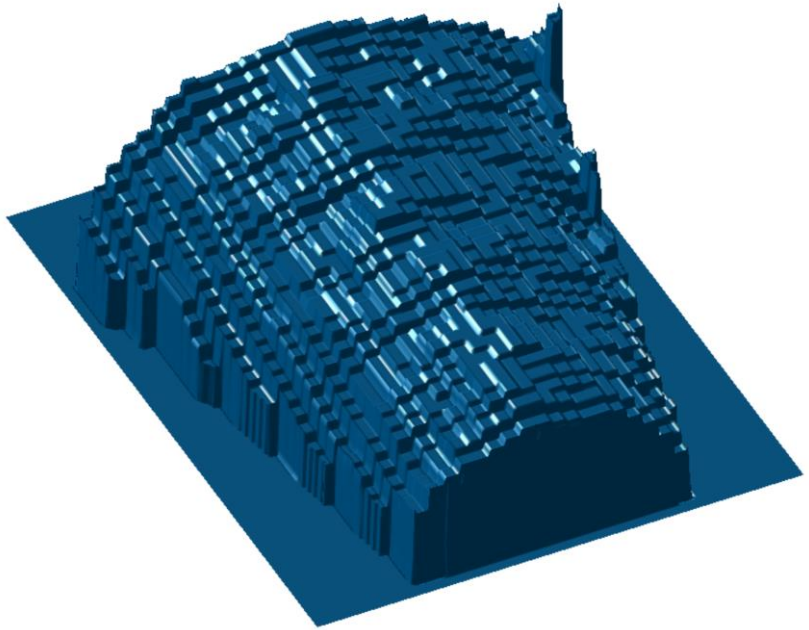
Emerging Vision Sensors for Self-Driving Cars

What’s next for 3D imaging?

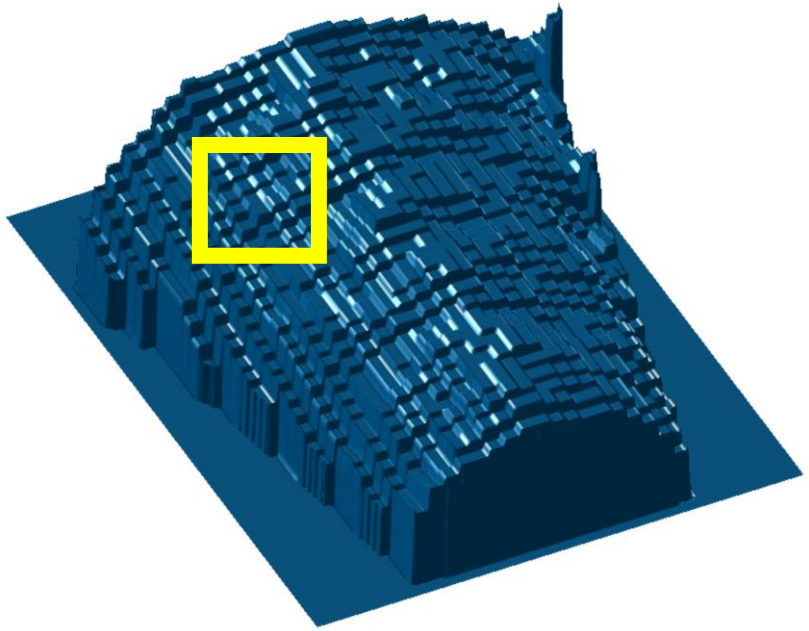


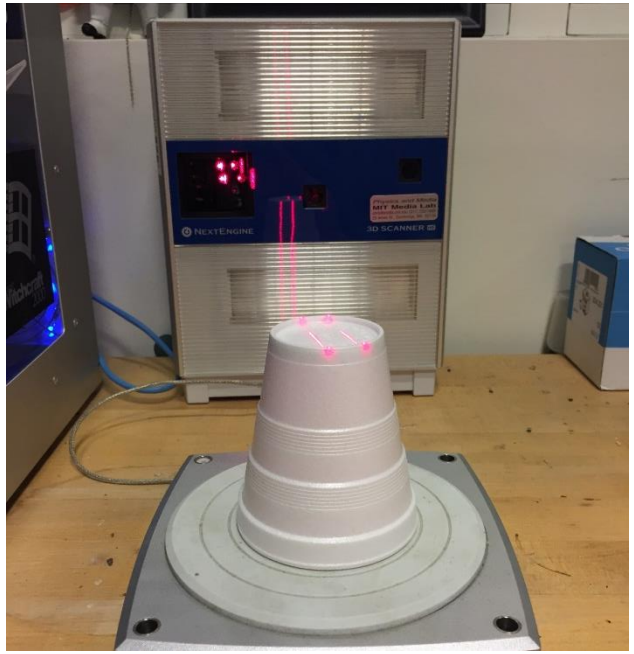
Microsoft Kinect v2

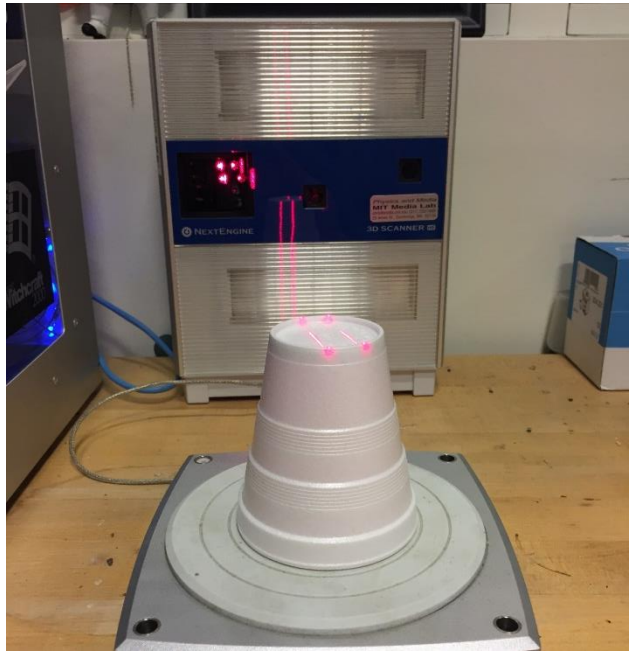
Microsoft Kinect v2



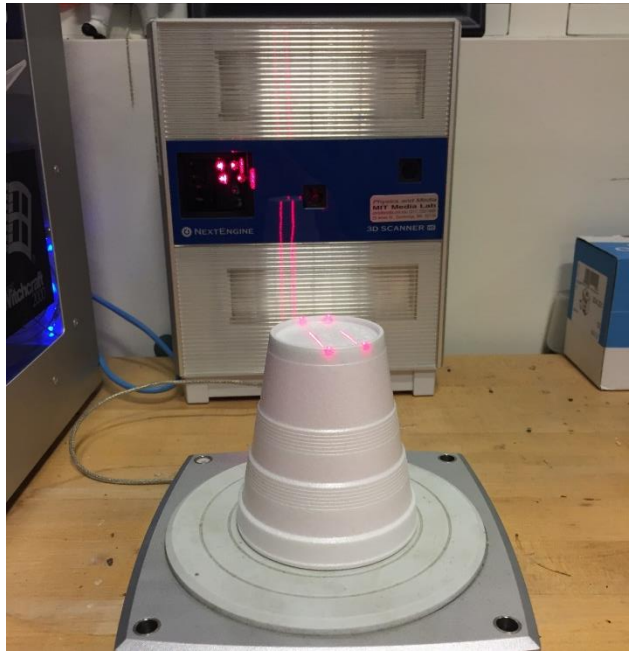
Microsoft Kinect v2



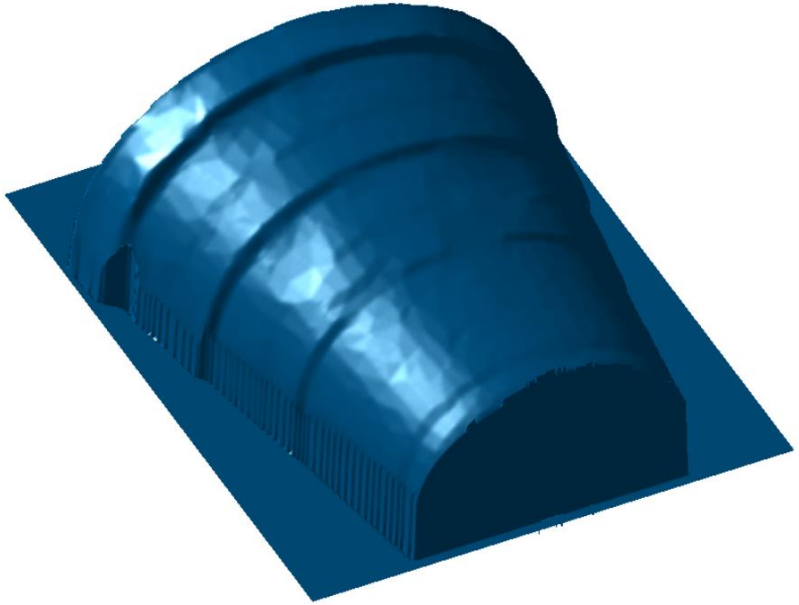

NEXTENGINE
3D SCANNER
MIT Media Lab

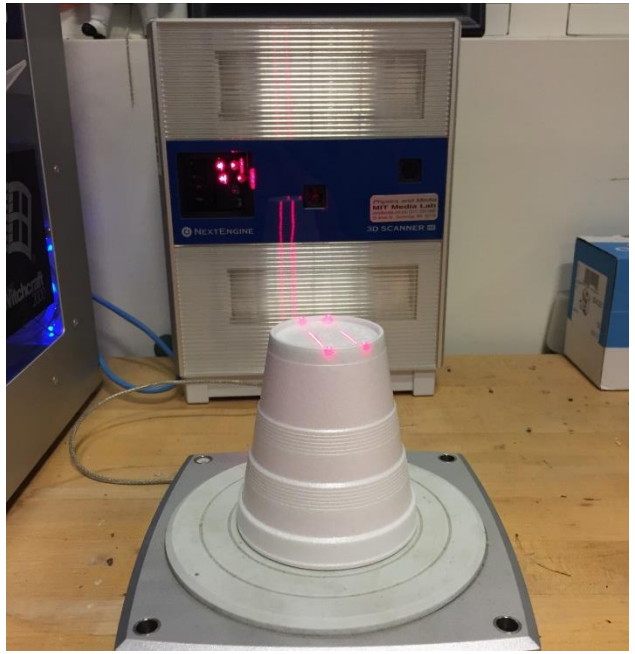


Multistripe Laser Scan



Multistripe Laser Scan



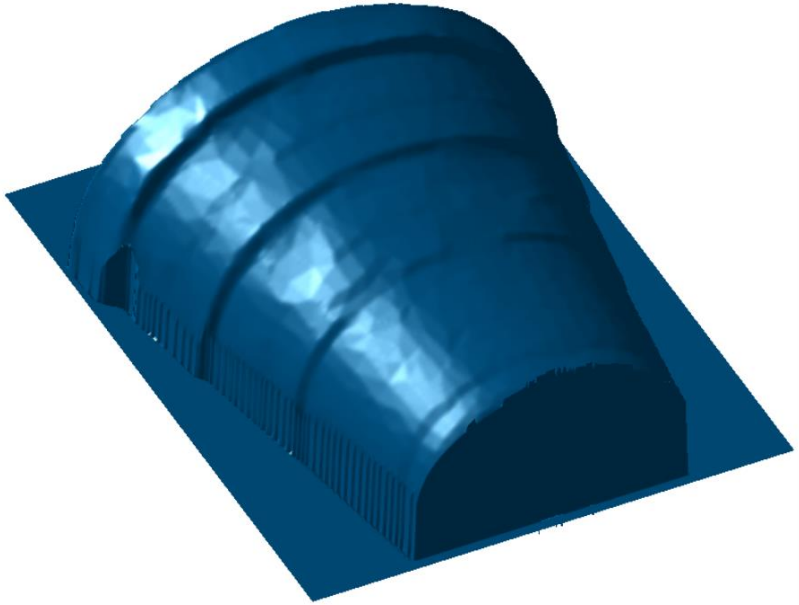


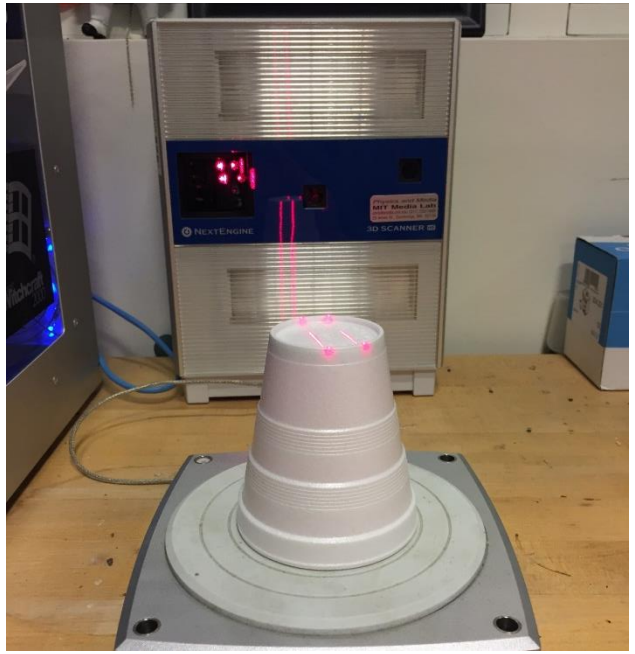
Multistripe Laser Scan

NextEngine 3D

$3000 USD

Raster





Multistripe Laser Scan

NextEngine 3D

$3000 USD

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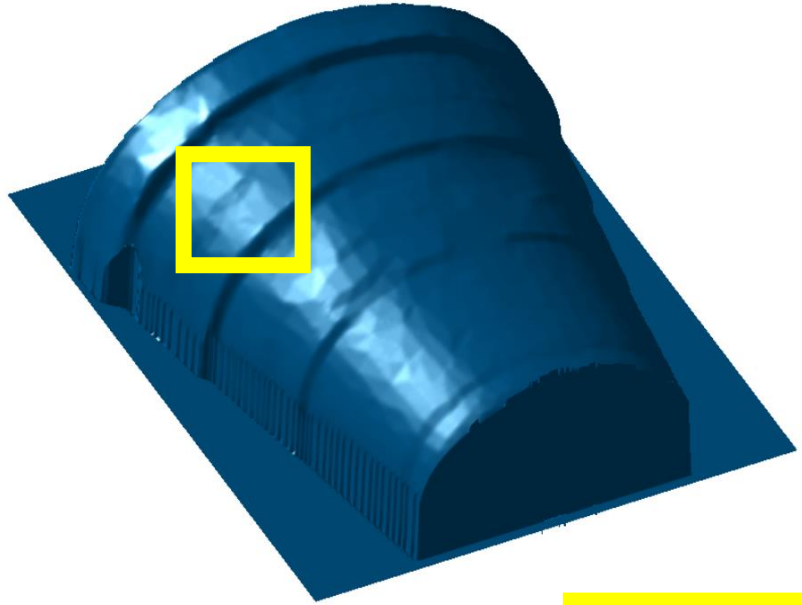


Polarized 3D

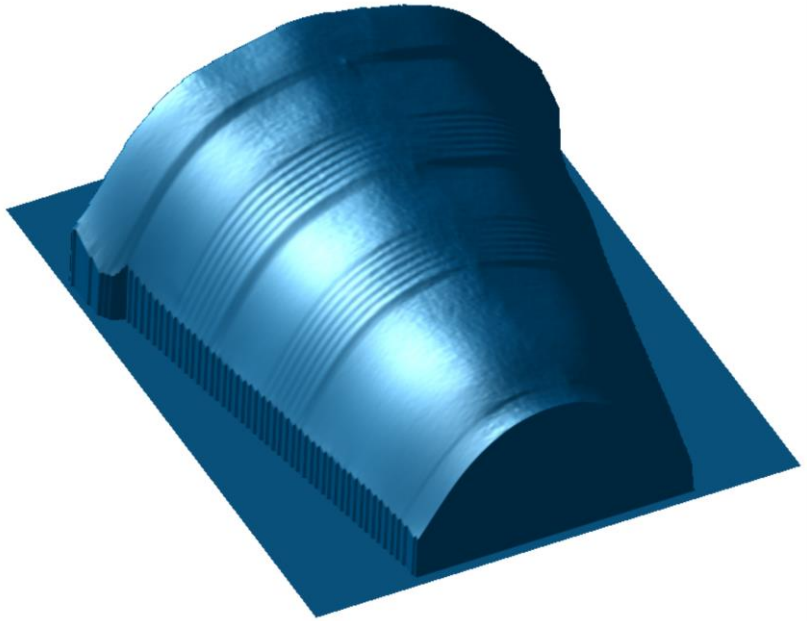
3D Photo w.

$30 Pol. Filter

Polarized 3D

3D Photo w.

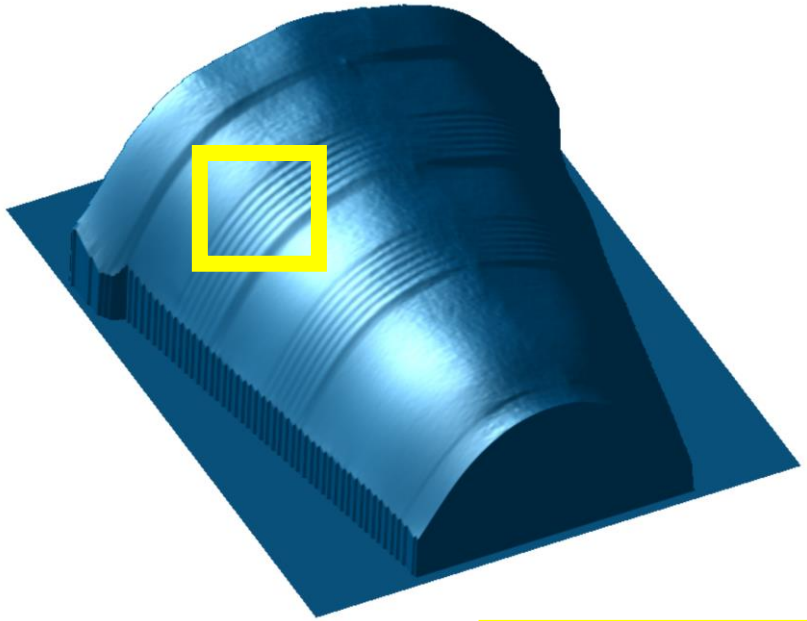
$30 Pol. Filter



Polarized 3D

3D Photo w.

$30 Pol. Filter



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Viewpoint Diversity
(Light Field Cam)

Wavelength Diversity
(Hyperspectral Cam)

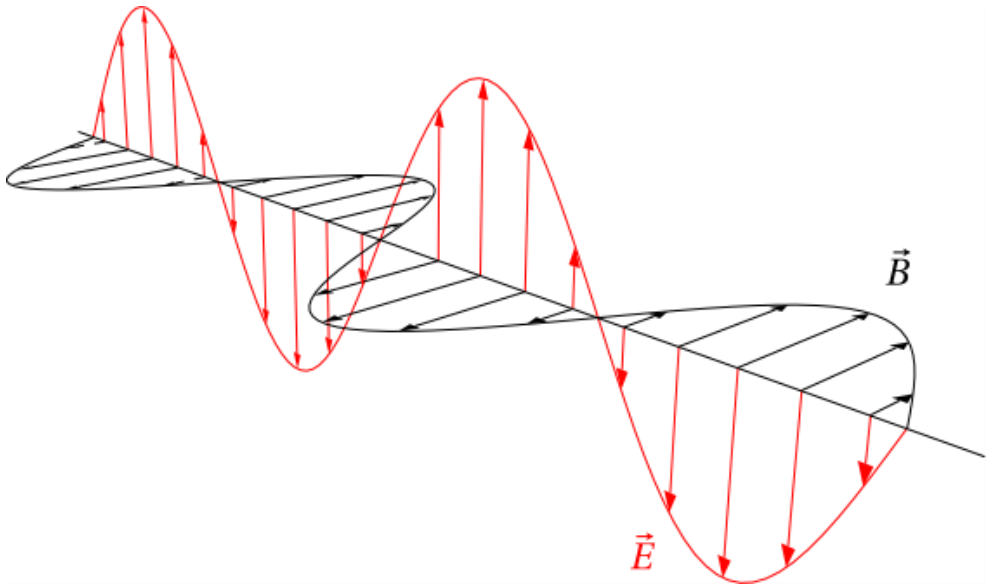
Polarization Diversity
(Photos, Shape, Scatter)

Time of Flight
(3D, Scattering)

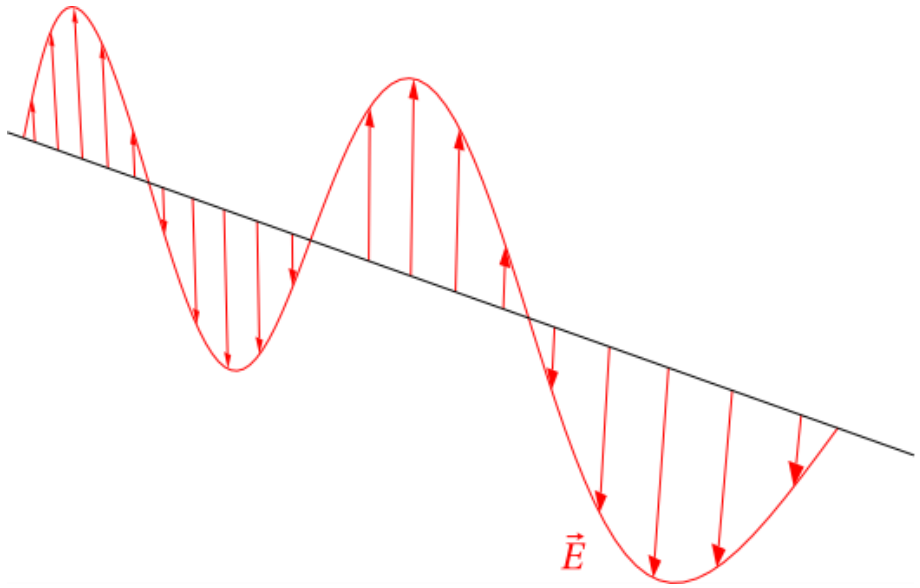
Bounce Index
(Scattering)

Adelson and Bergen "The Plenoptic Function…" MIT Press 1991

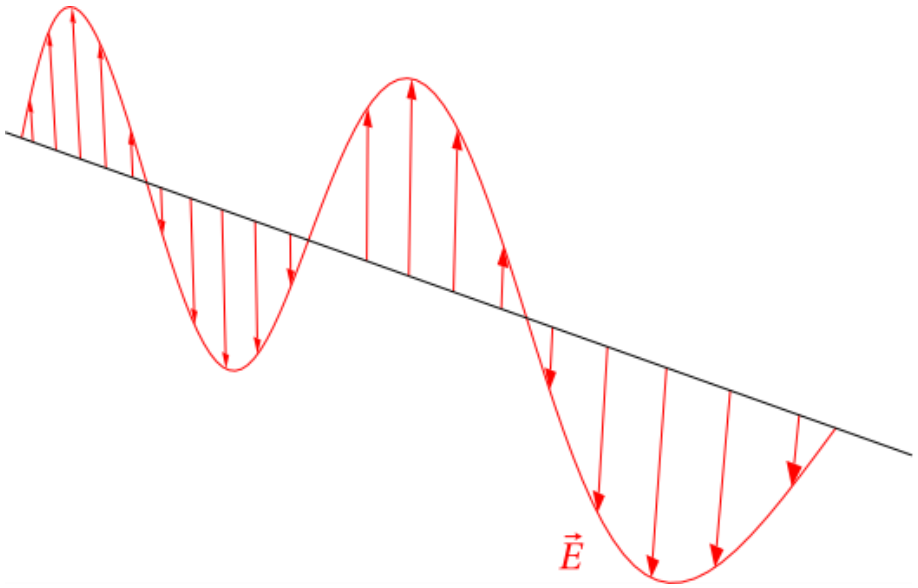
Polarization of Light



Polarization of Light

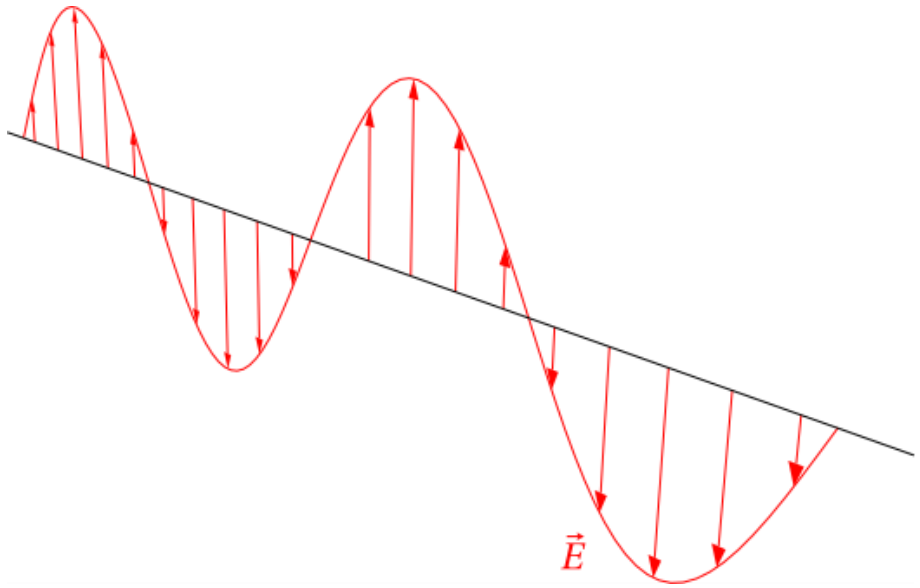


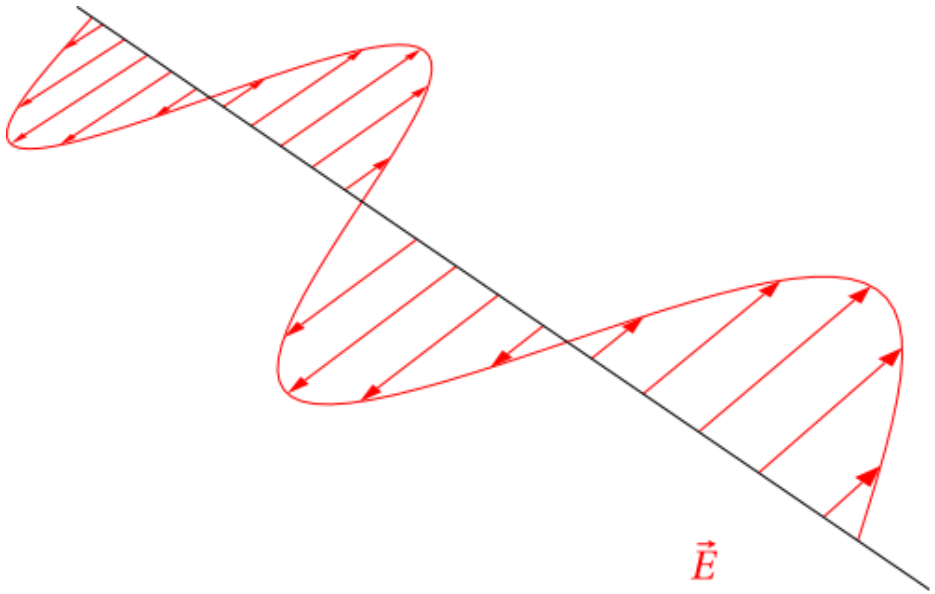
Polarization of Light



Plane of Polarization

Polarization of Light





Plane of Polarization

Plane of Polarization

Cool 2D Photos

Photo Credit: Bob Atkins

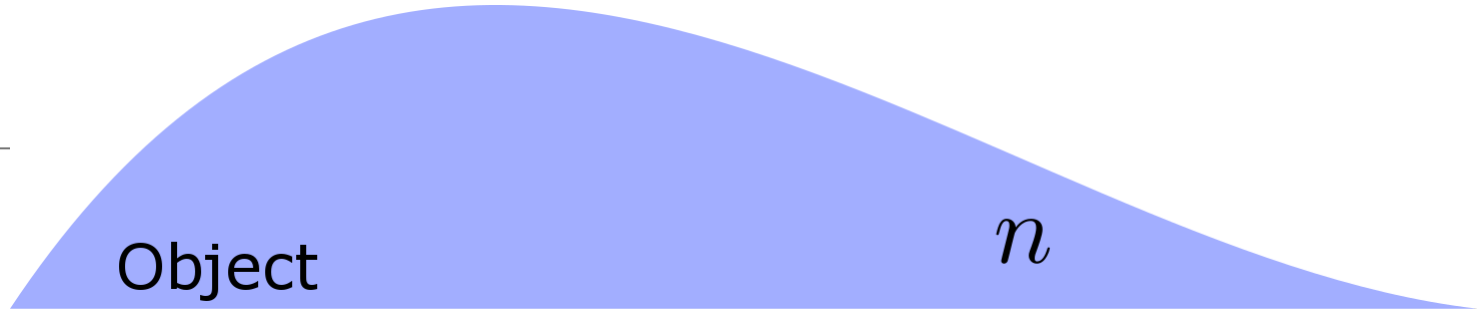
Cool 2D Photos

Photo Credit: Bob Atkins

Polarization used in 2D photography…

… But what about Polarizers for 3D Cams?

Shape from Polarization



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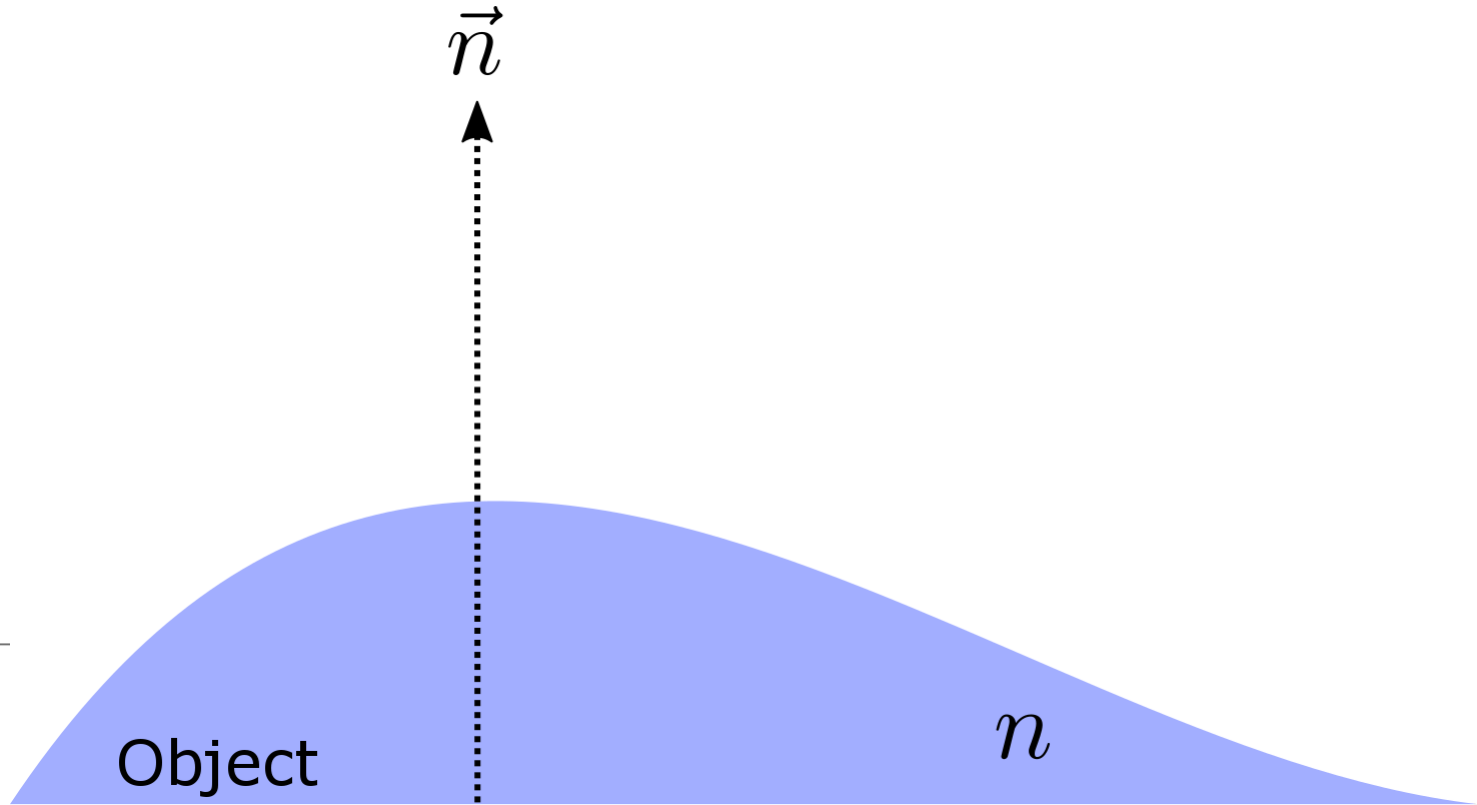

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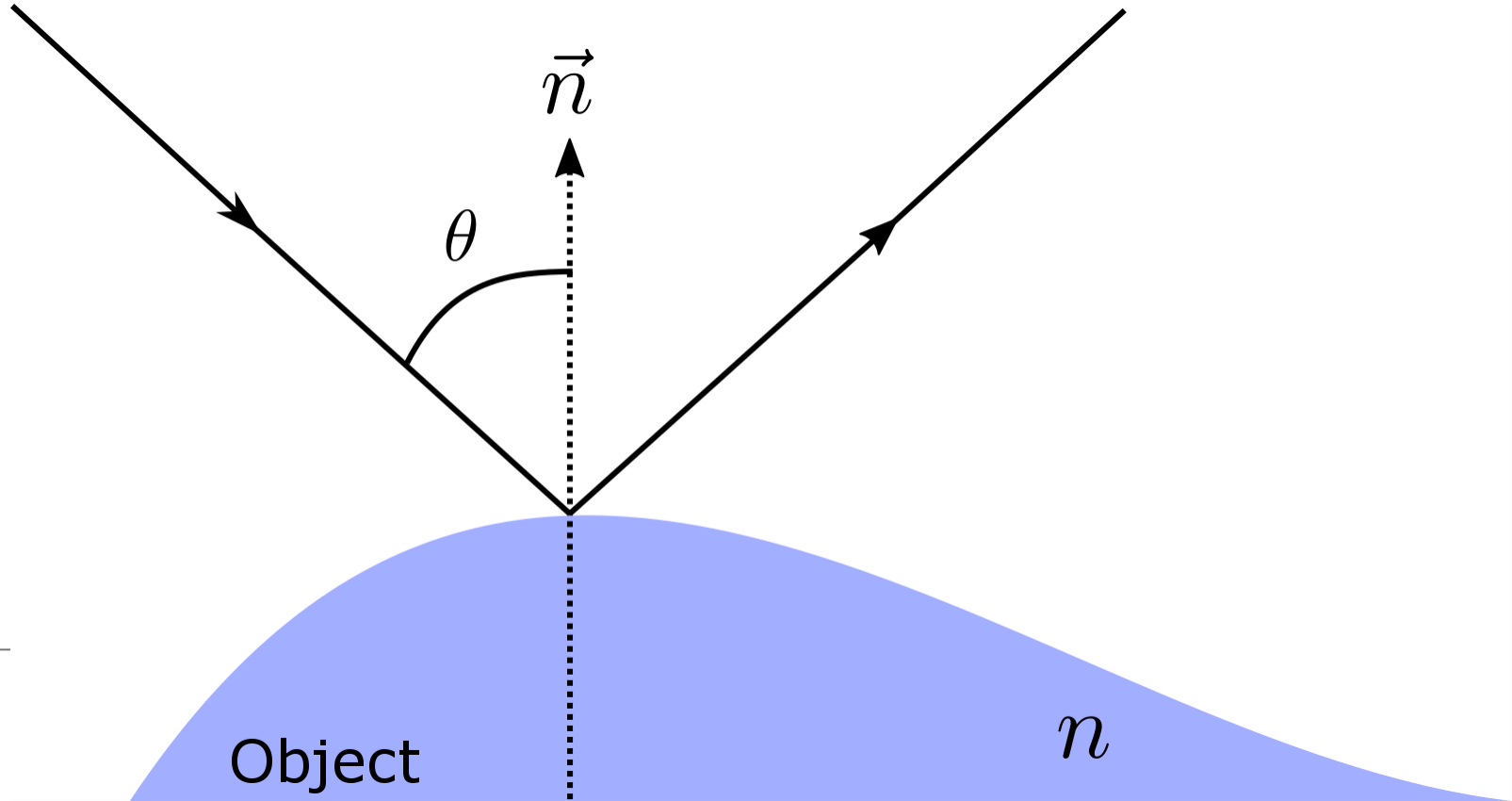
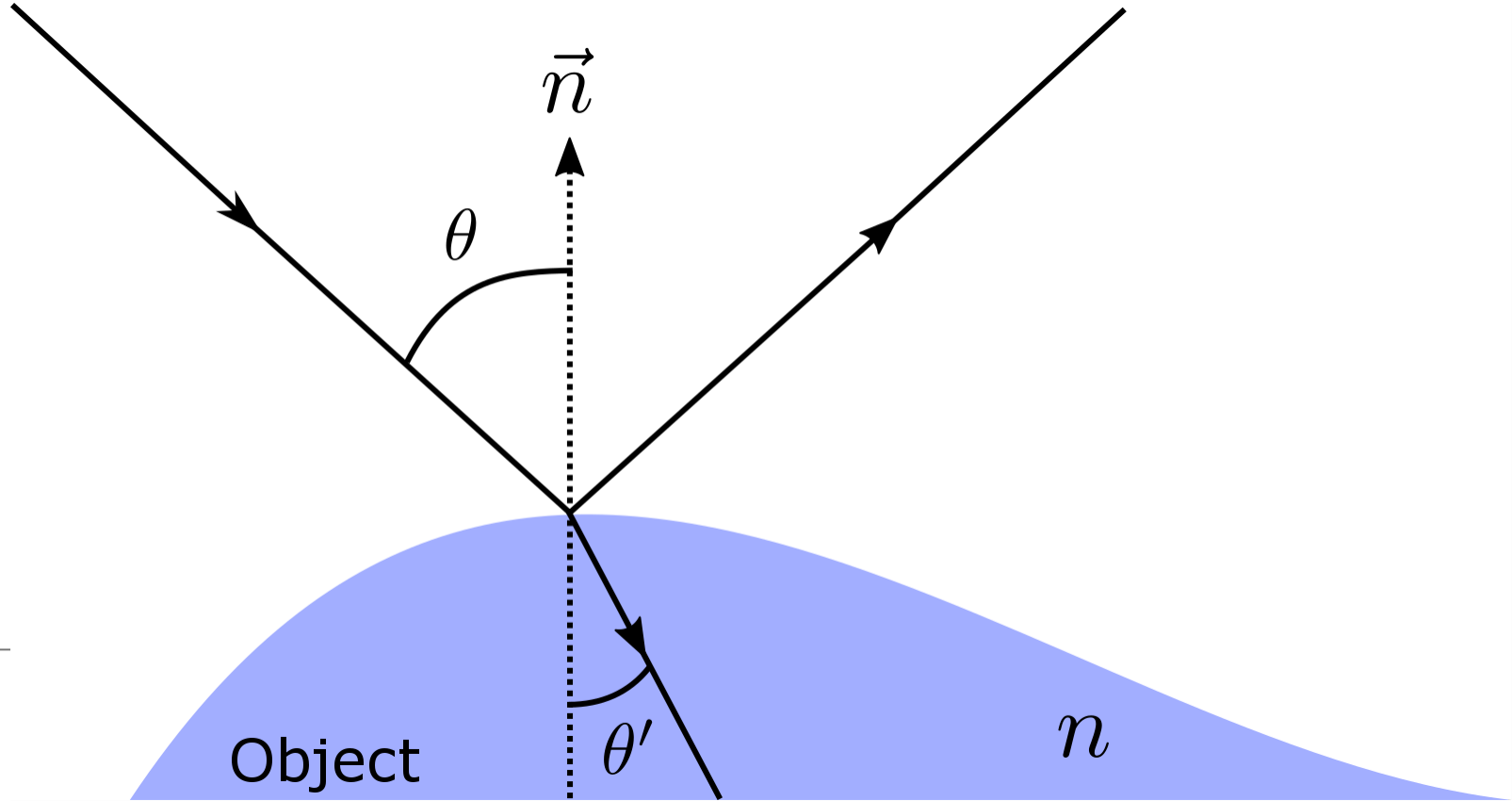
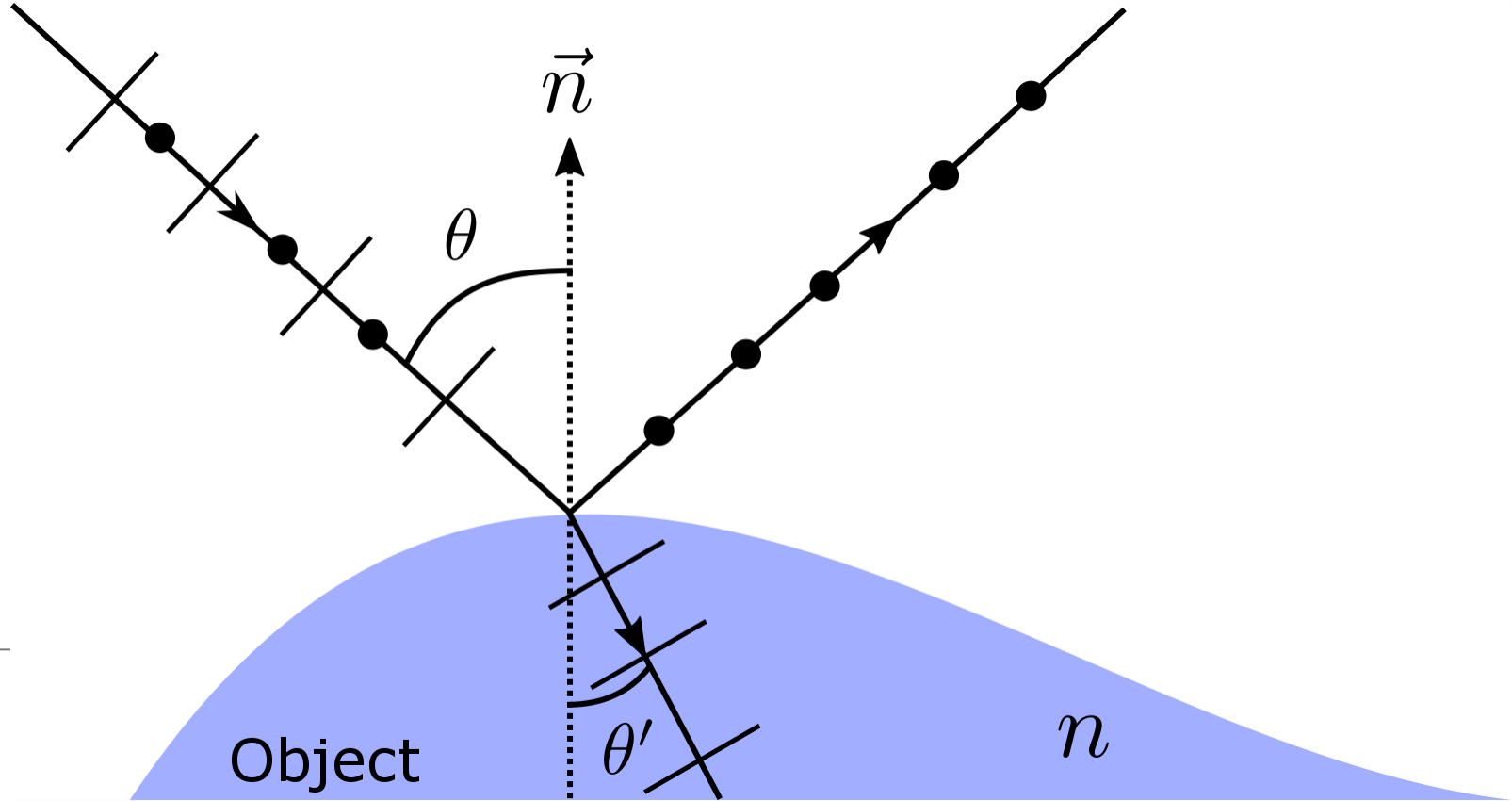


Shape from Polarization



Shape from Polarization



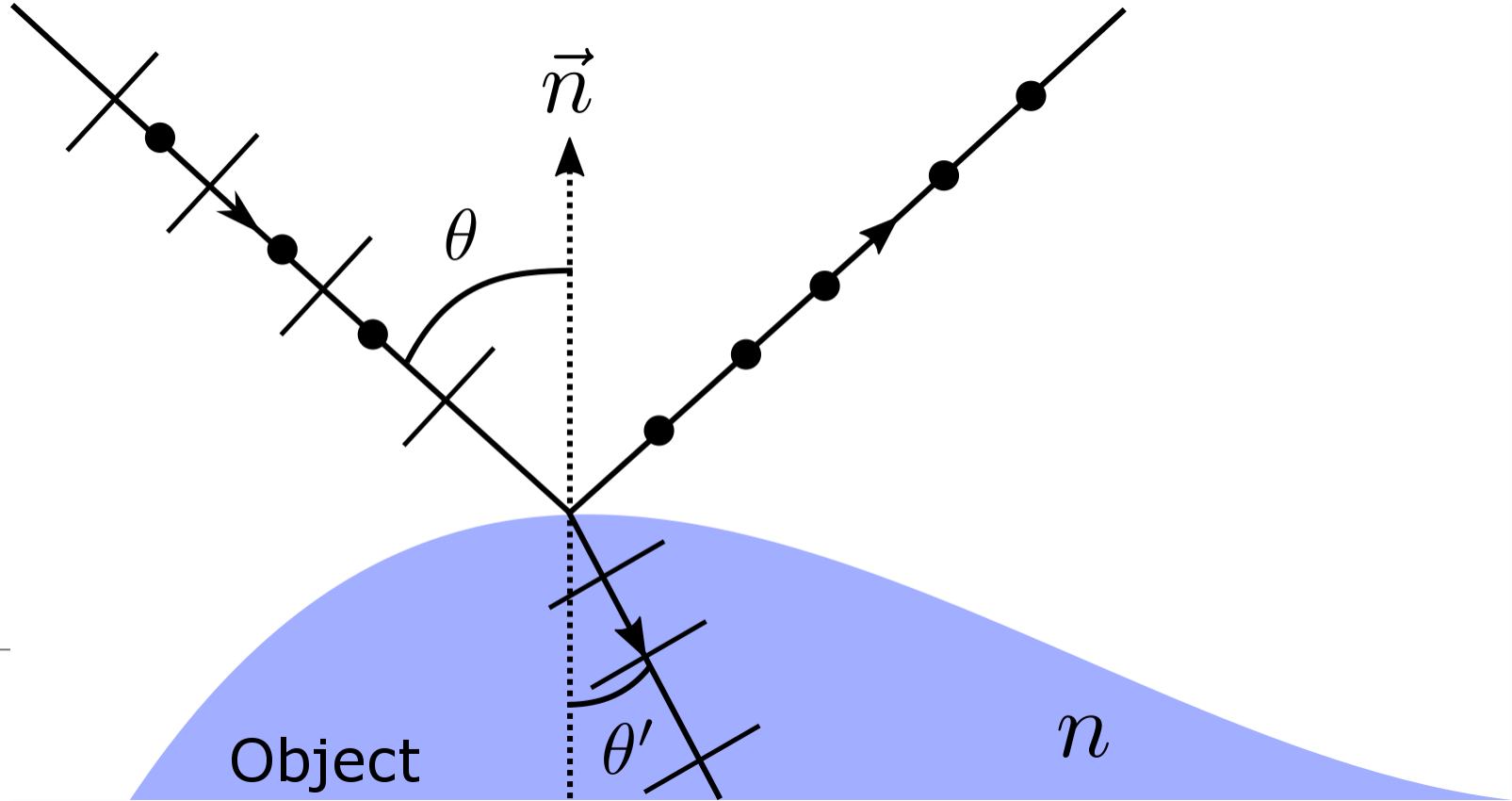
Shape from Polarization

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



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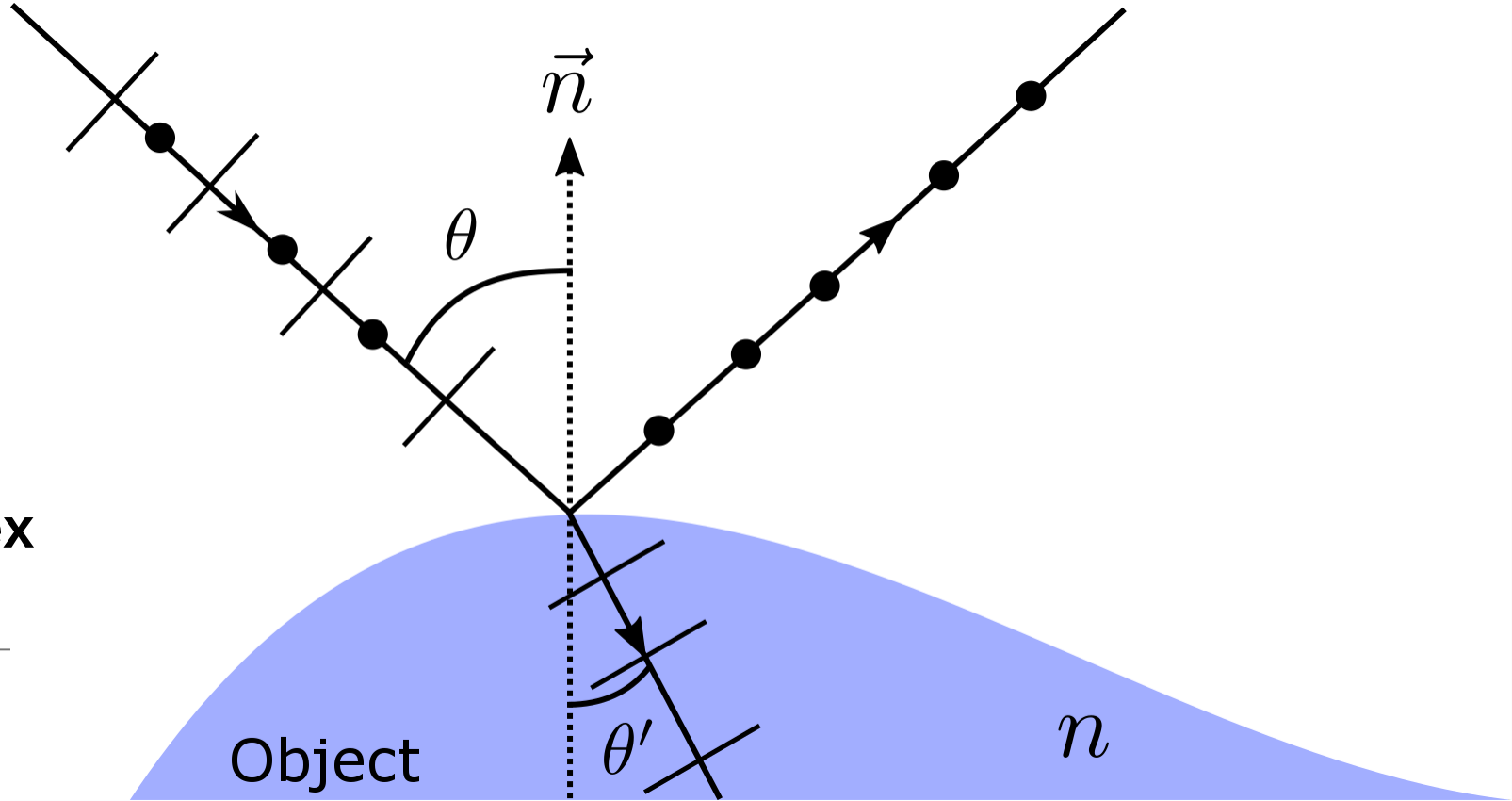
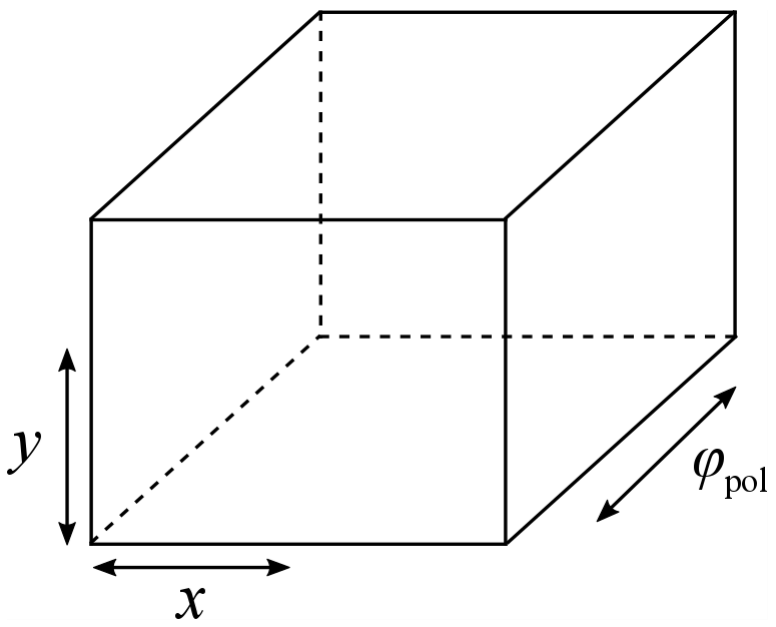
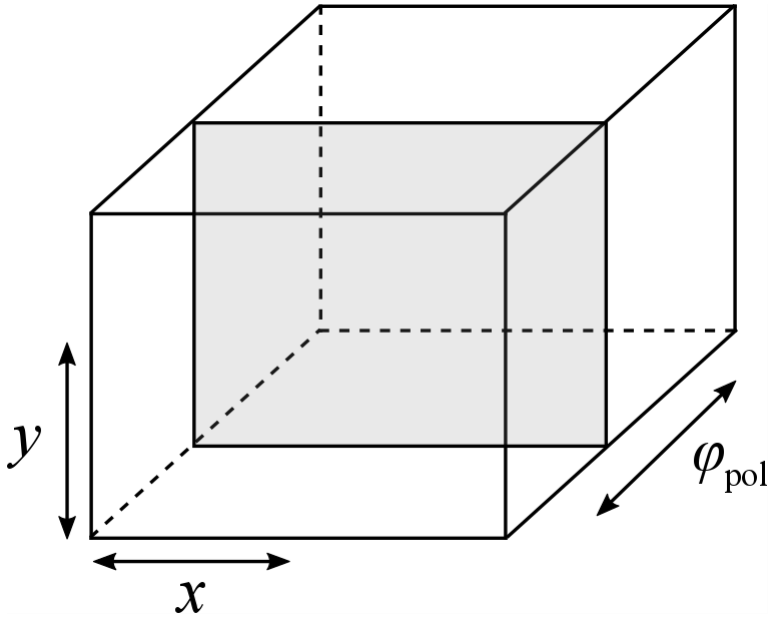
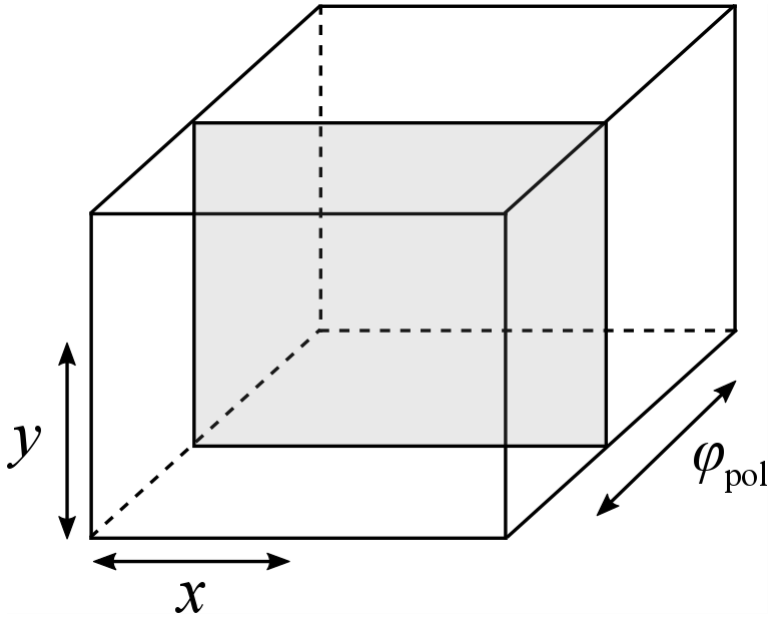
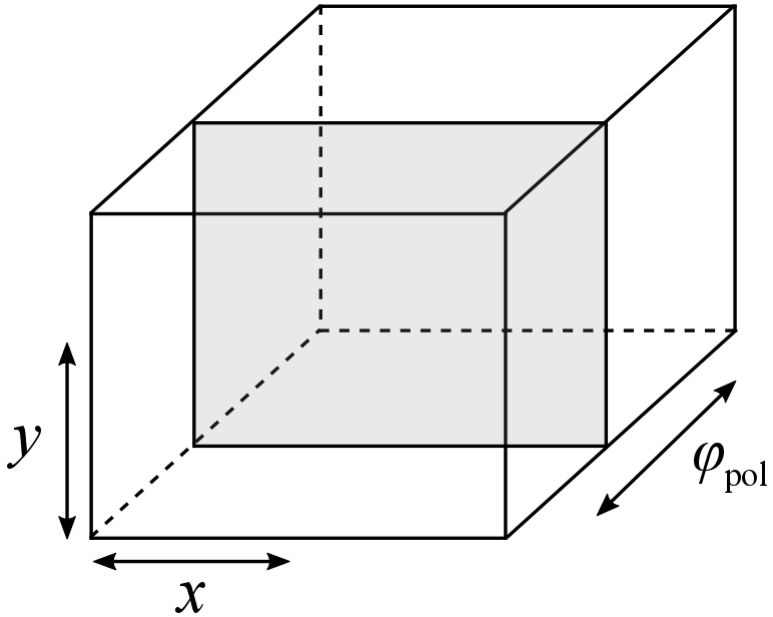
Need to know refractive index

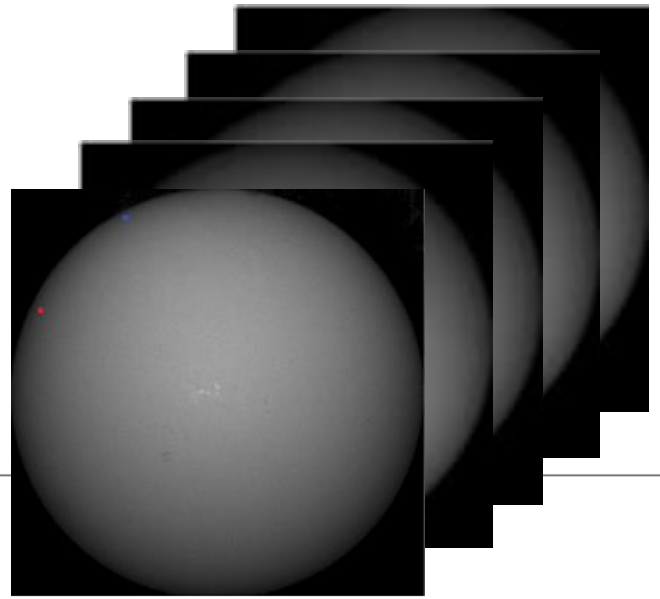


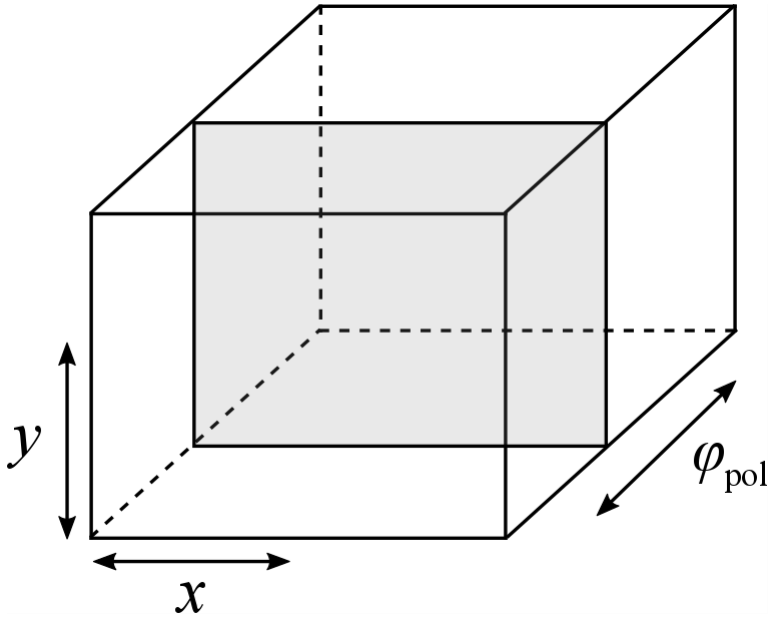

y
x
φ_{pol}

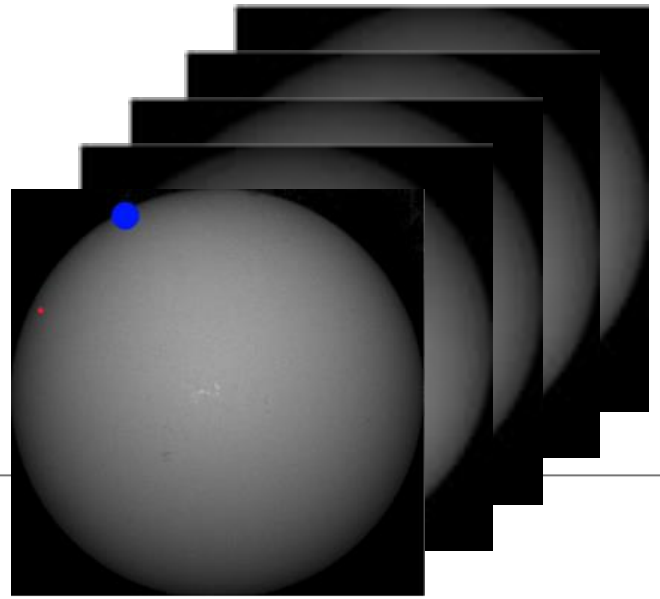

y
x
φ_{pol}

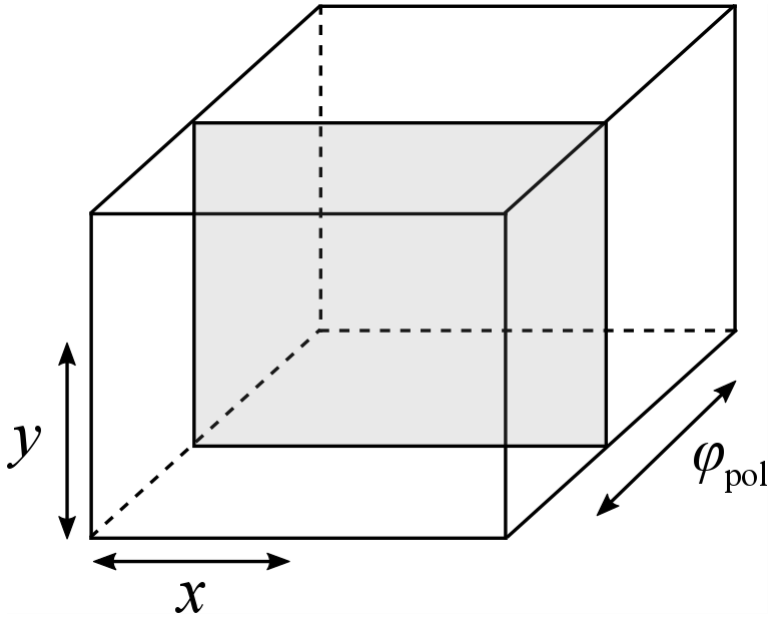

y
x
φ_{pol}

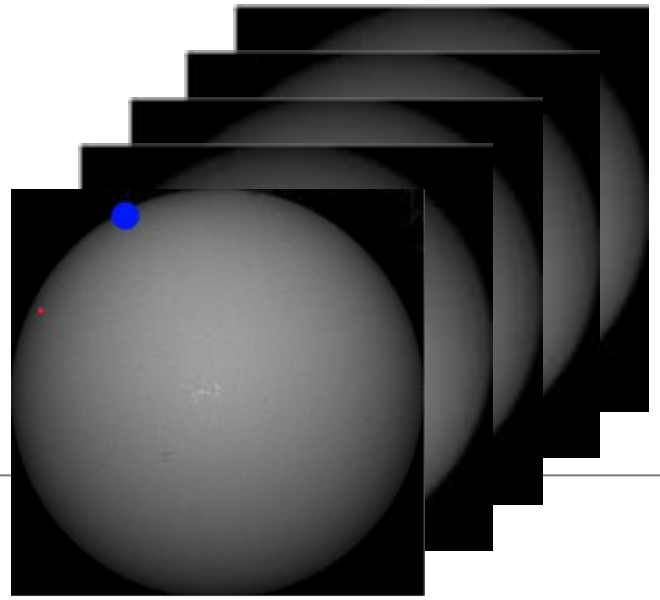

y
x
φ_{pol}

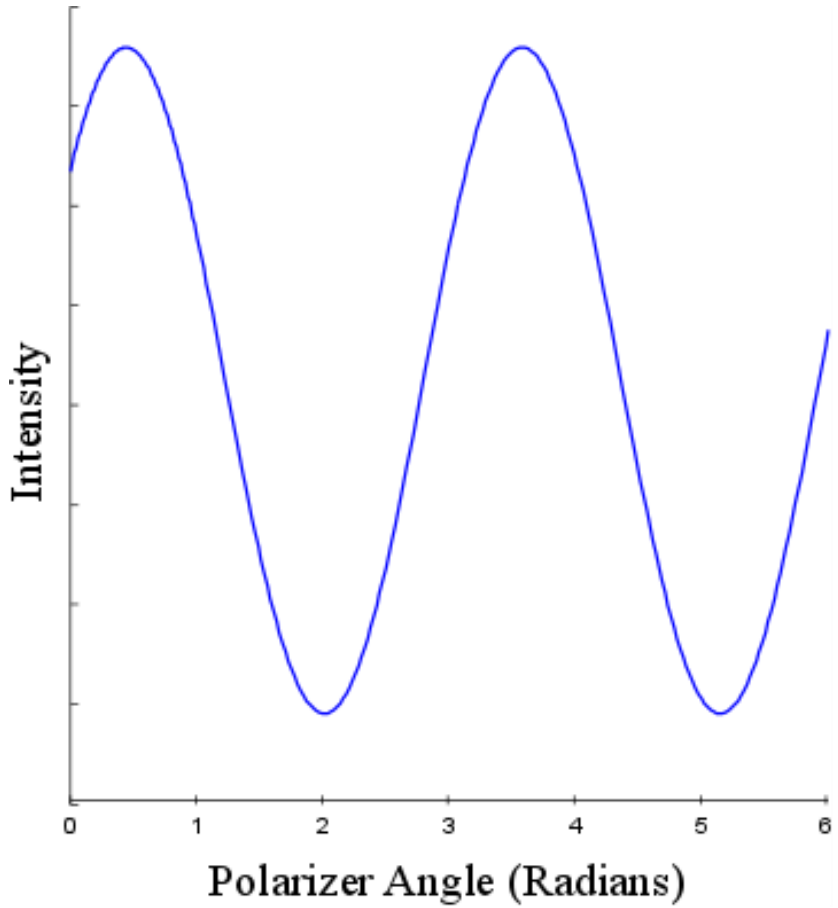


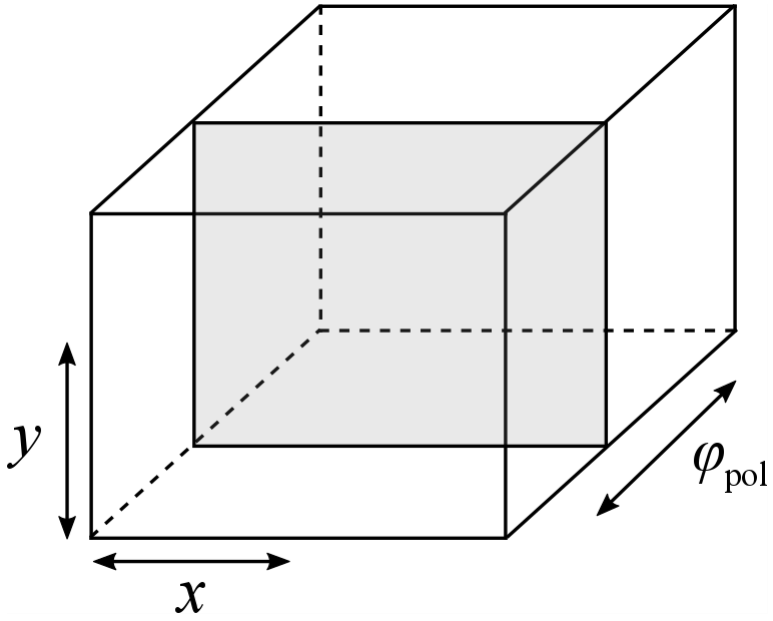

y
x
φ_{pol}

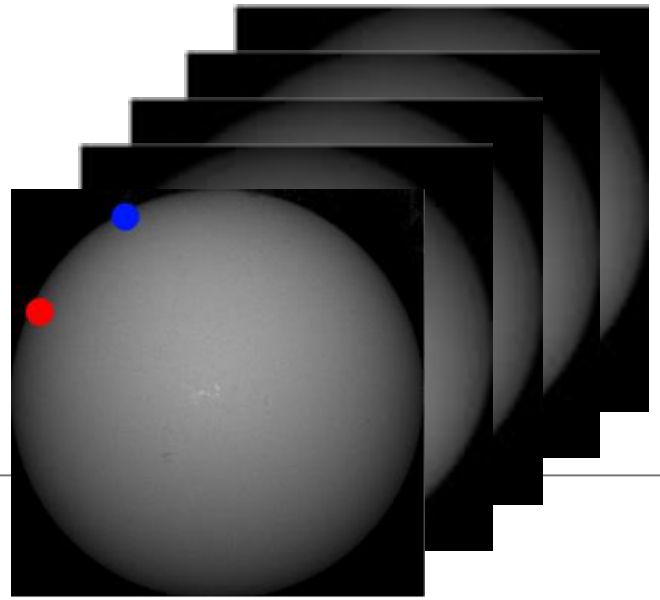


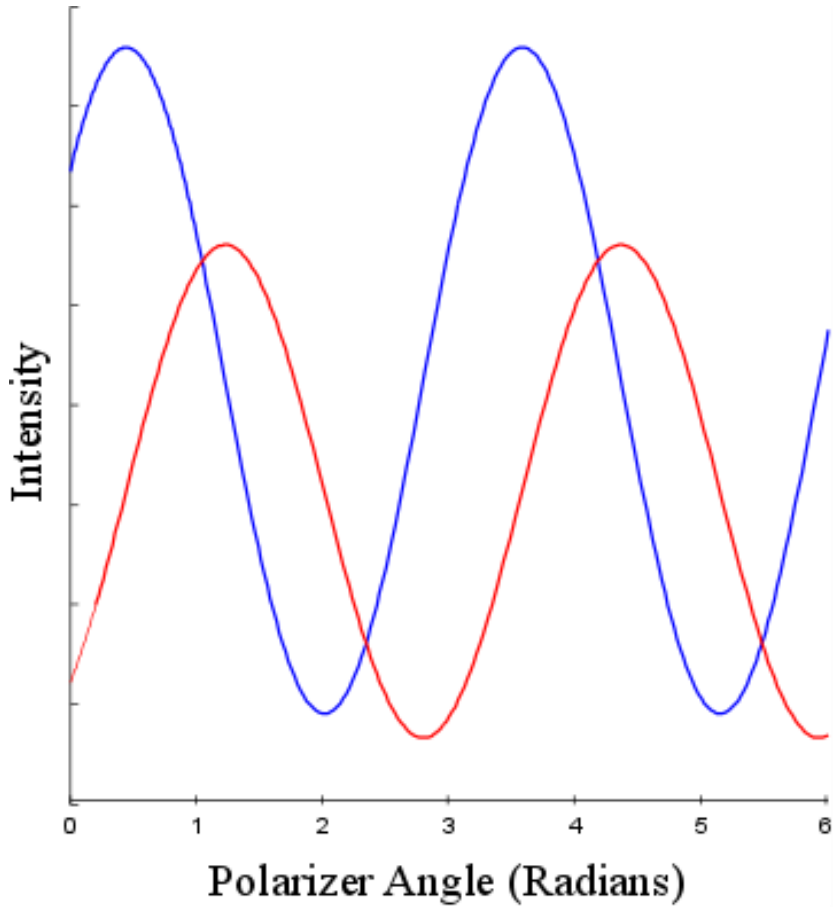

y
x
φ_{pol}




Intensity
0
1
2
3
4
5
6
Polarizer Angle (Radians)







Can use Schechner 15 ICCP

Image Formation Model

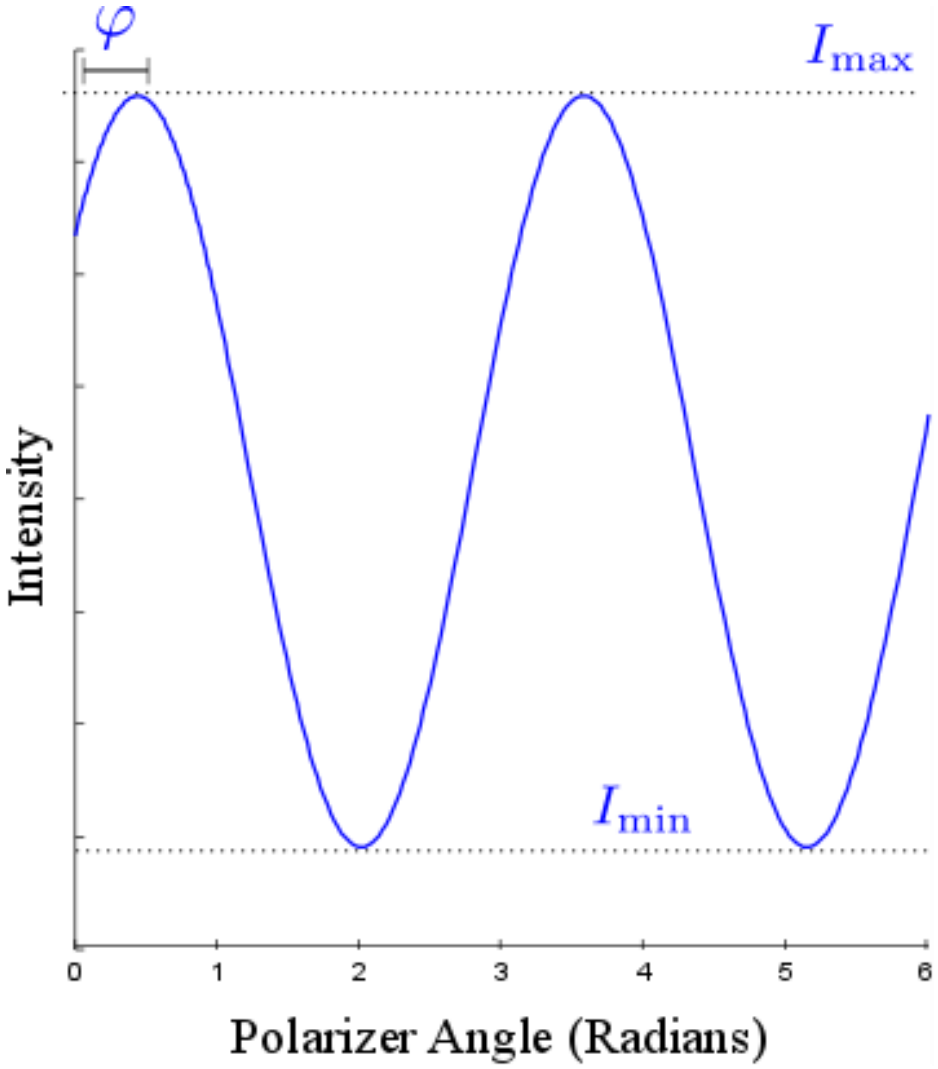
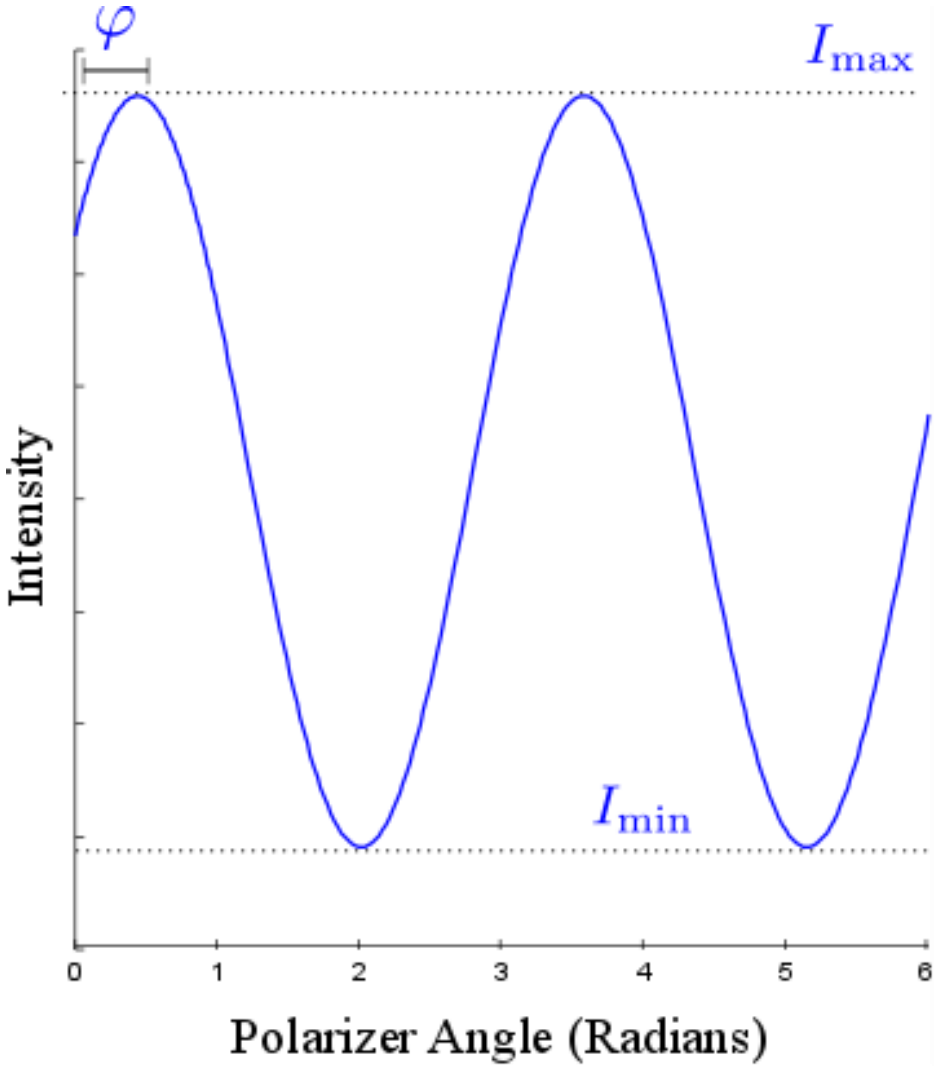


Image Formation Model



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

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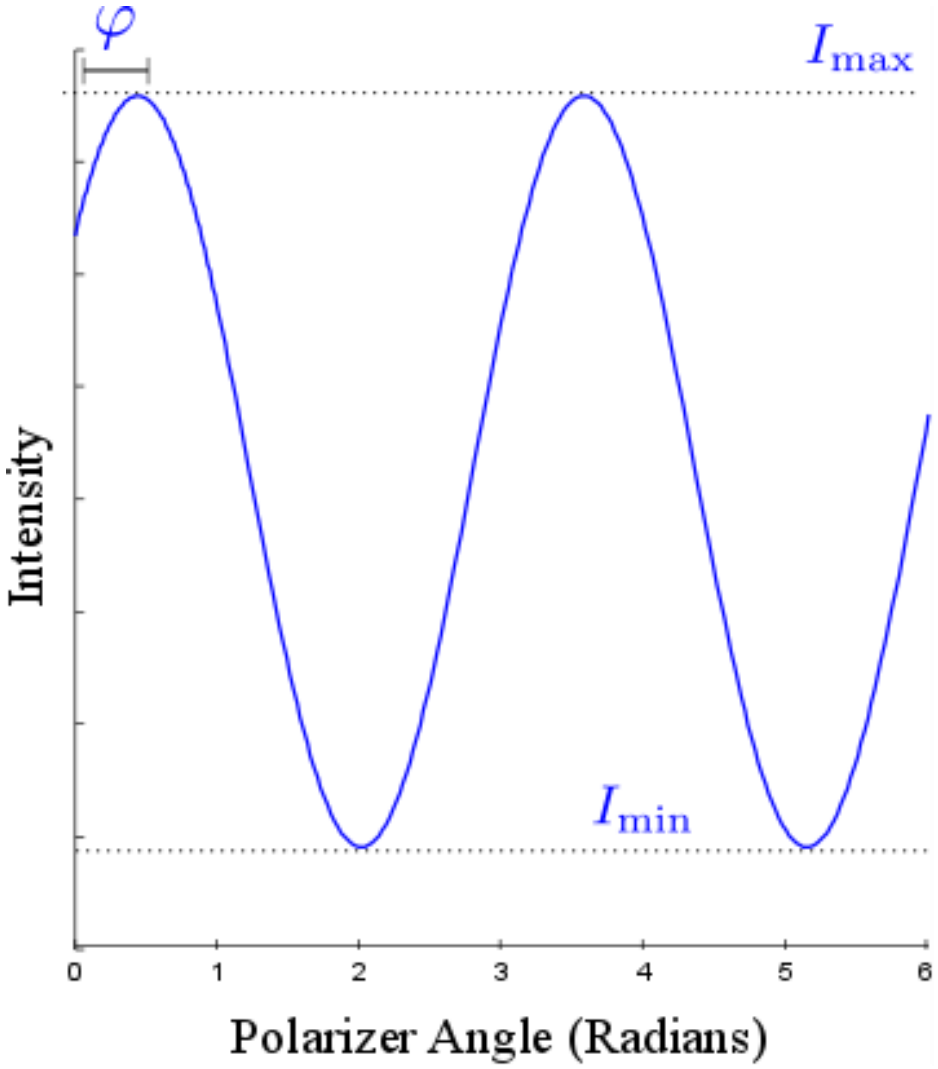

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Suppose $\exists\ \phi$ and $\phi' = \phi + \pi$

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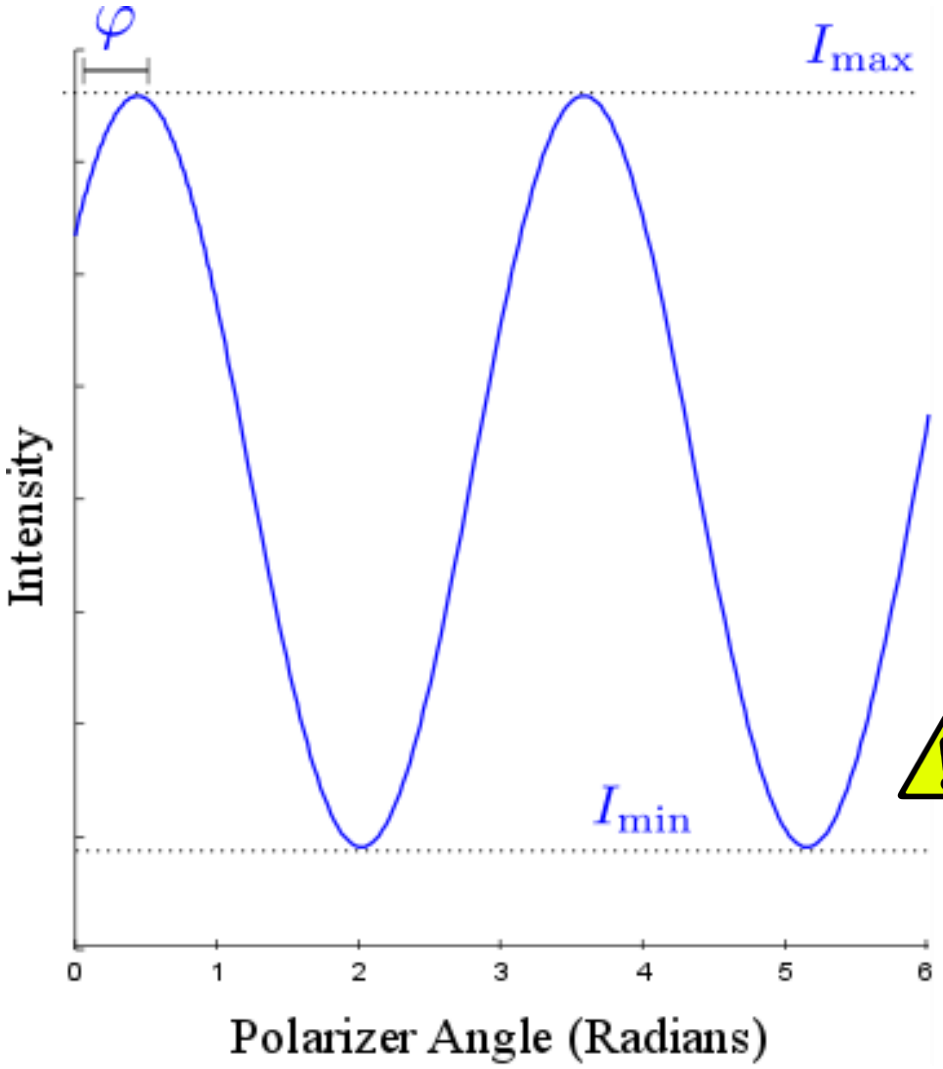

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Azimuthal Ambiguity problem with 2^P solutions

Why is Shape from Polarization Unpopular?

1. \pi Ambiguity in Surface Normal

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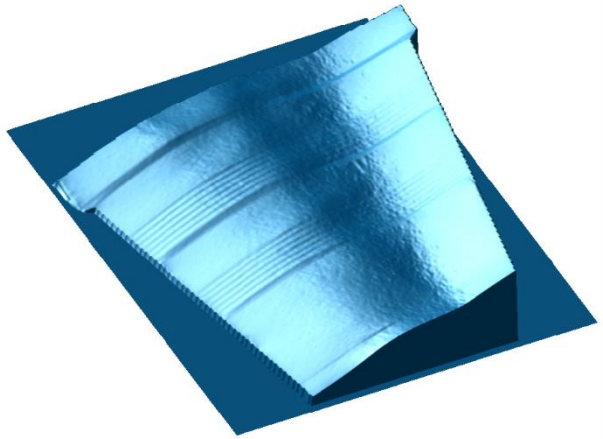

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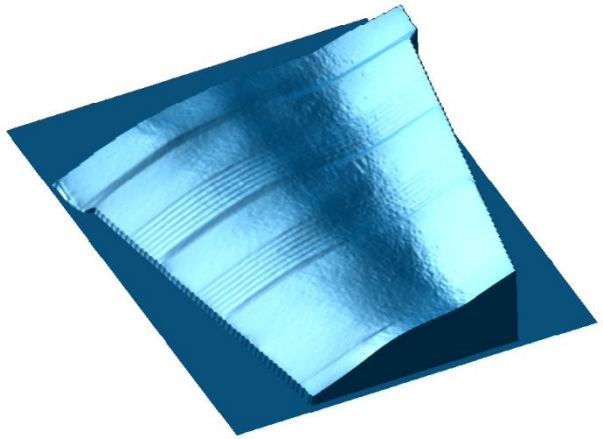

2. Refractive Distortion

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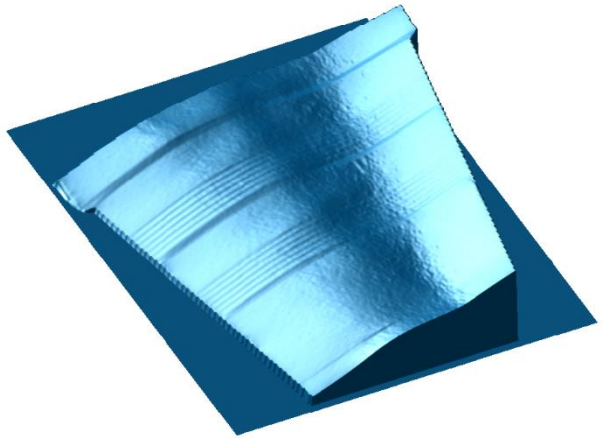

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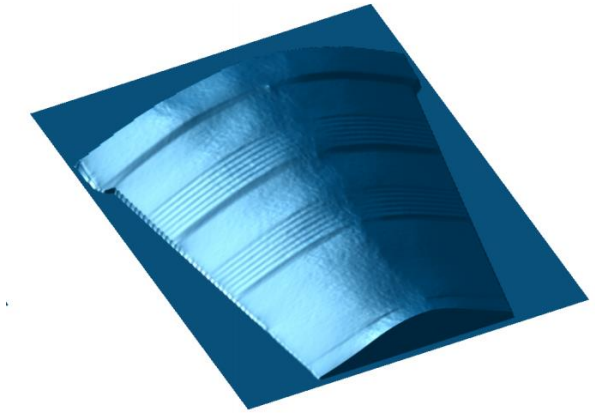

Why is Shape from Polarization Unpopular?

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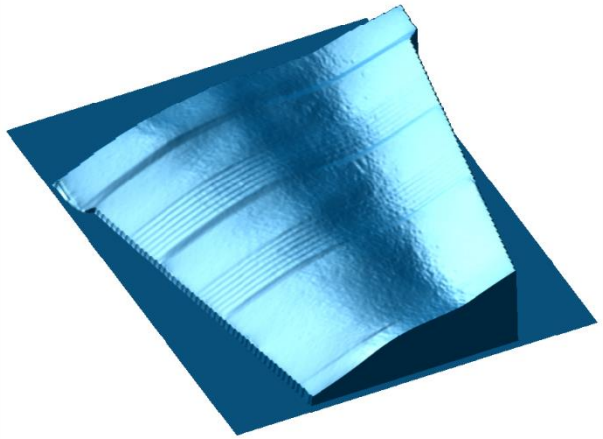
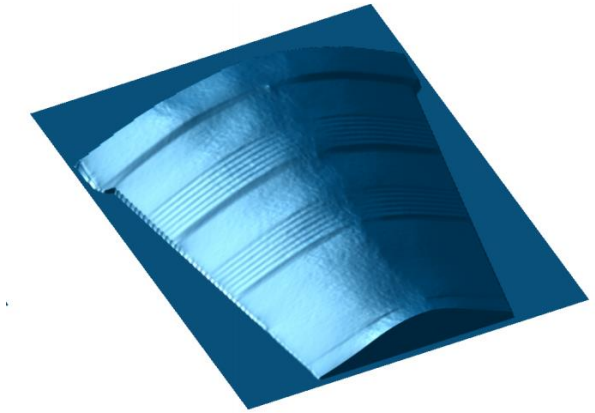


2. Refractive Distortion

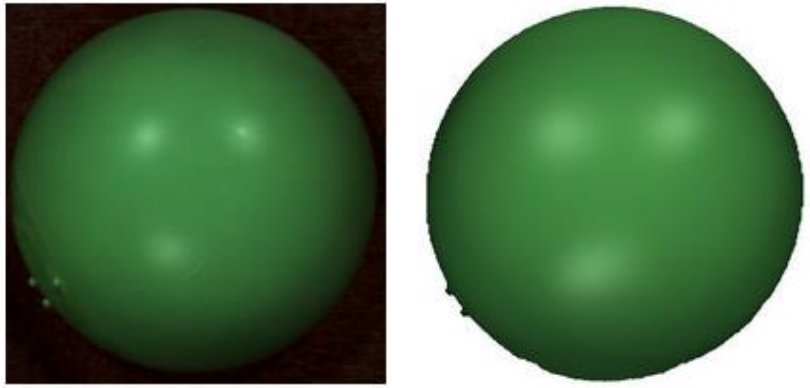
3. Low SNR for some geometries



4. Usual challenges of integrating surface normals..

Shape from Polarization in the Lab

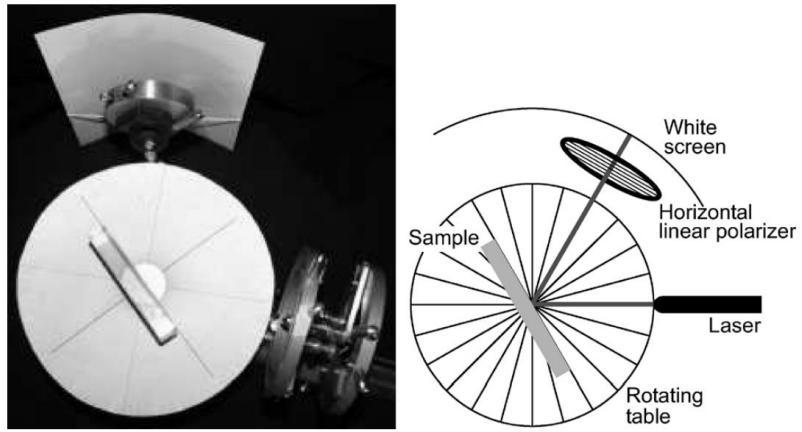
Polarization Inverse Rendering



Real Image Synthesized Image

Miyazaki ICCV 2003

Shape from Diffuse Polarization



Atkinson TIP 2006

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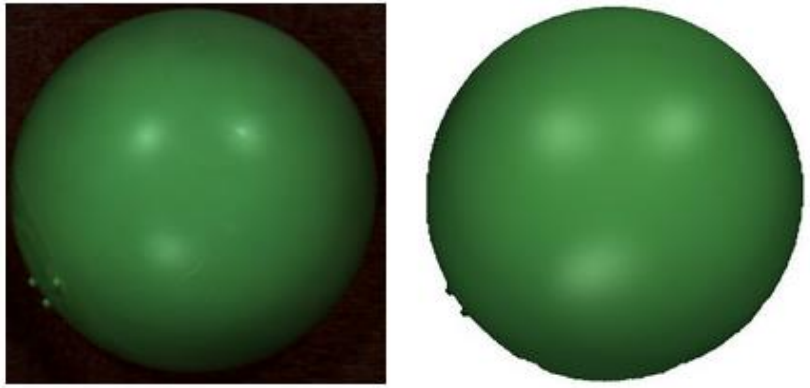

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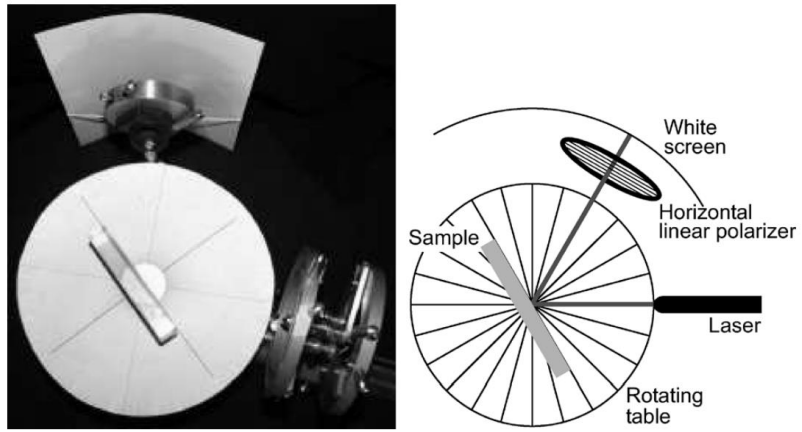
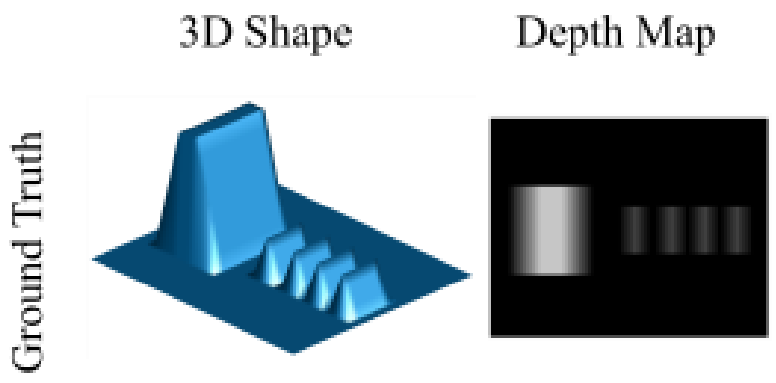


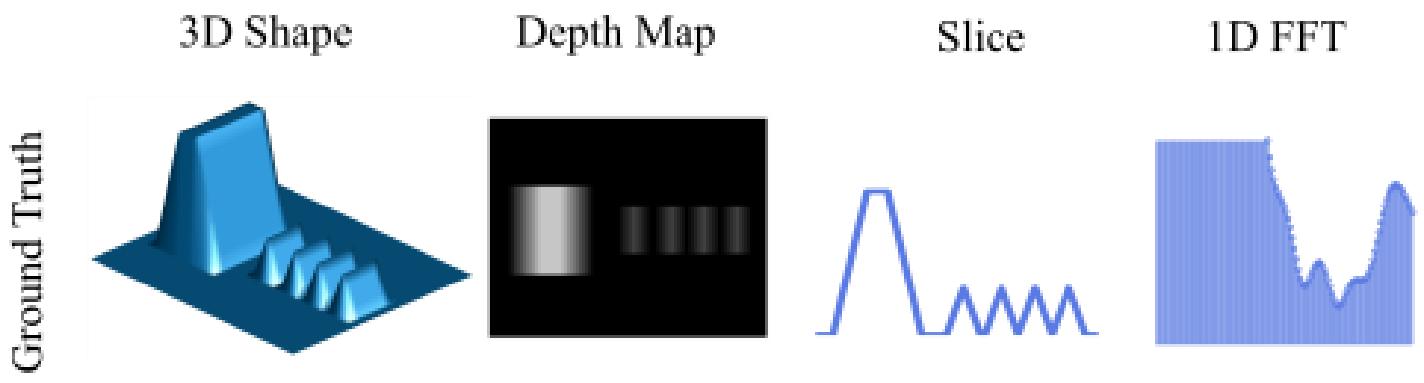
Atkinson TIP 2006

SfP never as popular as shading or photometric stereo

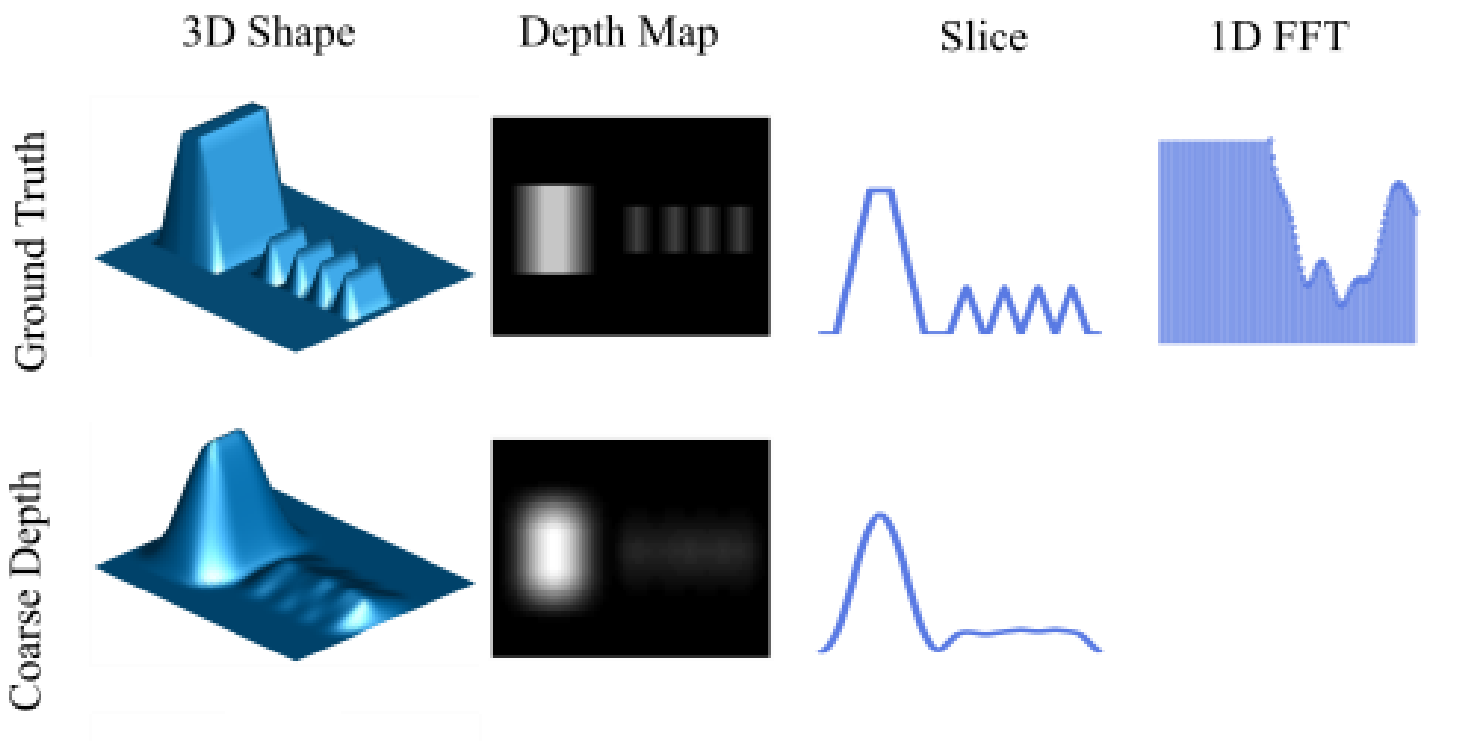
Frequency Analysis



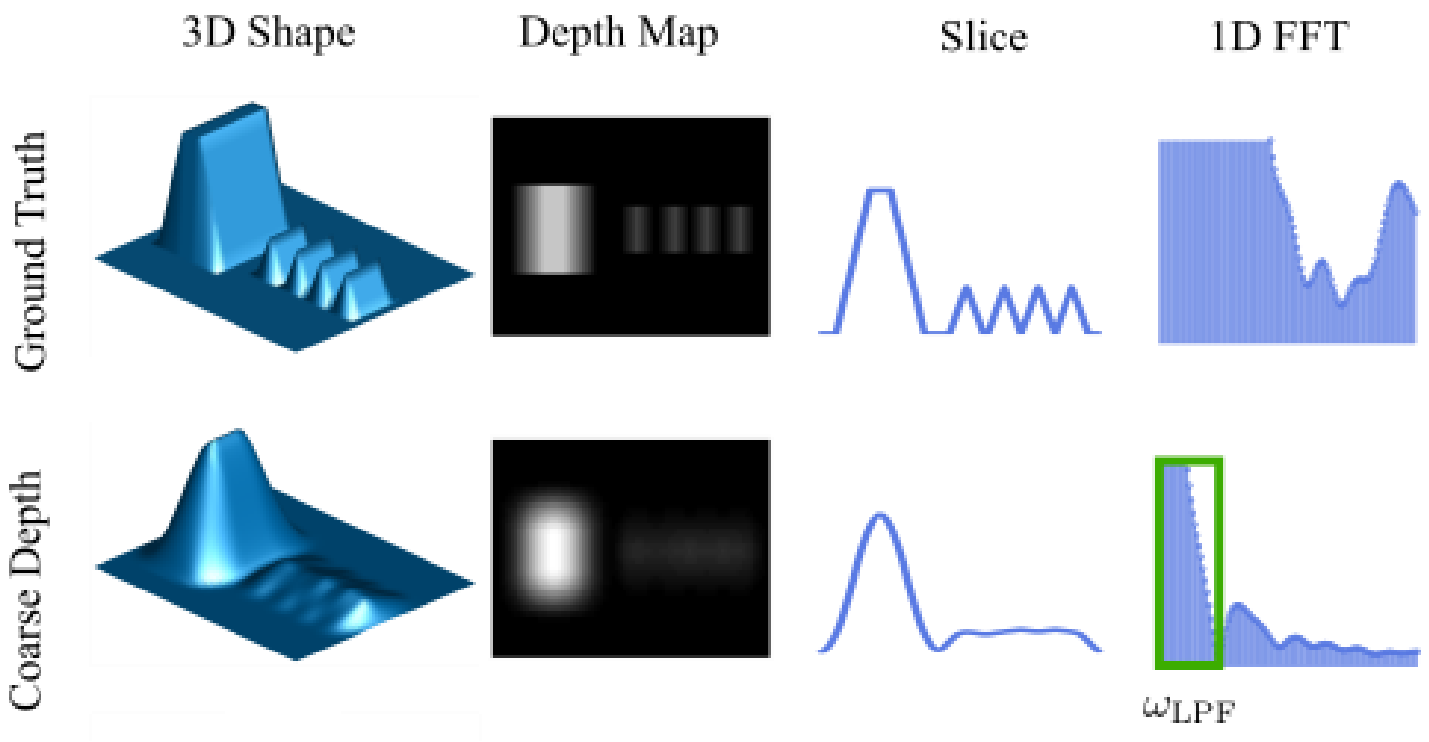
Frequency Analysis



Frequency Analysis



Frequency Analysis



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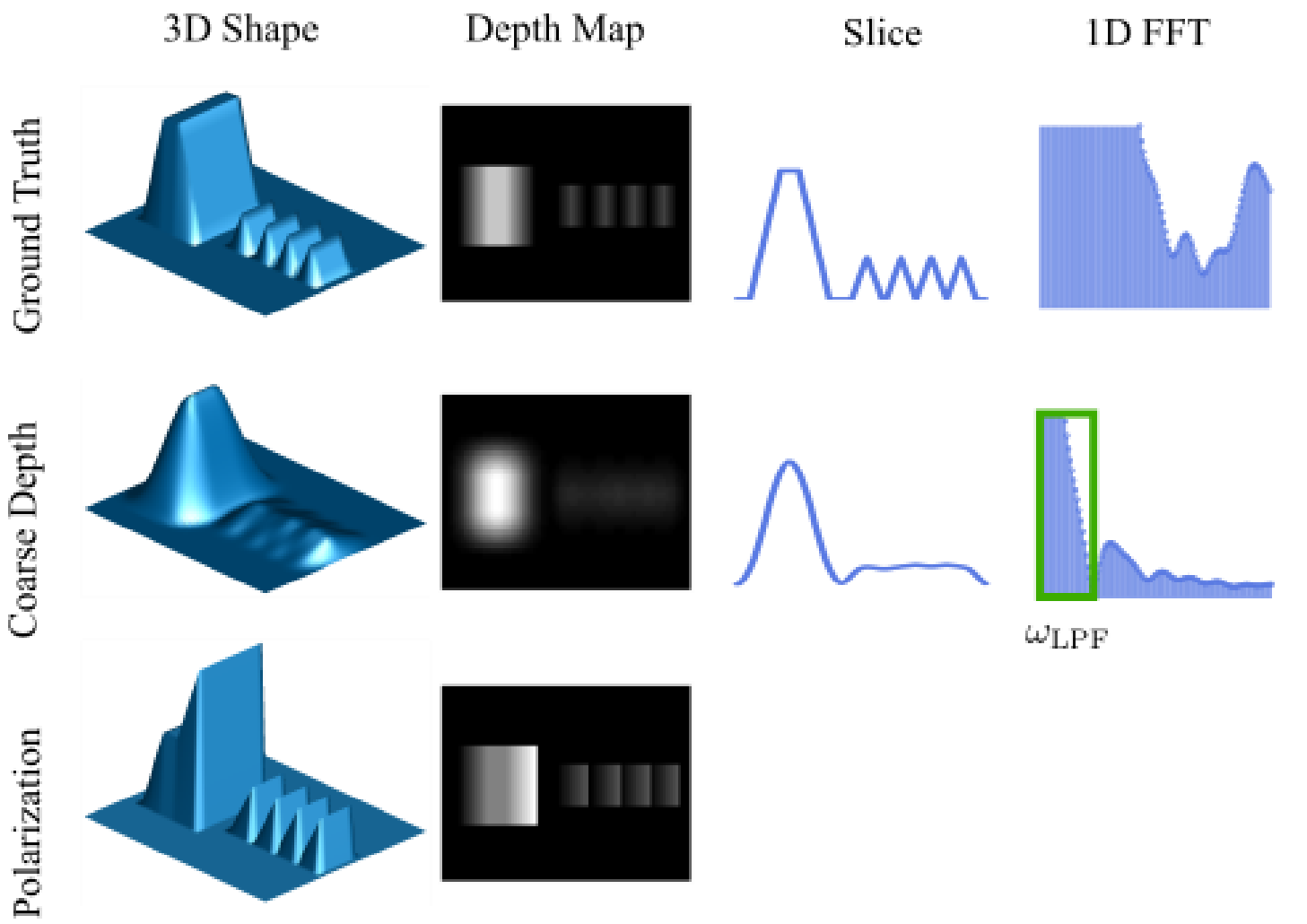

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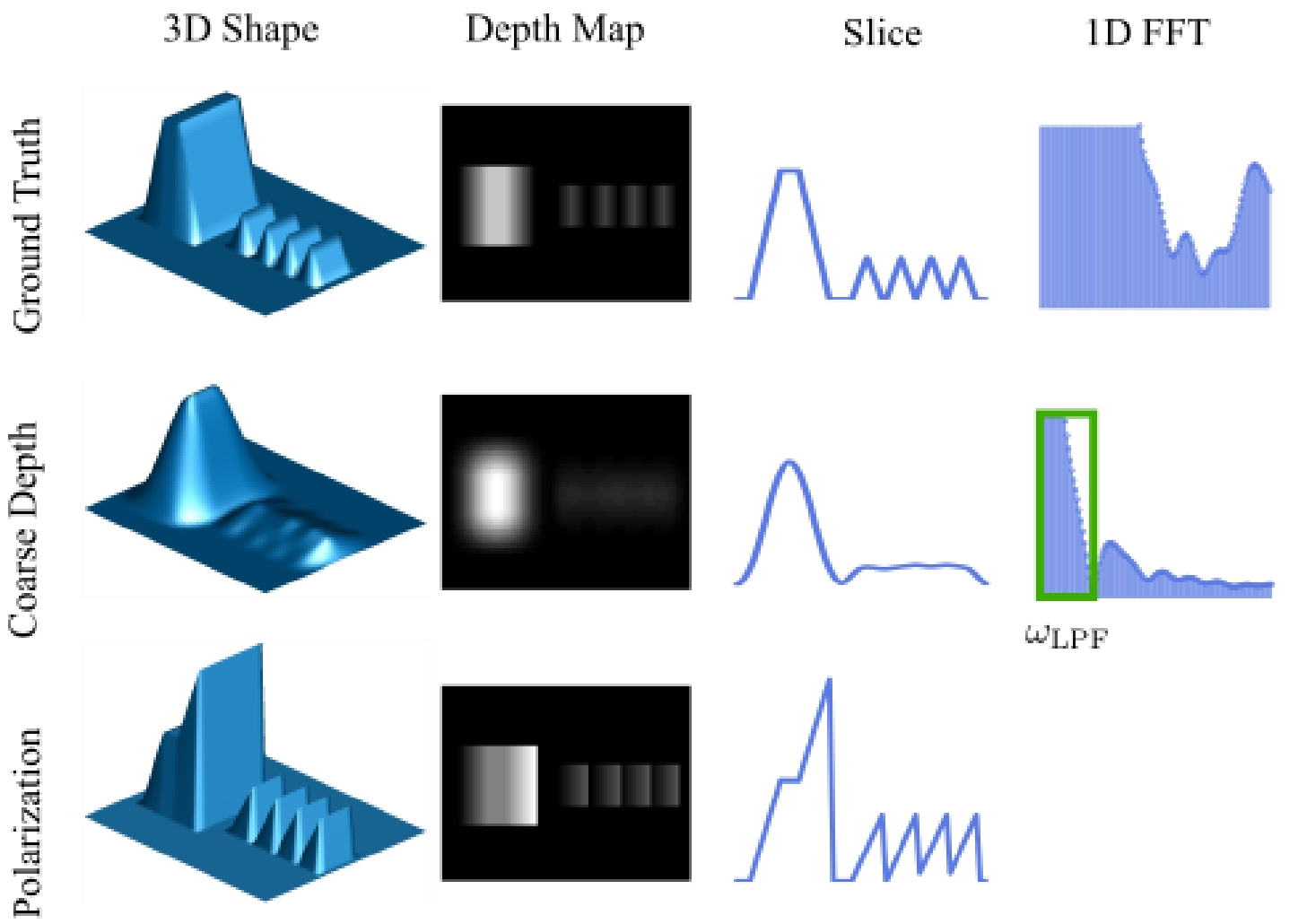

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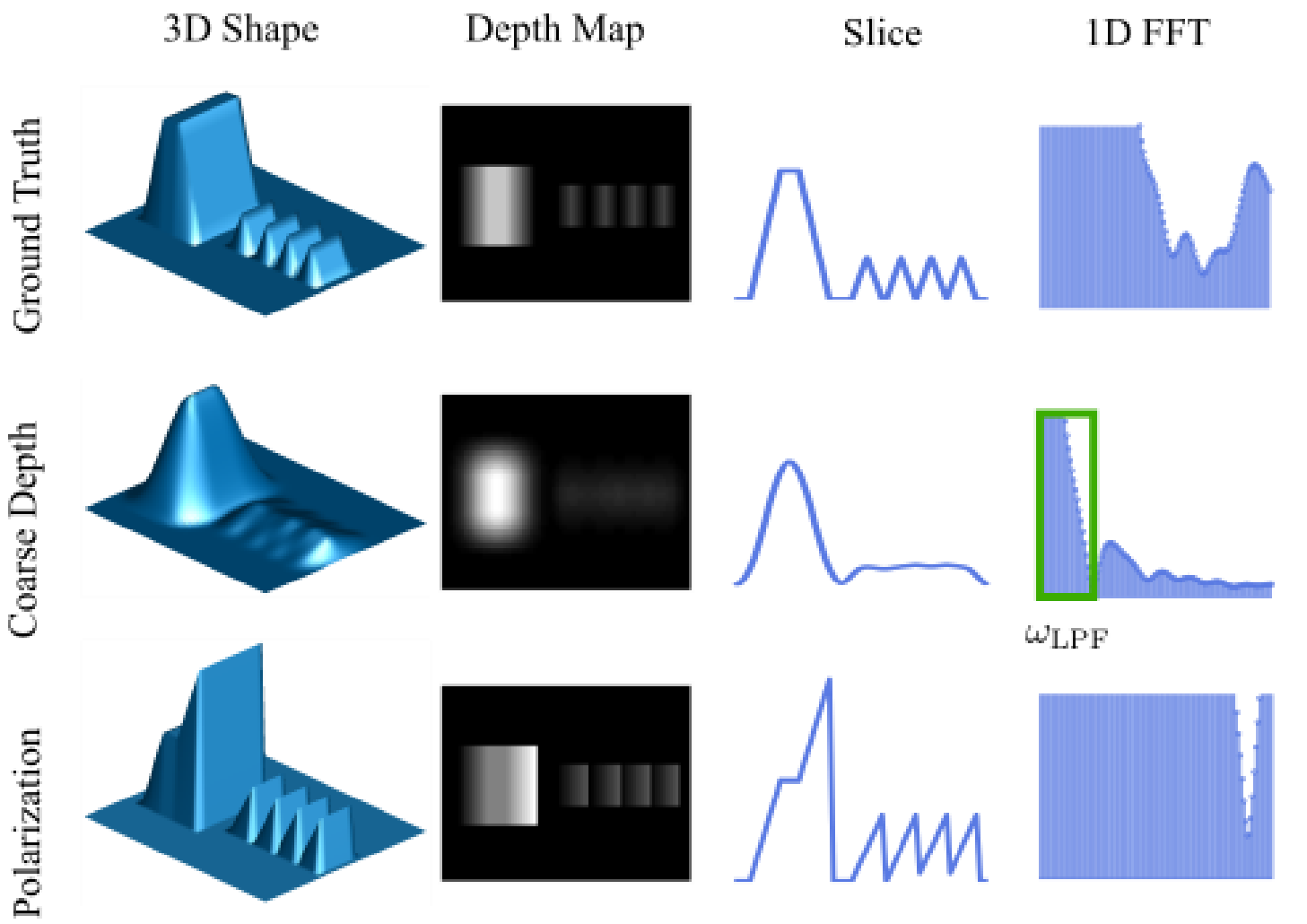
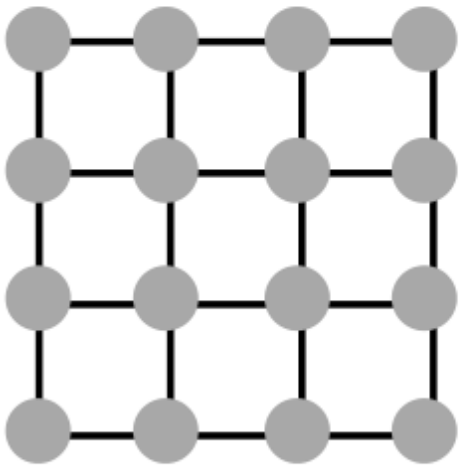


Polarized 3D Fuses Depth and Polarization

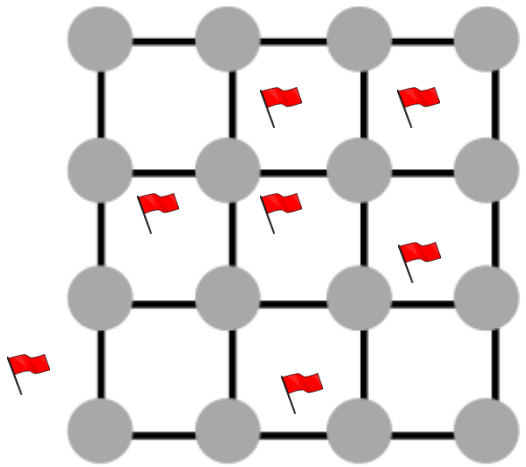
Spanning Tree Integration



Full Gradients

Polarized 3D Fuses Depth and Polarization

Spanning Tree Integration



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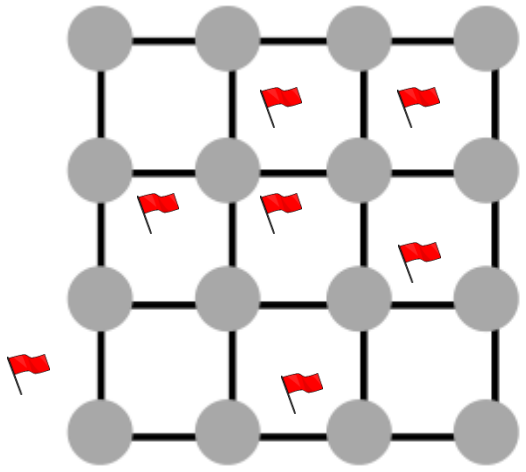
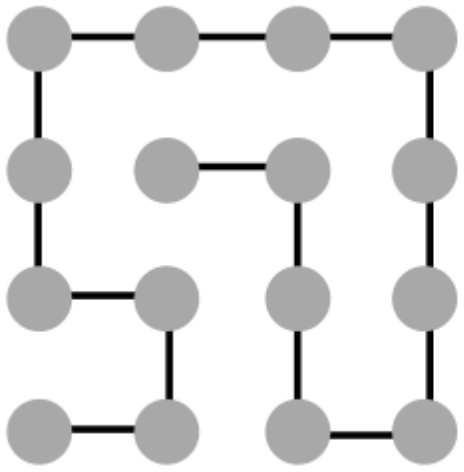


Full Gradients

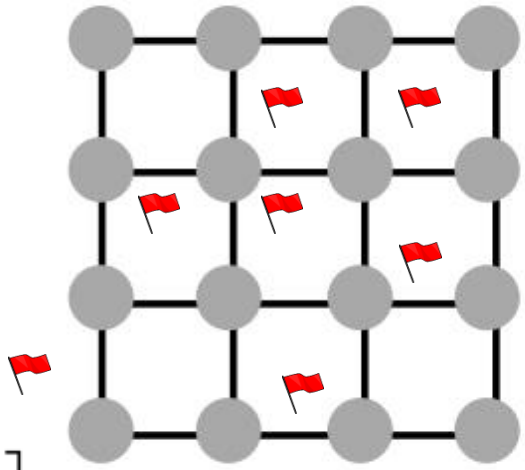


Minimum Spanning Tree

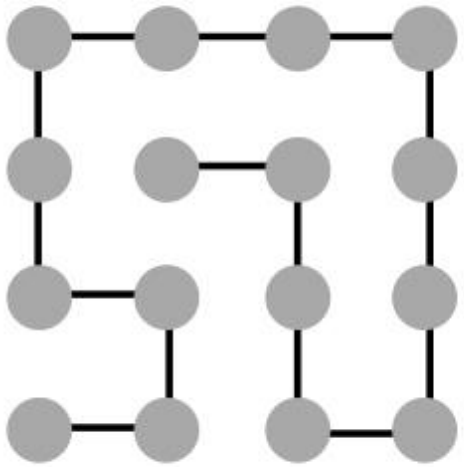
Polarized 3D Fuses Depth and Polarization

Spanning Tree Integration

$$\begin{bmatrix} \lambda \mathbf{M} \odot \mathbf{I} \\ \nabla_S^2 \end{bmatrix} \mathrm{VEC}\left(\widehat{\mathbf{D}}\right) = \begin{bmatrix} \lambda \mathrm{VEC}\left(\mathbf{M} \odot \mathbf{D}\right) \\ \nabla_S^T \left(\mathbf{N}^{\mathrm{corr}}\right) \end{bmatrix}$$



Full Gradients



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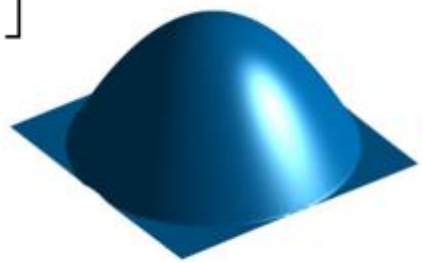
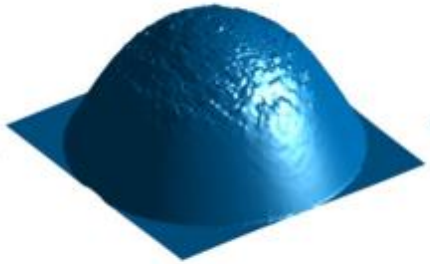
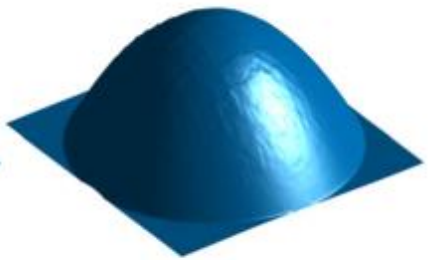


Ground Truth Surface



Full Integration



Spanning Tree Integration

Assumptions

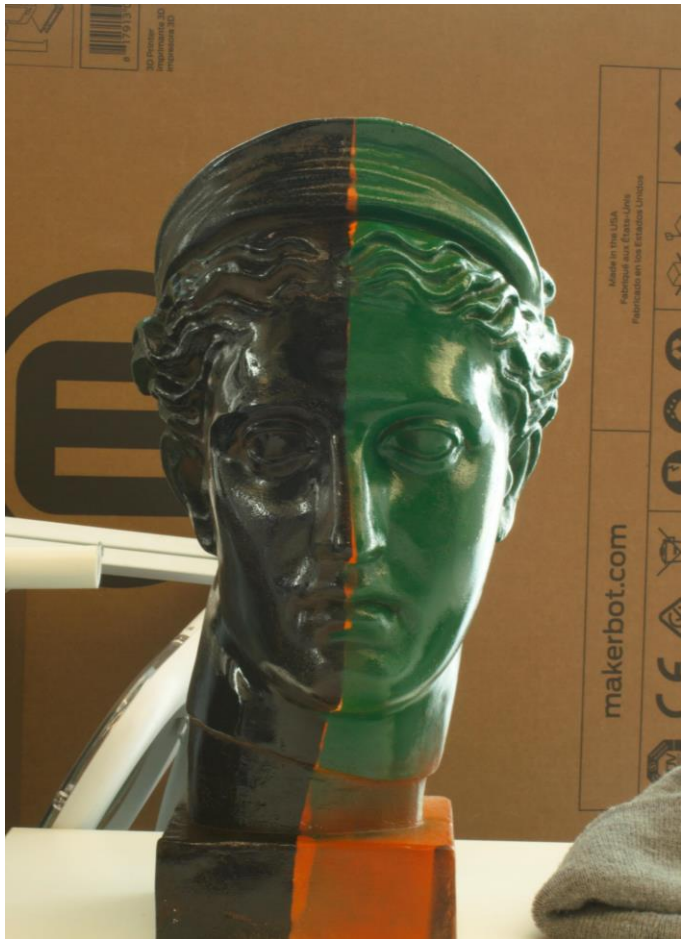
Unpolarized World Assumption

Dielectric or Low-frequency Material Transition

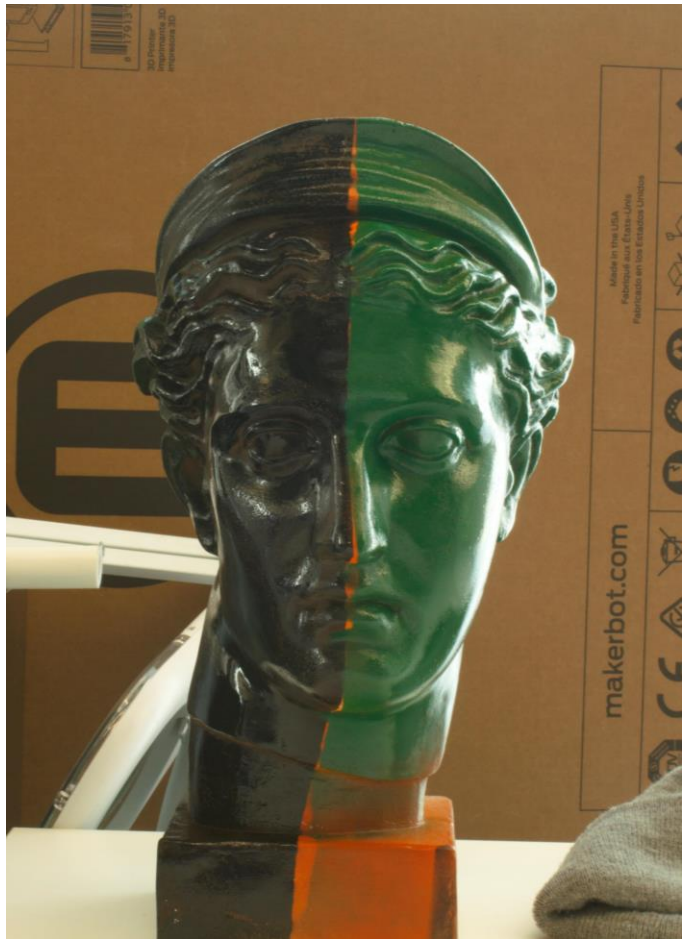
No specular interreflections

Diffuse-dominant or Specular-dominant surfaces with slack

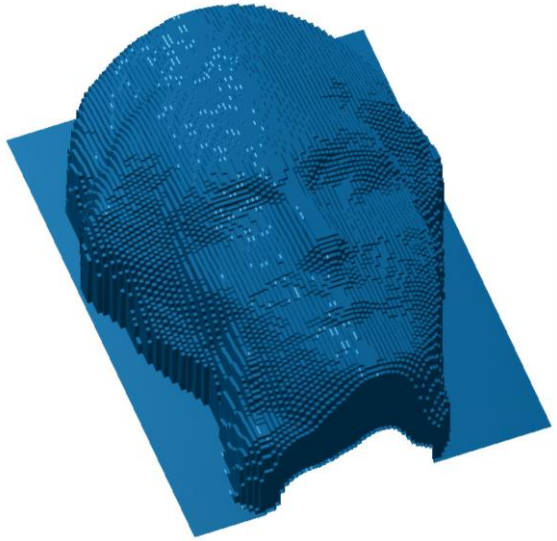
Challenging Materials



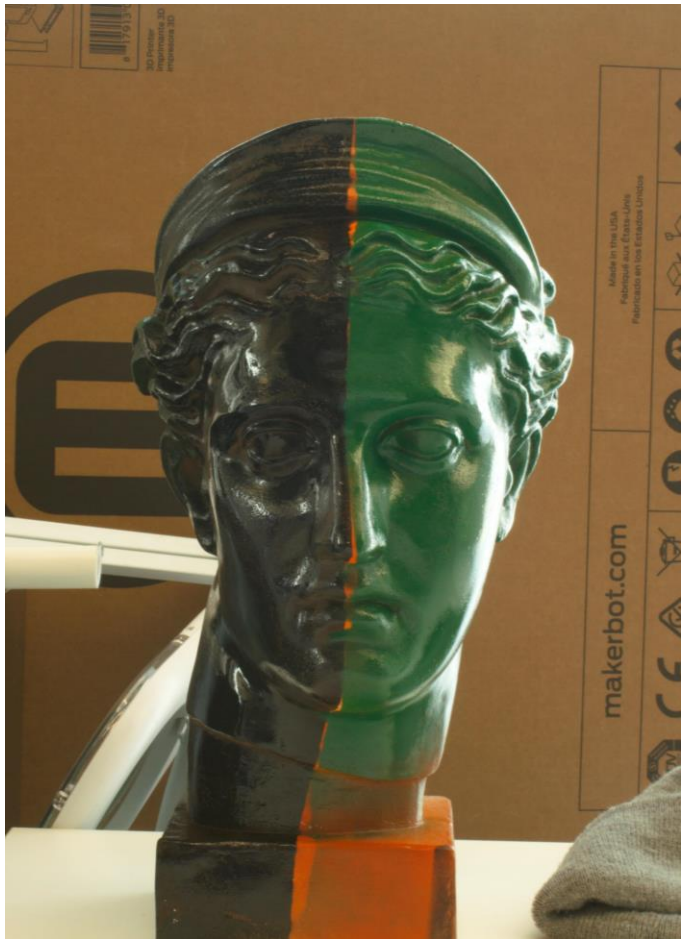
Challenging Materials



Kinect



Challenging Materials



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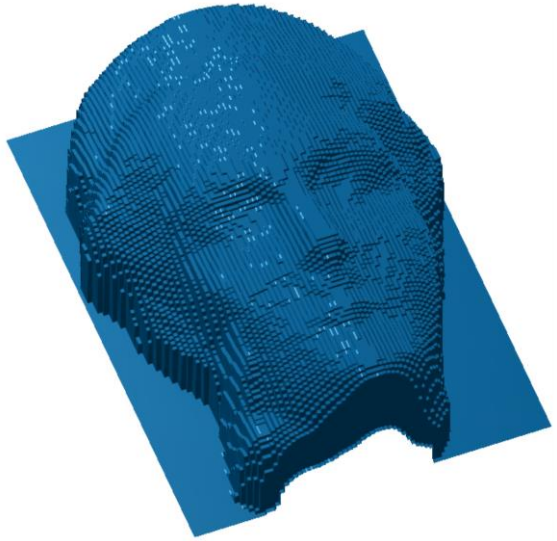
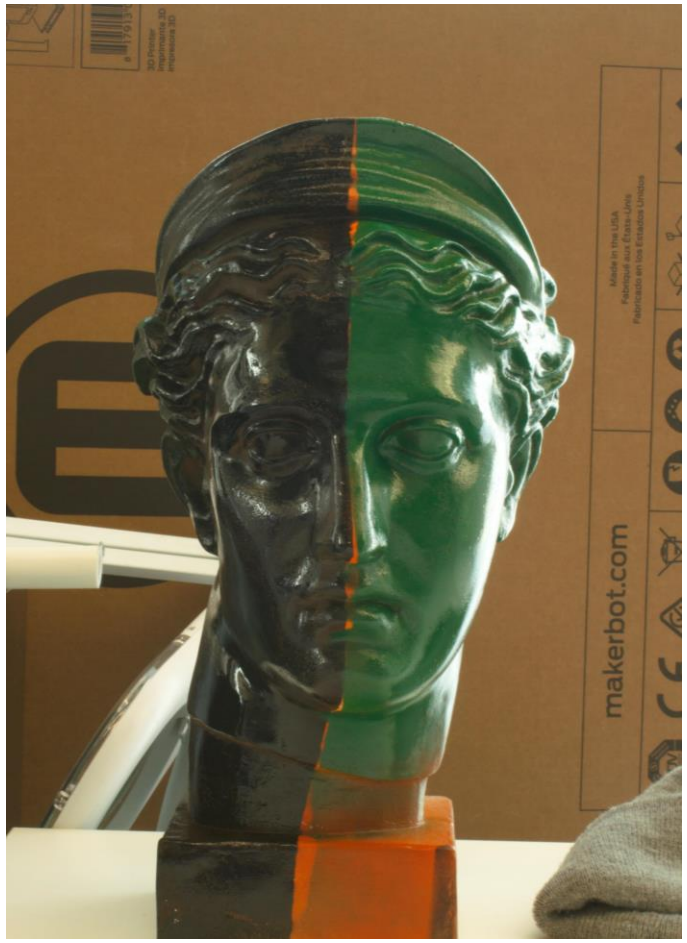


Shading [Wu 14]

Challenging Materials



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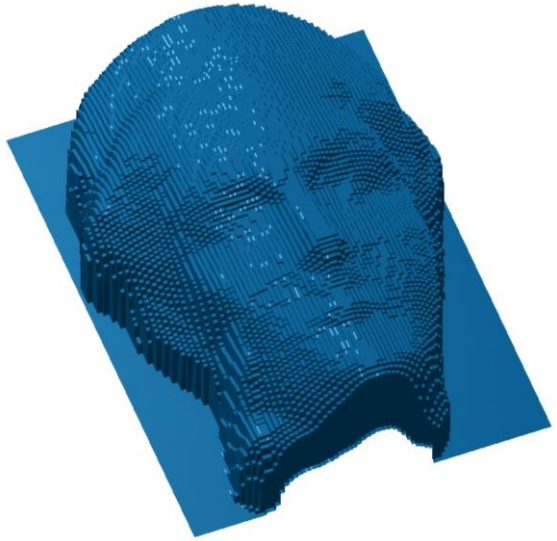
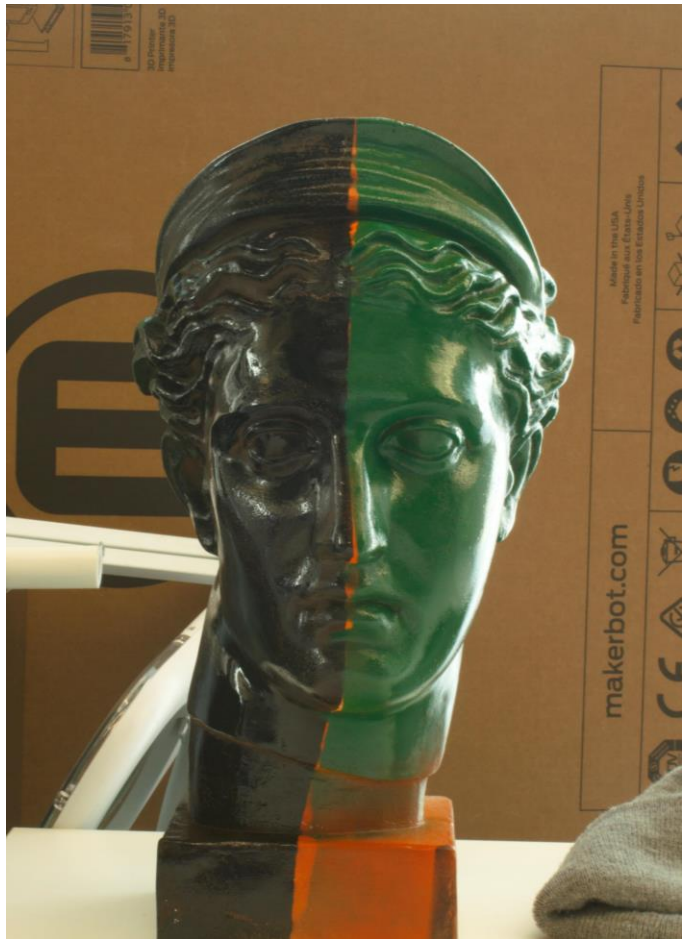


Shading [Wu 14]

Polarized 3D

Challenging Materials



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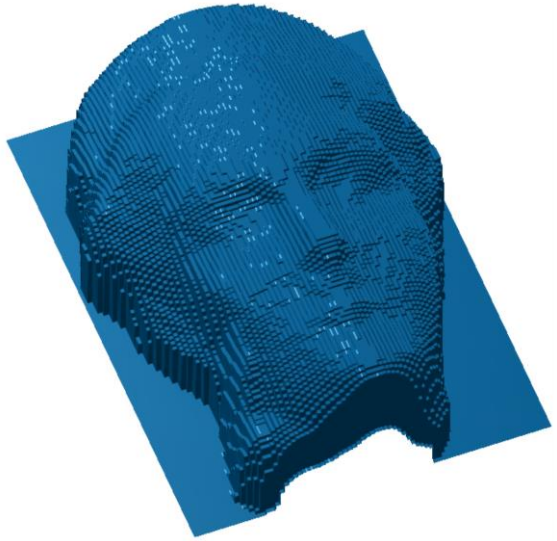
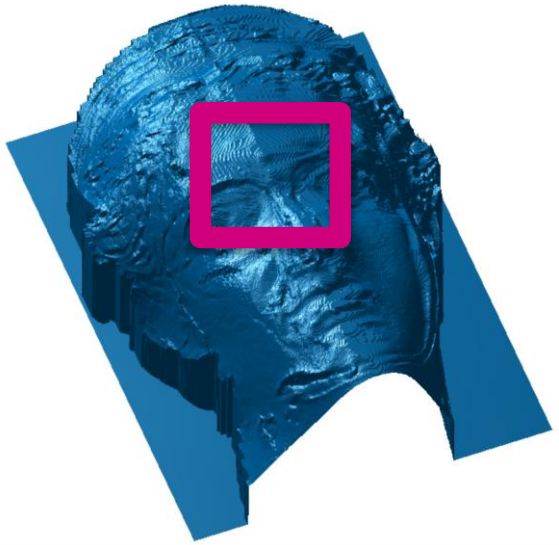
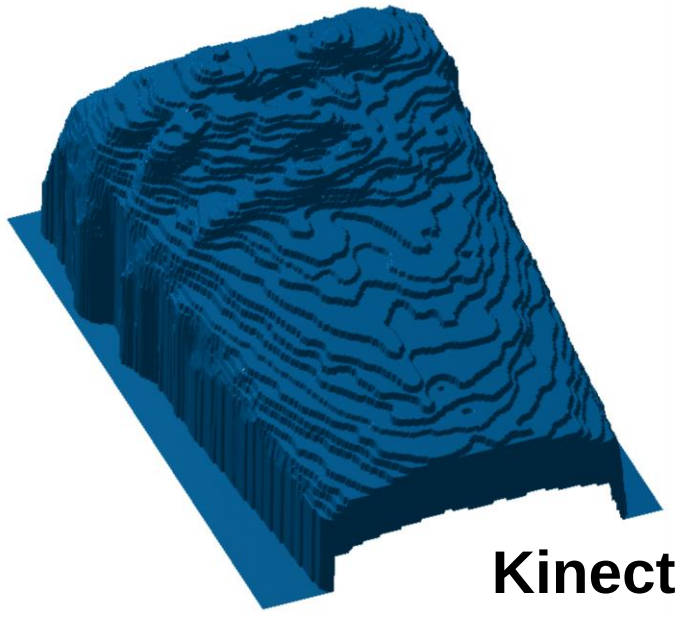


Shading [Wu 14]

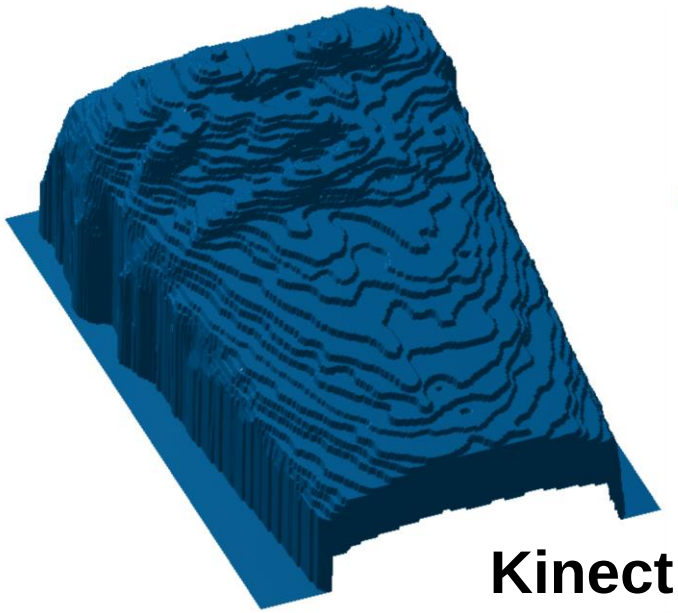


Polarized 3D

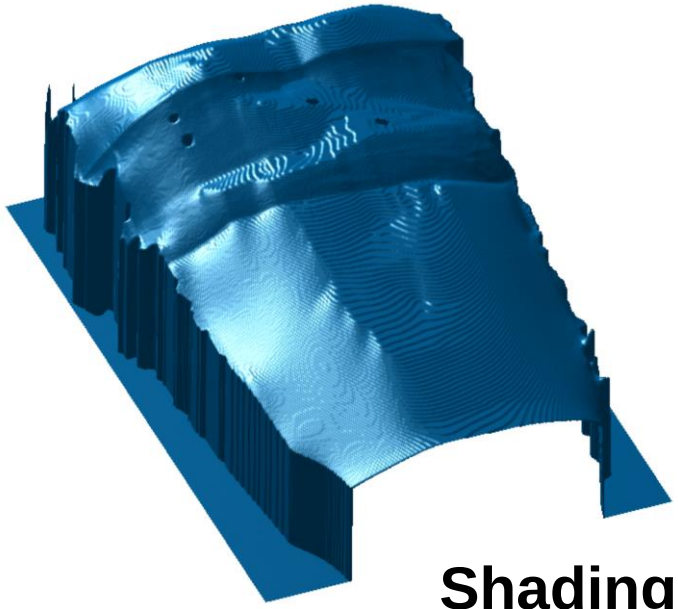
Break Lighting Assumptions



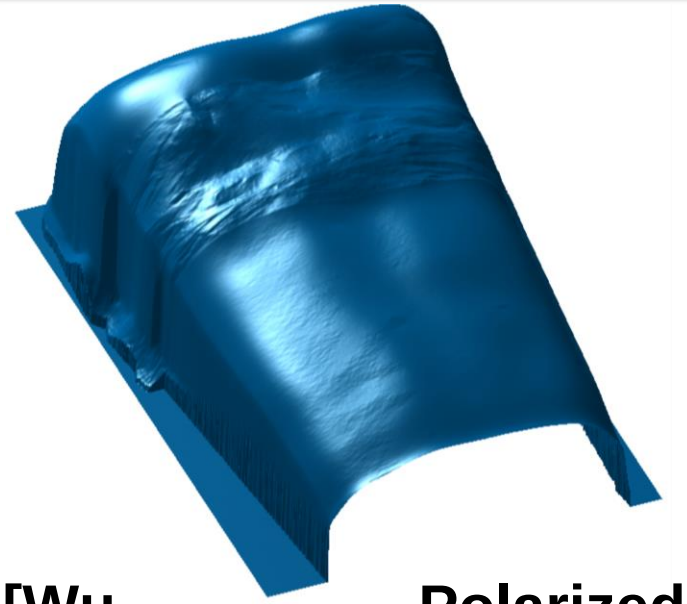
Break Lighting Assumptions



Kinect

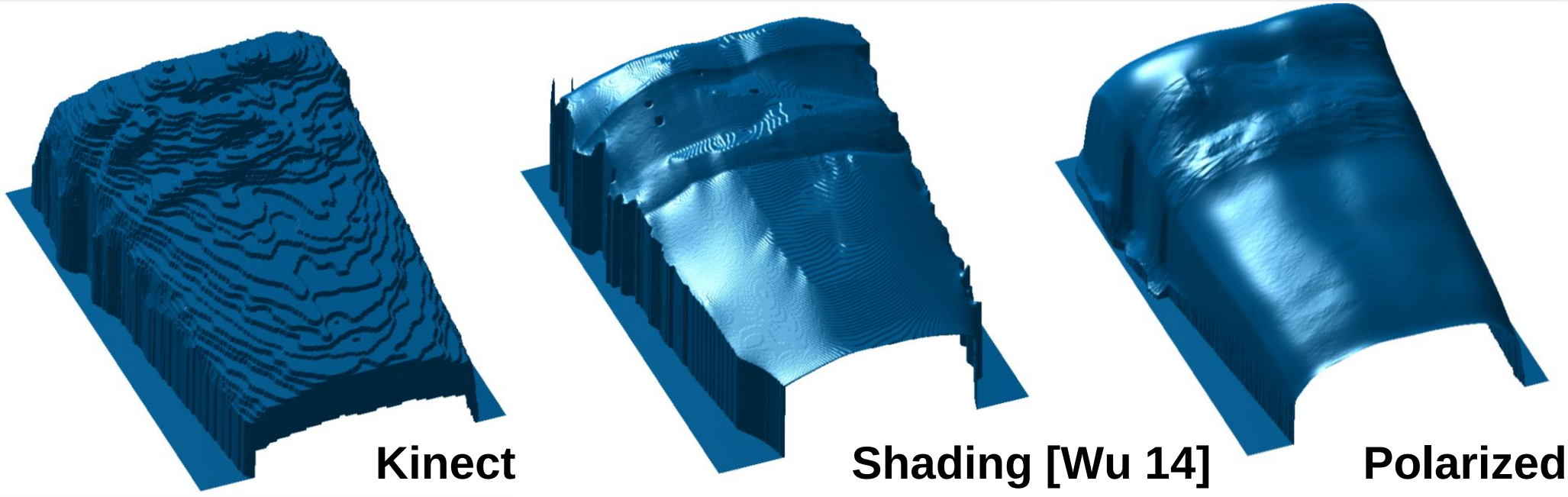


Shading [Wu 14]

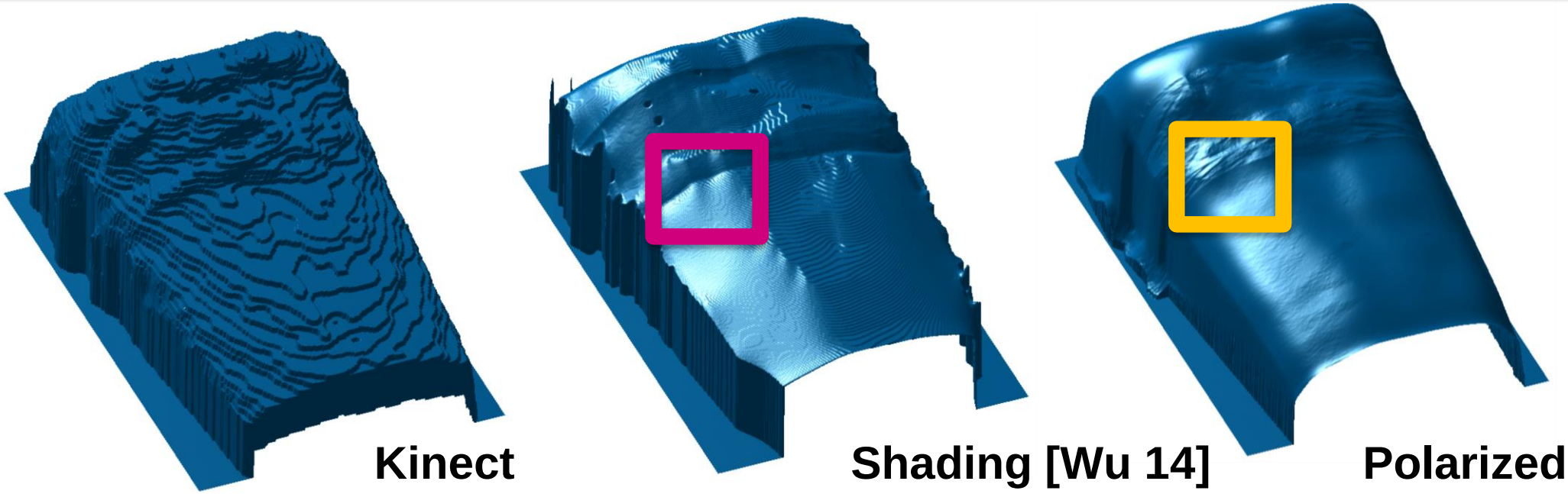


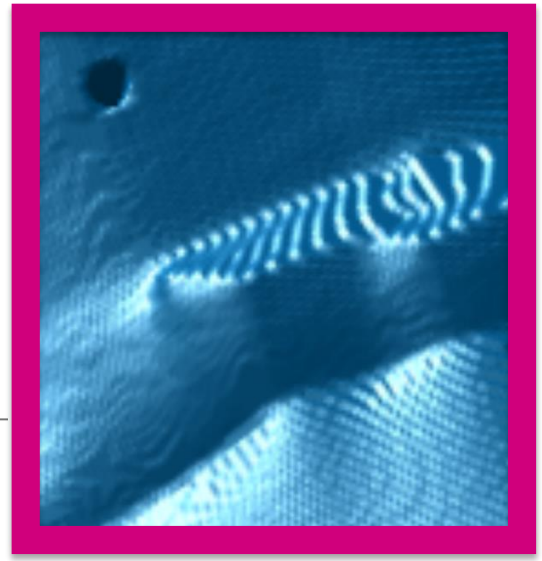
Polarized 3D

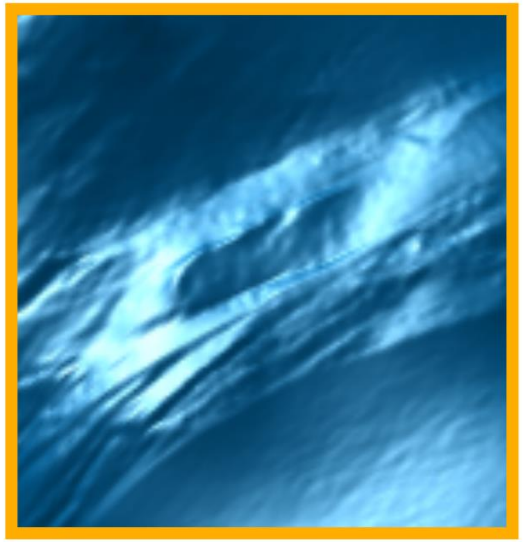
Break Lighting Assumptions



Break Lighting Assumptions

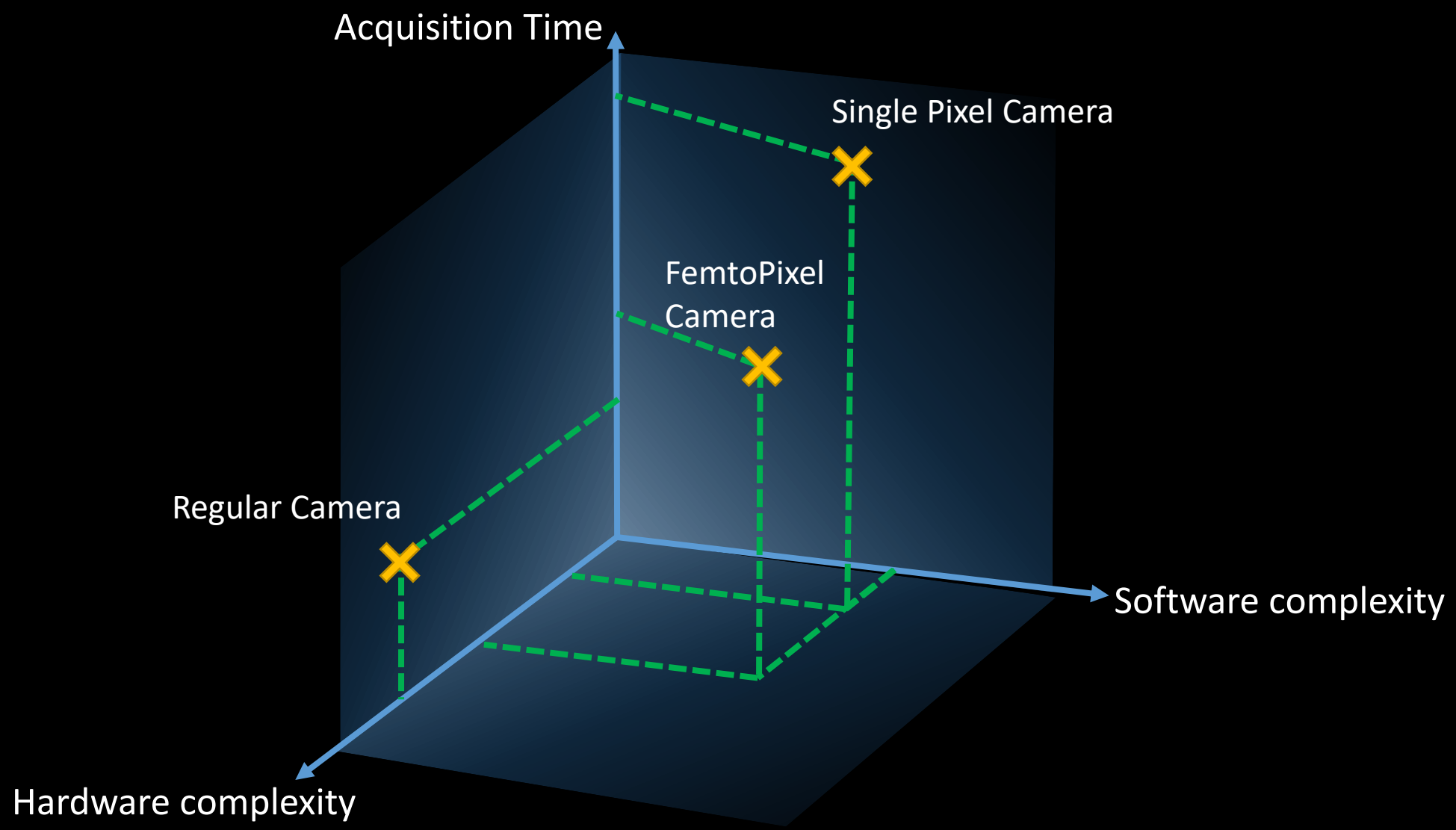




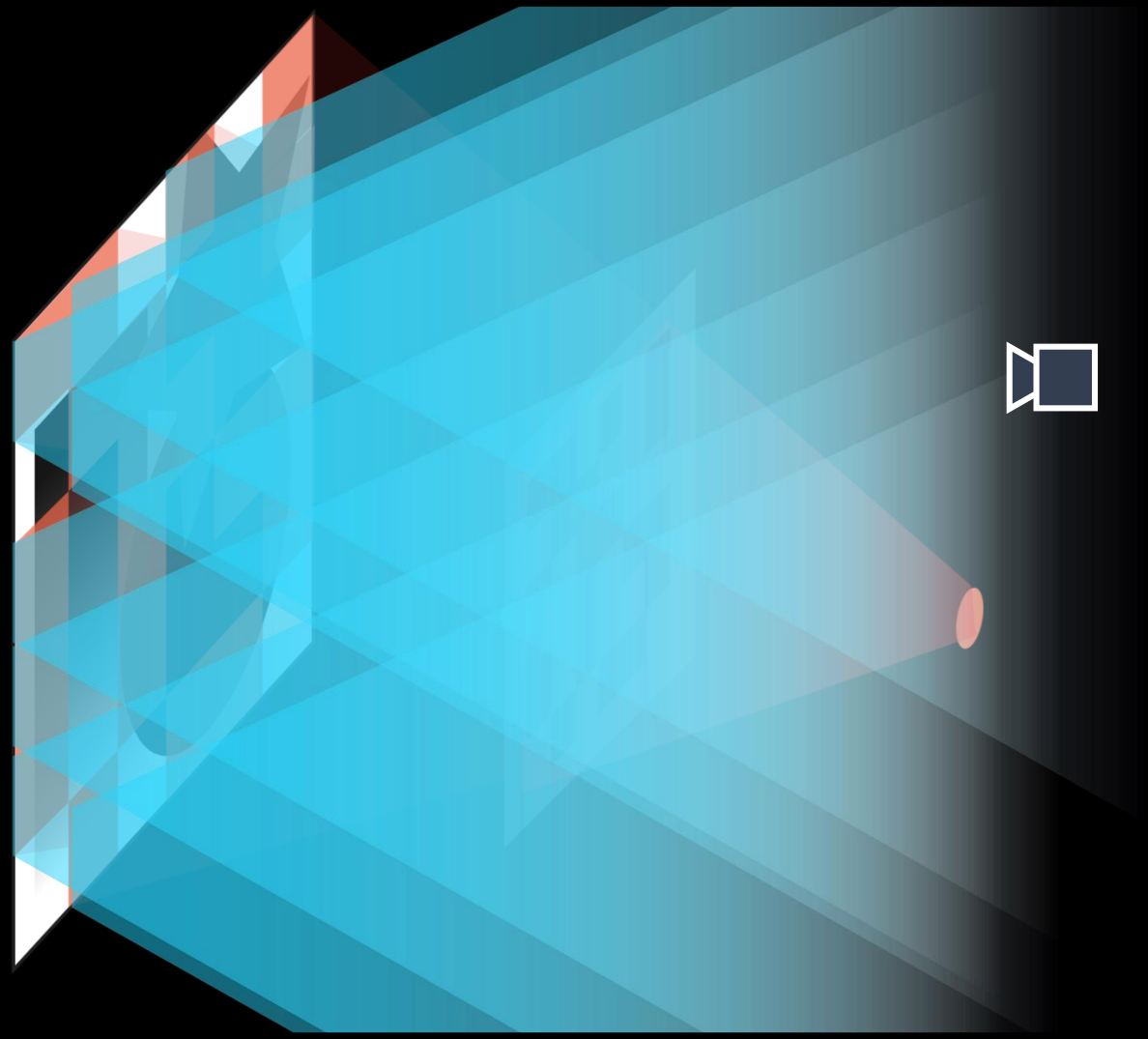


Sensing with Compressive Sampling

Single Pixel Camera – Pros and Cons

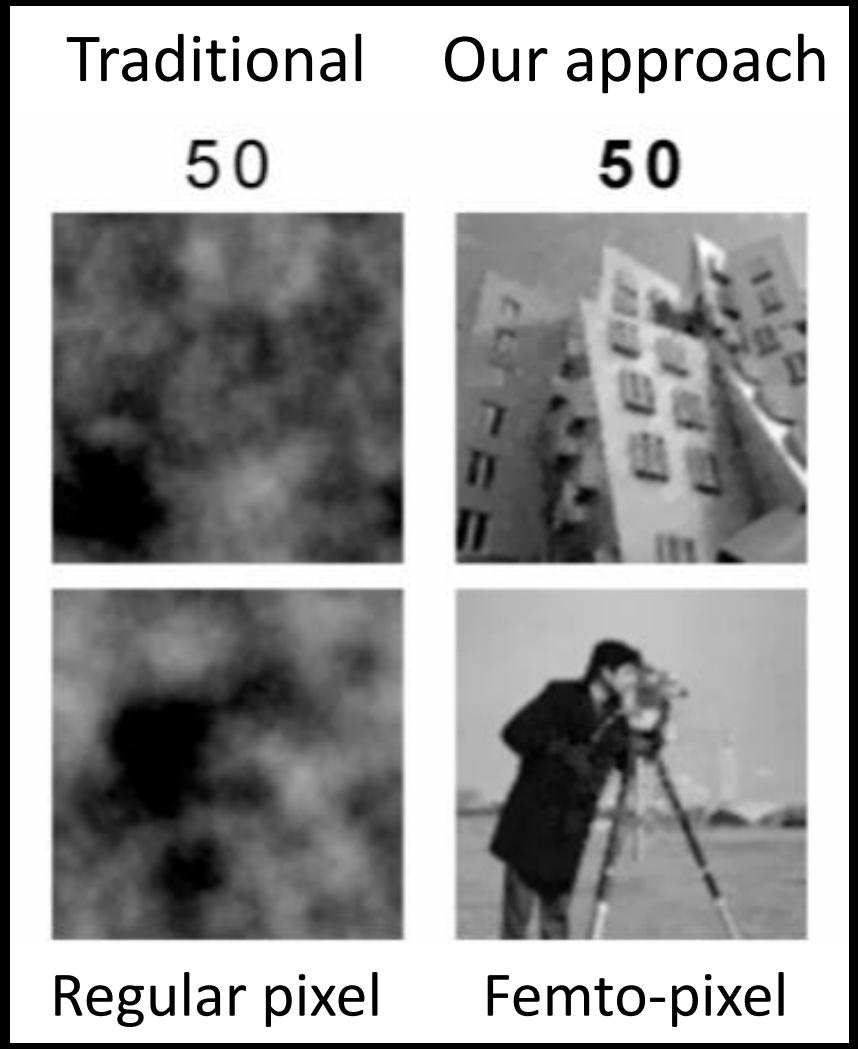


Lensless Imaging with a Femto-Pixel

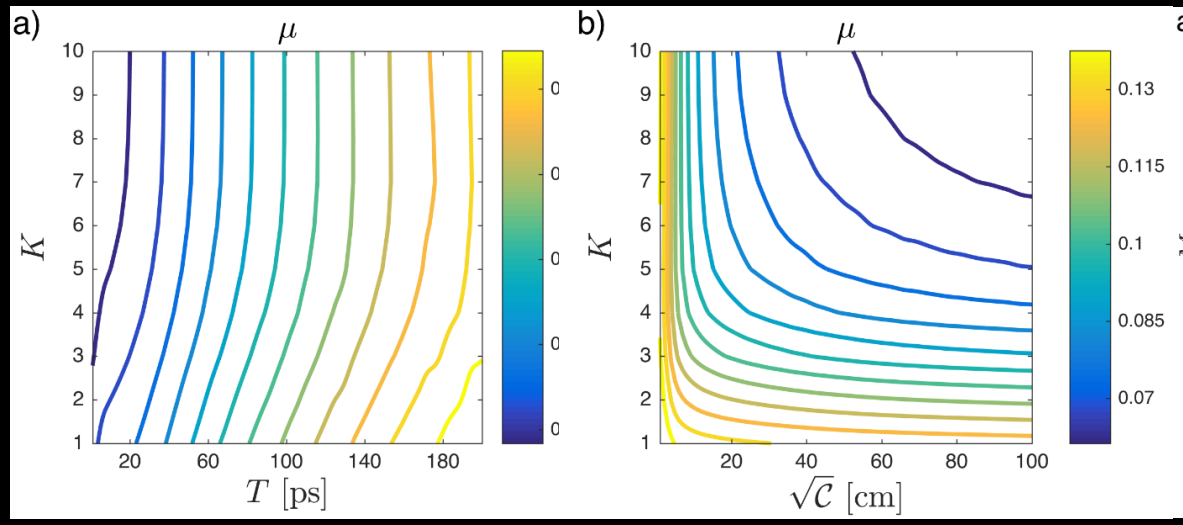


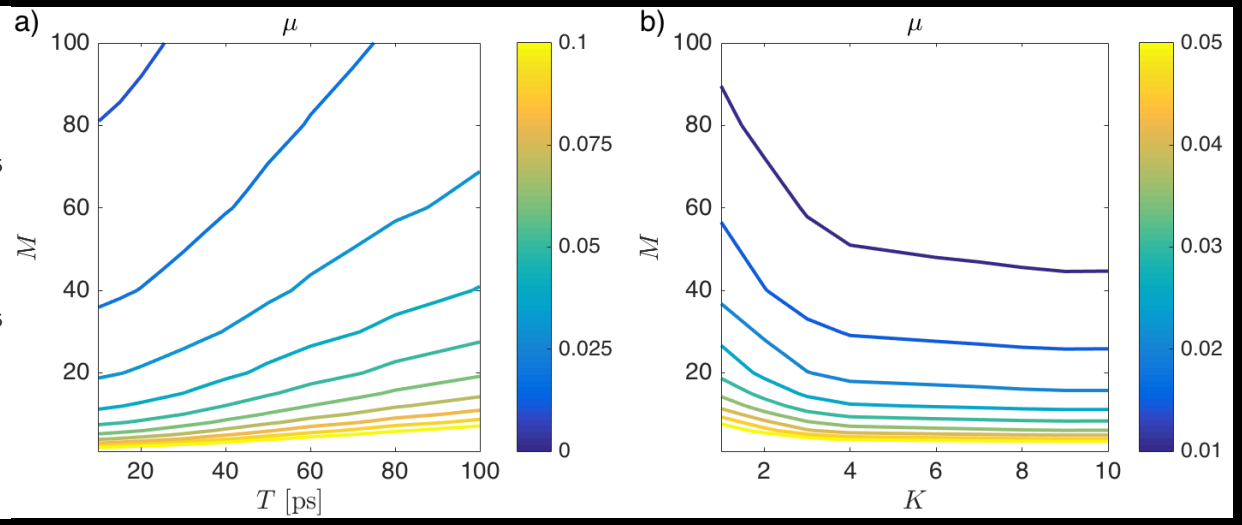
Satat, Tancik, Raskar *IEEE Trans. Computational Imaging* 2017

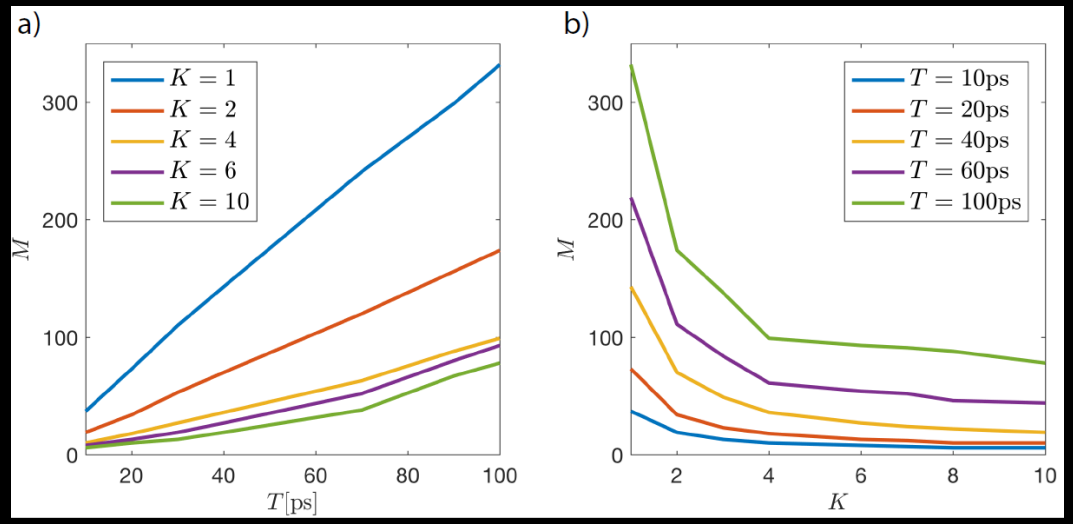
Lensless Imaging with a Femto-Pixel



Framework for Imaging with a Femto-Pixel







CVPR 2018

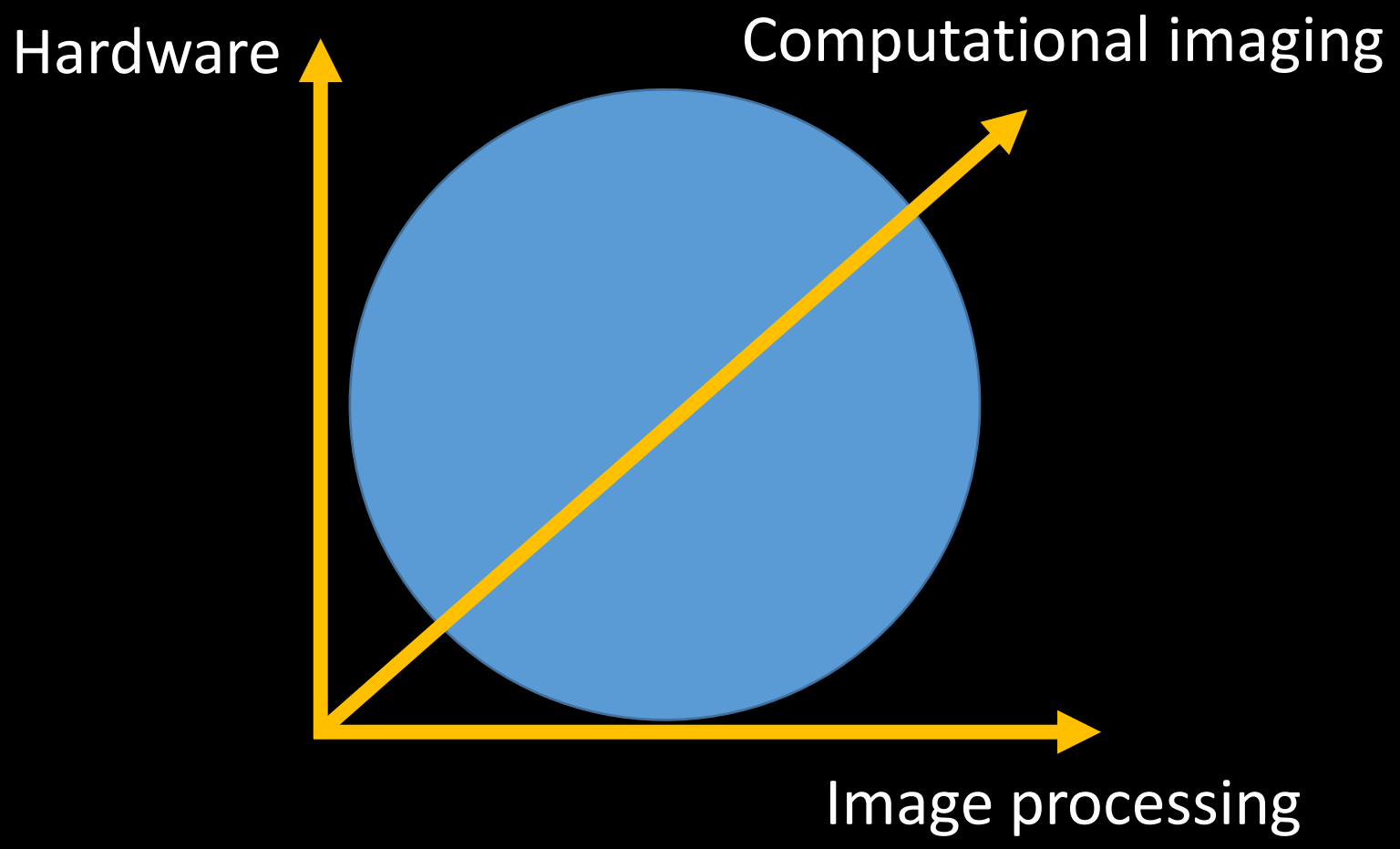
Computational Imaging for Autonomous Vehicles

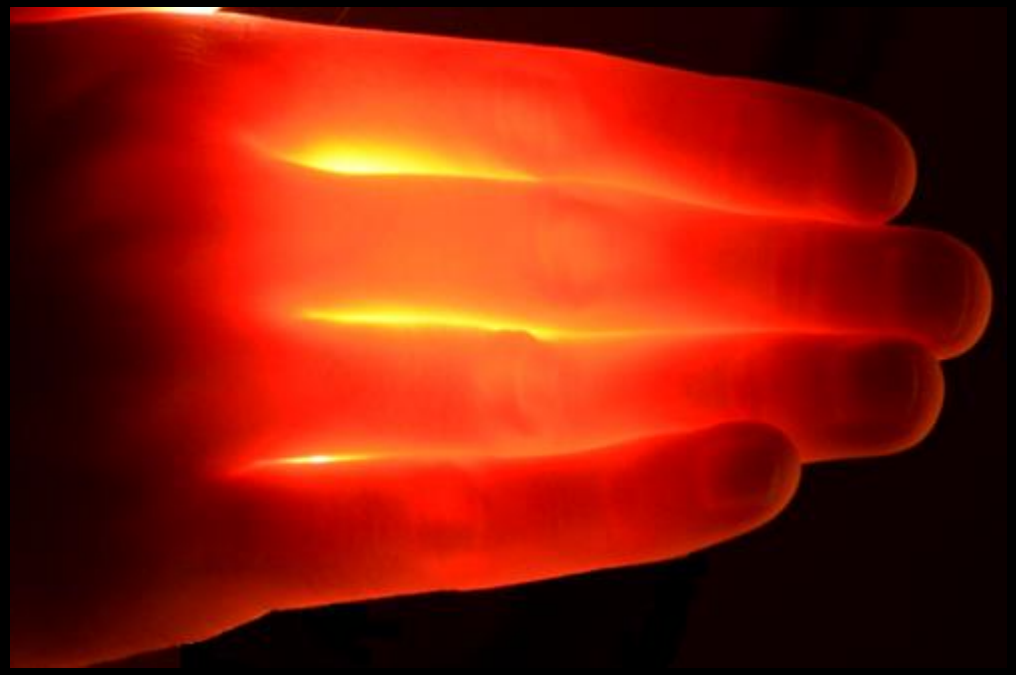
Sample Slides for Module 4:

Imaging in Challenging Weather Conditions

Light Scatters

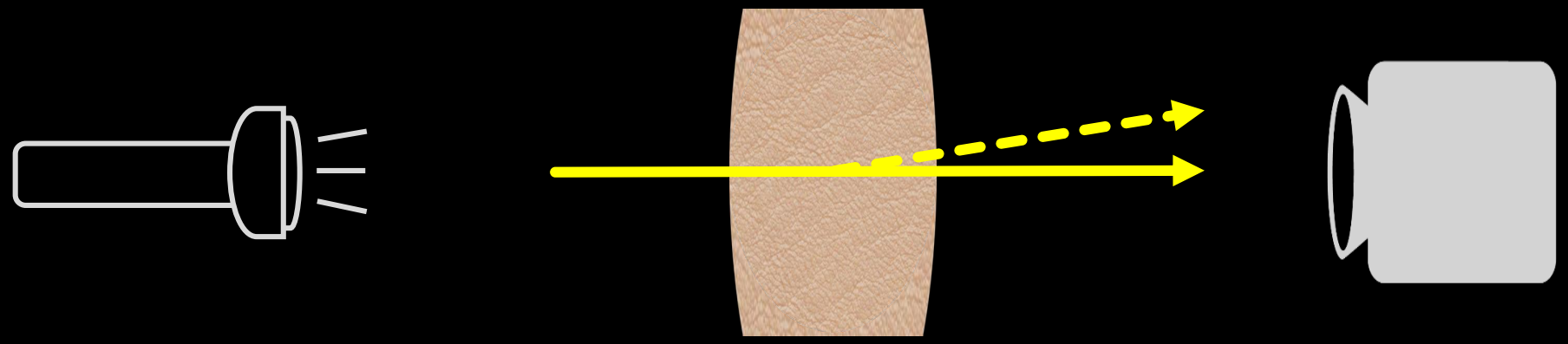
How to Overcome Scattering





Lessons learned from seeing into the body

Optics Based Solutions

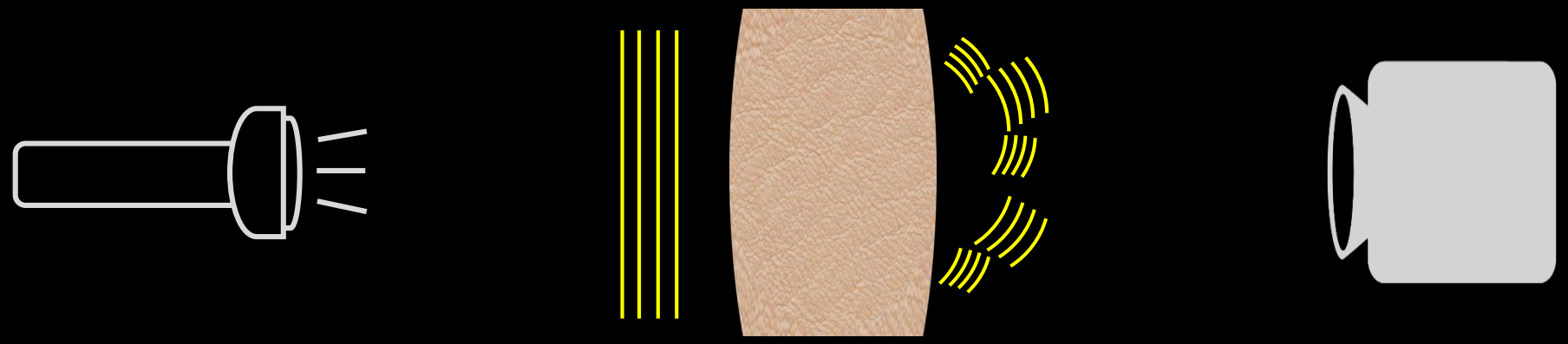


Photon gating:

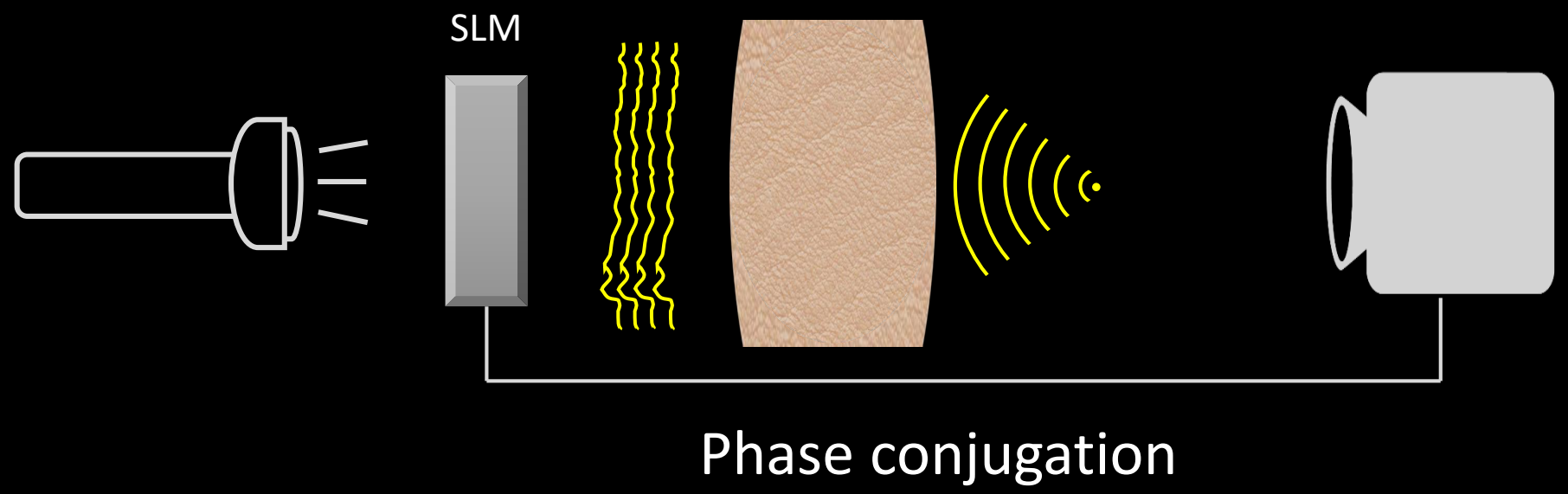
- Angle
- Time
- Polarization

Not enough photons

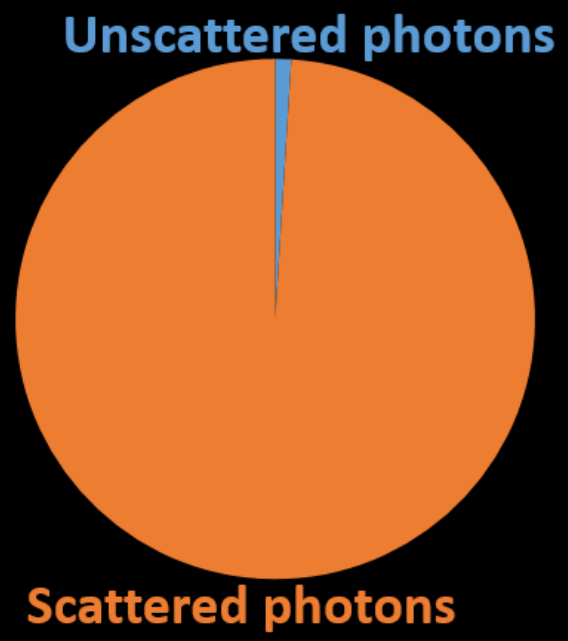
Optics Based Solutions



Optics Based Solutions



Long iterative process



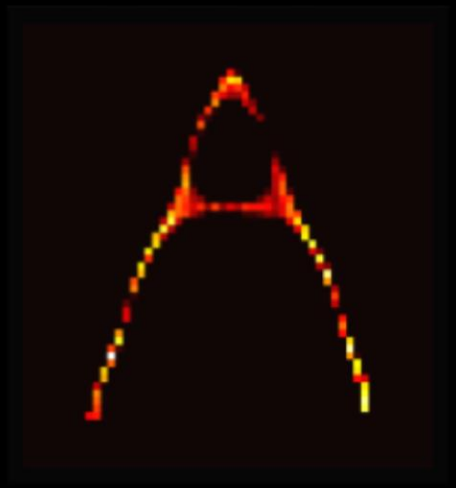
Use All Photons!

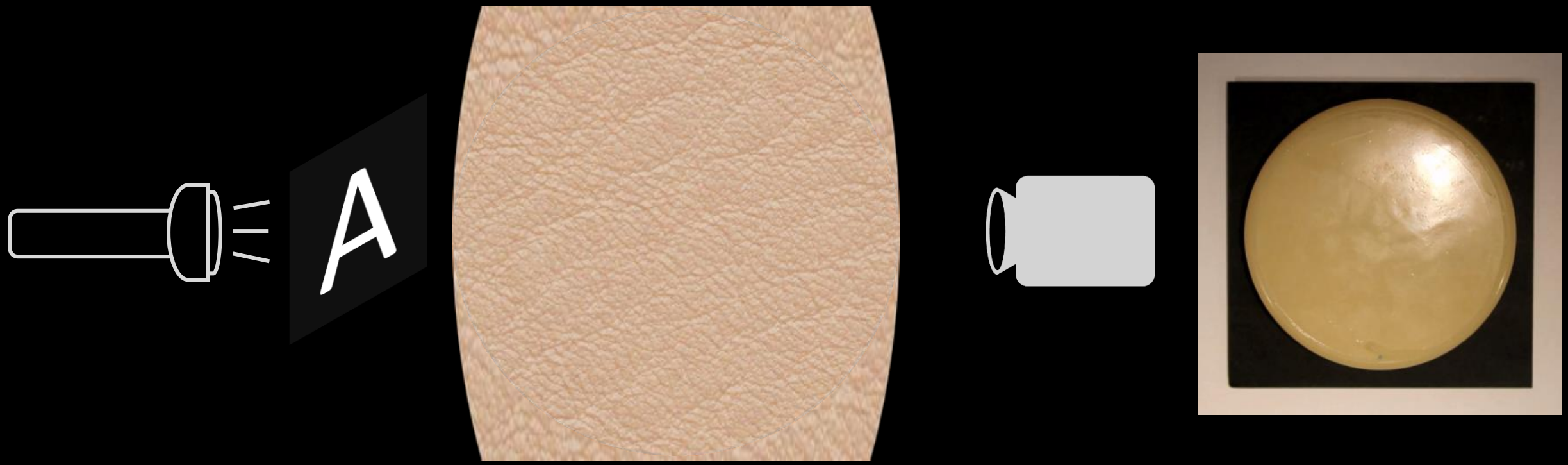
Computationally Invert Scattering

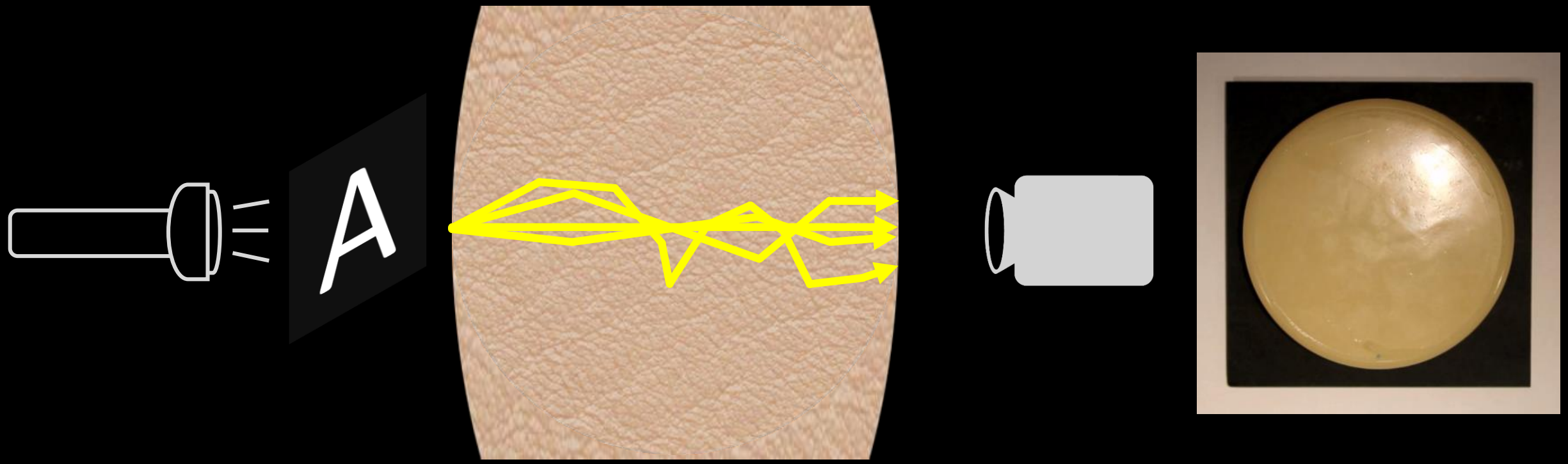
Satat, Heshmat, Raviv, Raskar *Nature Scientific Reports* 2016


A

- Estimate target
- Estimate scattering




A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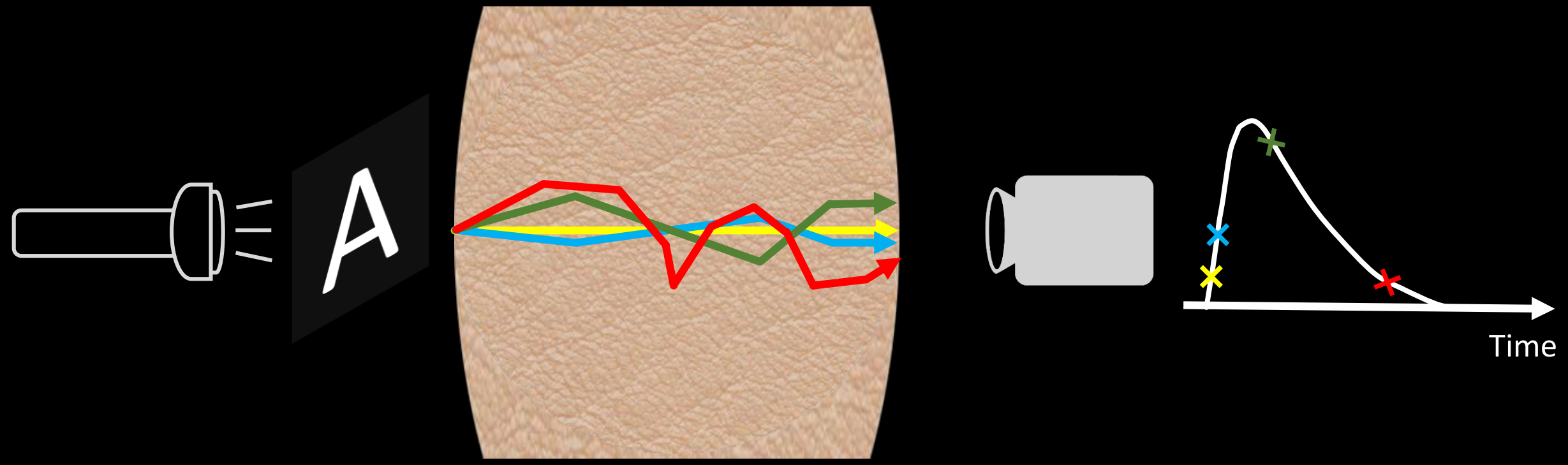
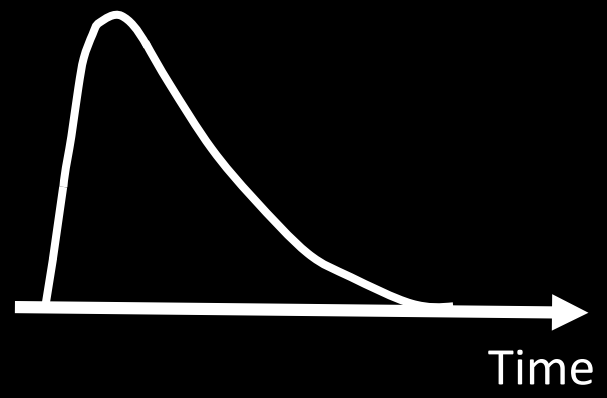
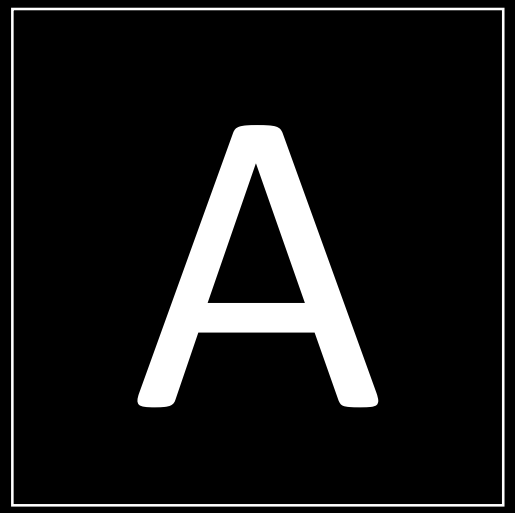

A
Time

10,000,000,000 Slower

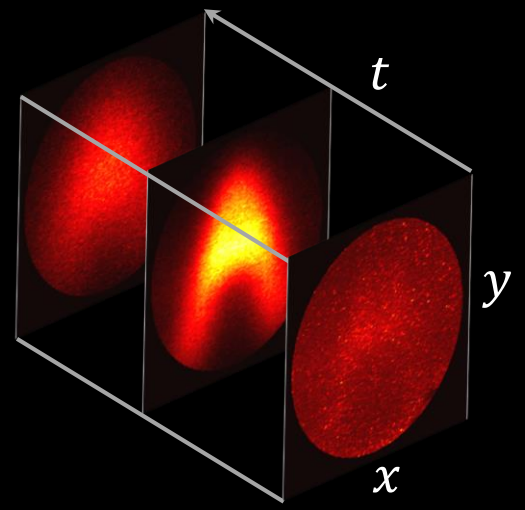


Scene

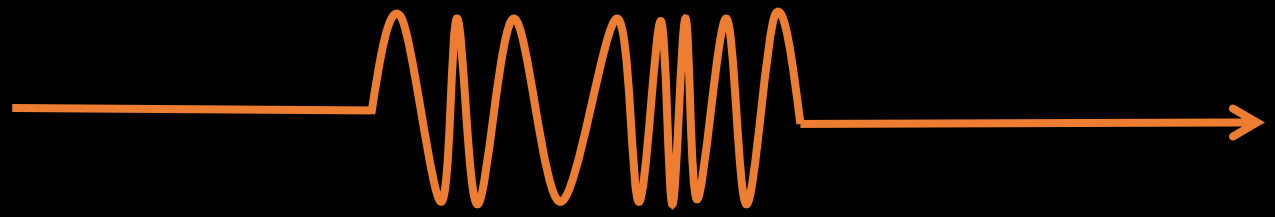


Scatterer

Measurement



Sharp
2D



Blurred
3D

$$s(x,y) \quad * \quad K(x,y,t) \quad = \quad m(x,y,t)$$

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

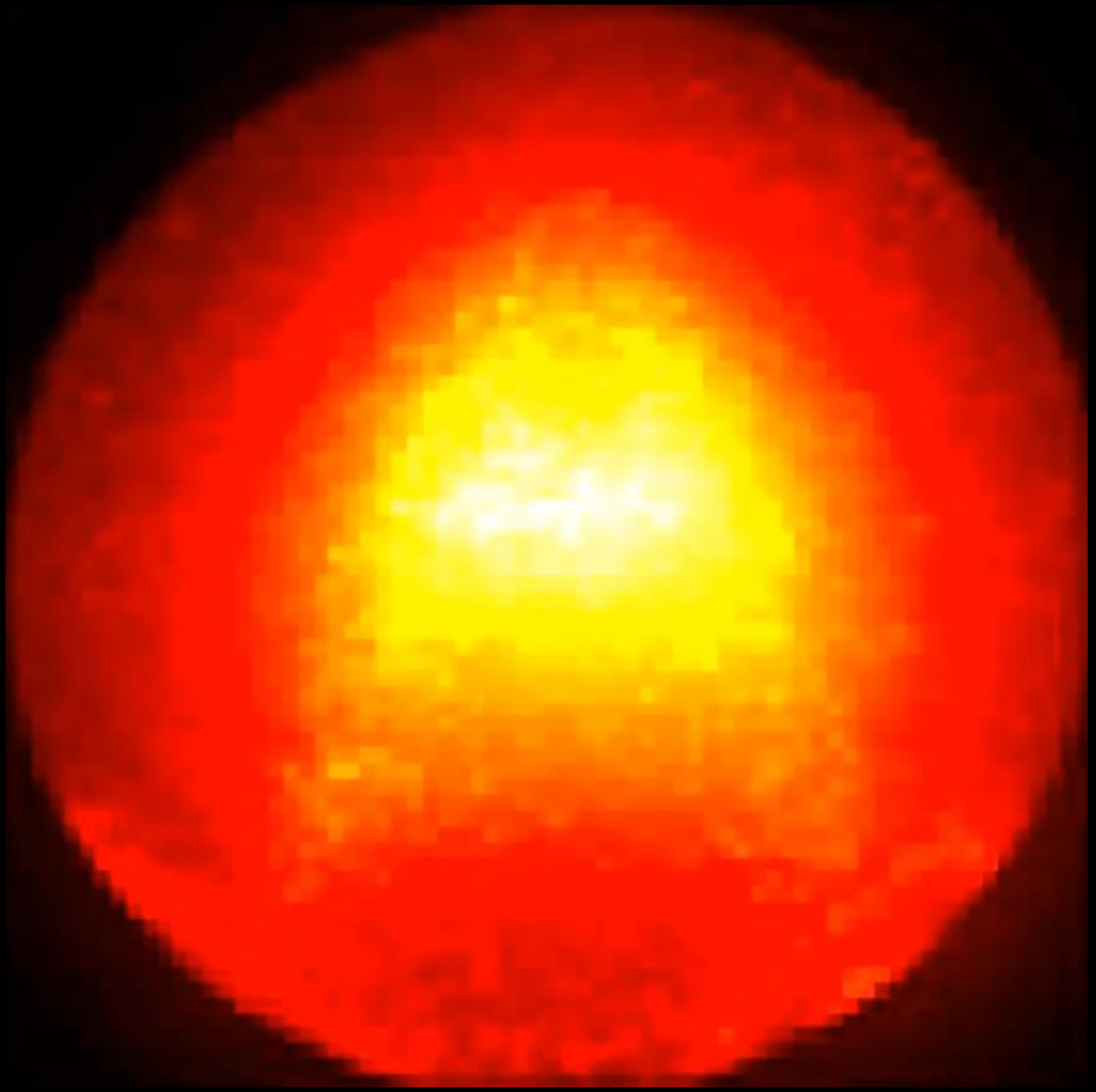
Given the time, probability to measure a photon at location x, y

Estimating the Scattering - $K(x, y, t)$

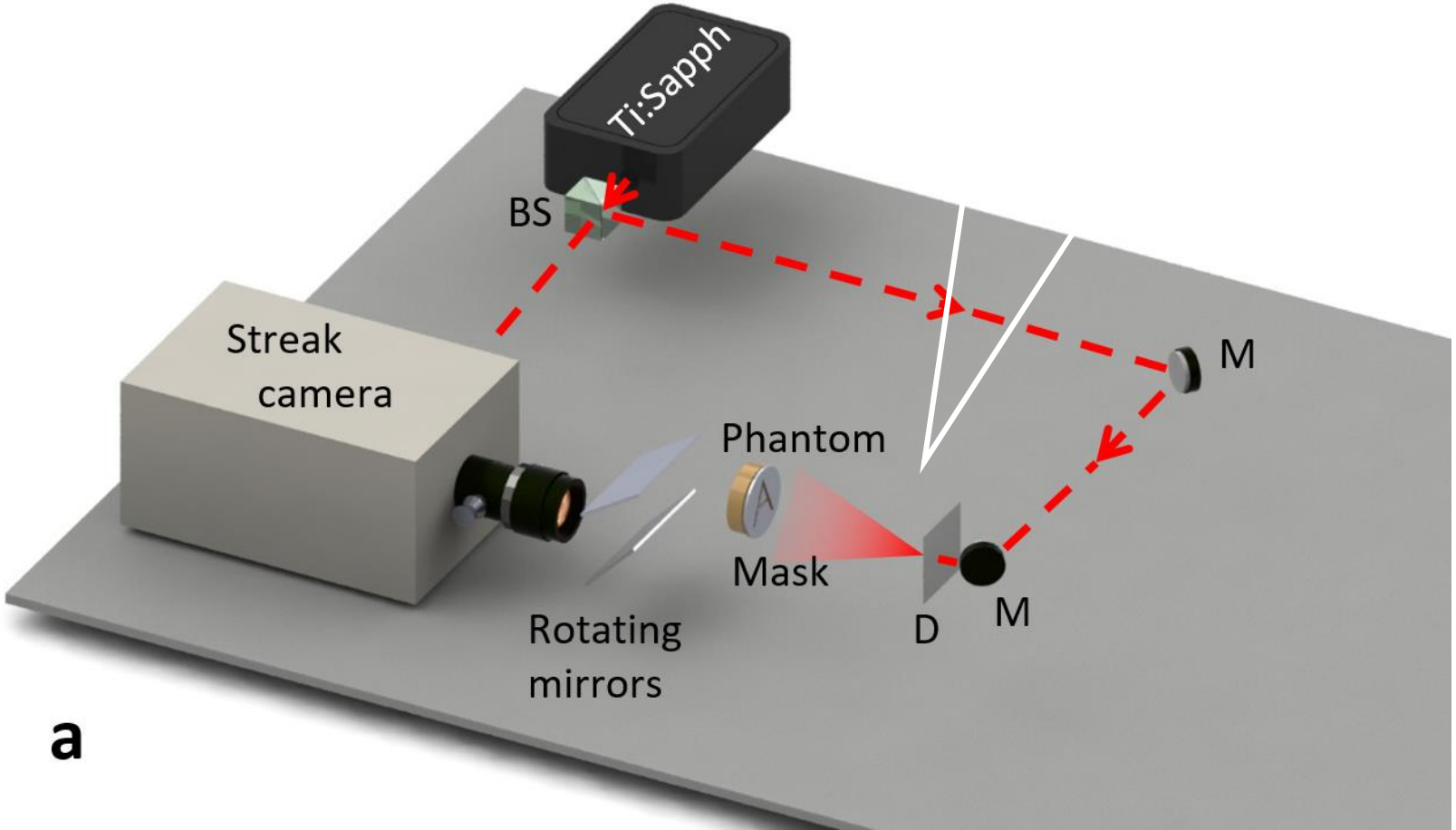
$$K(x, y, t) = f_T(t)\, W(x, y|t)$$

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

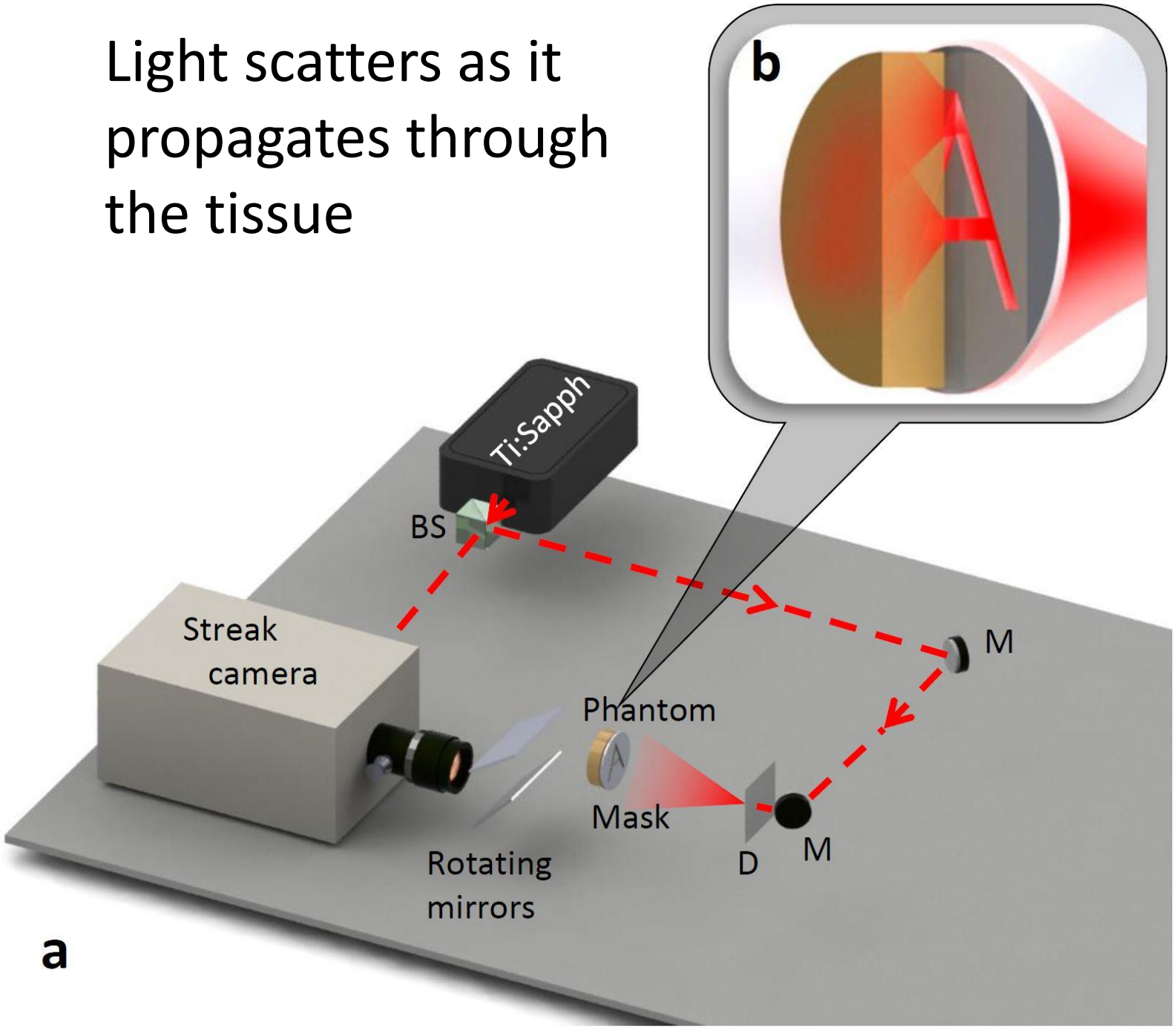
- Assumptions:
  - Enough samples to satisfy law of large numbers

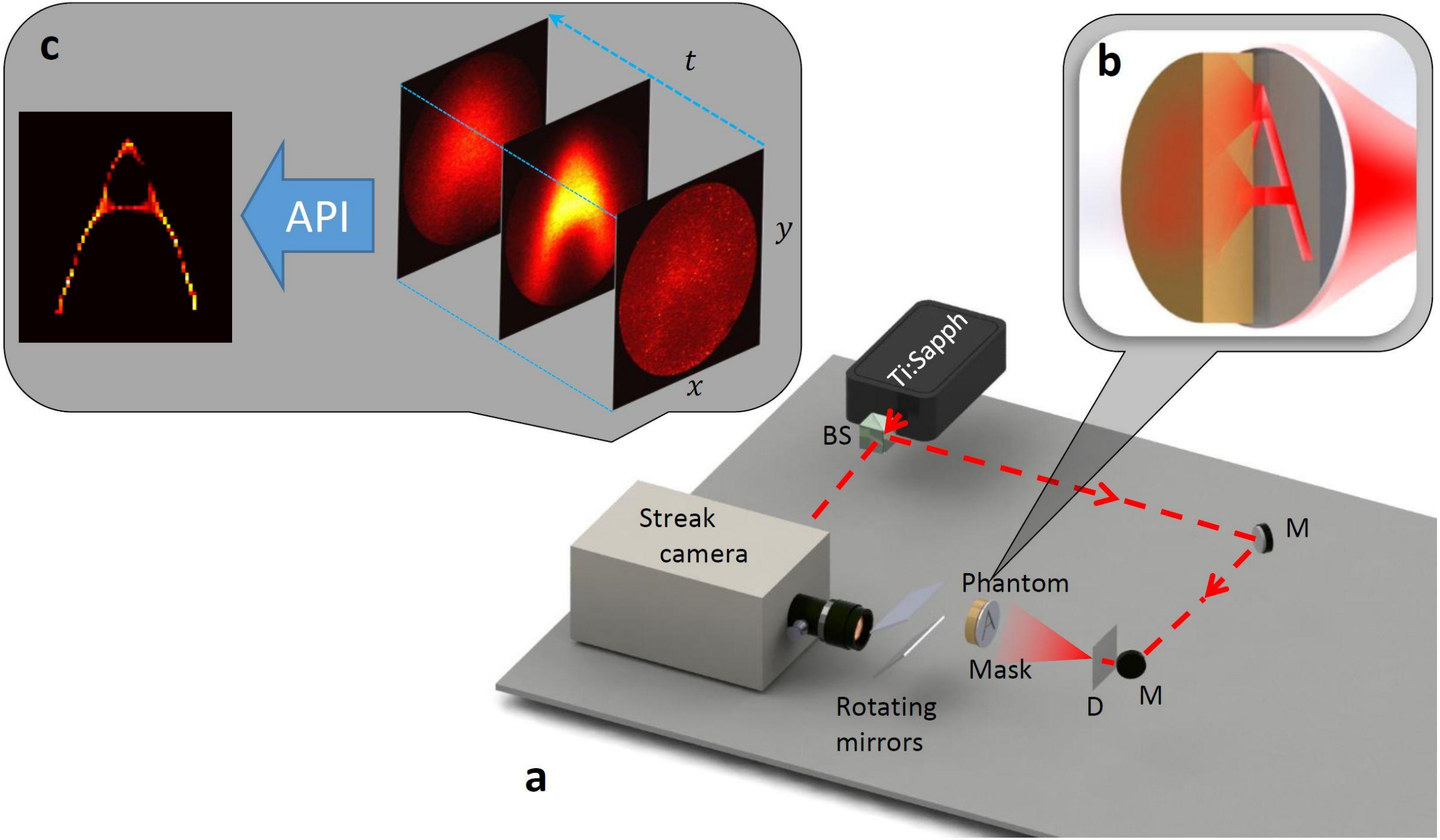


We illuminate the entire object simultaneously with a pulse of light

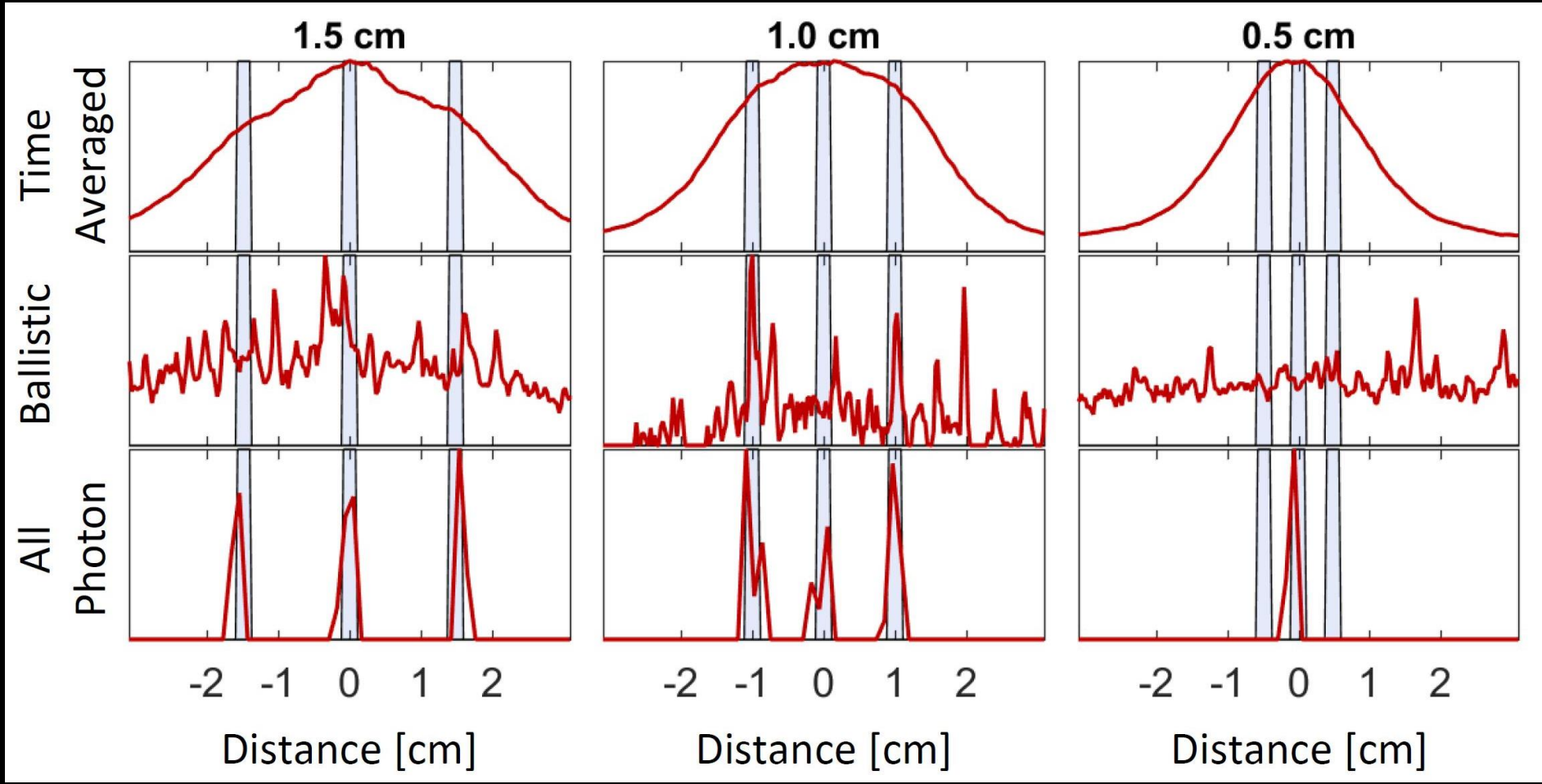


Light scatters as it propagates through the tissue

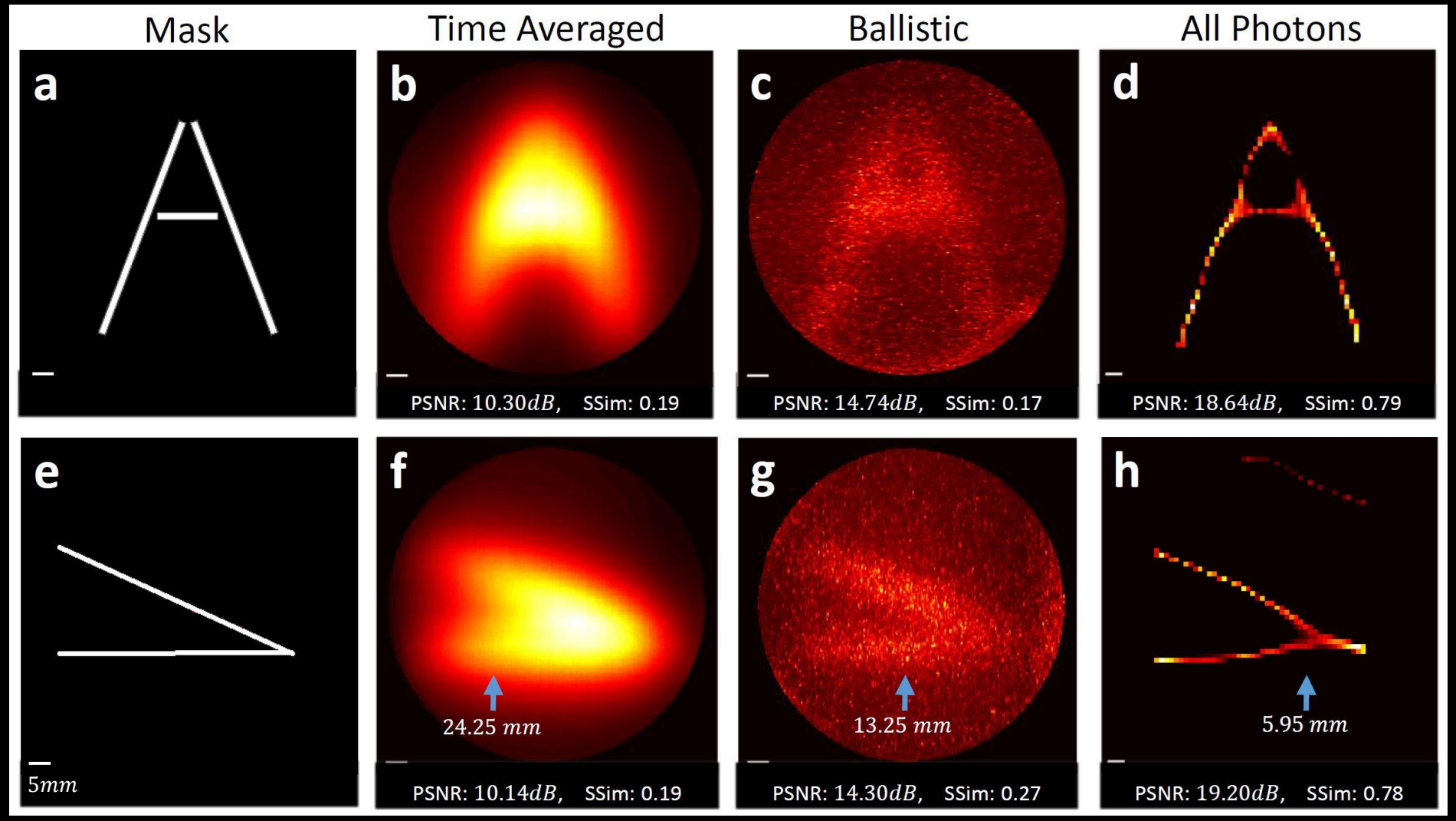



c
API
t
y
x
b
Ti:Sapph
BS
Streak
camera
M
Phantom
Mask
D
M
Rotating
mirrors
a

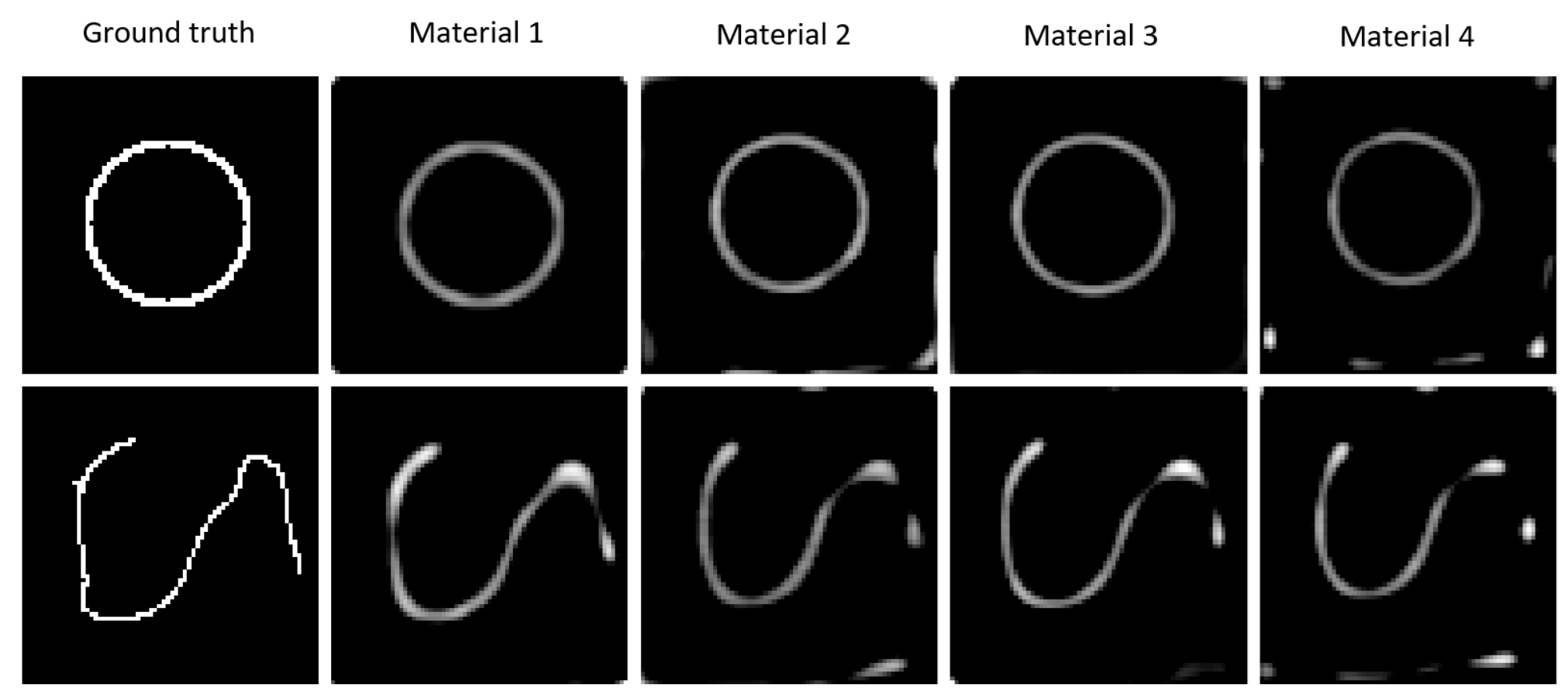
Recovery of Slits



Results


Mask
Time Averaged
Ballistic
All Photons
a
b
c
d
PSNR: 10.30dB, SSim: 0.19
PSNR: 14.74dB, SSim: 0.17
PSNR: 18.64dB, SSim: 0.79
e
f
g
h
5mm
24.25 mm
13.25 mm
5.95 mm
PSNR: 10.14dB, SSim: 0.19
PSNR: 14.30dB, SSim: 0.27
PSNR: 19.20dB, SSim: 0.78

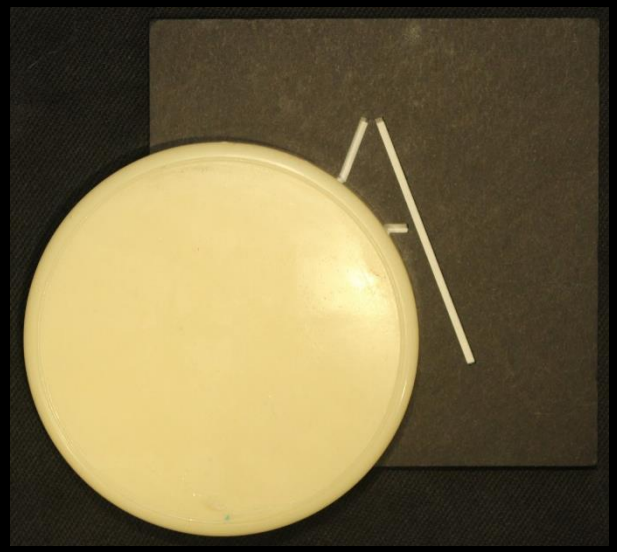
Invariant to Layered Material

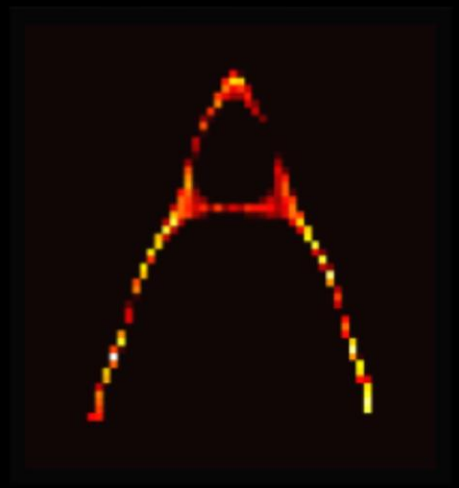


Satat, Heshmat, Raskar *COSI* 2017

Properties of All Photons Imaging

- Recovers scatterer and target
  - Calibration free
- Minimal assumptions
- Works with layered materials
- Doesn't require raster scan





Challenges

CVPR 2018

Computational Imaging for Autonomous Vehicles

Sample Slides for Module 5:

Data Driven Computational Imaging