Course Schedule

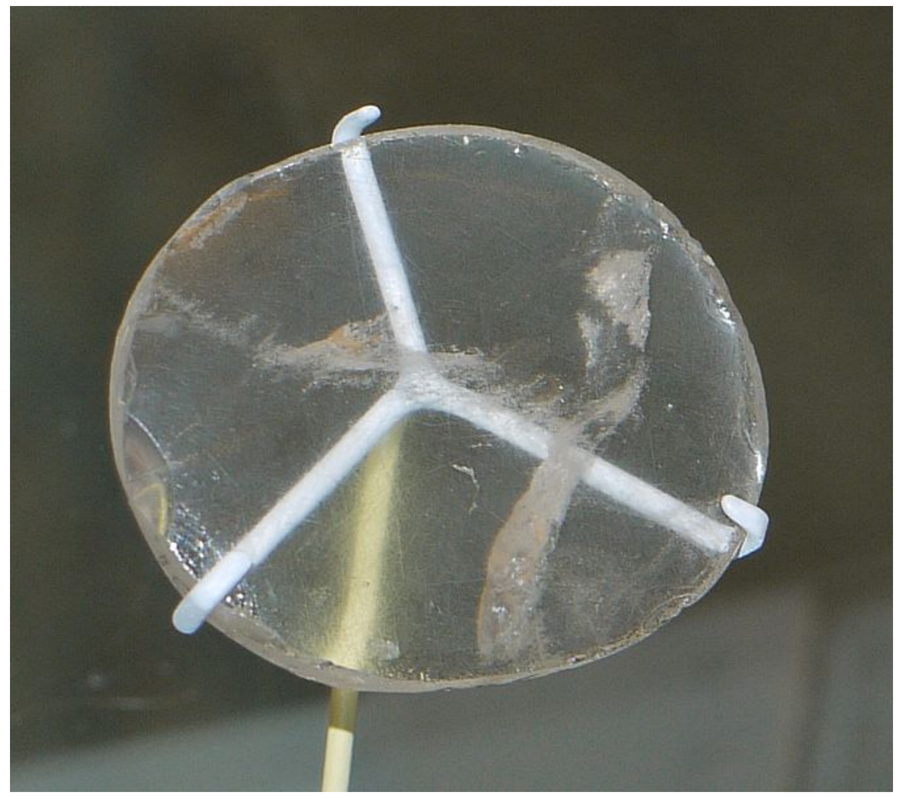
http://imagingav.media.mit.edu

13:30 – 13:50	Course Introduction *Ramesh Raskar (MIT)*
13:50 – 15:00	Existing Sensors and Their Limits *Guy Satat (MIT), Achuta Kadambi (UCLA)*
15:00 – 15:10	Break
15:10 – 15:50	Emerging 3D Sensors *Achuta Kadambi (UCLA)*
15:50 – 16:30	Imaging in Bad Weather *Guy Satat (MIT)*
16:30 – 16:40	Break
16:40 – 17:20	Deep Learning-based Computational Imaging *Jan Kautz (NVIDIA)*
17:20 – 17:30	Conclusion and Open Problems

Computational Cameras: Redefining the Image

Achuta Kadambi (*University of California, Los Angeles*)

Revolutions in Imaging

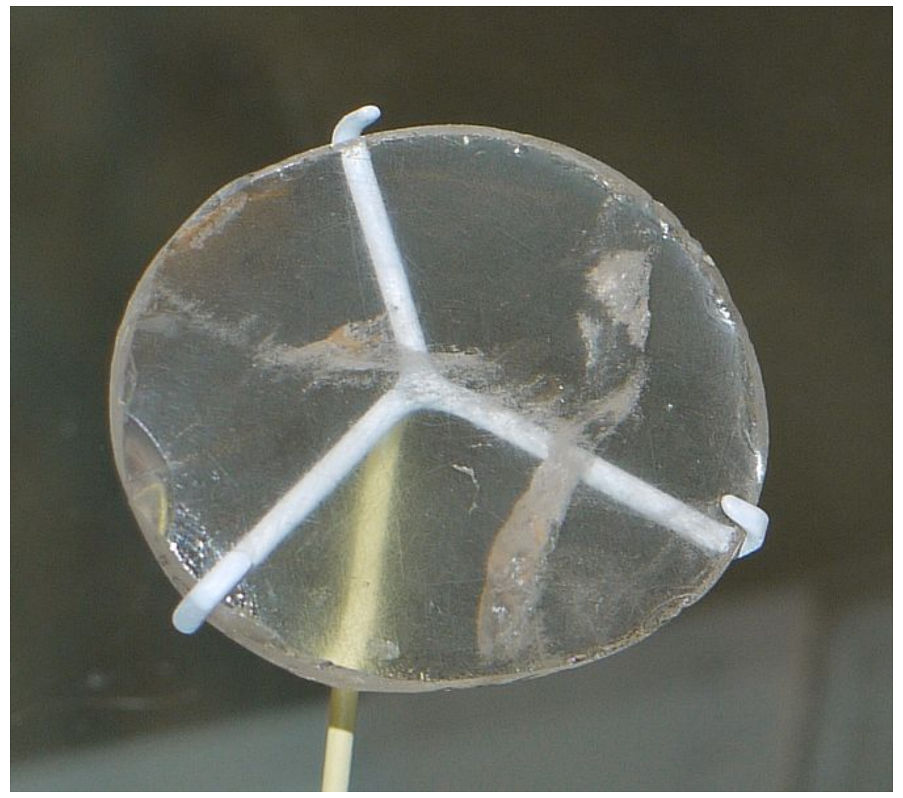


750 BC

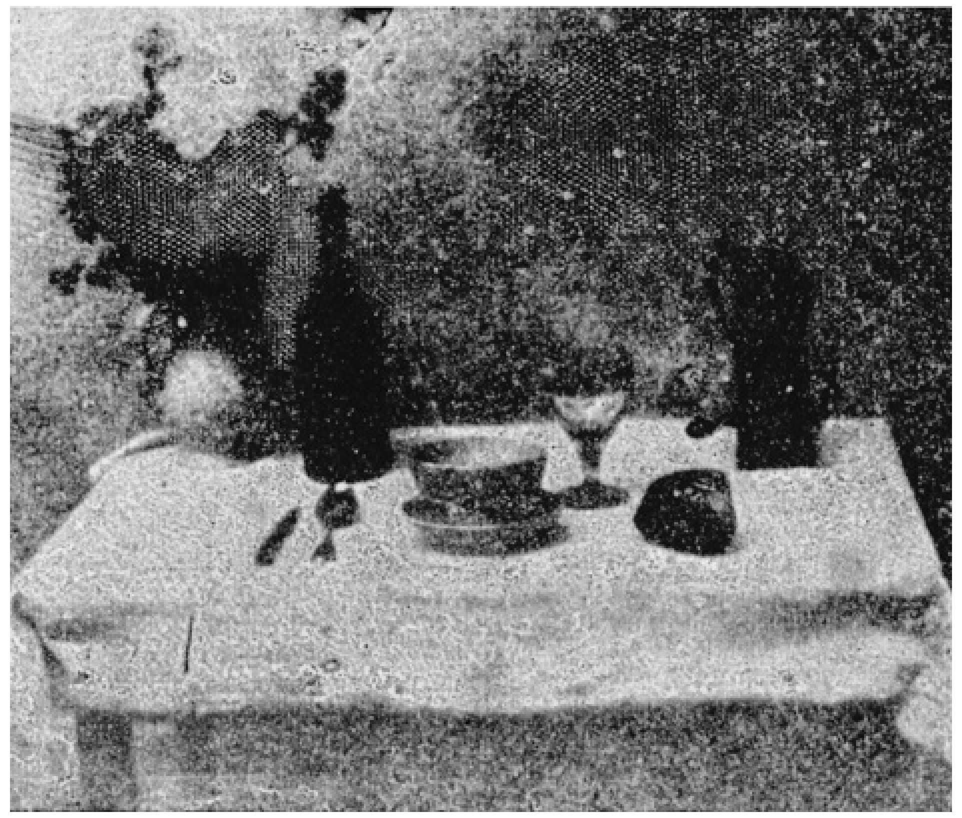
(The First Lens)

Ancient Assyria

Revolutions in Imaging

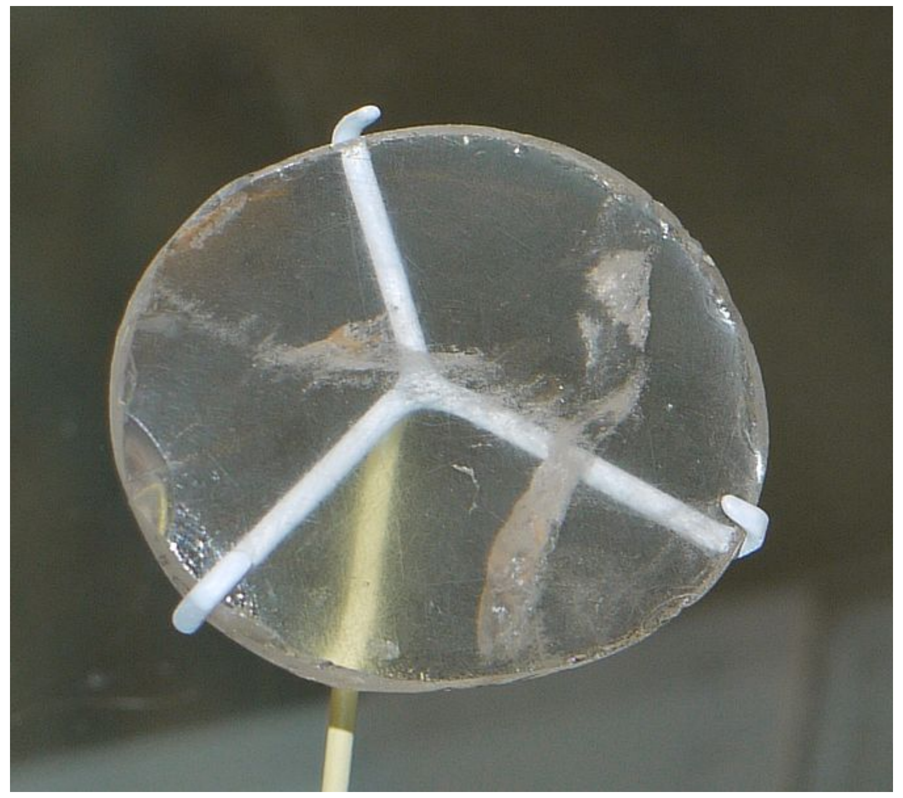


750 BC
(The First Lens)
Ancient Assyria

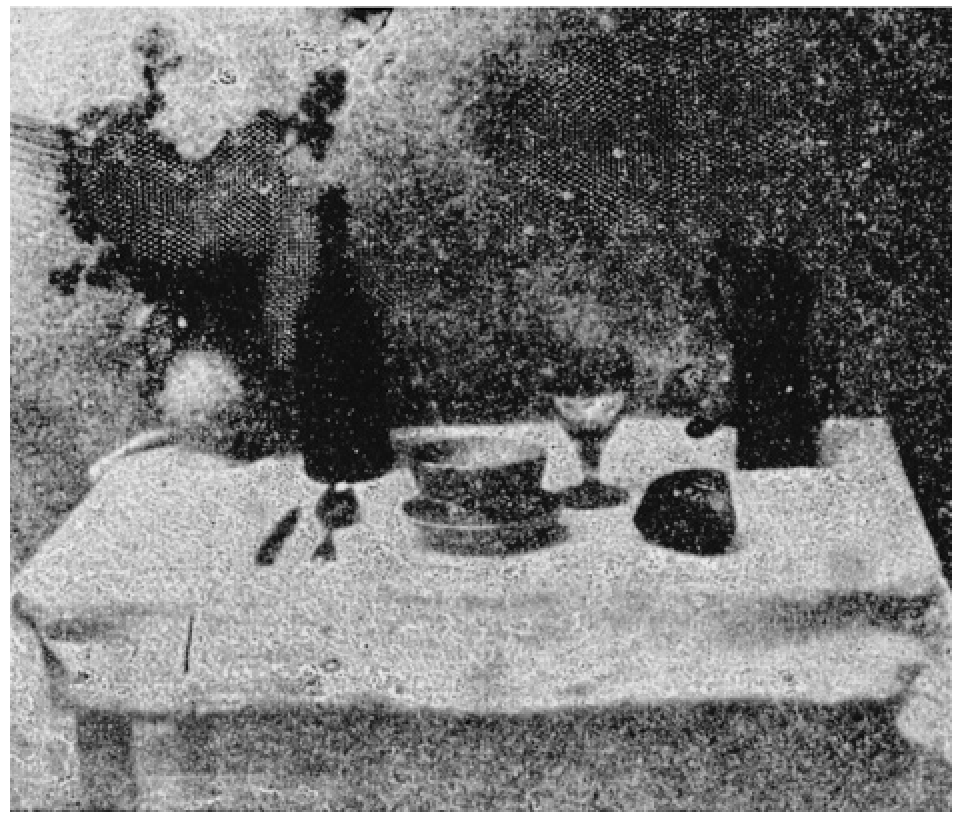


1816 AD
(The First Photo)
Joseph Niepce

“Revolutions” in Imaging



750 BC
(The First Lens)
Ancient Assyria



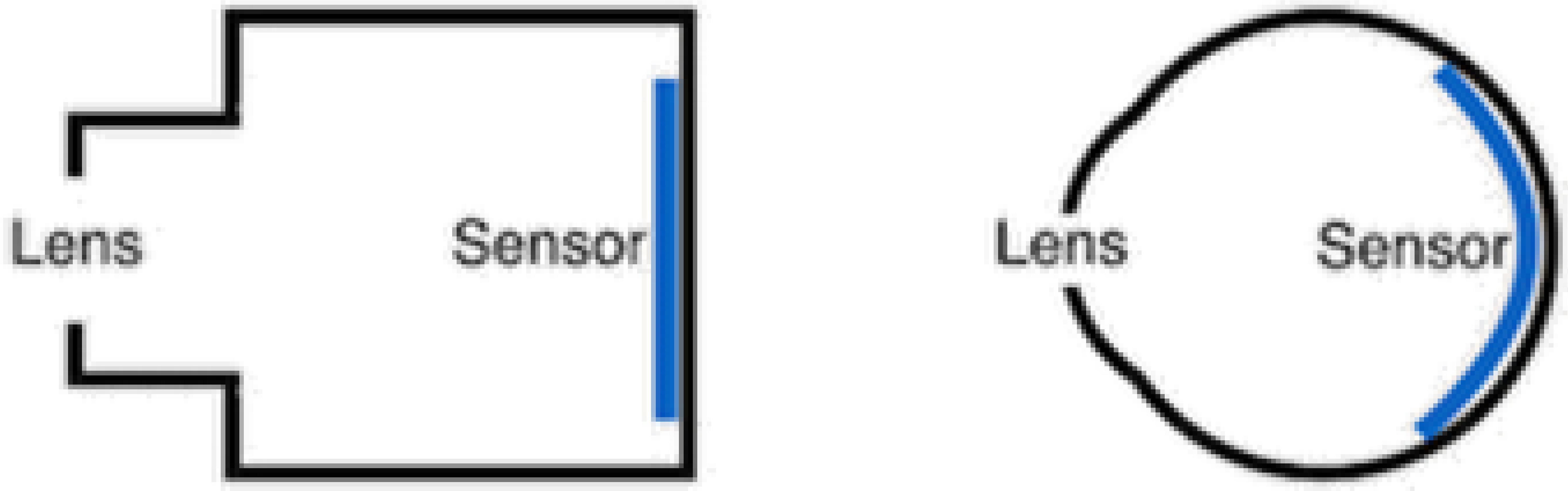
1816 AD
(The First Photo)
Joseph Niepce

Is this really a revolution?
(Modern Photograph)

Ordinary Cameras are Boring

Capture of 2D Phenomena

$$I(x, y)$$

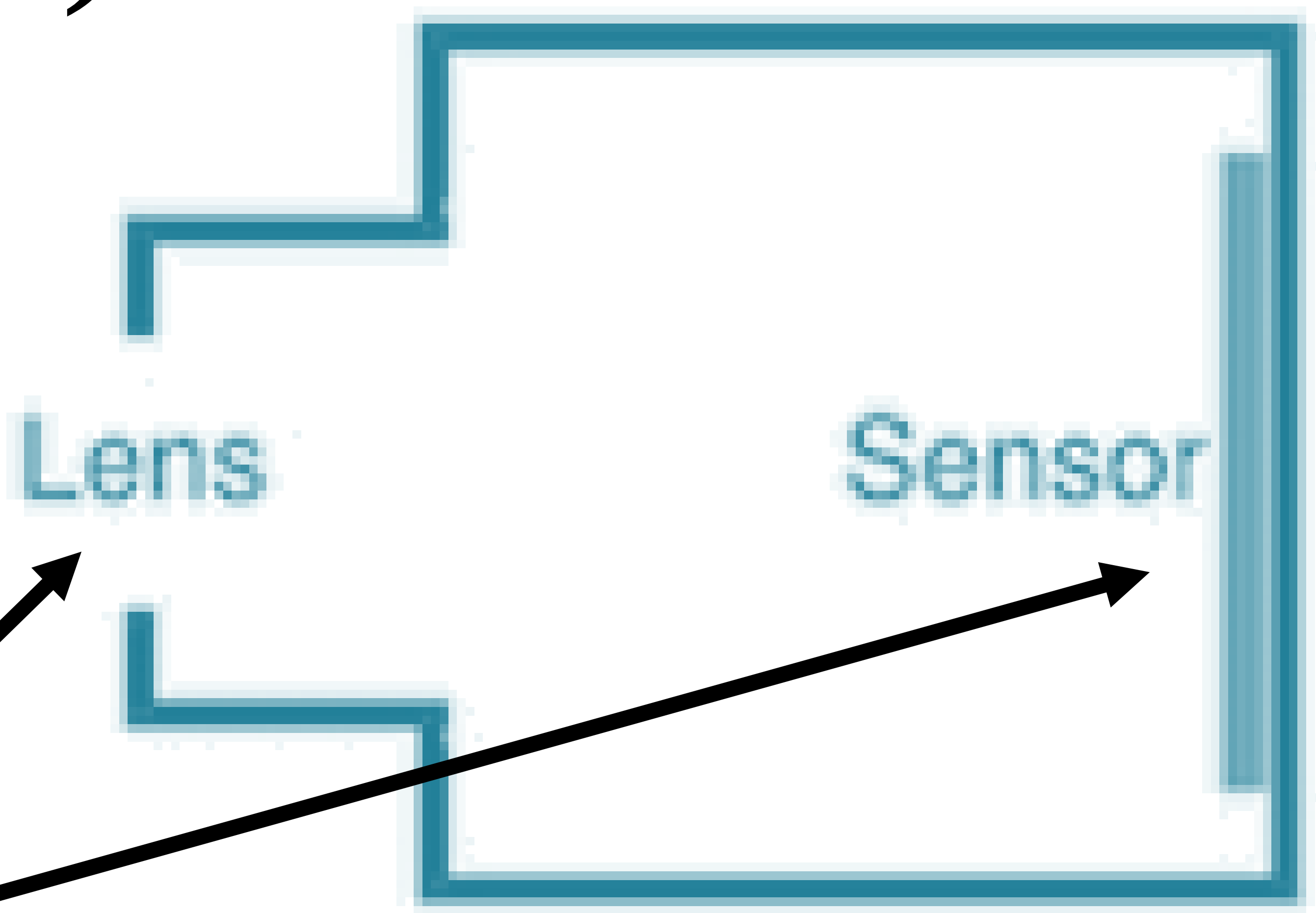


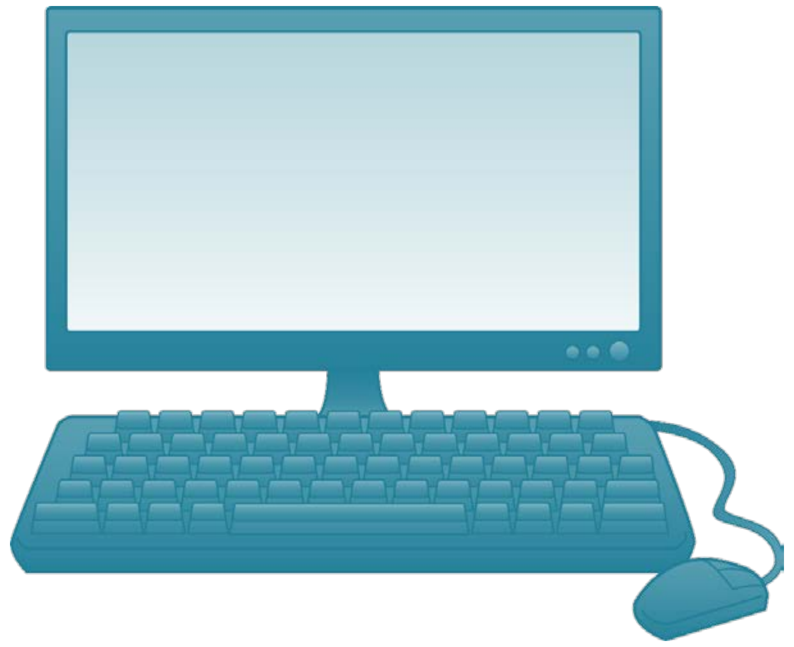
Computational Imaging Revolution

Generalized Physics

7D Brightness Sampling

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



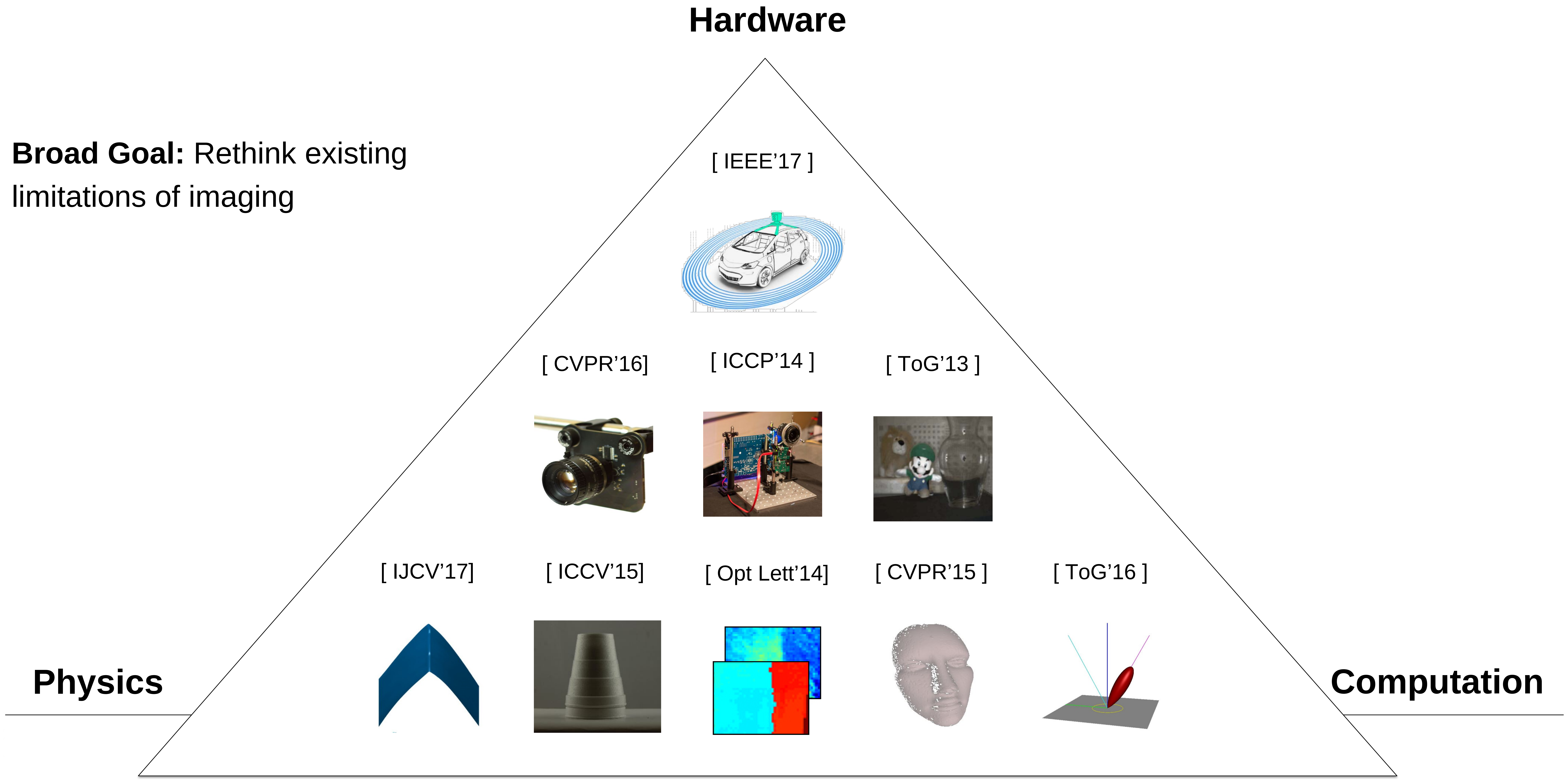


Generalized Algorithms

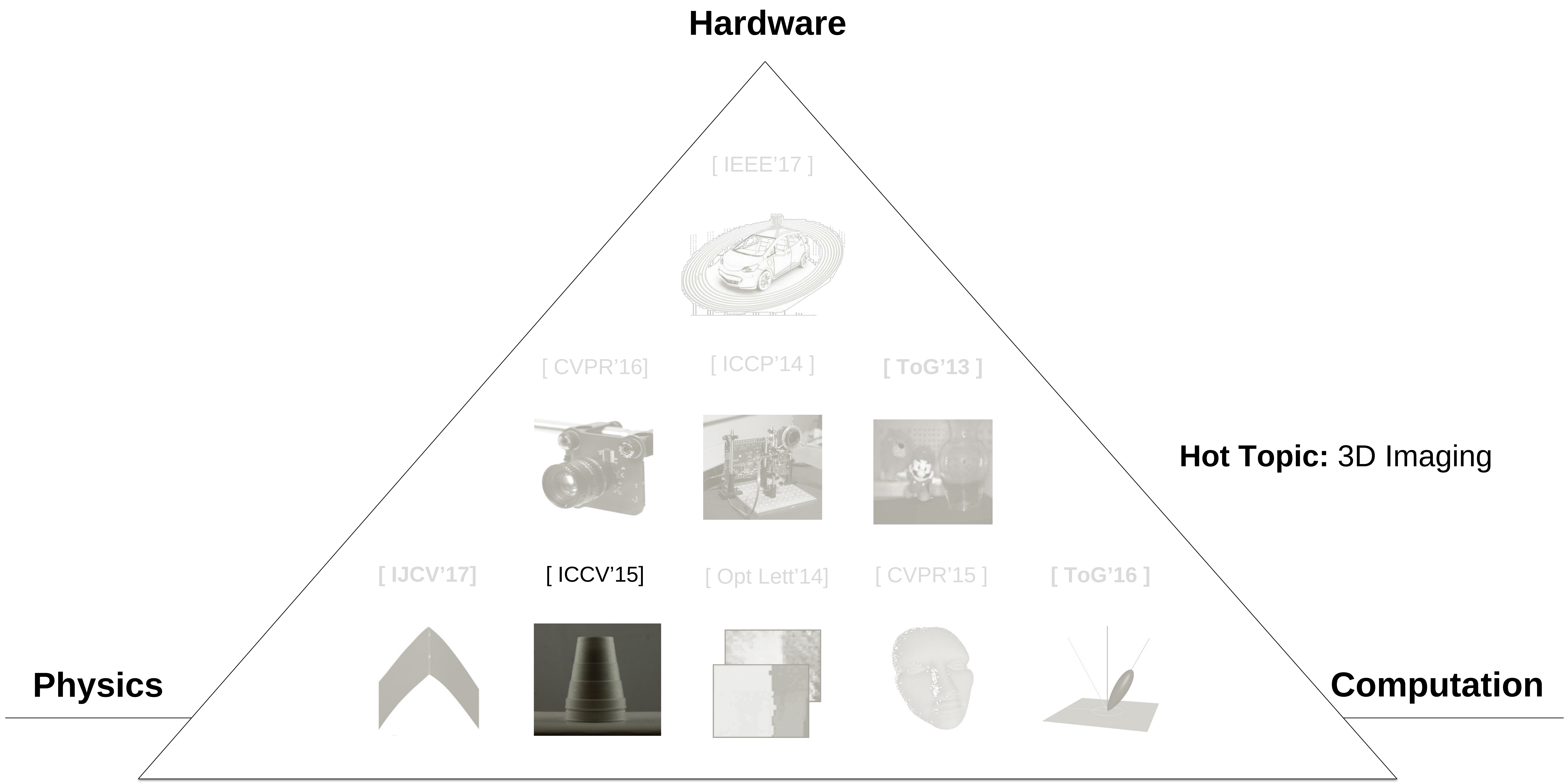
Generalized Hardware

Physics, Hardware, and Computation

Broad Goal: Rethink existing limitations of imaging



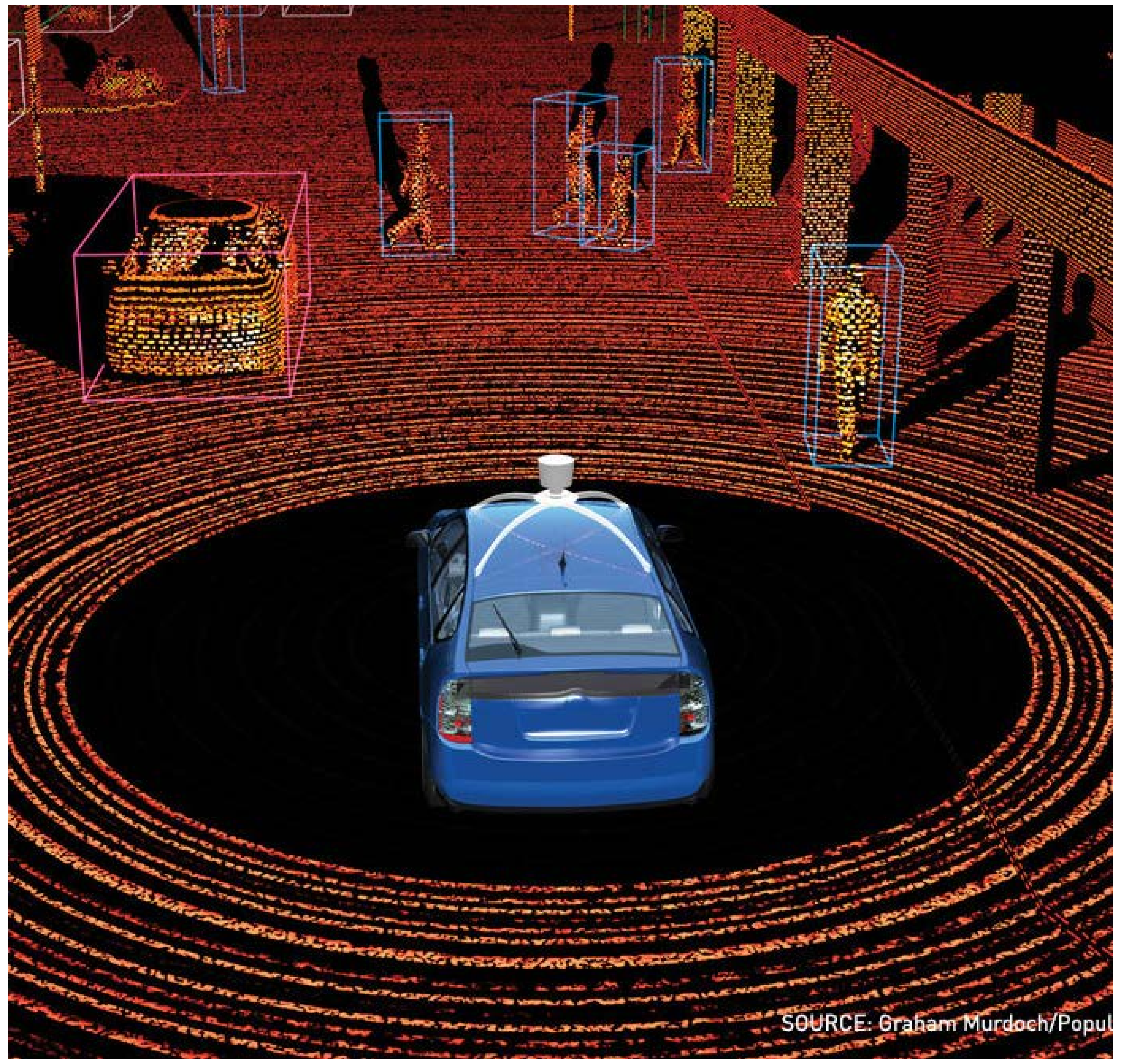
Physics, Hardware, and Computation



Hot Topic: 3D Imaging

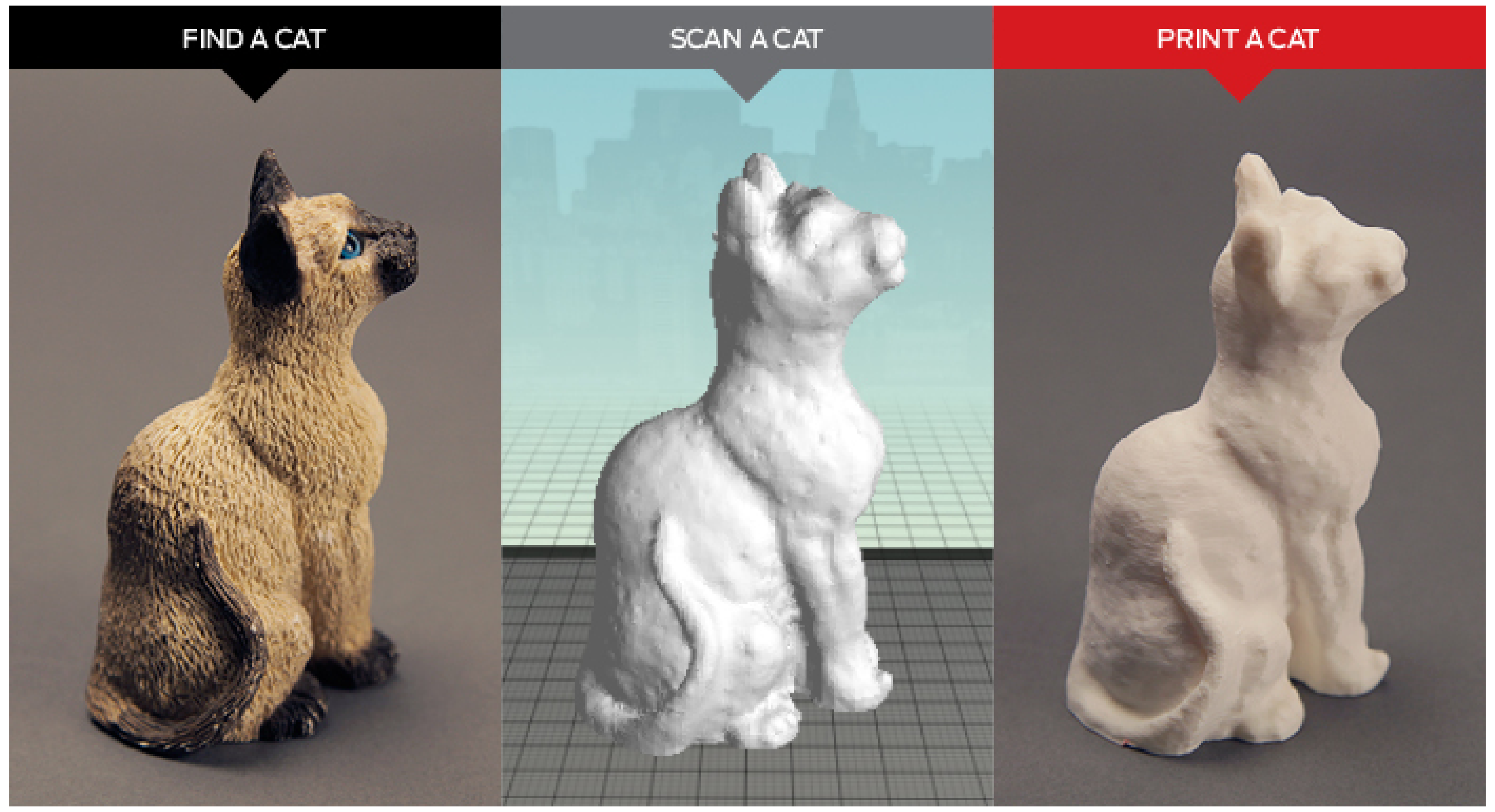
3D Cameras are Ready to Disrupt

3D cameras capture the (x,y,z) position of light reflections



Helping cars navigate

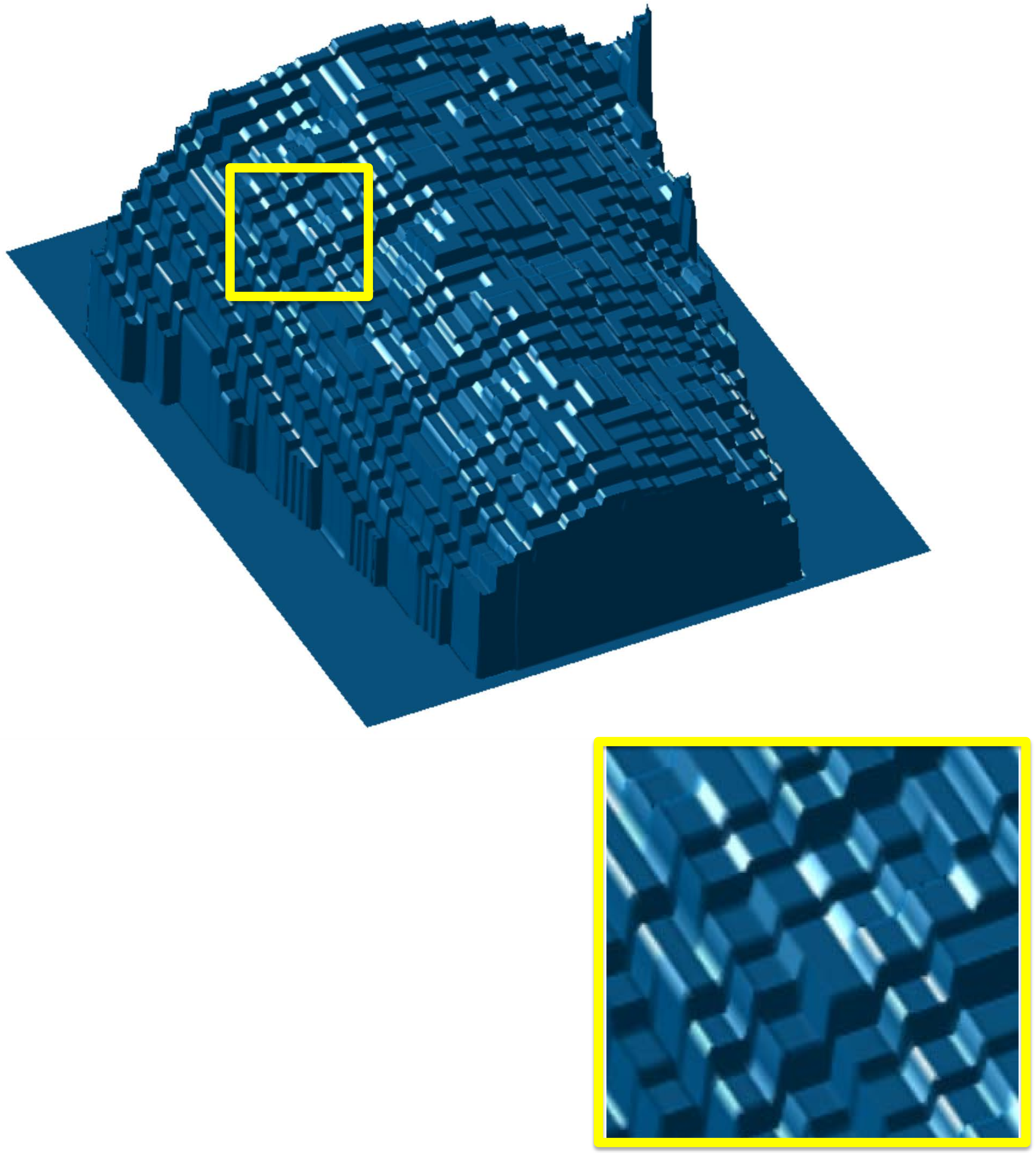
Guiding medical robots

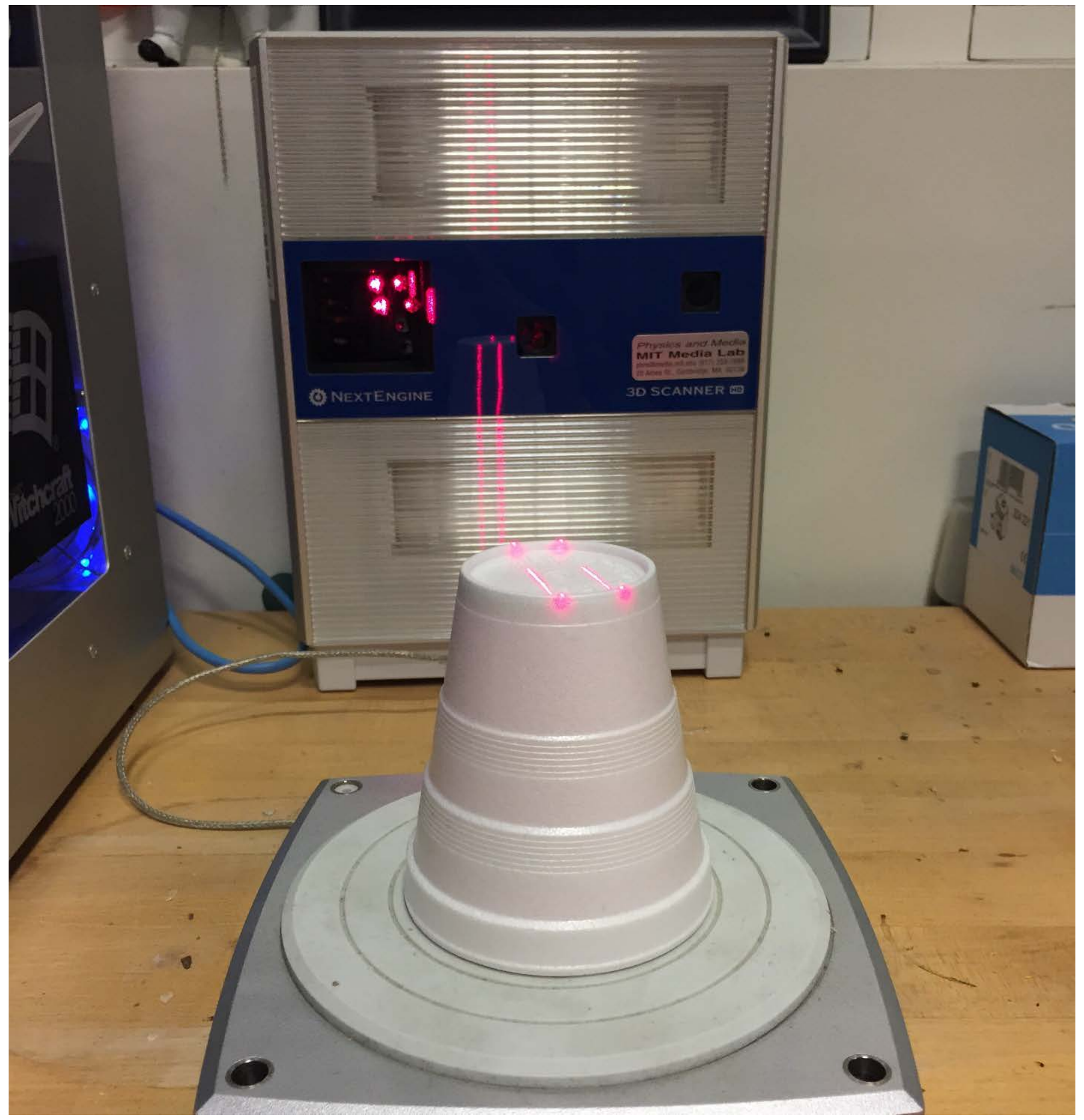


Scanning and printing objects

Microsoft Kinect v2

Microsoft Kinect v2



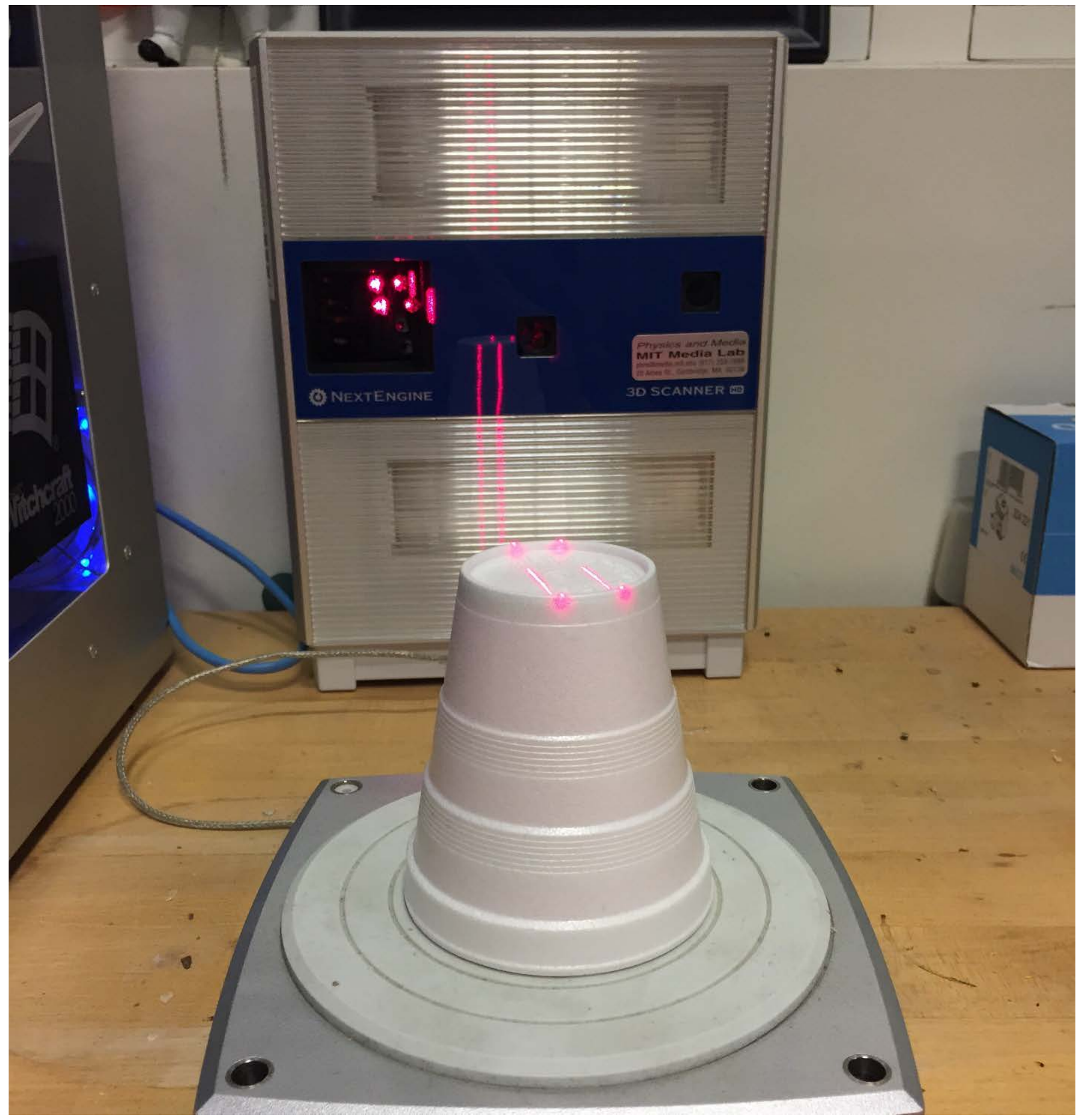


Multistripe Laser Scan

NextEngine 3D

$3000 USD

Raster



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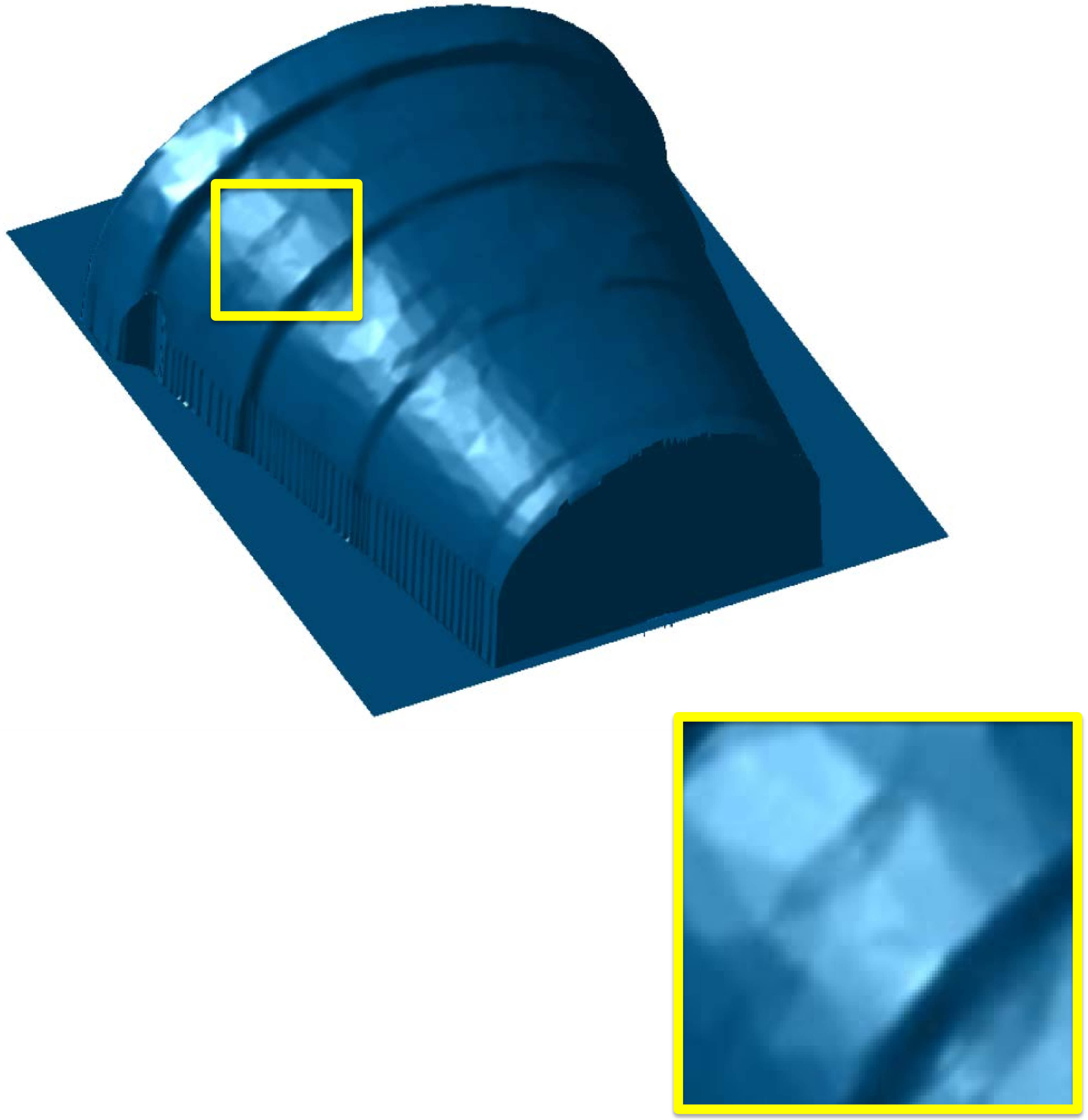
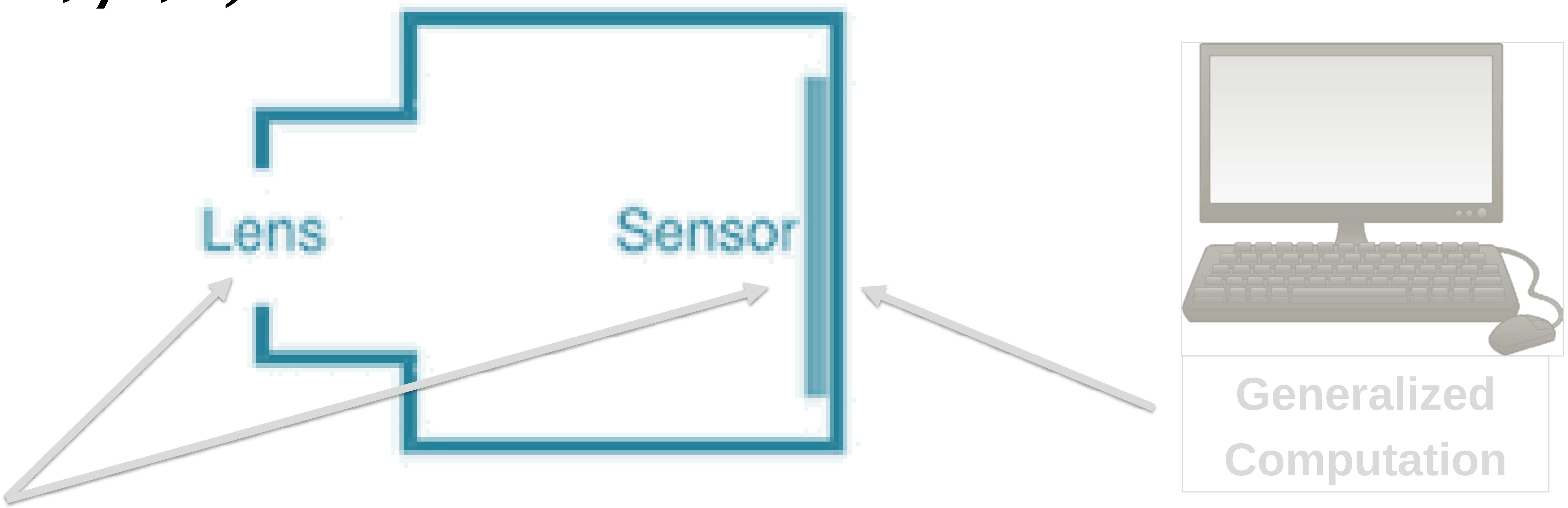


Bring in Physics

7D Brightness Sampling

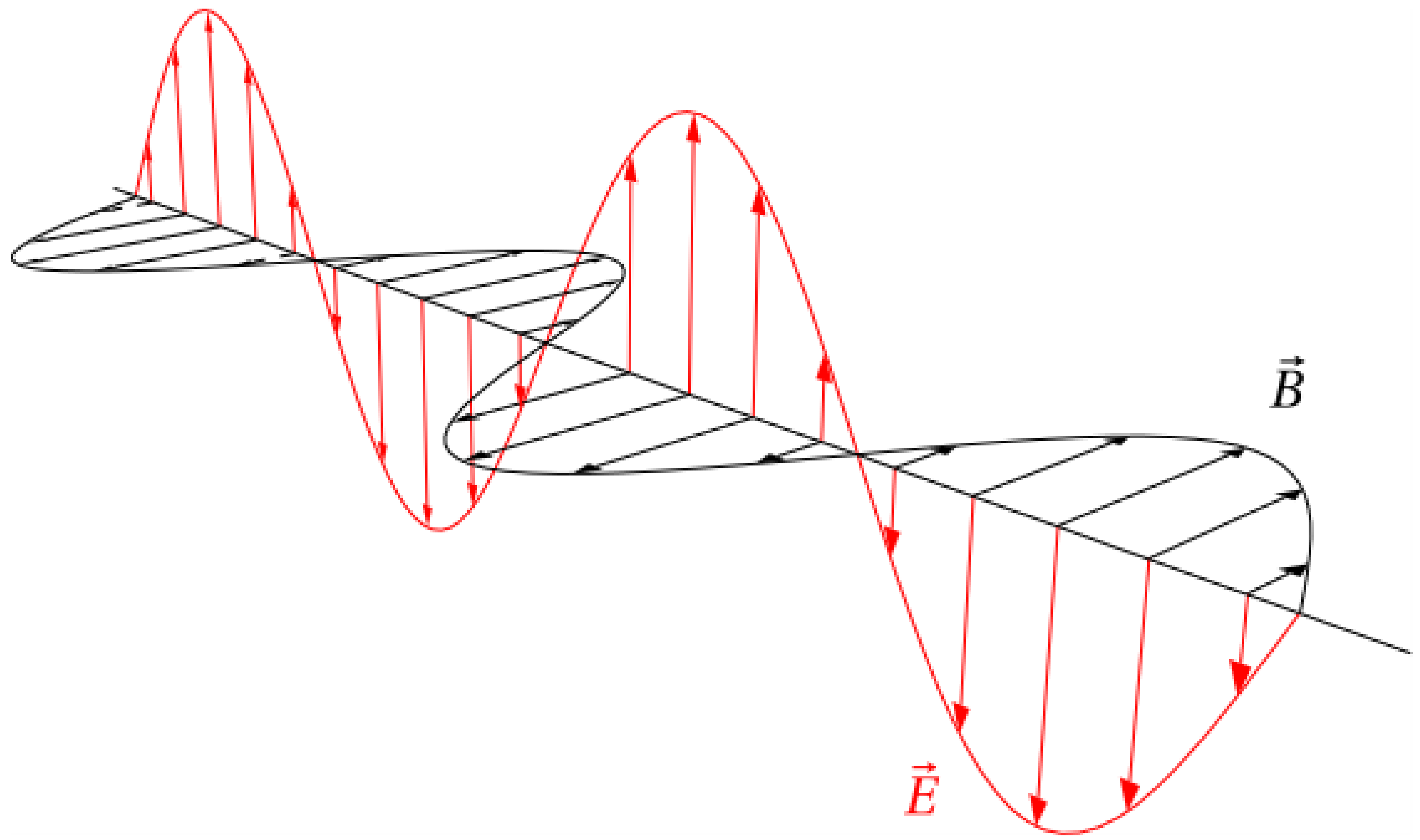
$$I(x, y, \theta_1, \theta_2, \lambda, \rho, t)$$

Generalized Physics

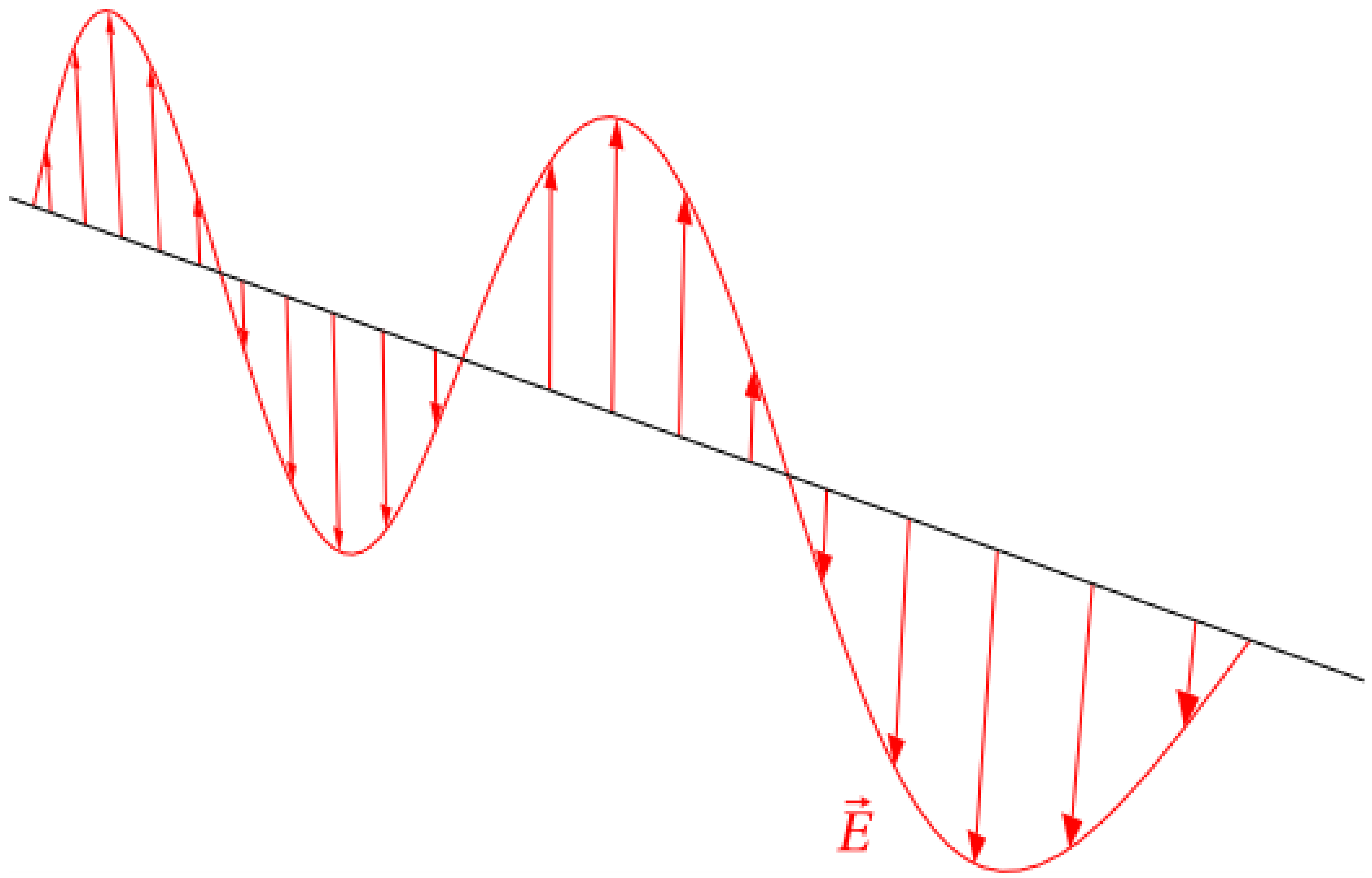


Generalized Hardware

Polarization of Light

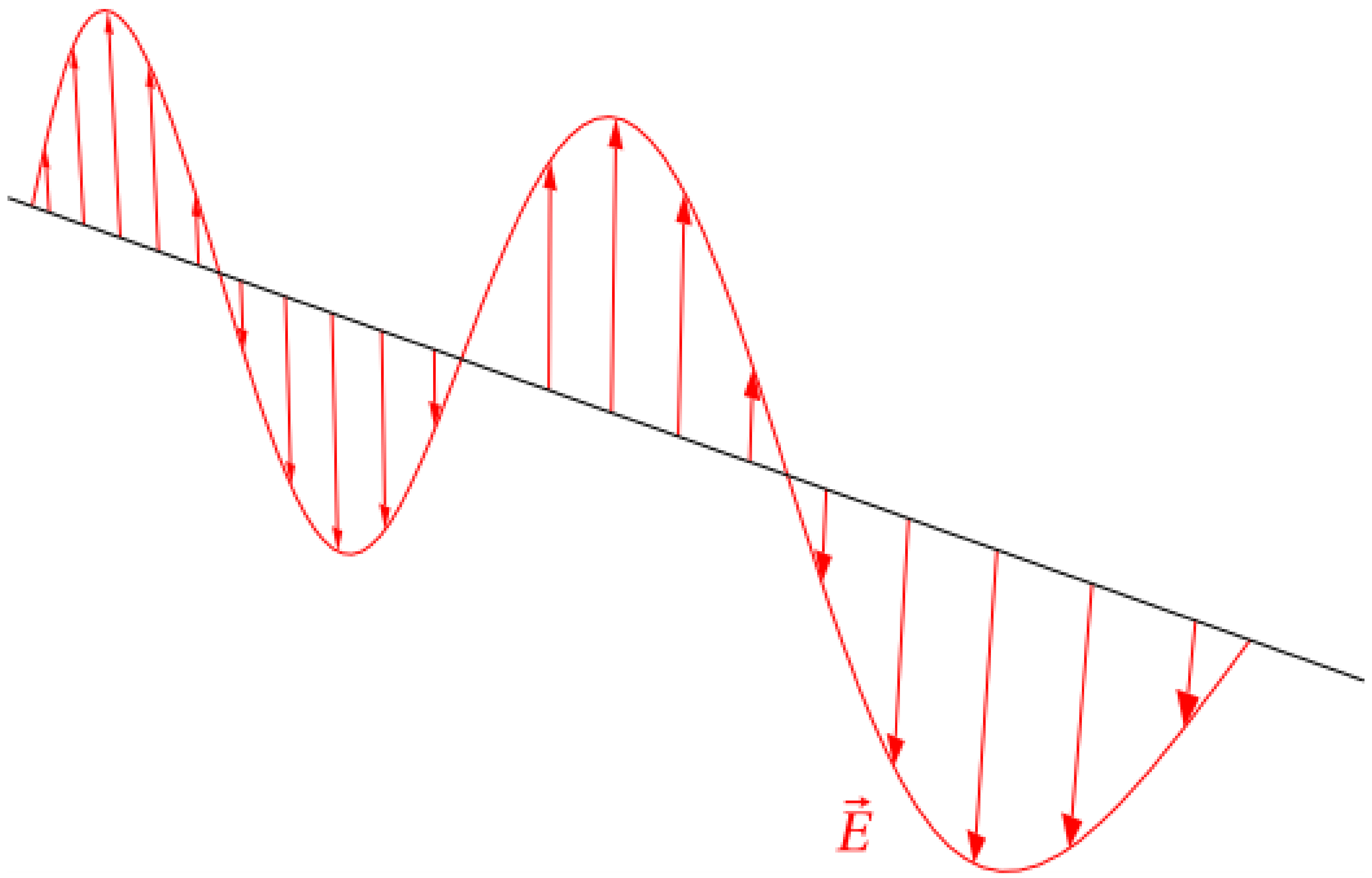


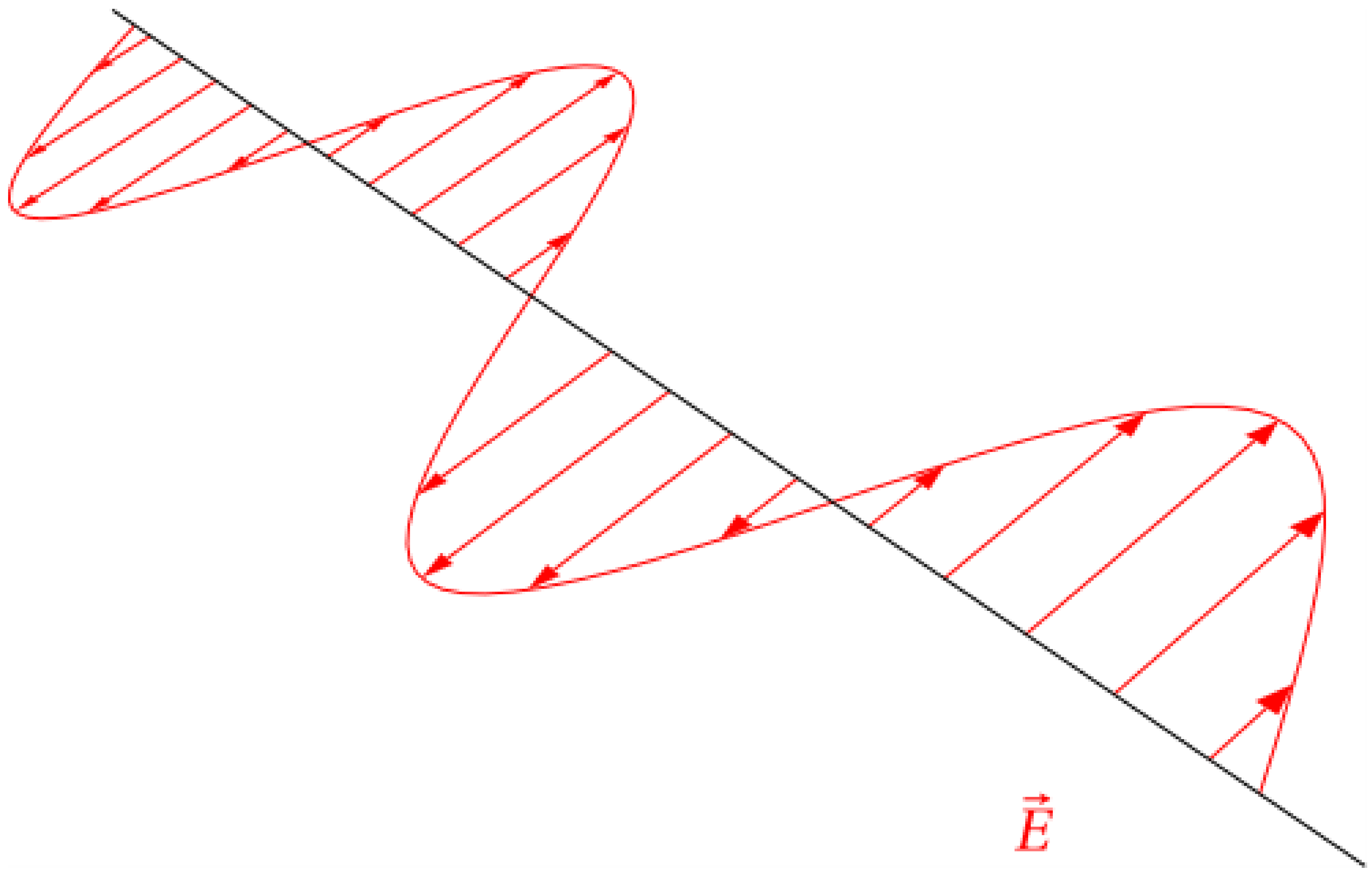
Polarization of Light



Plane of Polarization

Polarization of Light

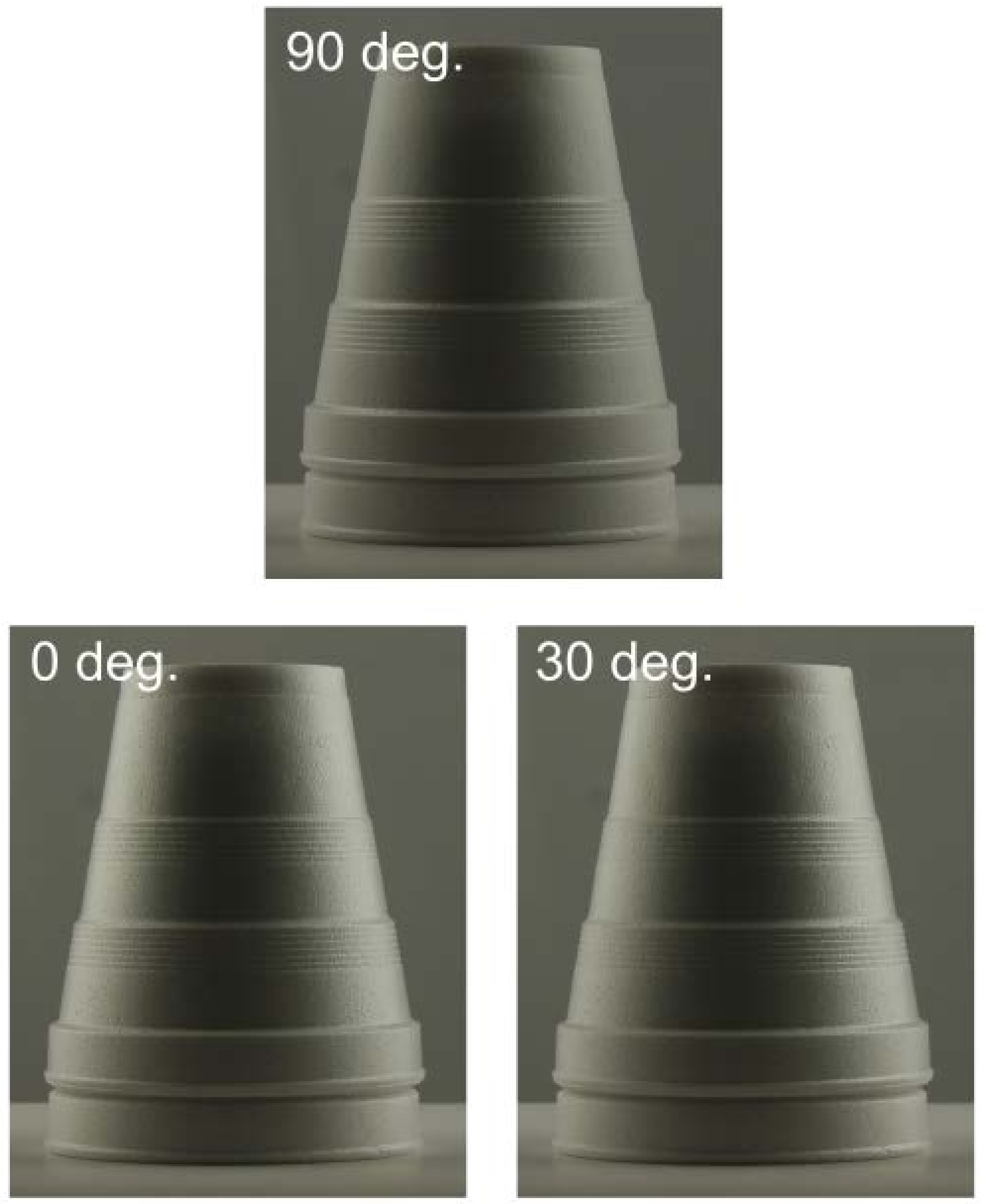




Plane of Polarization

Plane of Polarization

$30 Polarizing
Filter



Photos at Different Angles

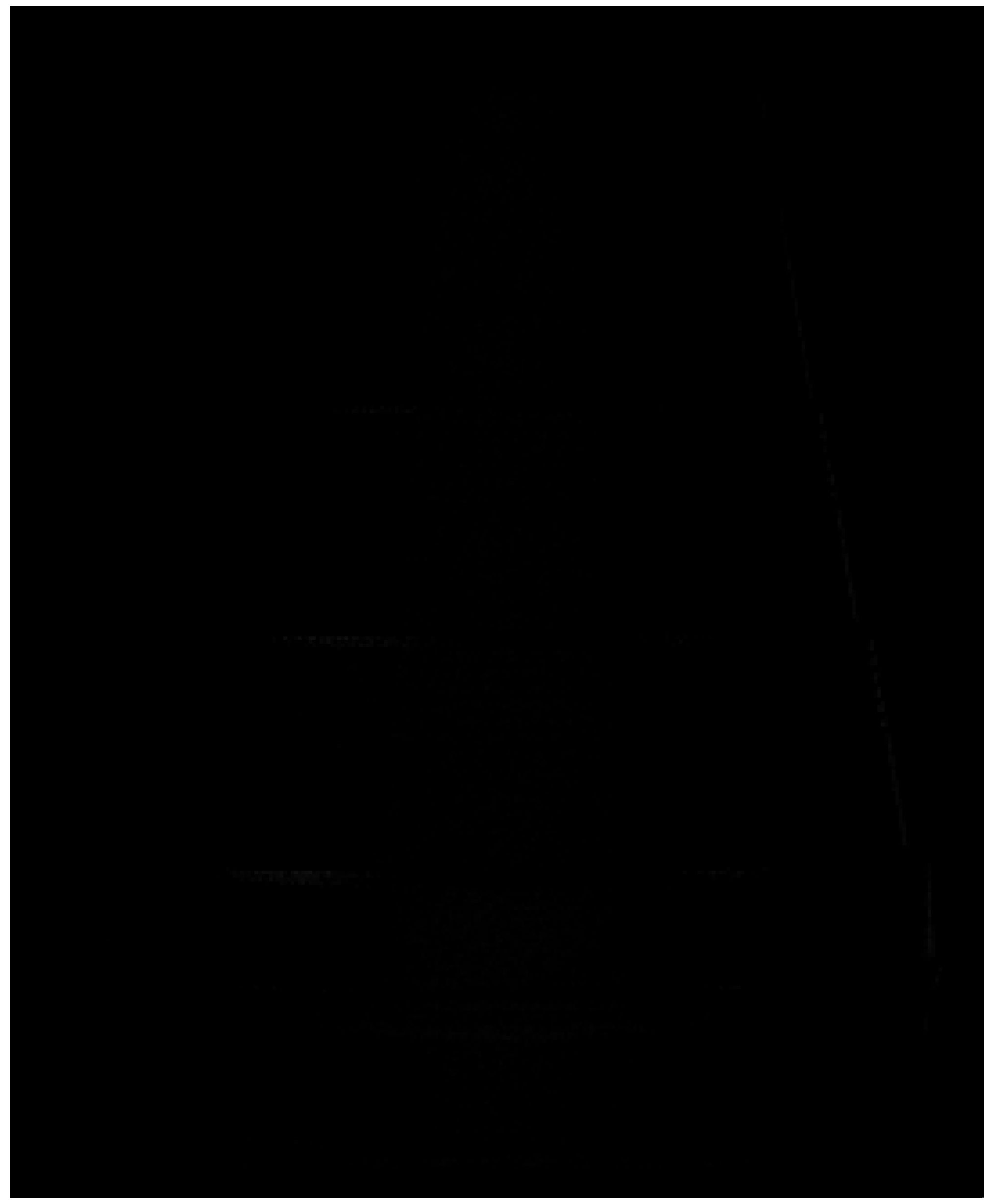
Horizontal Filter Orientation

Vertical Filter Orientation

Colors map to 8-bit grayscale

Horizontal Filter Orientation

Vertical Filter Orientation

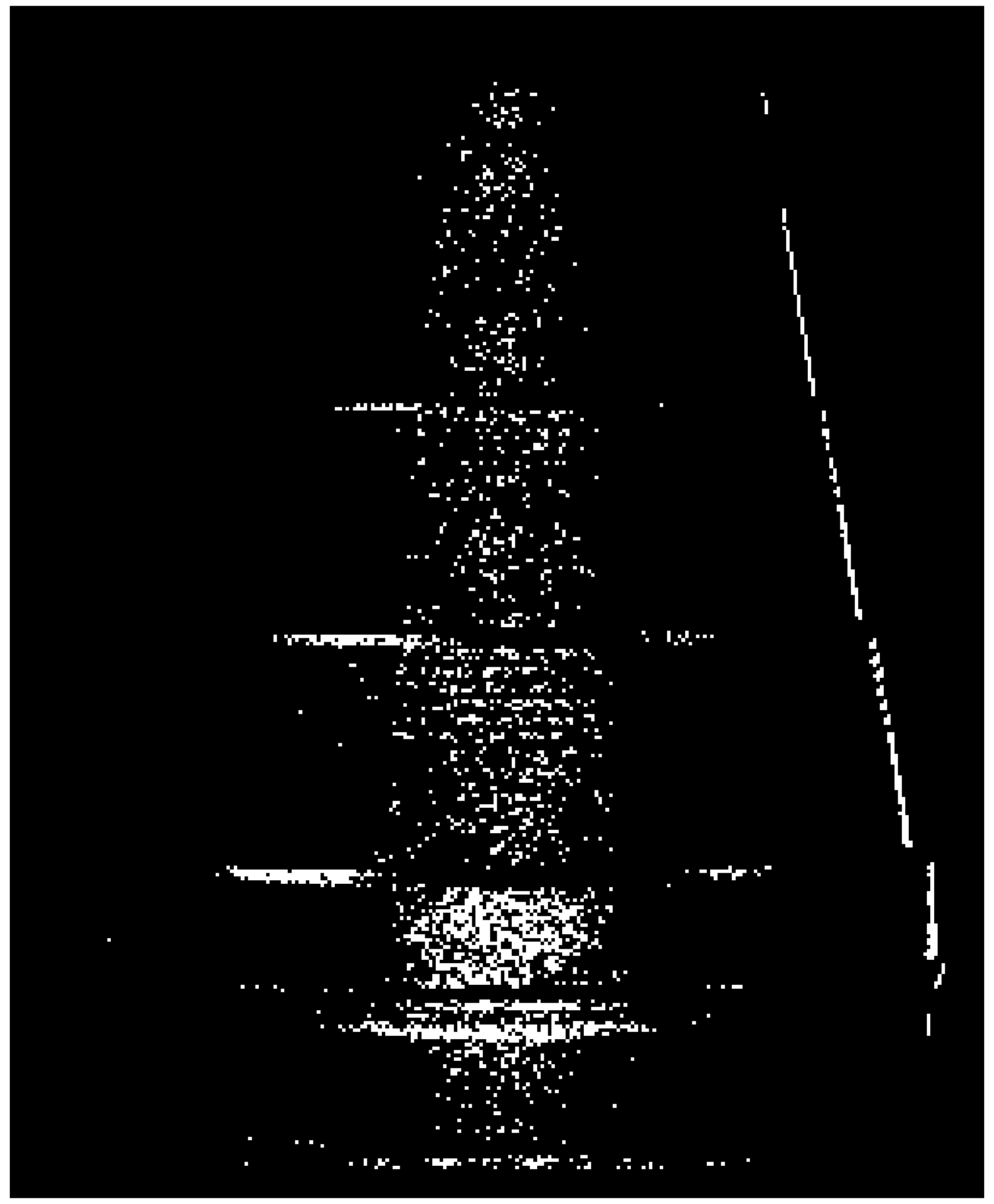


Difference Image

Colors map to 8-bit grayscale

Horizontal Filter Orientation

Vertical Filter Orientation



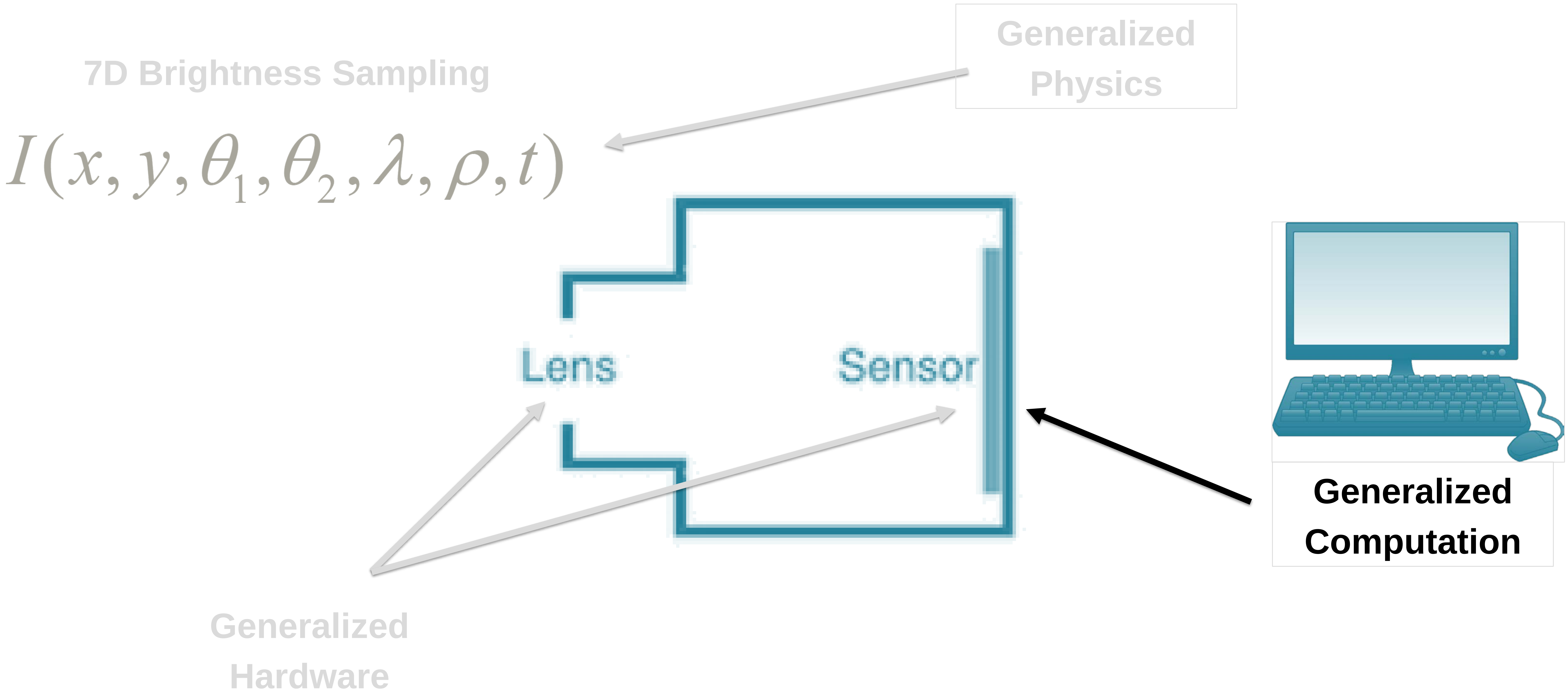
Difference Image

(Tonemapped to 8-bit)

We need to add computation!

Colors map to 8-bit grayscale

Final Ingredient: Bring in Computation



Graphic inspired by L. Waller

"Polarized 3D"

Computational Imaging

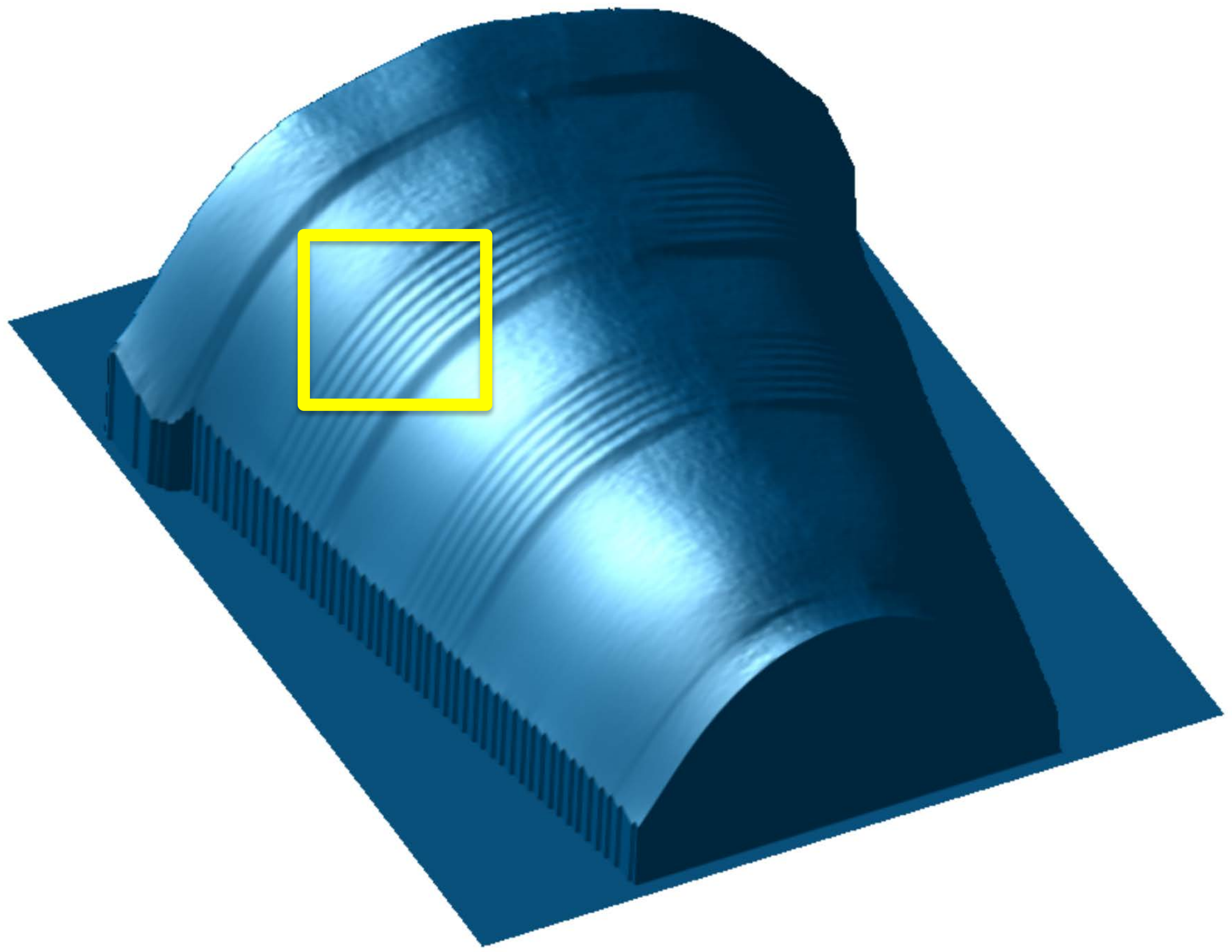
Using Polarization

[Kadambi et al. IJCV 2017]

“Polarized 3D”

Computational Imaging

Using Polarization

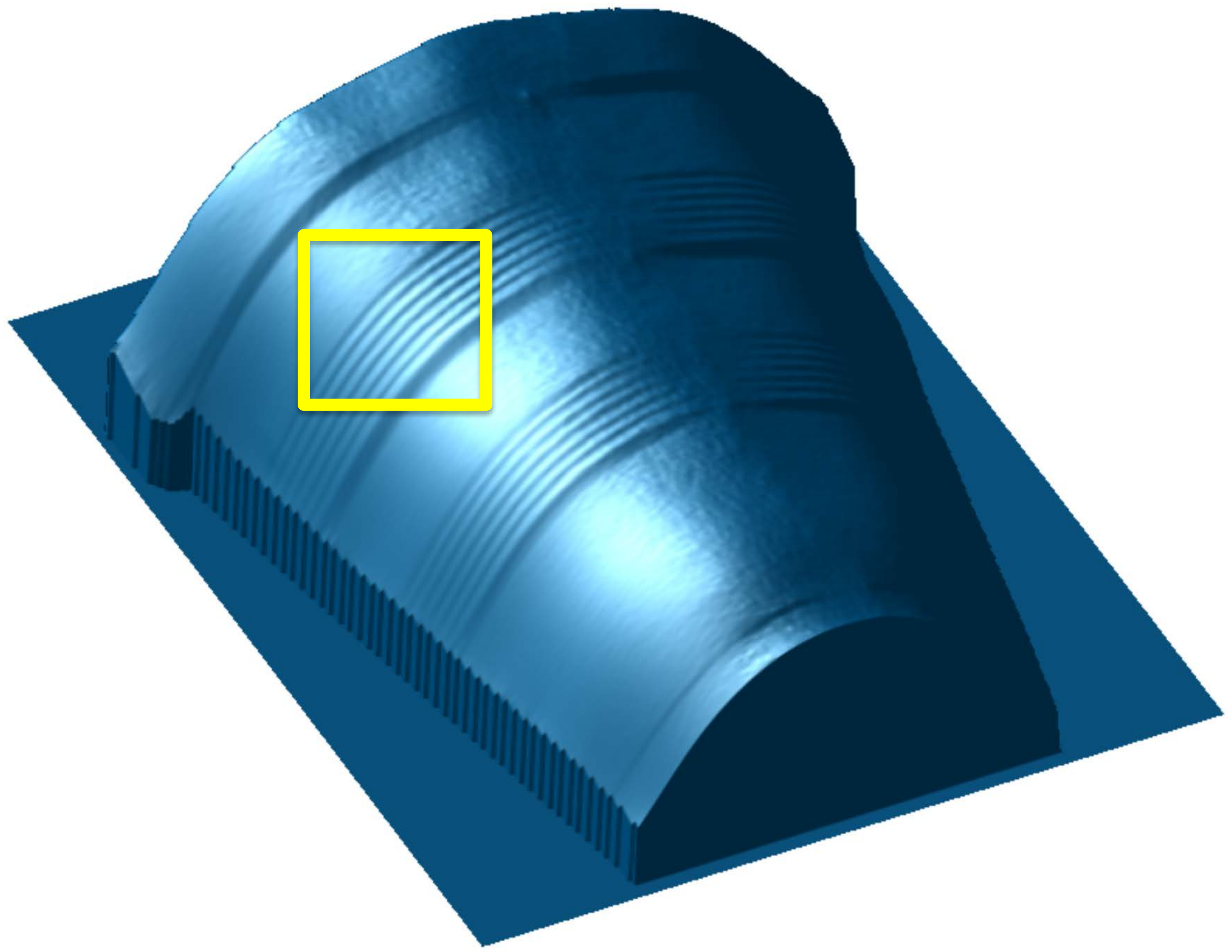


[Kadambi et al. IJCV 2017]

"Polarized 3D"

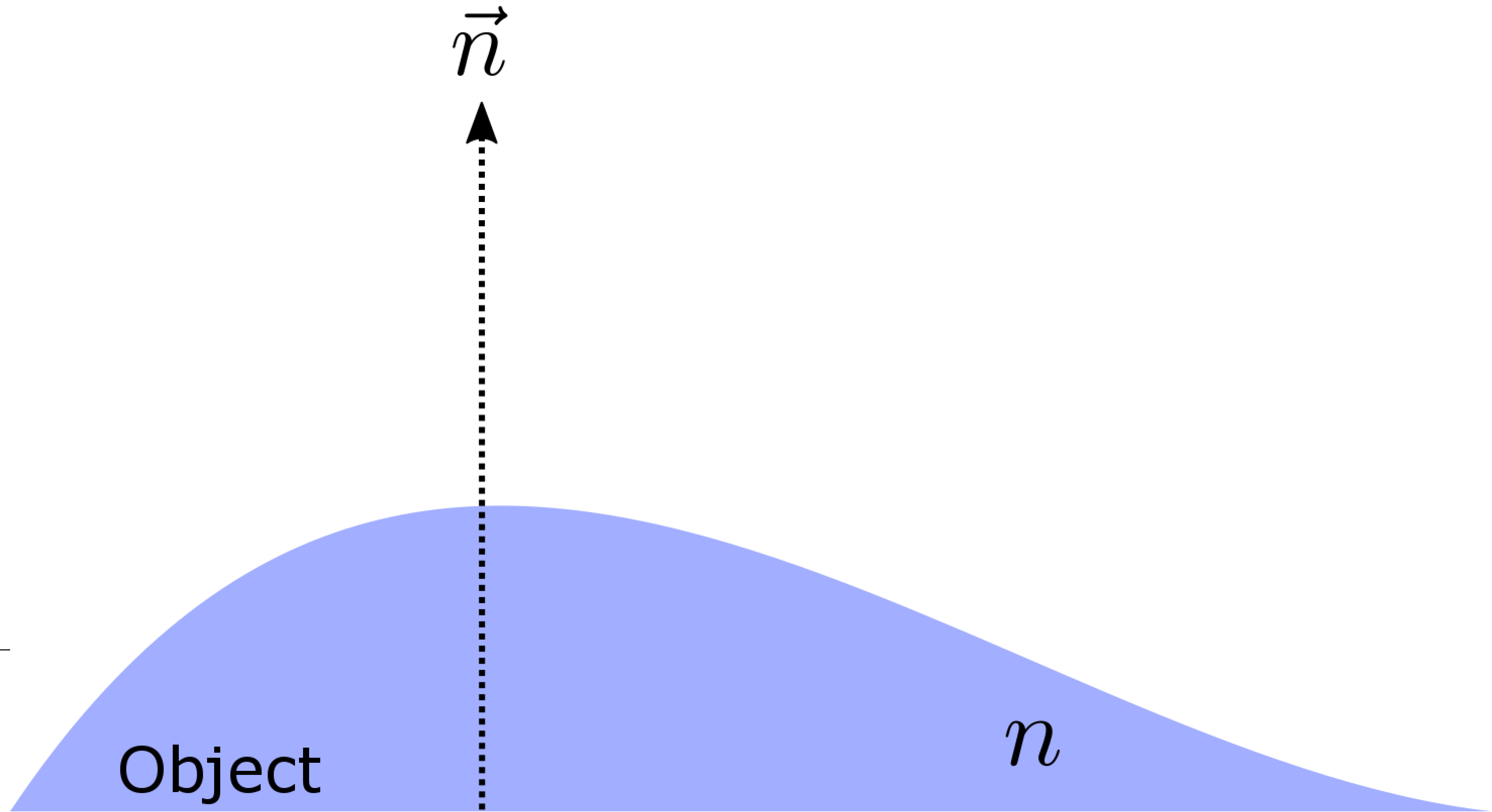
Computational Imaging

Using Polarization



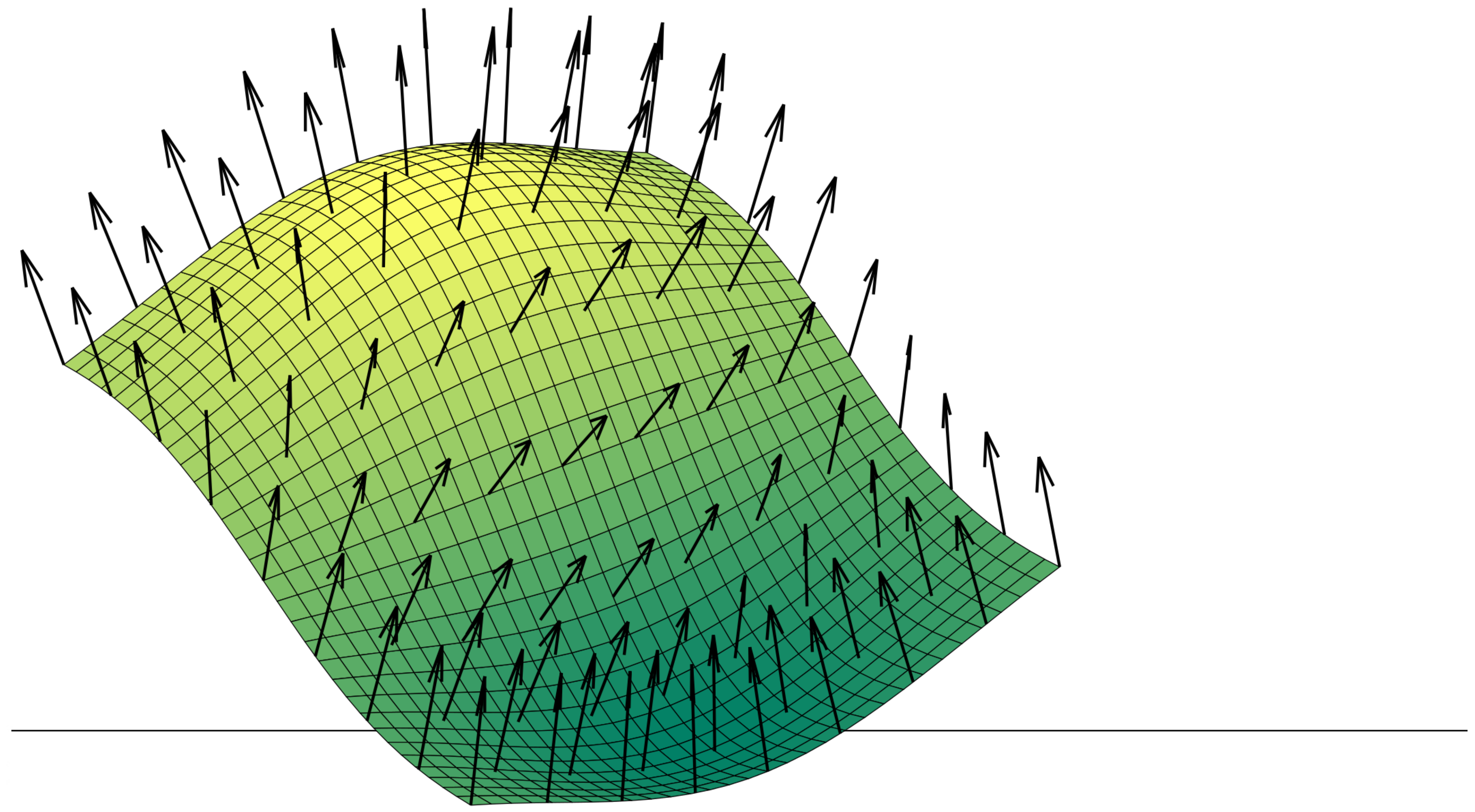
[Kadambi et al. ICCV 2015]

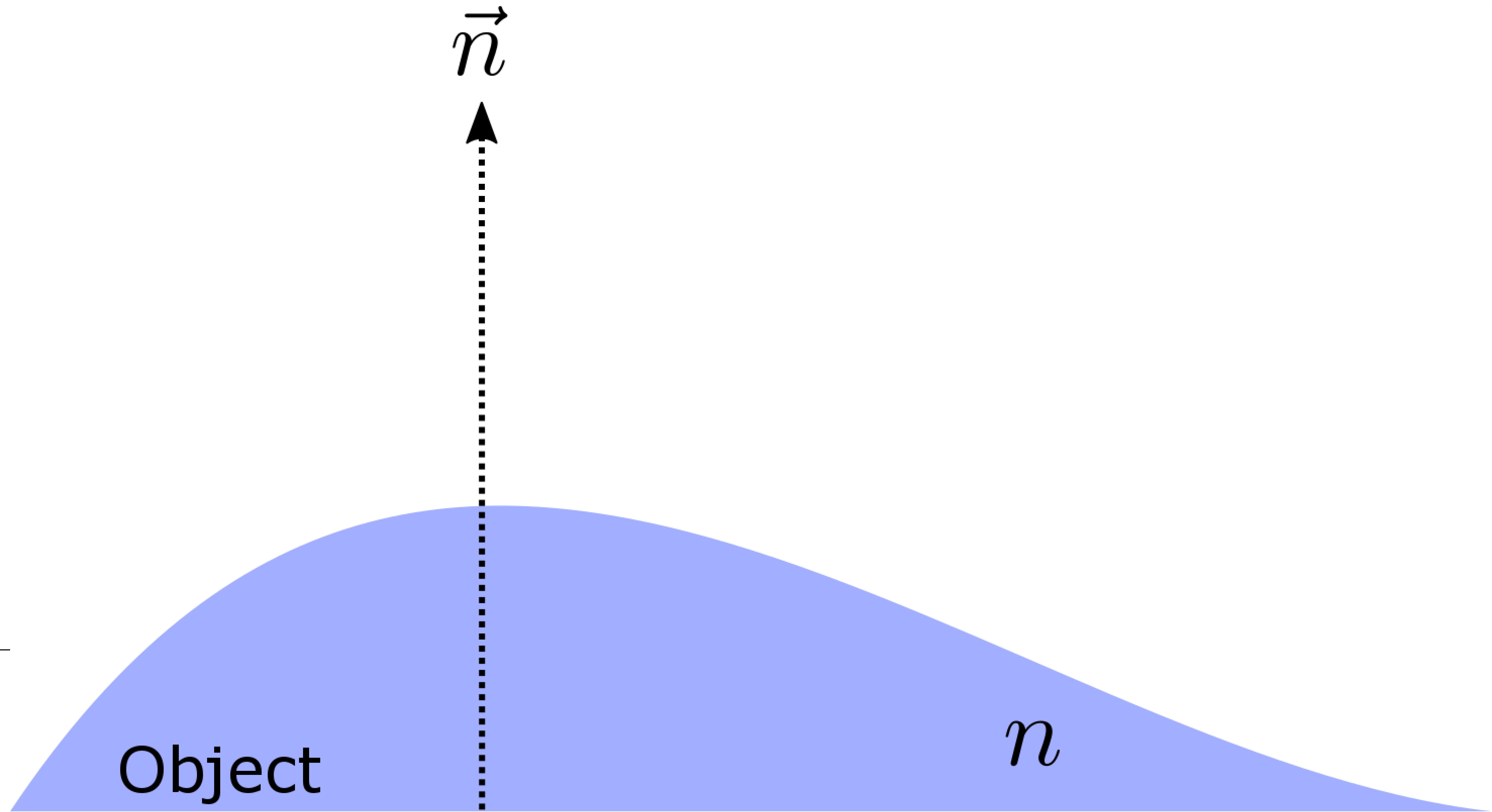
Fresnel Electromagnetic Equations



Fresnel Electromagnetic Equations

Integrating normals to obtain 3D shape





Fresnel Electromagnetic Equations

Integrating normals to
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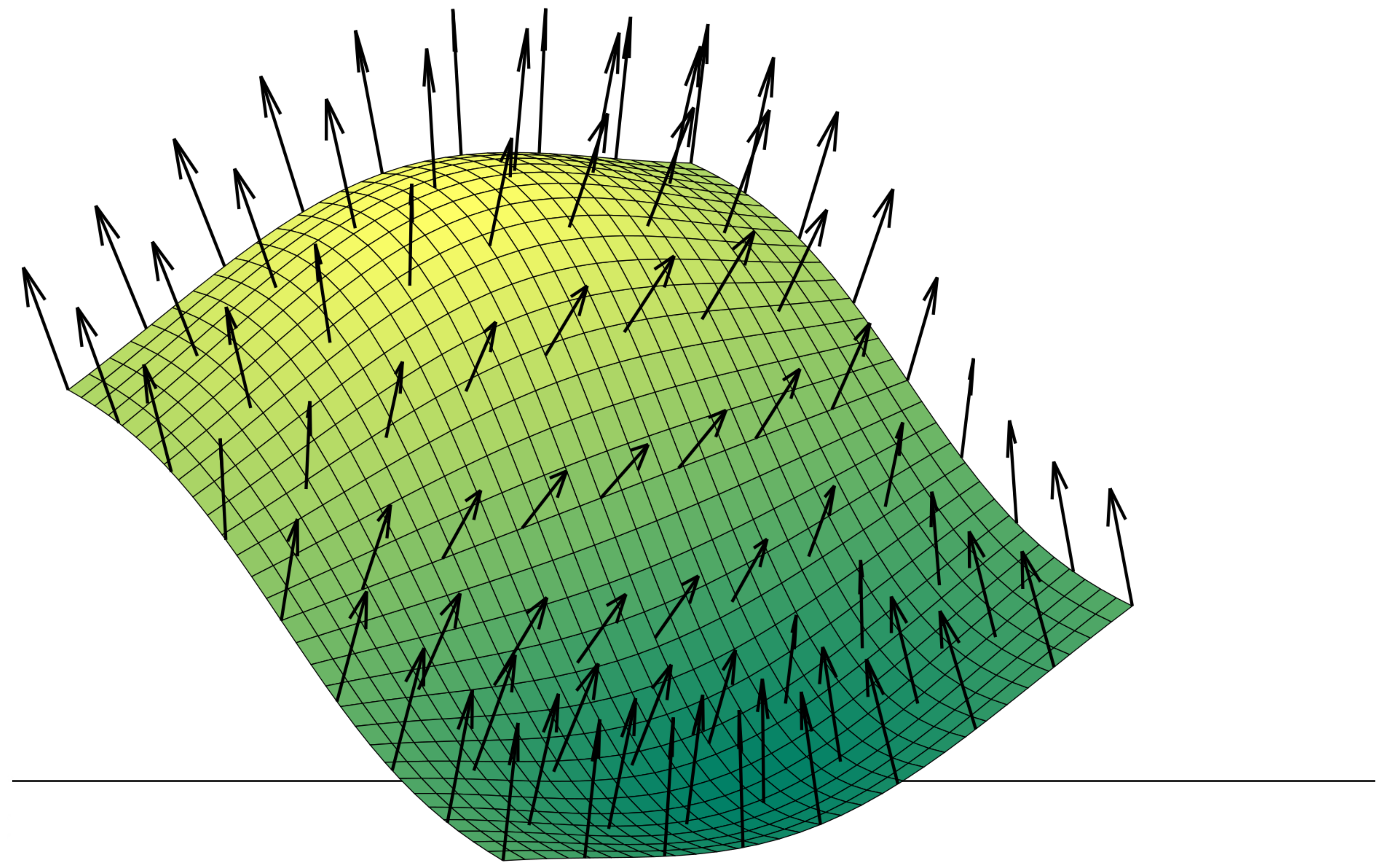
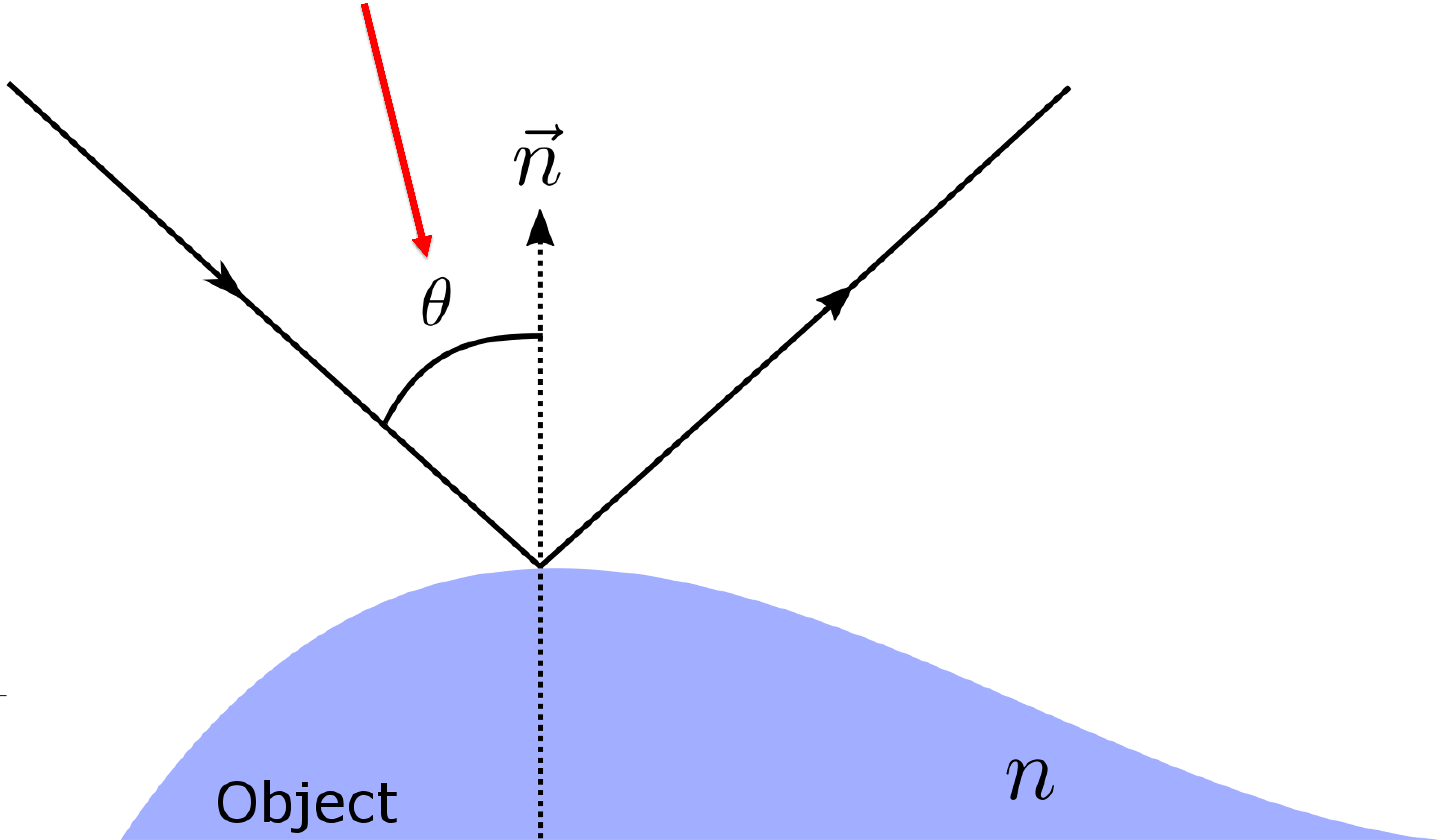


Goal: Solve for zenith angle at
each position



Fresnel Electromagnetic Equations

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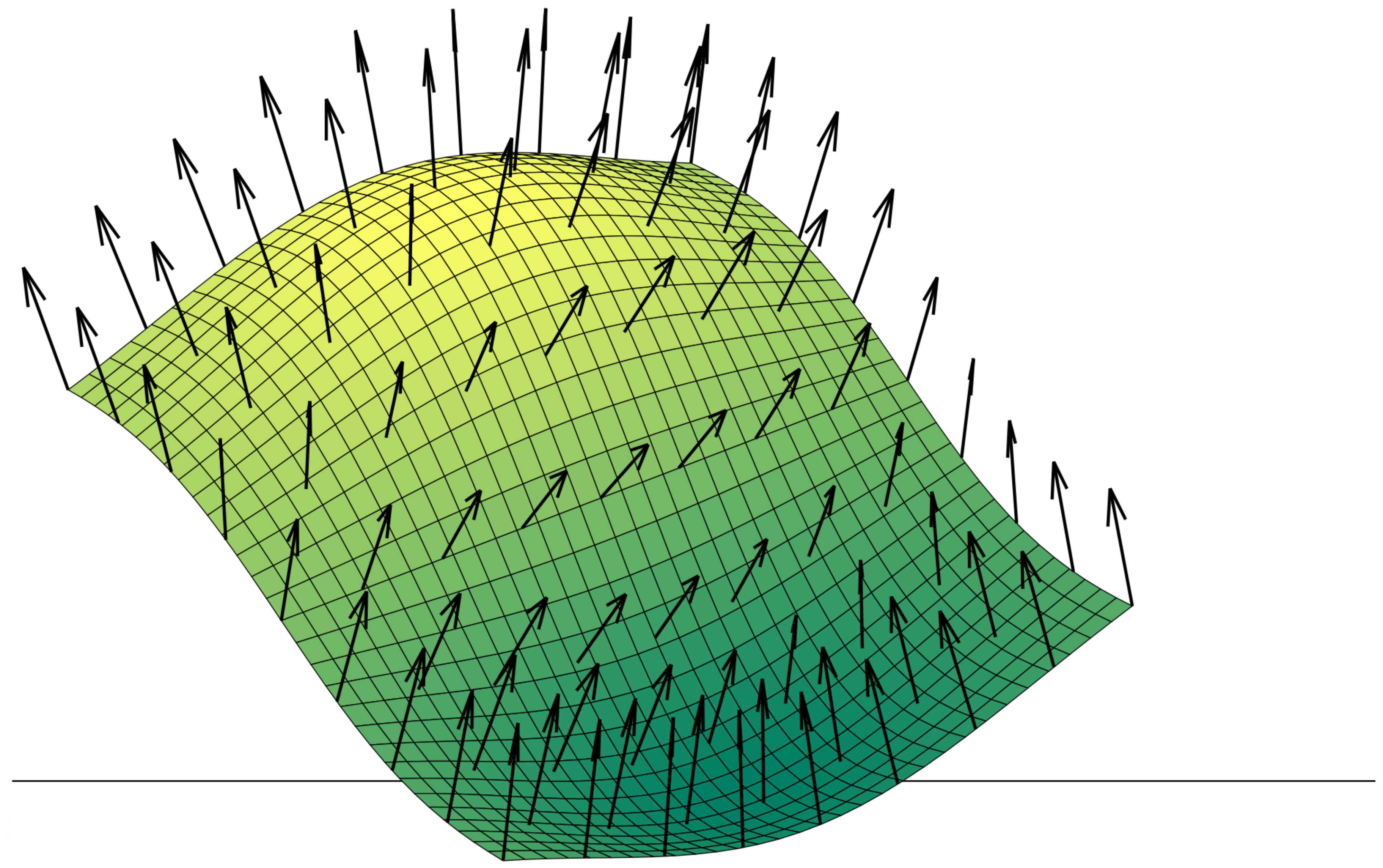

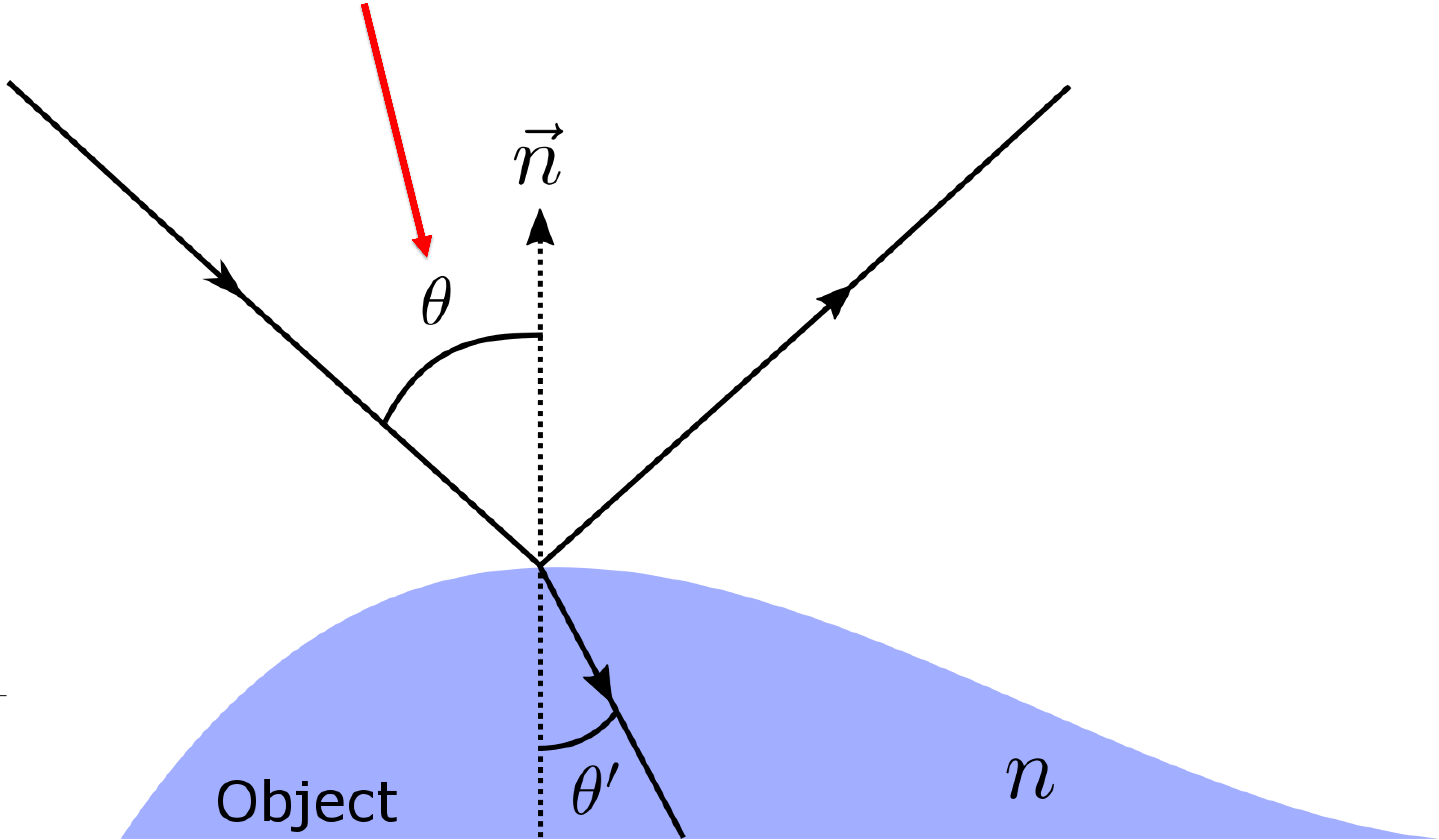

Fresnel Electromagnetic Equations

Goal: Solve for zenith angle at each position

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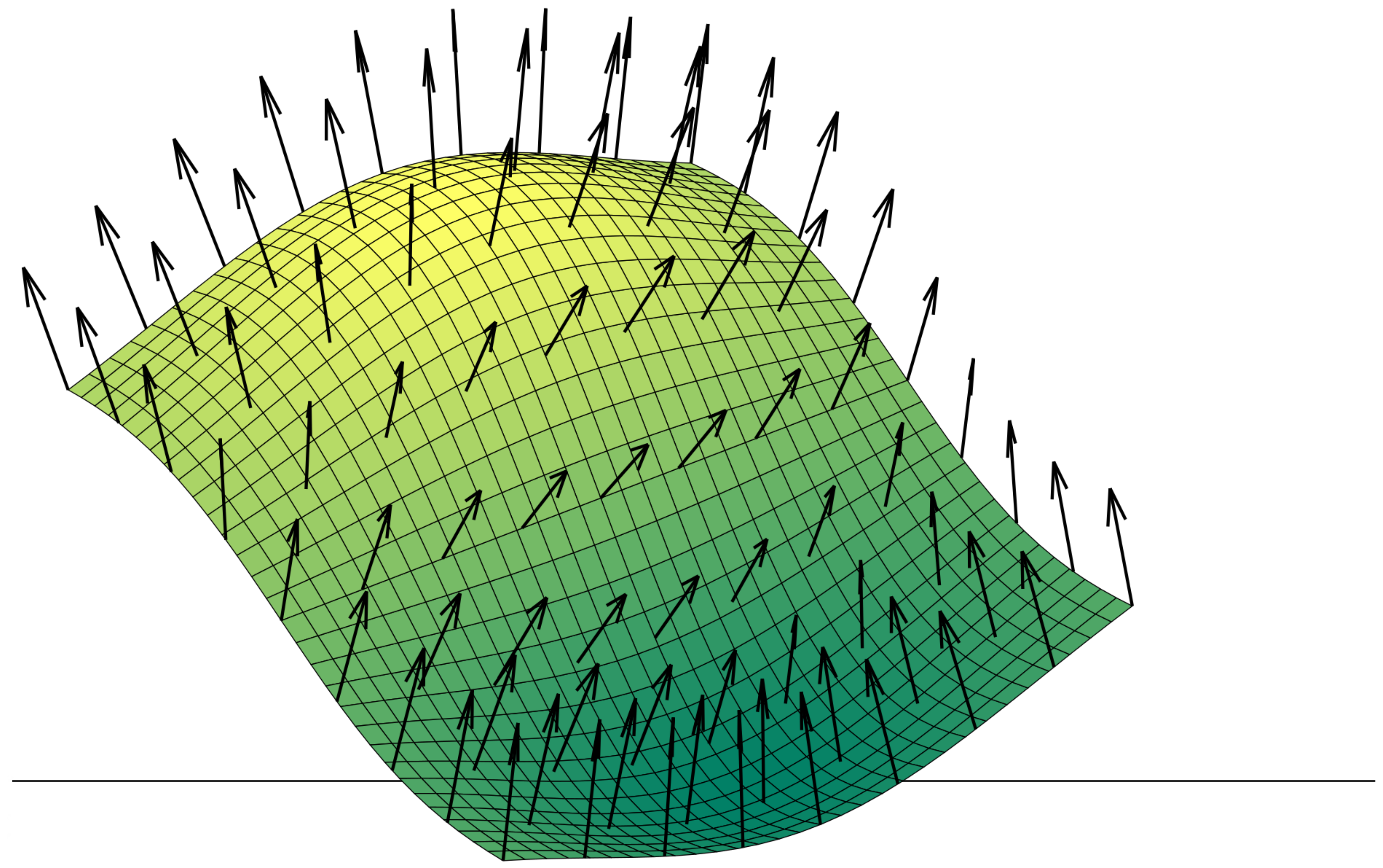
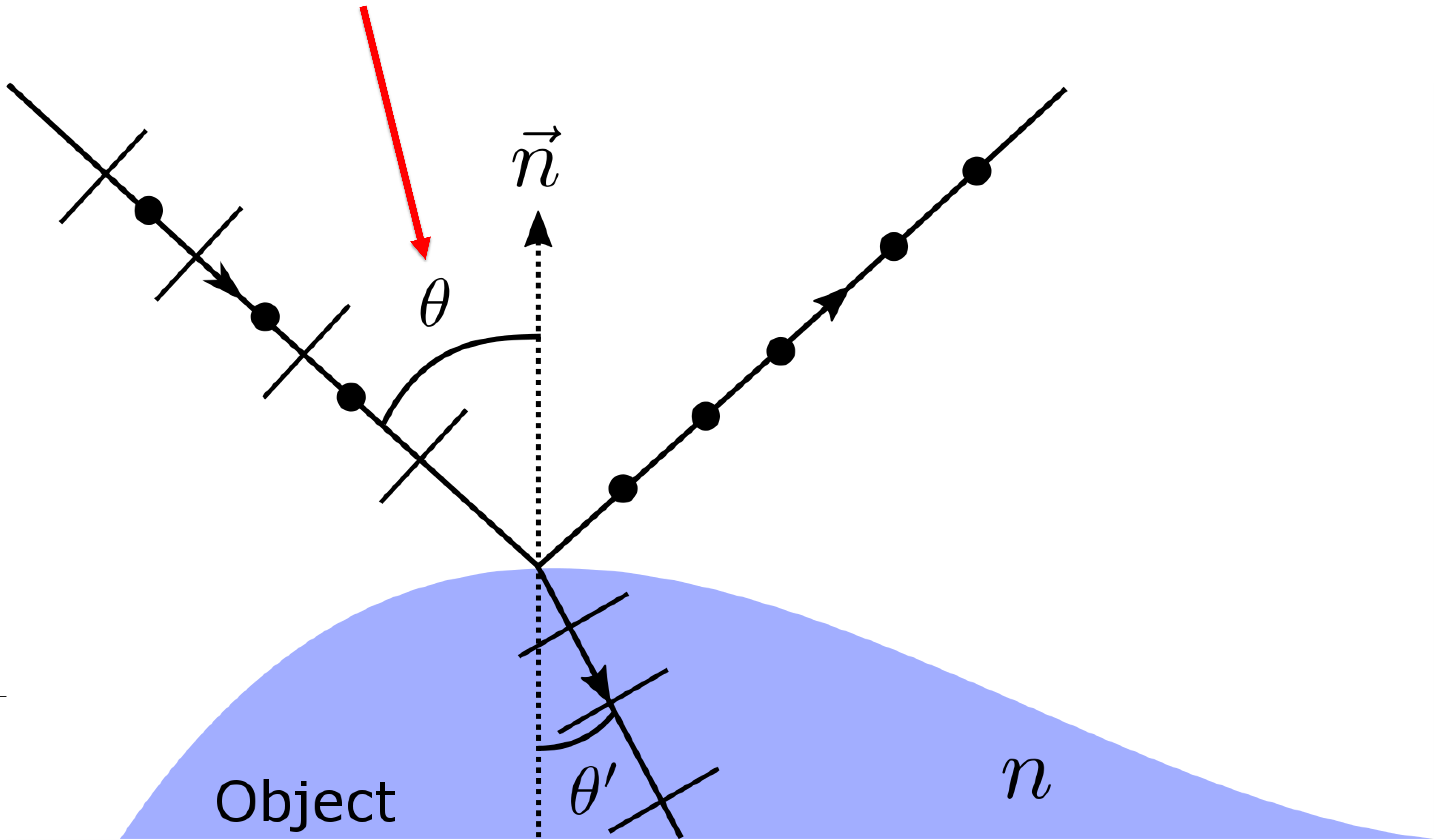




Fresnel Electromagnetic Equations

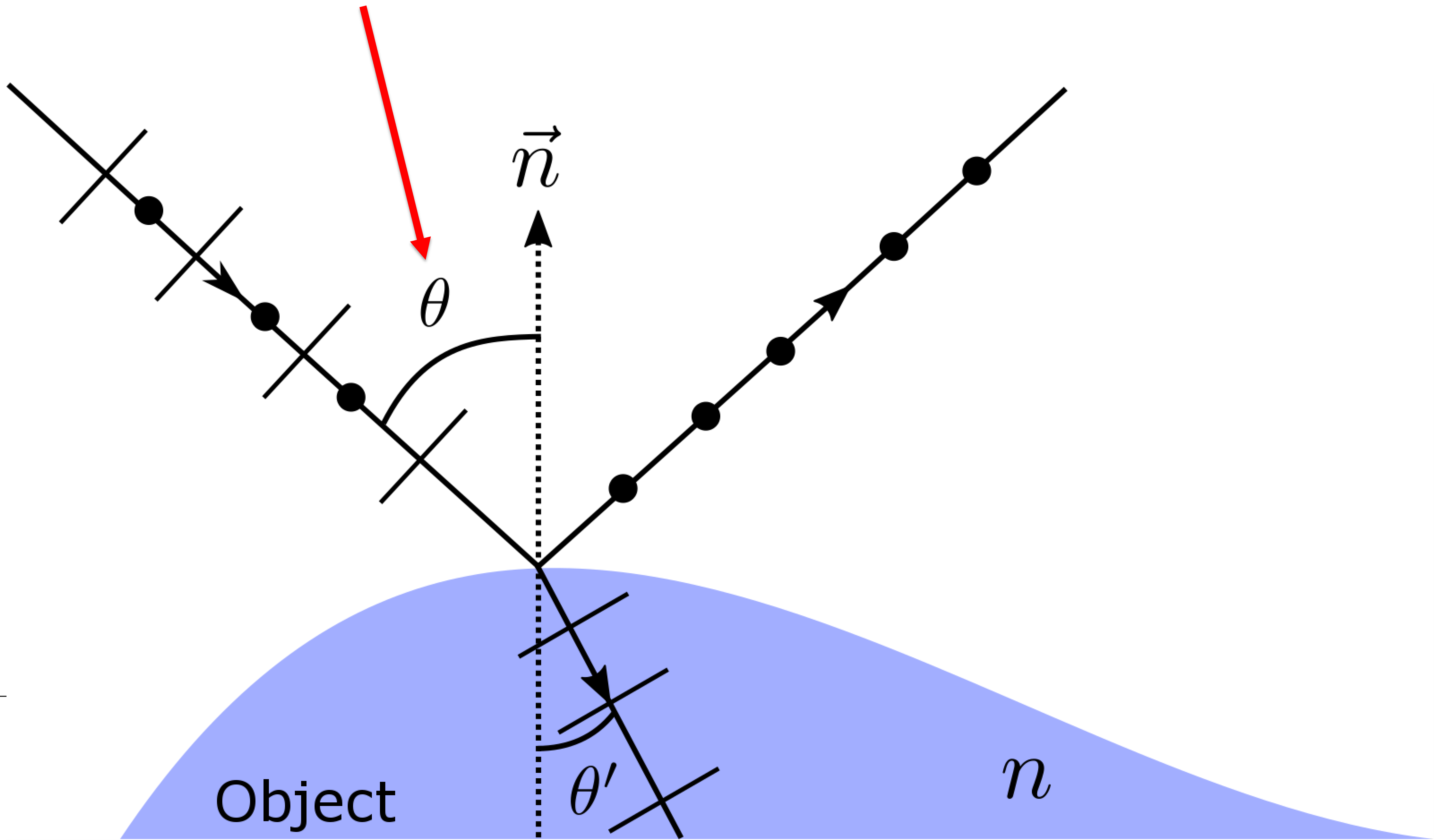
Old Principle [Fresnel 1819]

$$r_\perp = \frac{\cos\theta_i - n\cos\theta_t}{\cos\theta_i + n\cos\theta_t}$$

$$r_\parallel = \frac{\cos\theta_i - n\cos\theta_t}{\cos\theta_t + n\cos\theta_i}$$

SfP crux: Solve for theta

Goal: Solve for zenith angle at each position



Fresnel Electromagnetic Equations

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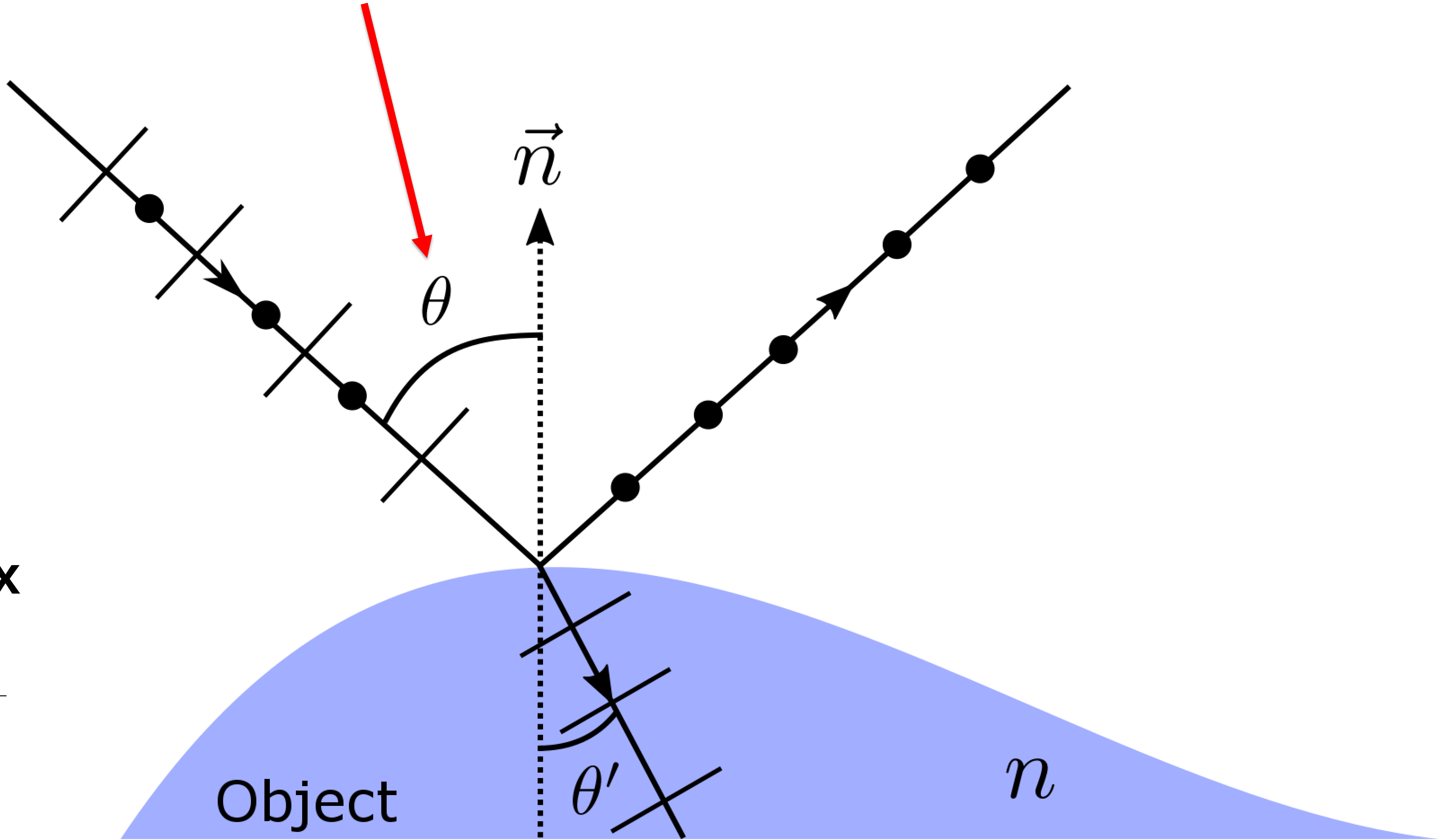
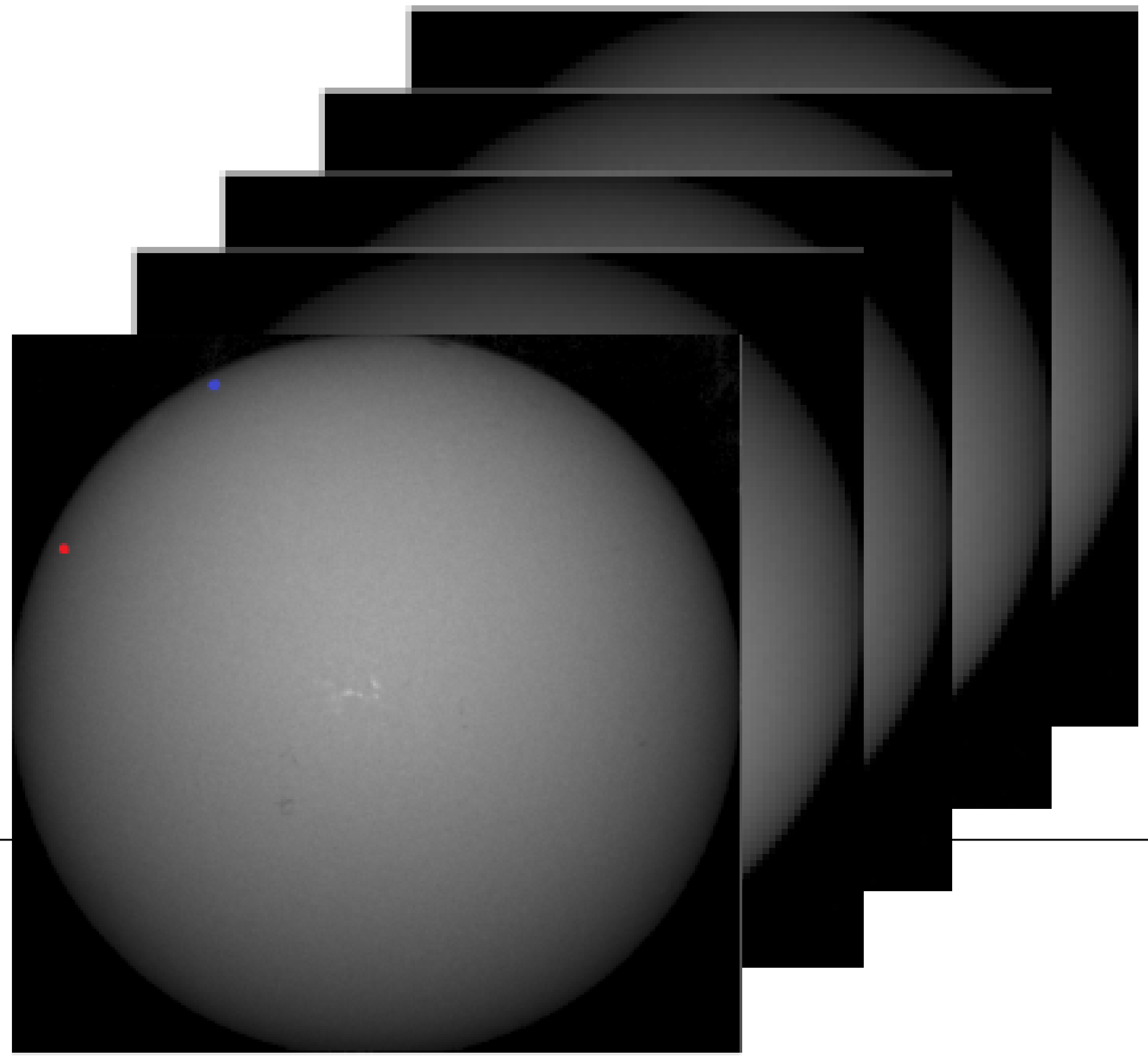
$$r_{\parallel} = \frac{\cos\theta_i - n\cos\theta_t}{\cos\theta_t + n\cos\theta_i}$$

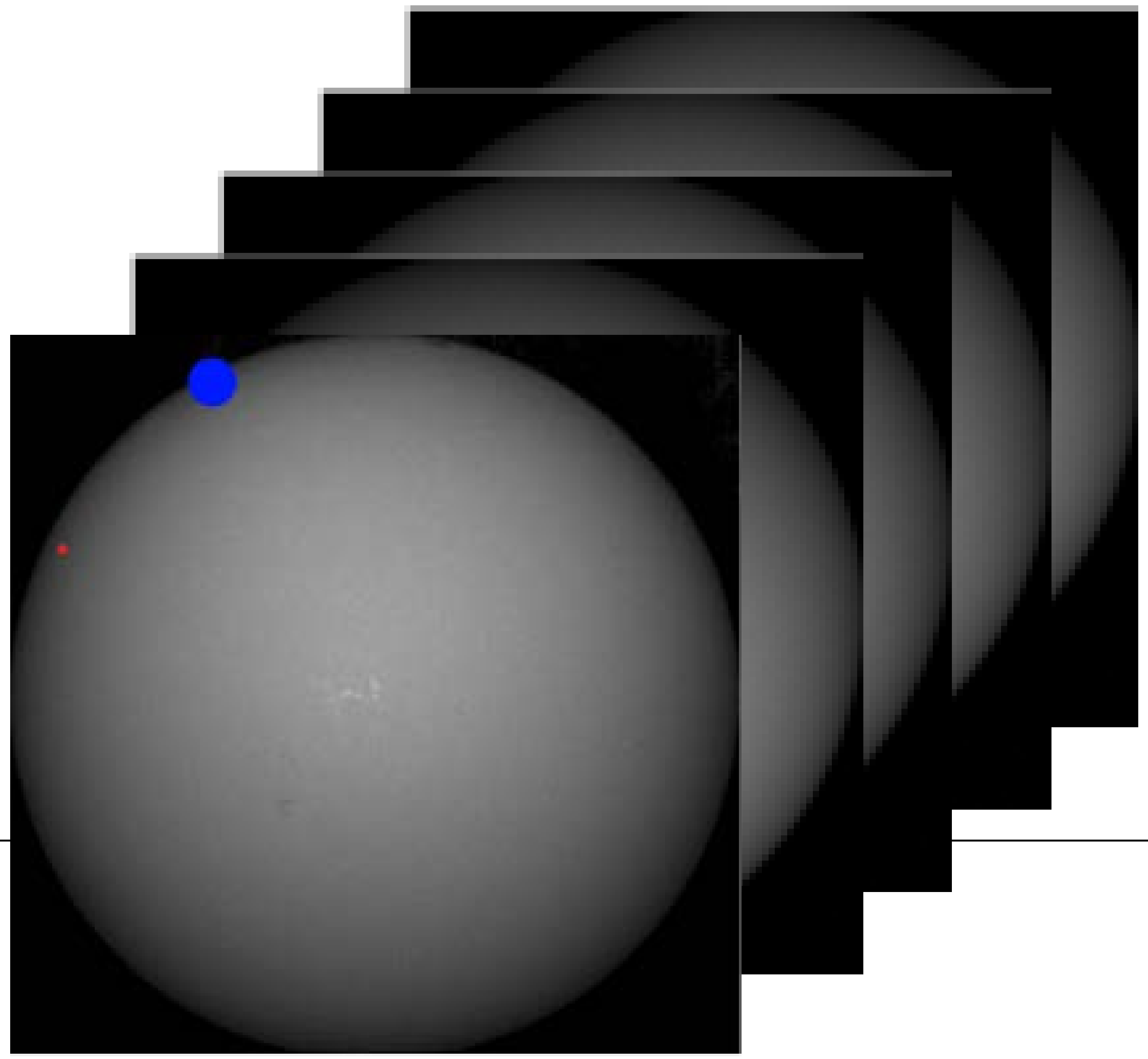
SfP crux: Solve for theta

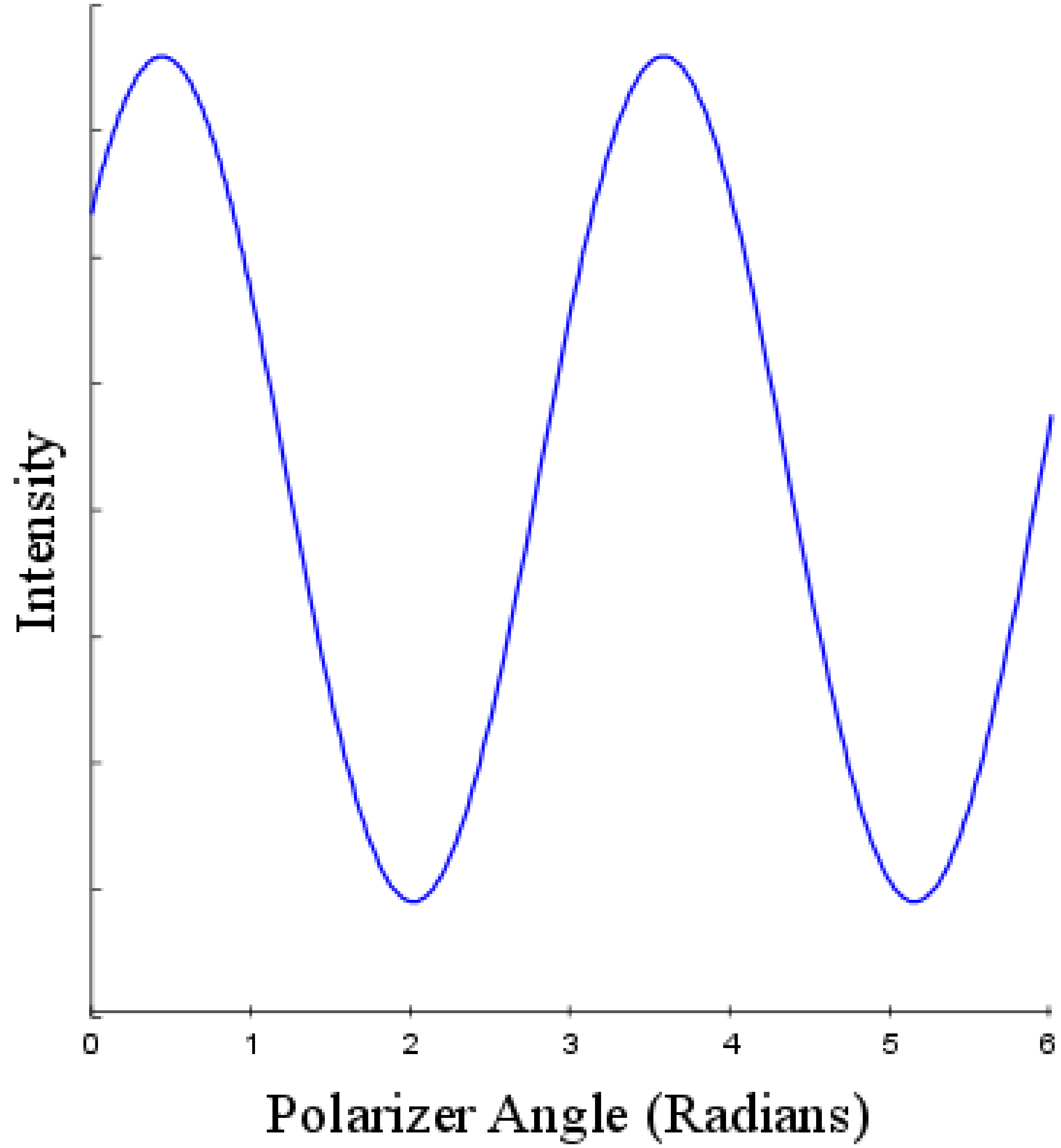
⚠ **Need to know refractive index**

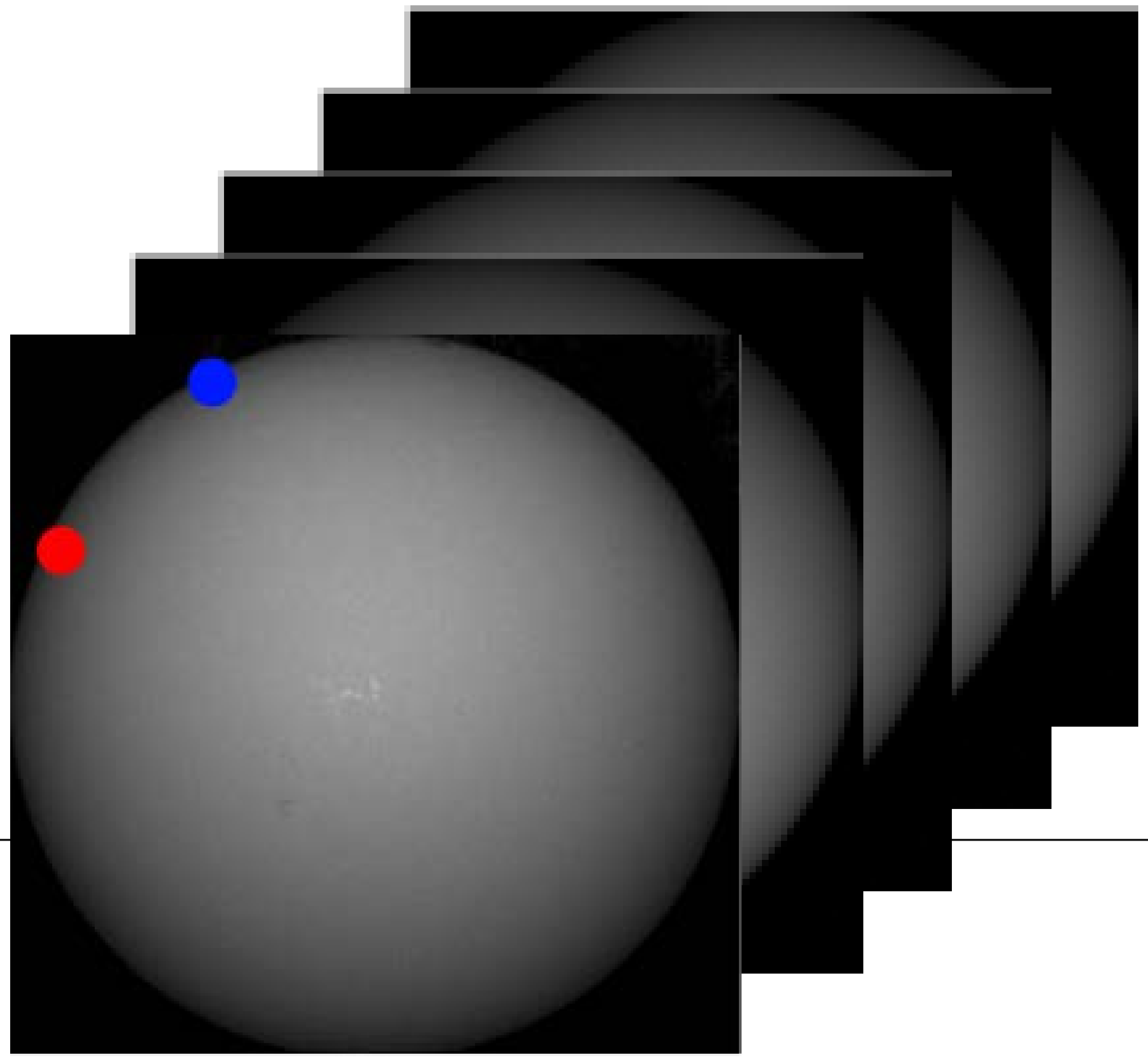
Goal: Solve for zenith angle at each position

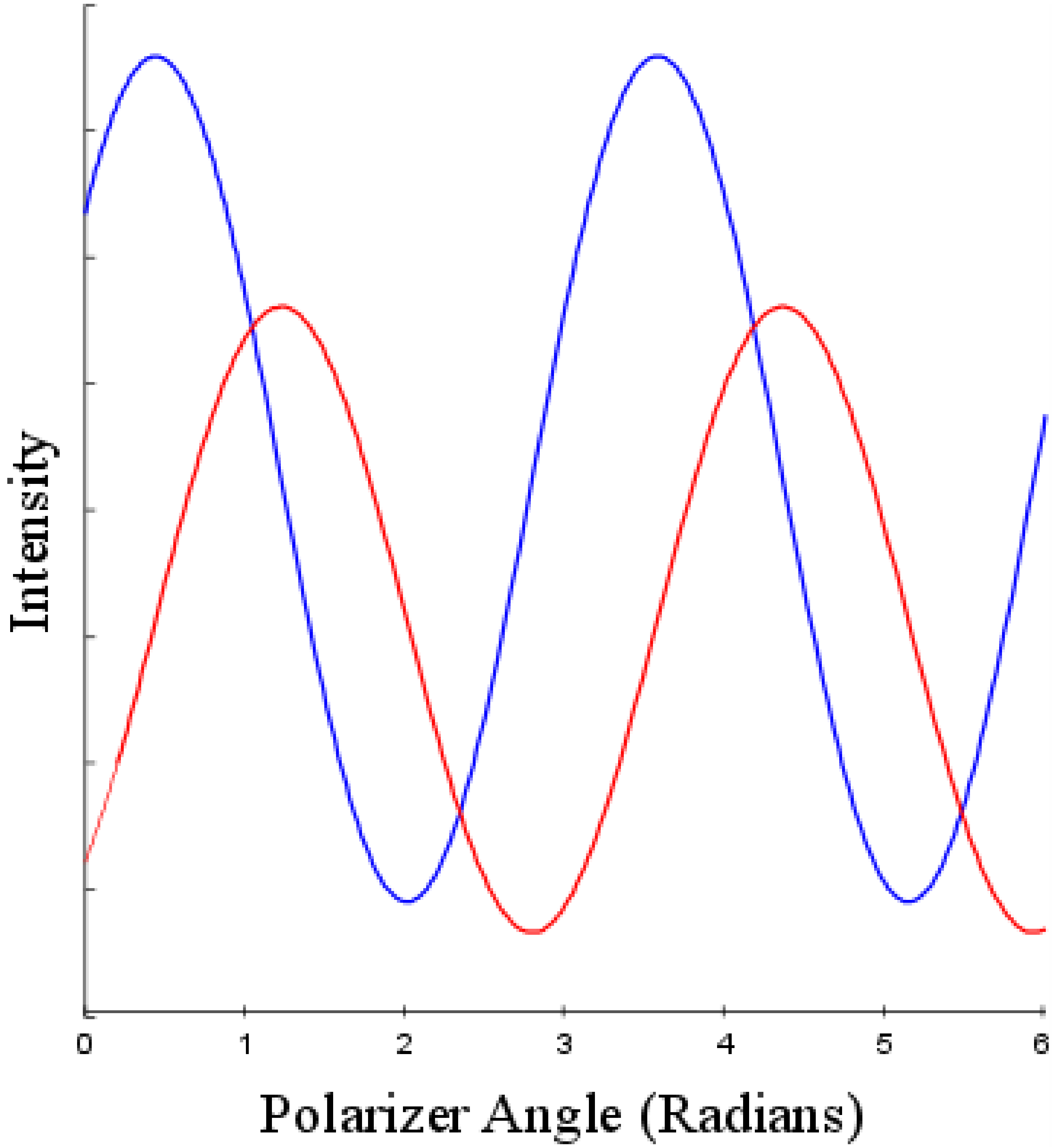







Intensity
0
1
2
3
4
5
6
Polarizer Angle (Radians)




Intensity
0
1
2
3
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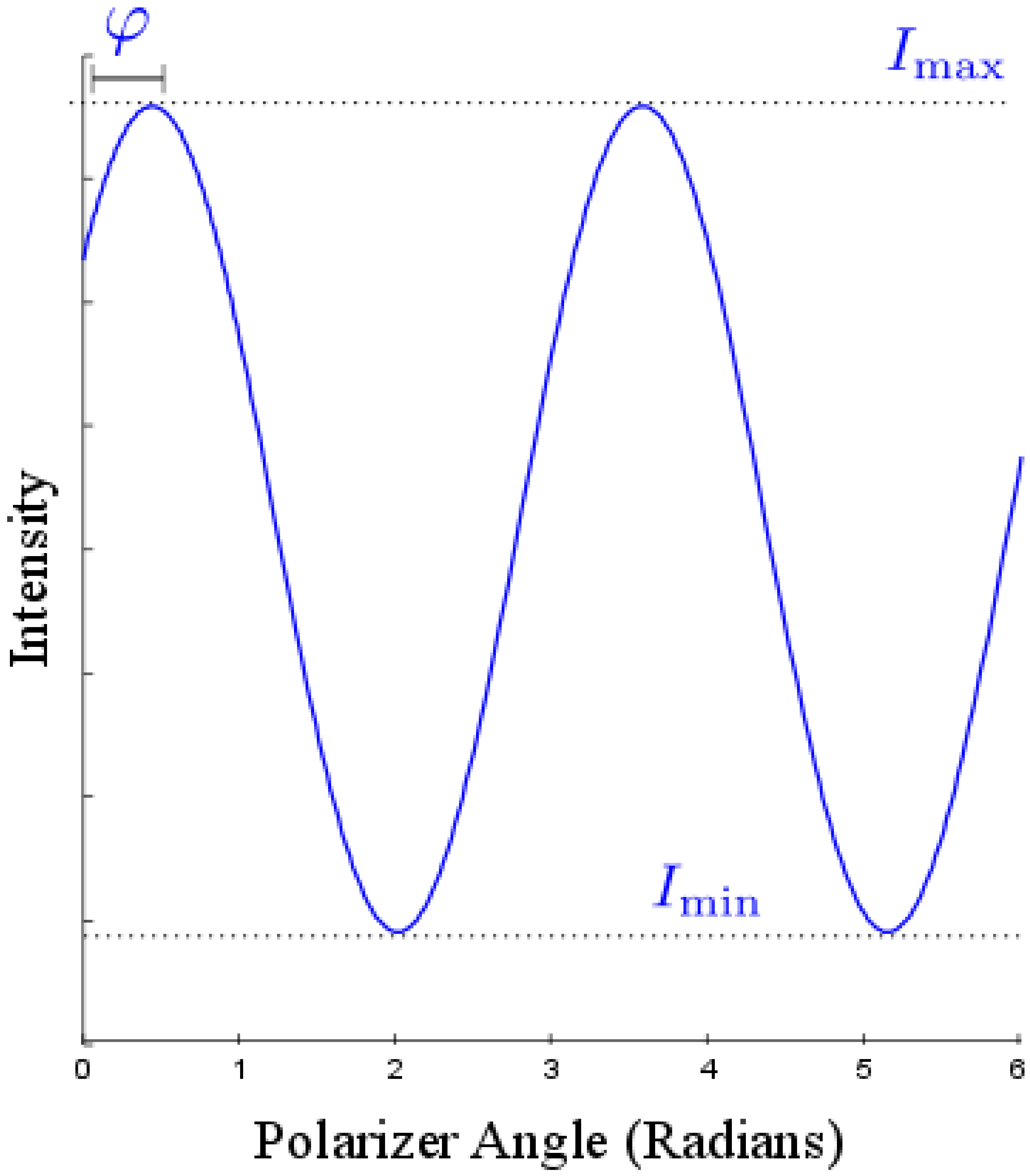
Polarizer Angle (Radians)

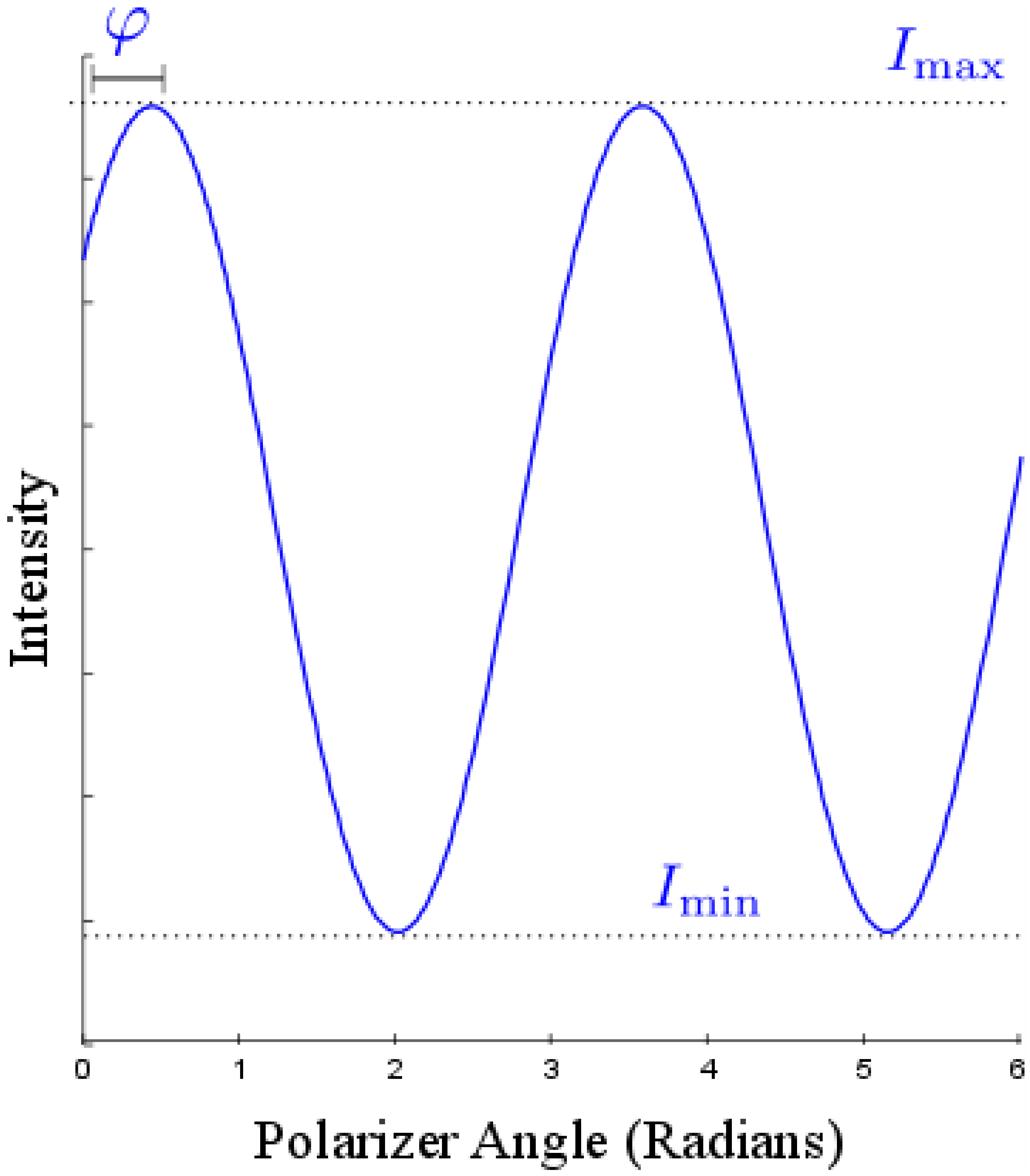
Image Formation Model



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

Goal: Solve for azimuth phase

Image Formation Model



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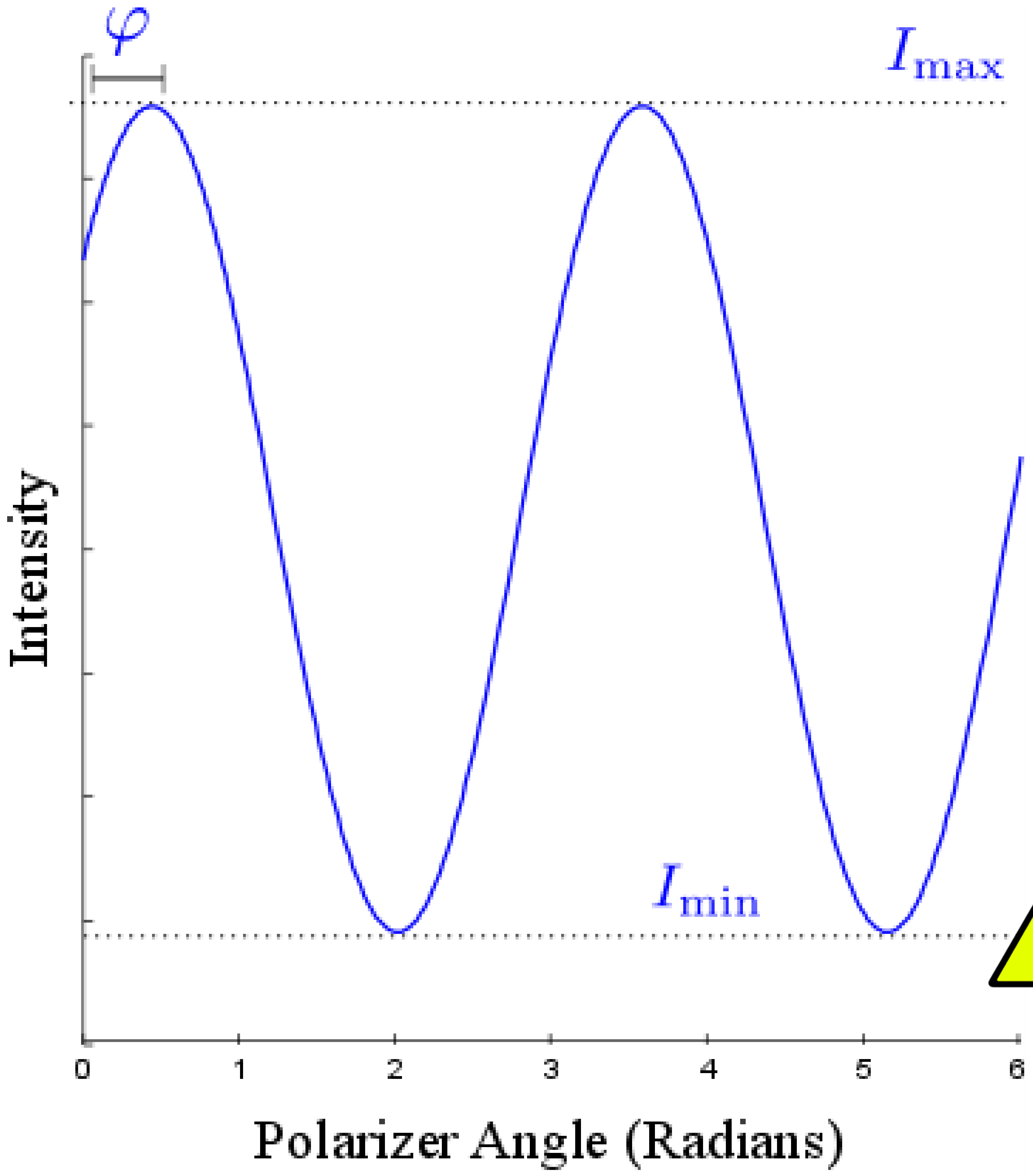
$$\text{Suppose } \exists\ \phi \text{ and } \phi' = \phi + \pi$$

Goal: Solve for azimuth phase

Image Formation Model



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

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

Goal: Solve for azimuth phase

⚠ Azimuthal Ambiguity problem with 2^P solutions

TLDR: EM analysis alone is underconstrained

1. **Refractive Index Needs to be Known**

2. **\pi Ambiguity in Surface Normal**

Challenges have impacted previous approaches: [Miyazaki ICCV 03] [Atkinson IEEE TIP 06]

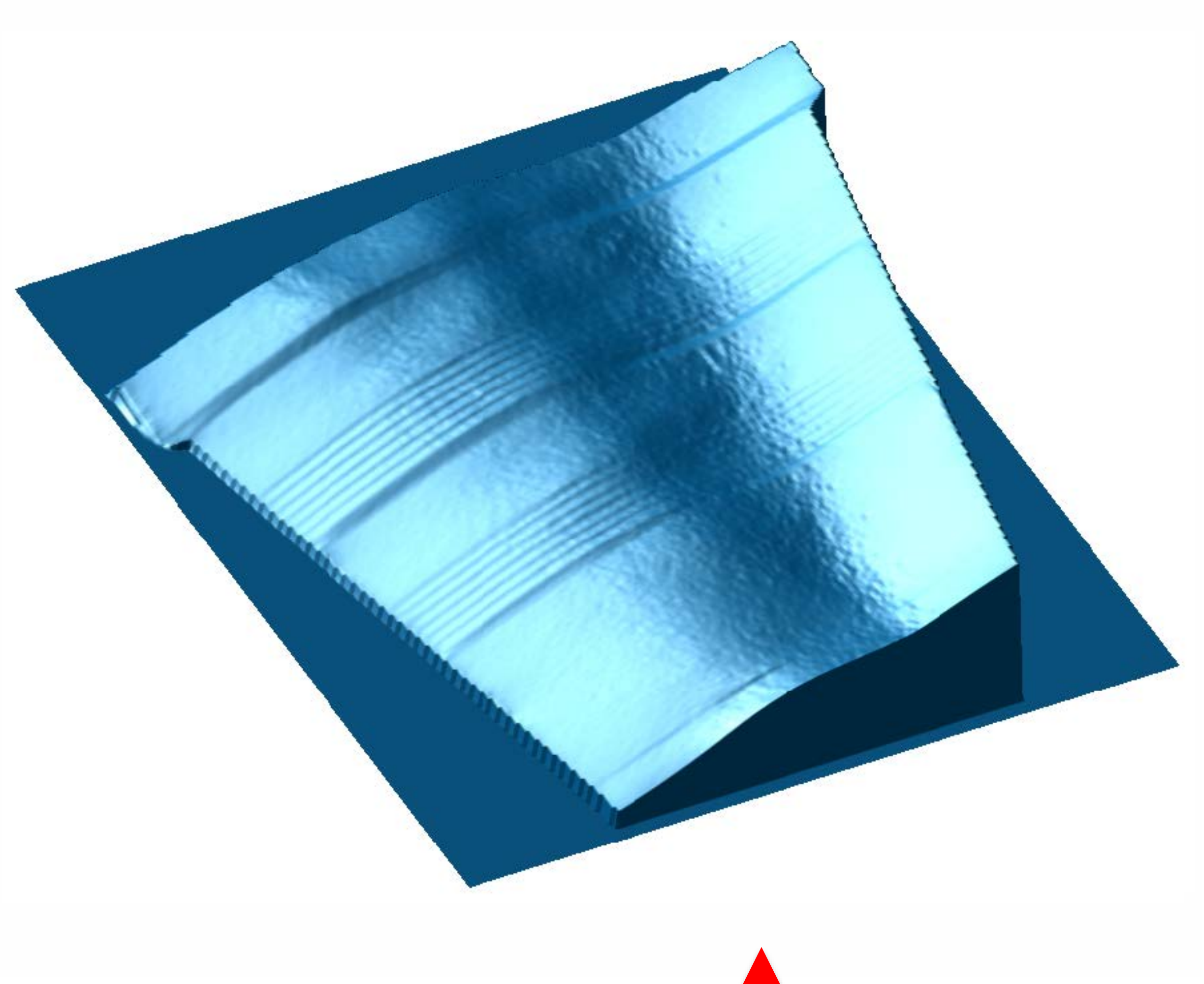
EM analysis alone is underconstrained

1. **Refractive Index Needs to be Known**

2. **\pi Ambiguity in Surface Normal**

3. **Low SNR for some geometries**

4. **Surface conforms to existing Fresnel models**



State of the art using EM analysis

Challenges have impacted previous approaches: [Miyazaki ICCV 03] [Atkinson IEEE TIP 06]

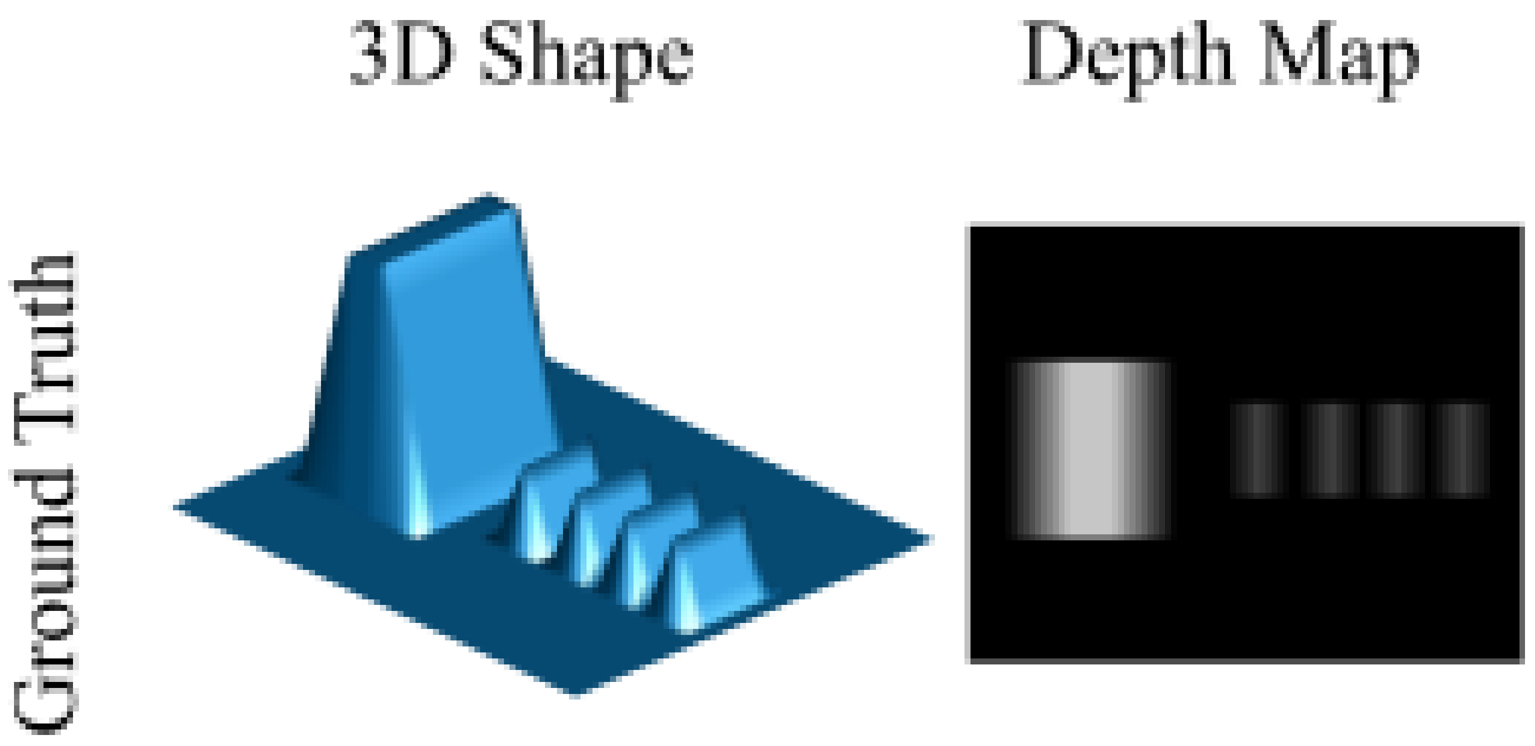
Are we barking up the right tree?

Emailing Sr. Researchers: “Why did you stop working on this problem?” (Rephrased)

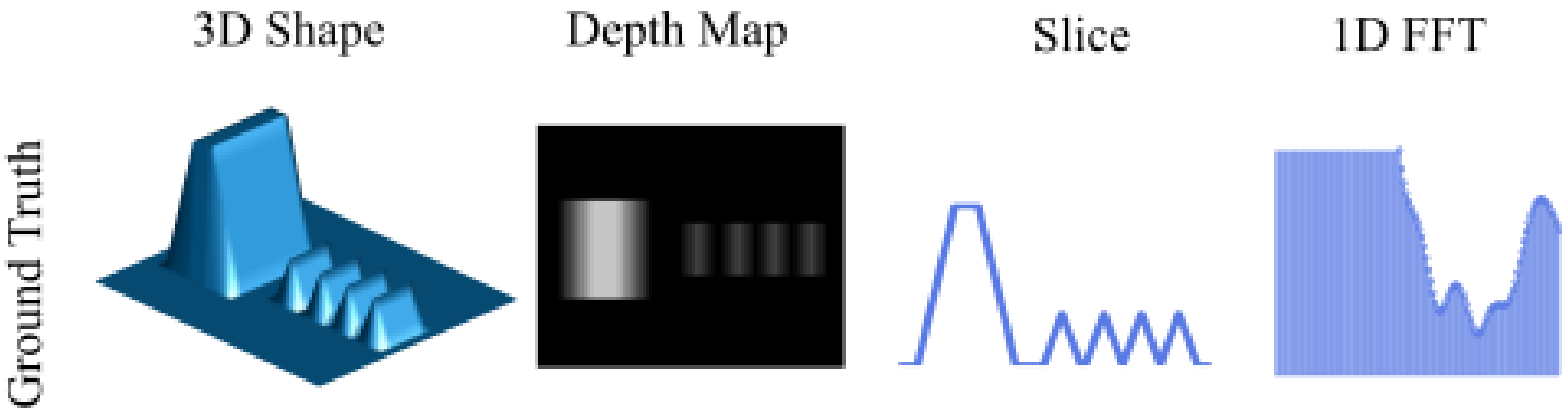
Exemplary Response: “The polarization signal is subtle and too many physical constants unknown”

- A Senior Professor in Computer Vision

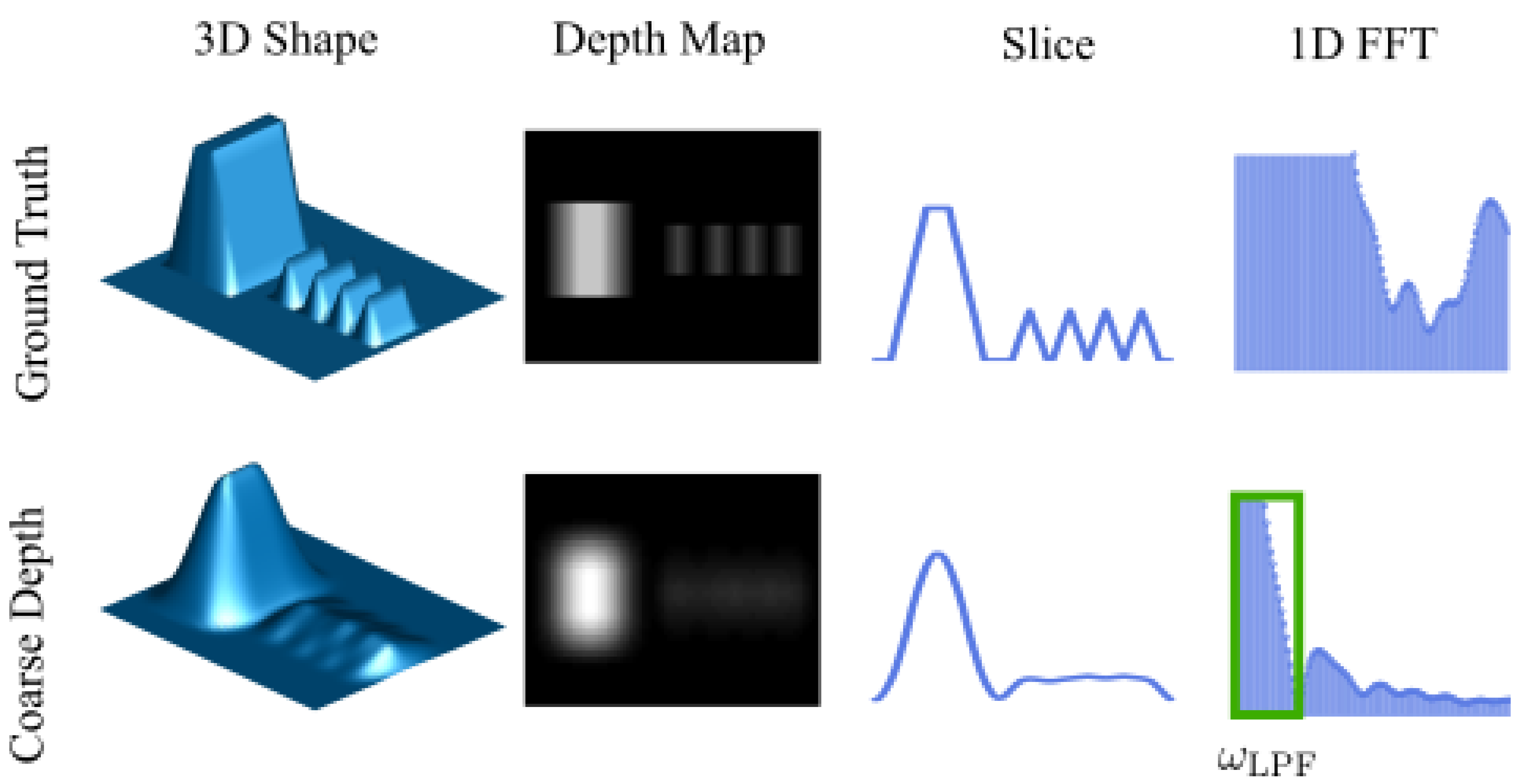
Frequency Analysis



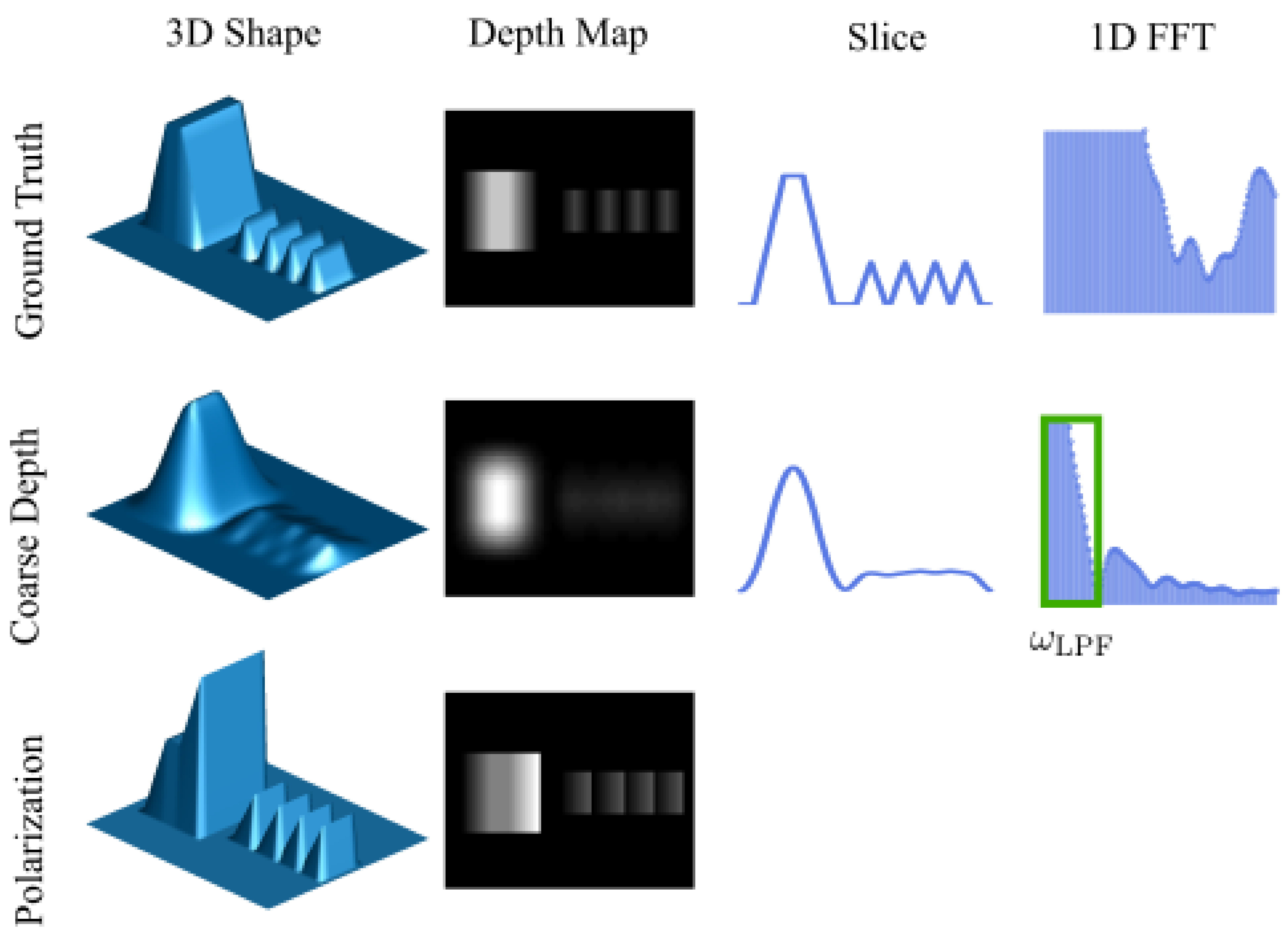
Frequency Analysis



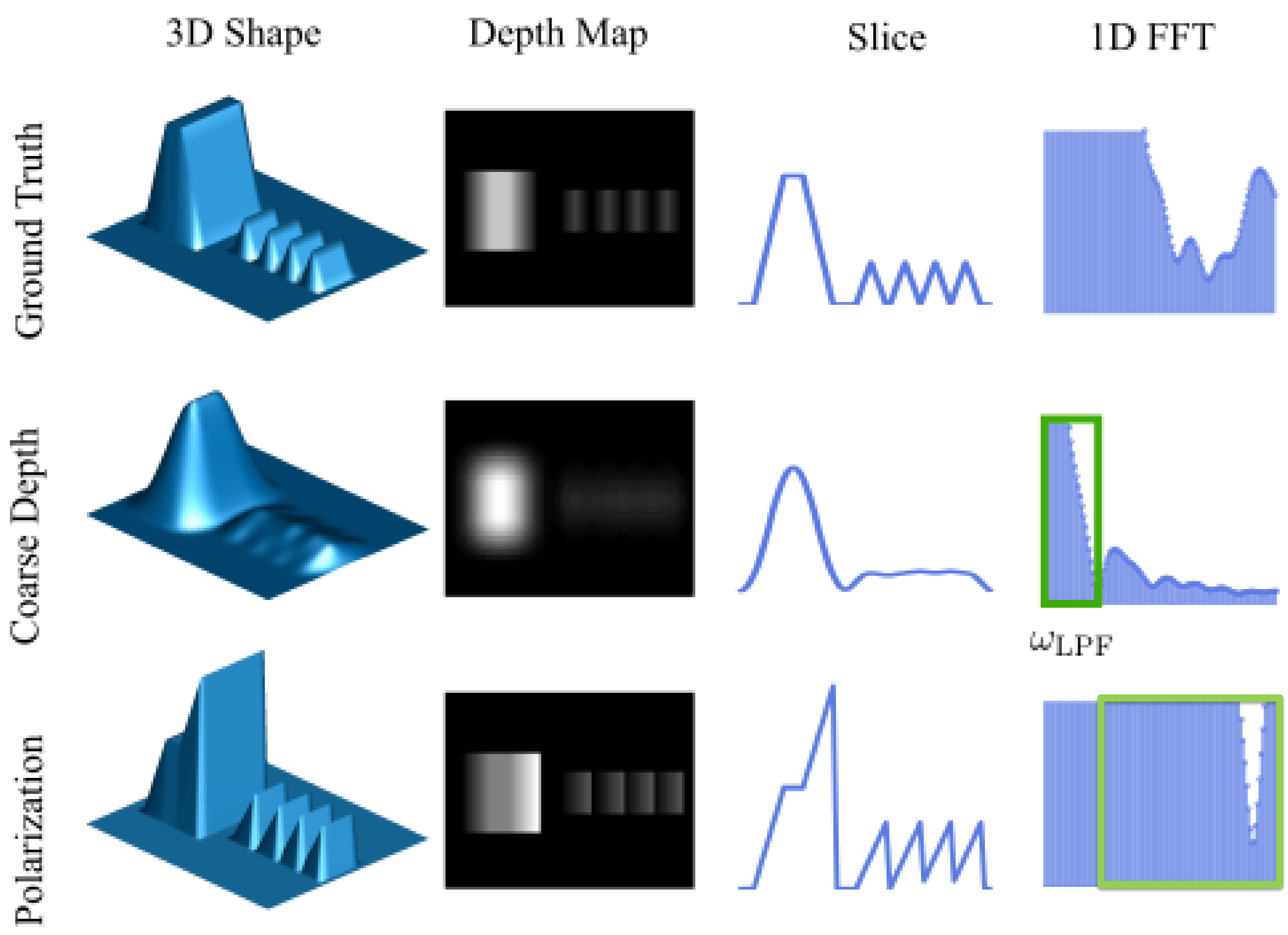
Frequency Analysis



Frequency Analysis

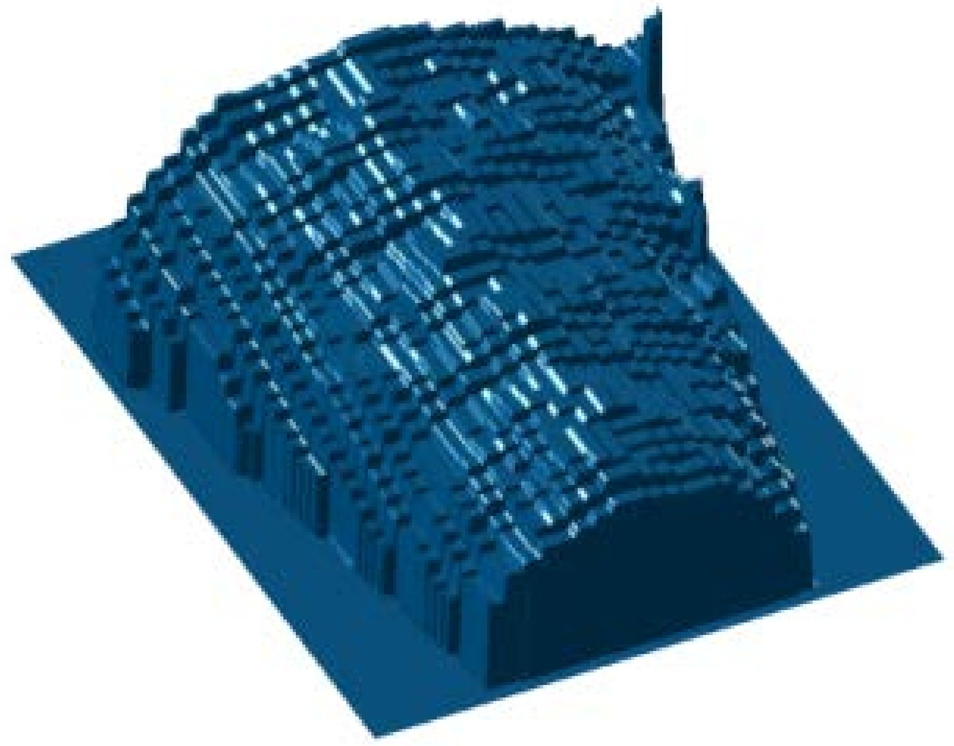


Frequency Analysis



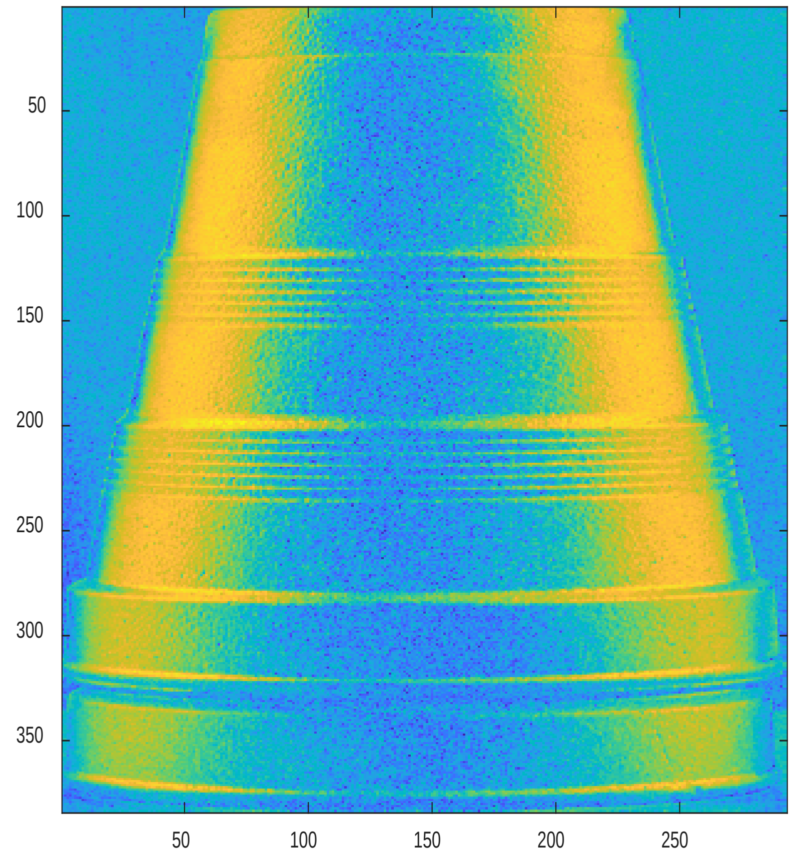
Goal: Combine low-frequency and high-frequency.

Understanding our Input Data



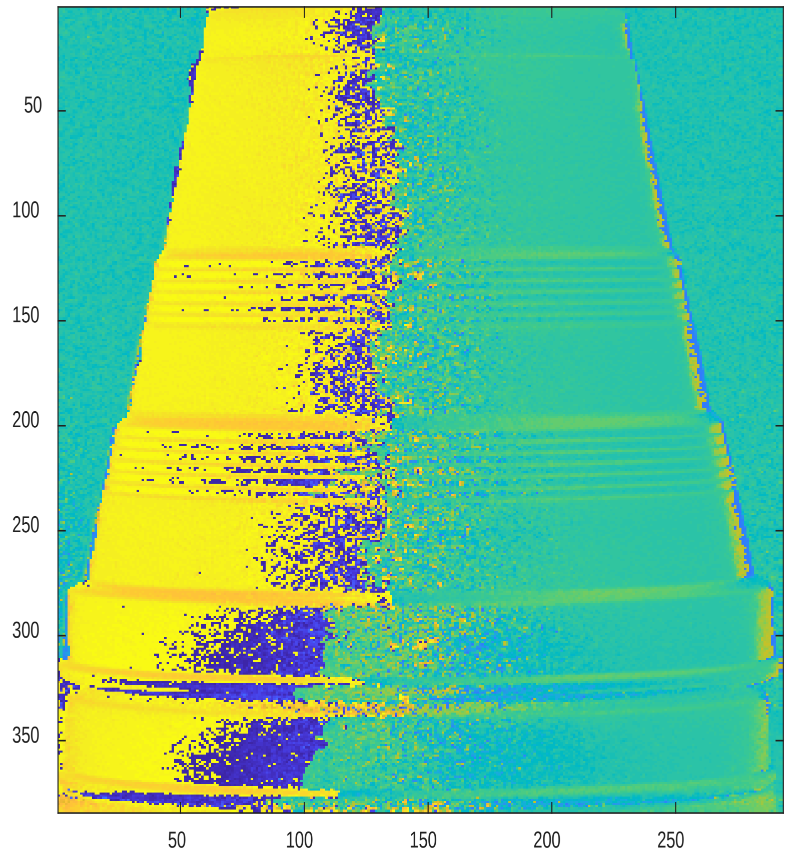
Coarse Depth Estimate

ϕ



Zenith Angle

θ



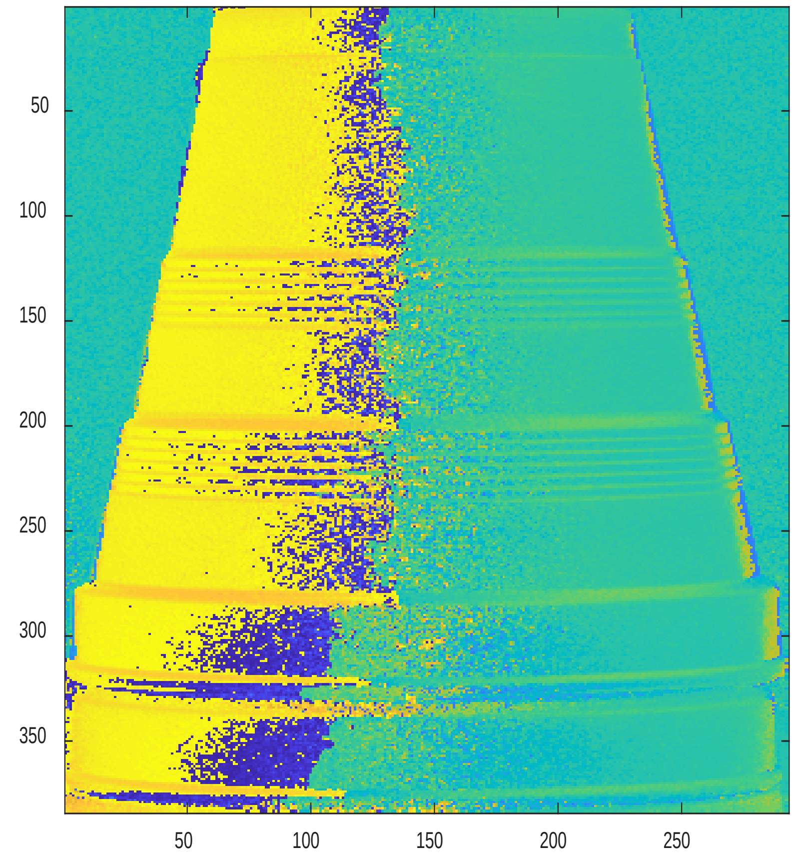
Azimuth Angle

Obtained from Any Depth Estimator

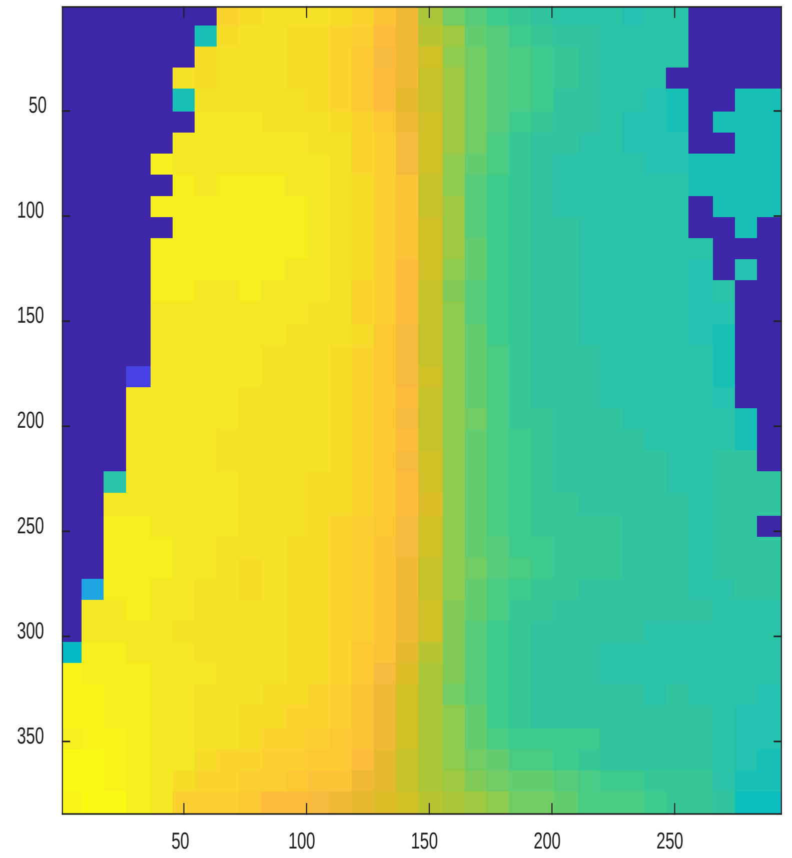
Estimated from Fresnel Equations

Gradient Domain Correction (Azimuth Only)

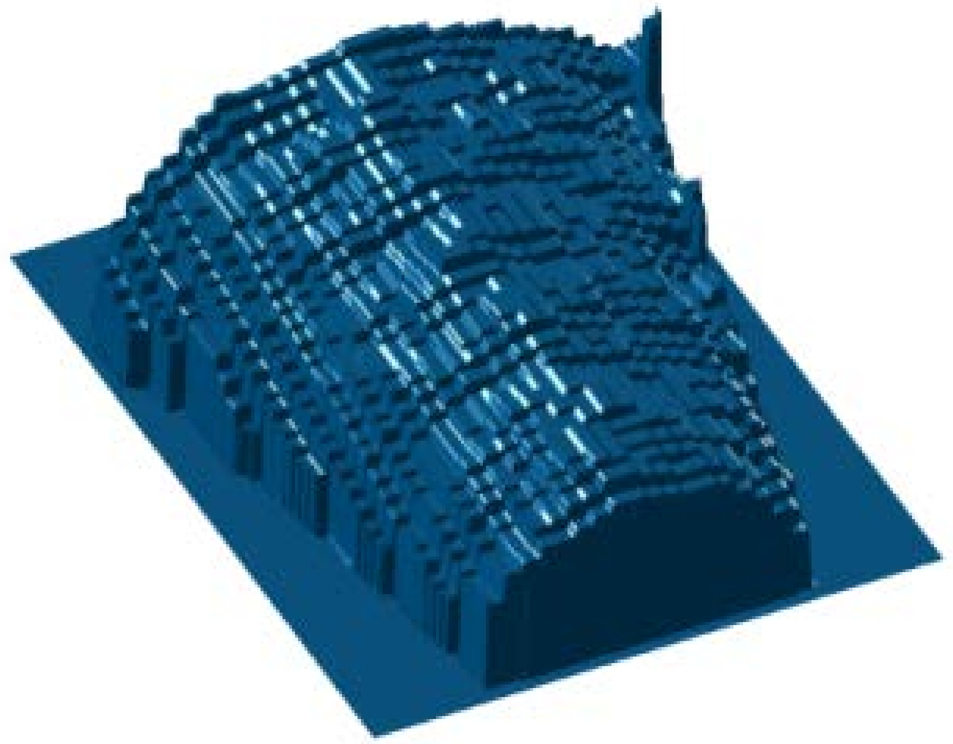
Azimuth Angle
from Fresnel Eq.



Azimuth Angle of
Deriv. Depth

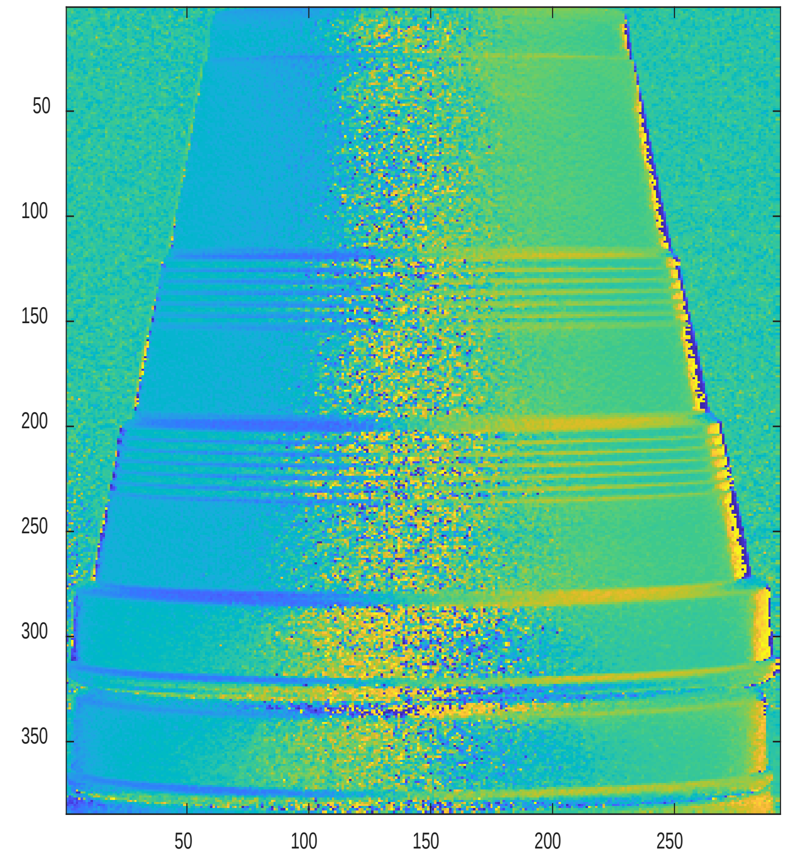


Differentiate



Gradient
Domain
Correction

Constrained
Azimuth



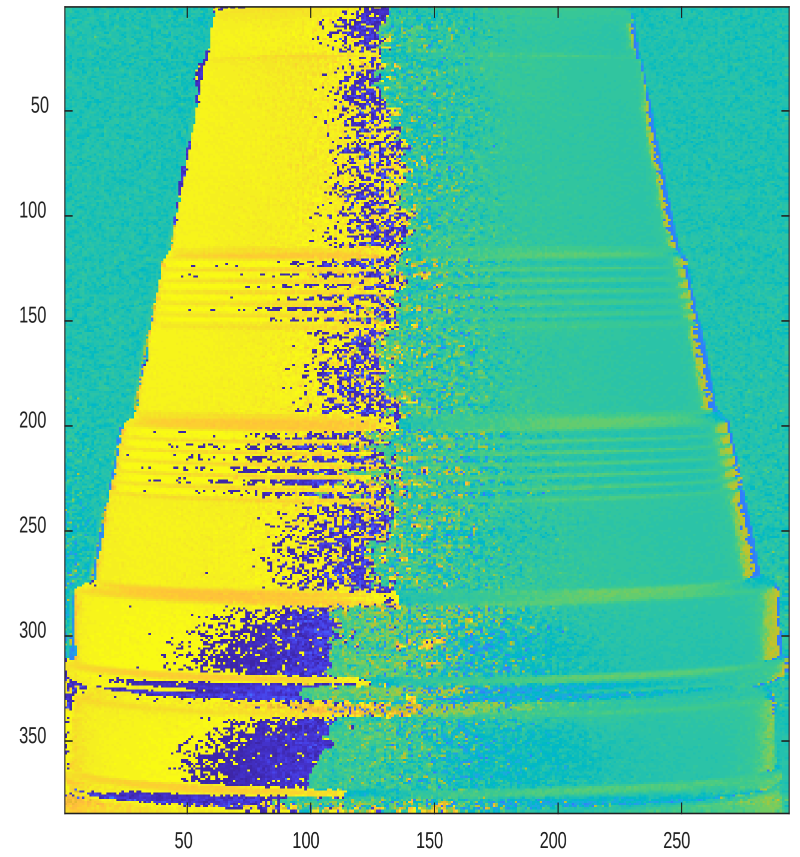
$$\widehat{\mathscr{A}} = \arg\min_{\mathscr{A}} \left\| \mathbf{N}^{\text{depth}} - \mathscr{A}\left(\mathbf{N}^{\text{polar}}\right) \right\|_2^2 + \gamma\, \mathscr{T}_2\left(\mathbf{A}\right)$$

$$\text{subject to} \quad \mathbf{A} \in \{0, 1\},$$

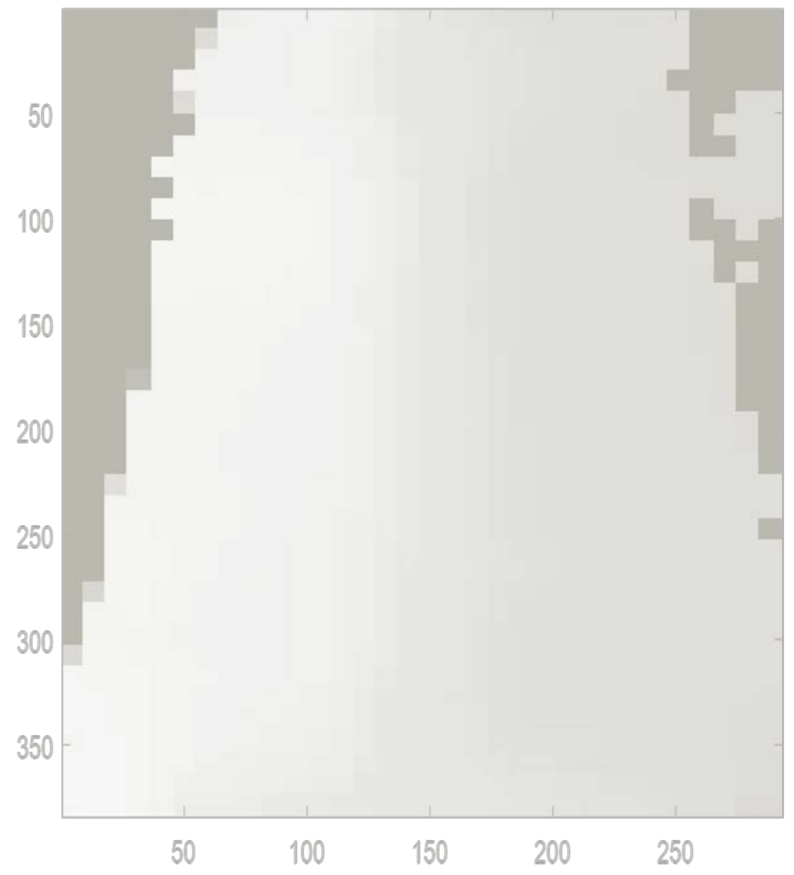
[Kadambi et al. IJCV 2017]

Gradient Domain Correction (Azimuth Only)

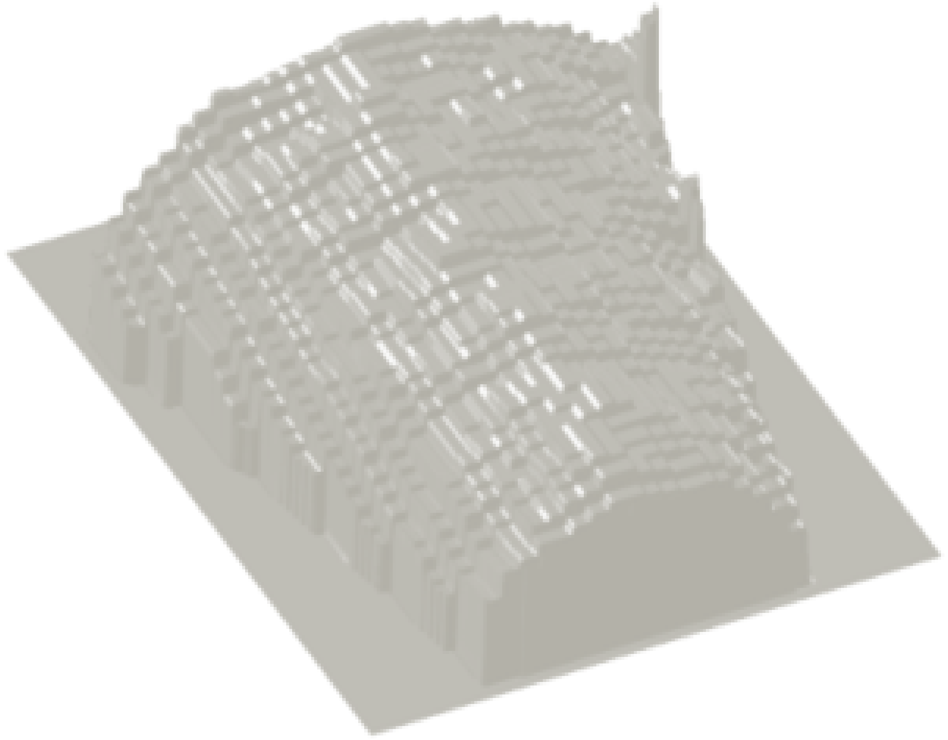
Azimuth Angle
from Fresnel Eq.



Azimuth Angle of
Deriv. Depth

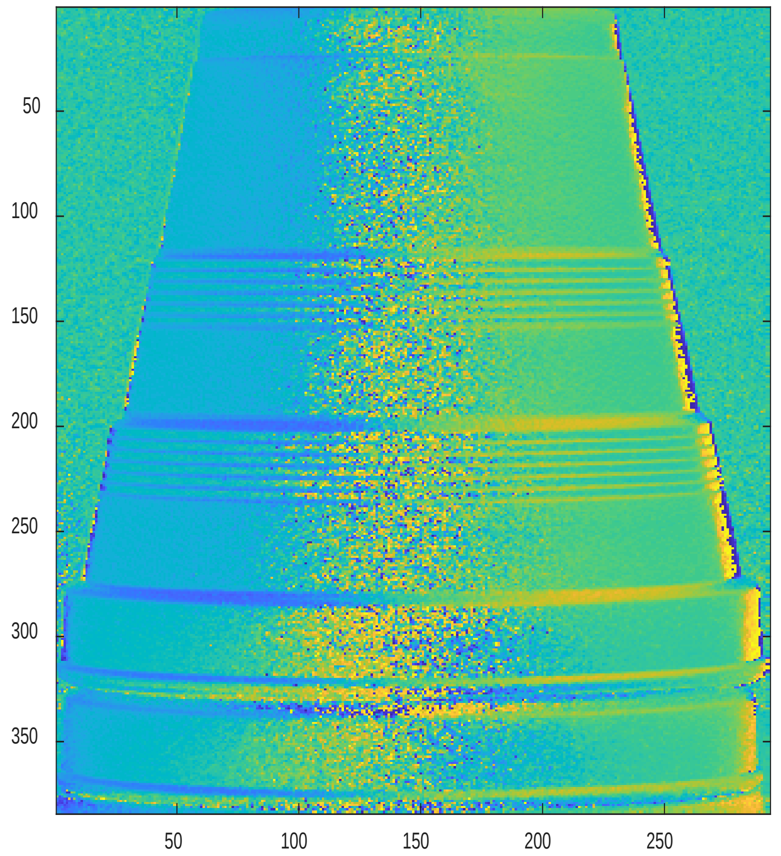


Differentiate



Gradient
Domain
Correction

Constrained
Azimuth

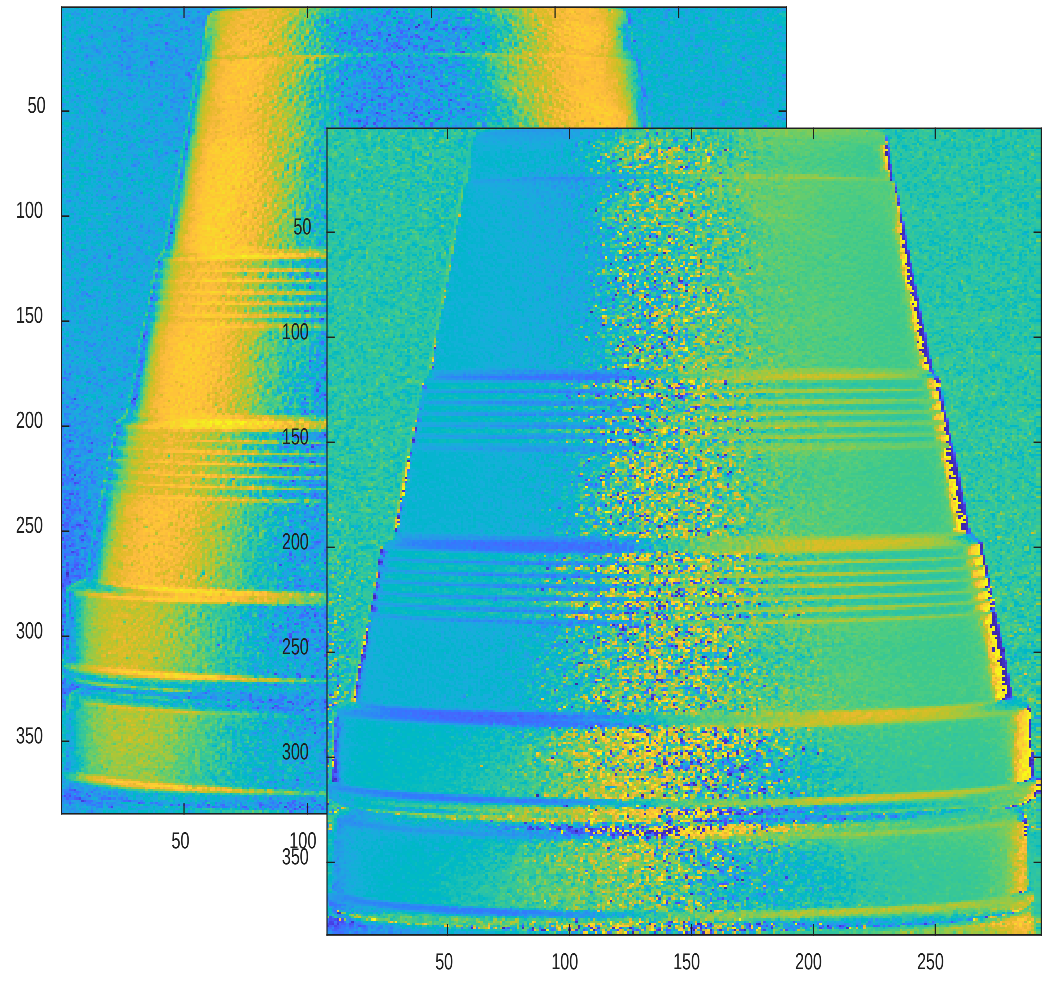


$$\widehat{\mathscr{A}} = \underset{\mathscr{A}}{\arg\min} \left\| \mathbf{N}^{\text{depth}} - \mathscr{A}\left(\mathbf{N}^{\text{polar}}\right) \right\|_2^2 + \gamma \, \mathscr{T}_2\left(\mathbf{A}\right)$$

$$\text{subject to} \quad \mathbf{A} \in \{0, 1\},$$

[Kadambi et al. IJCV 2017]

Integrate the Surface (Naïve)

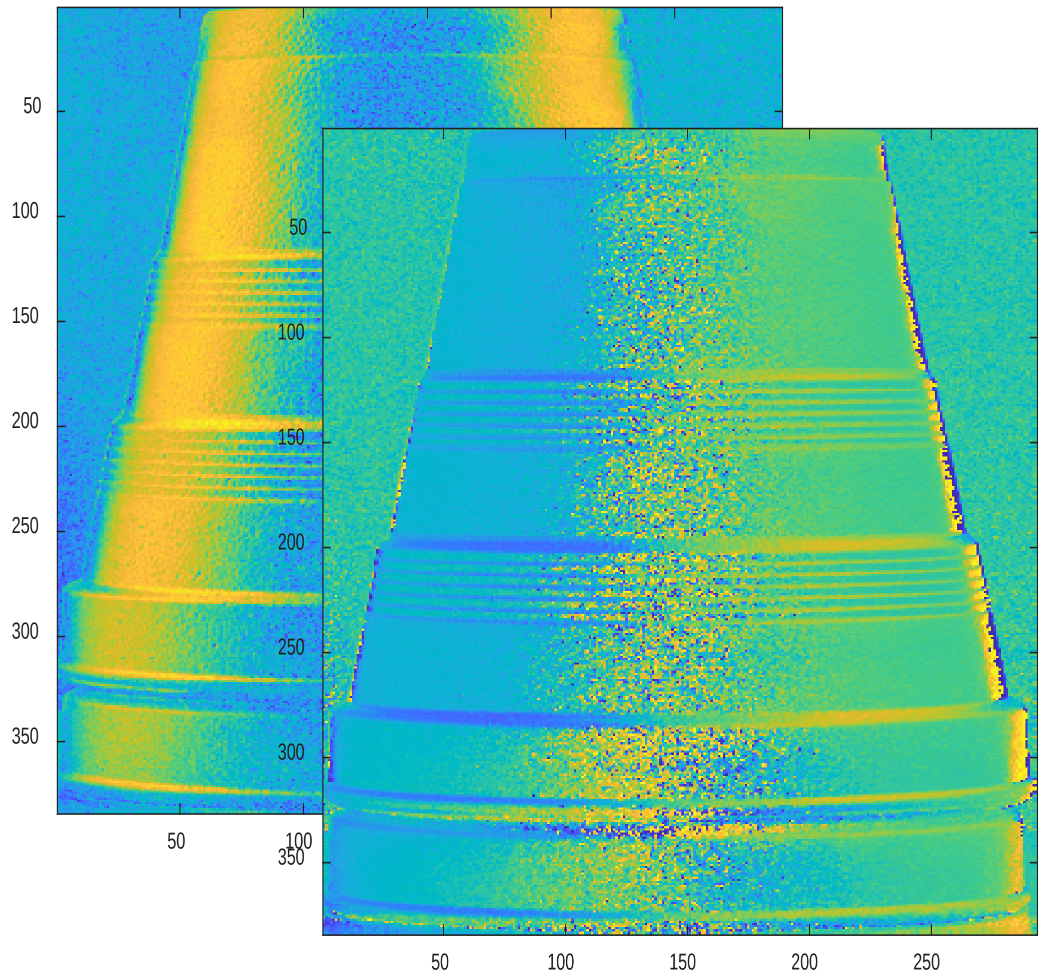


Corrected
Gradients

Integration
Algorithm

Output

Regularized Integrator



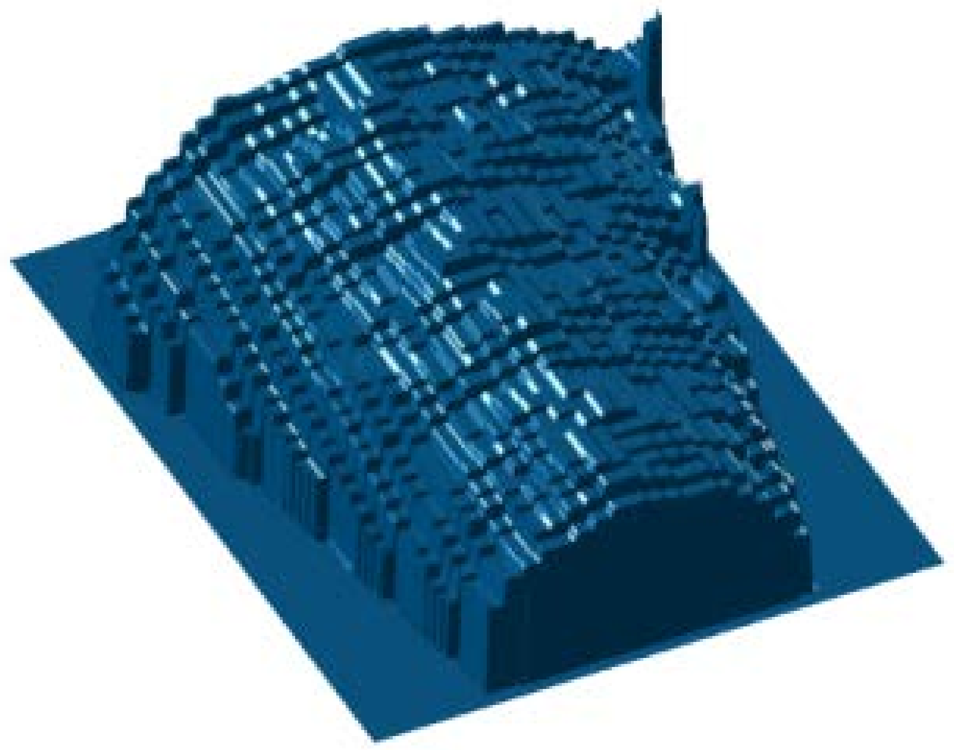
Corrected Gradients

Integration Algorithm

Output

Regularizer

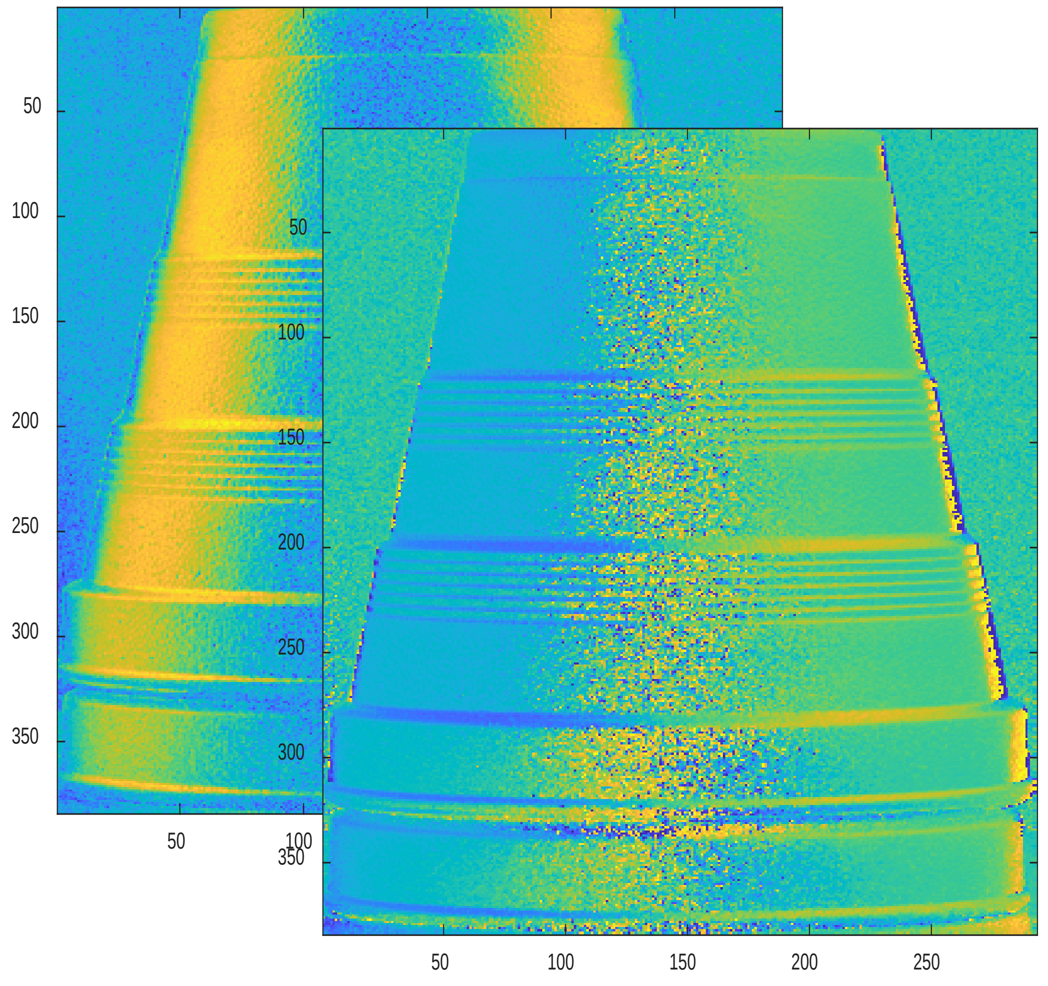
Coarse 3D Shape



Naïve Regularizer Strategy: Penalize deviations in the surface normal integration with the coarse depth map

[Kadambi et al. IJCV 2017]

Regularized Integrator

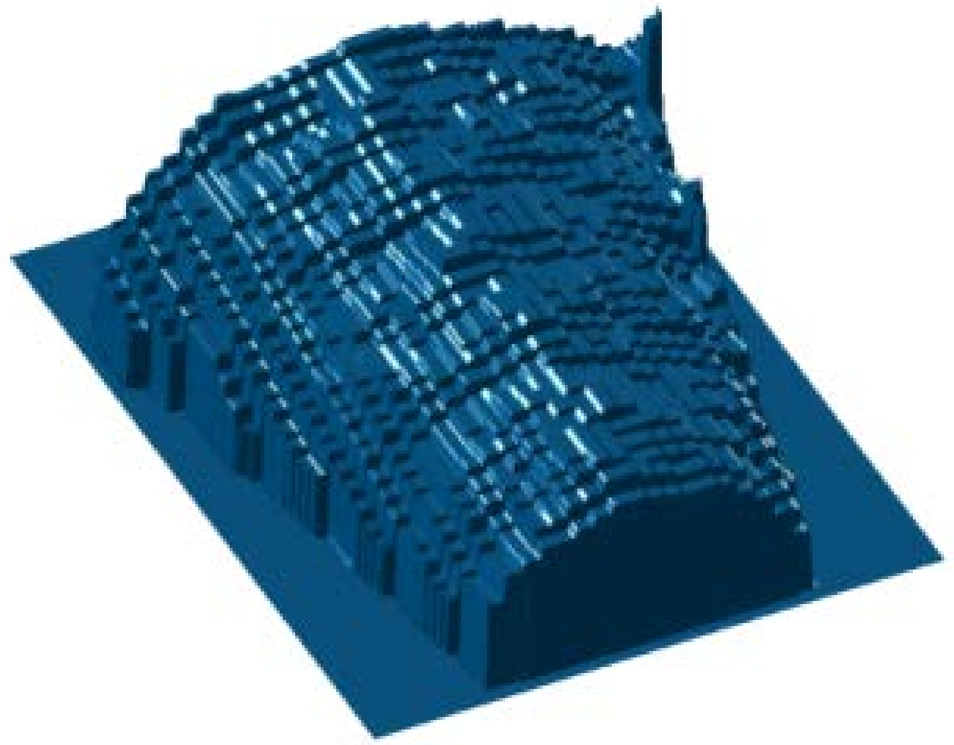


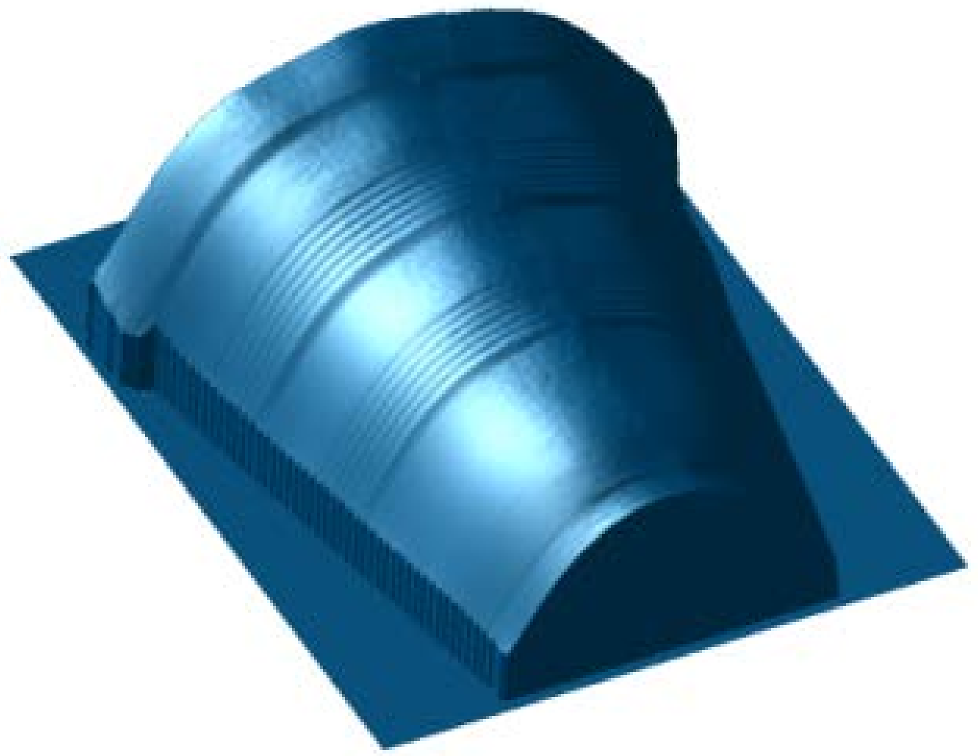
Corrected Gradients

Integration Algorithm

Physics-based Regularizer

Coarse 3D Shape





Nuanced Goals

Minimize O(n^2) operations

FFT(LPF(estimate)) = FFT(Depth)

Addresses Refractive Index Problem

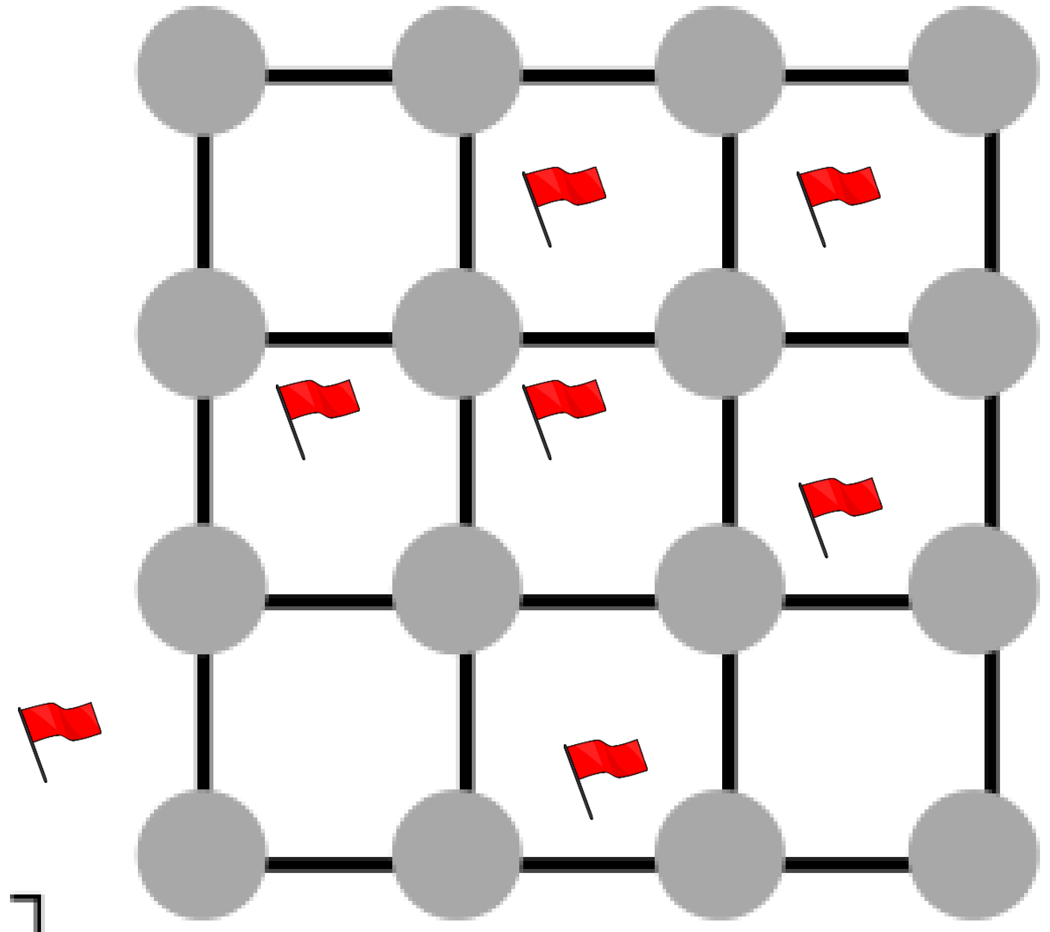
[Kadambi et al. IJCV 2017]

Integration Algorithm Posed as Graph Problem

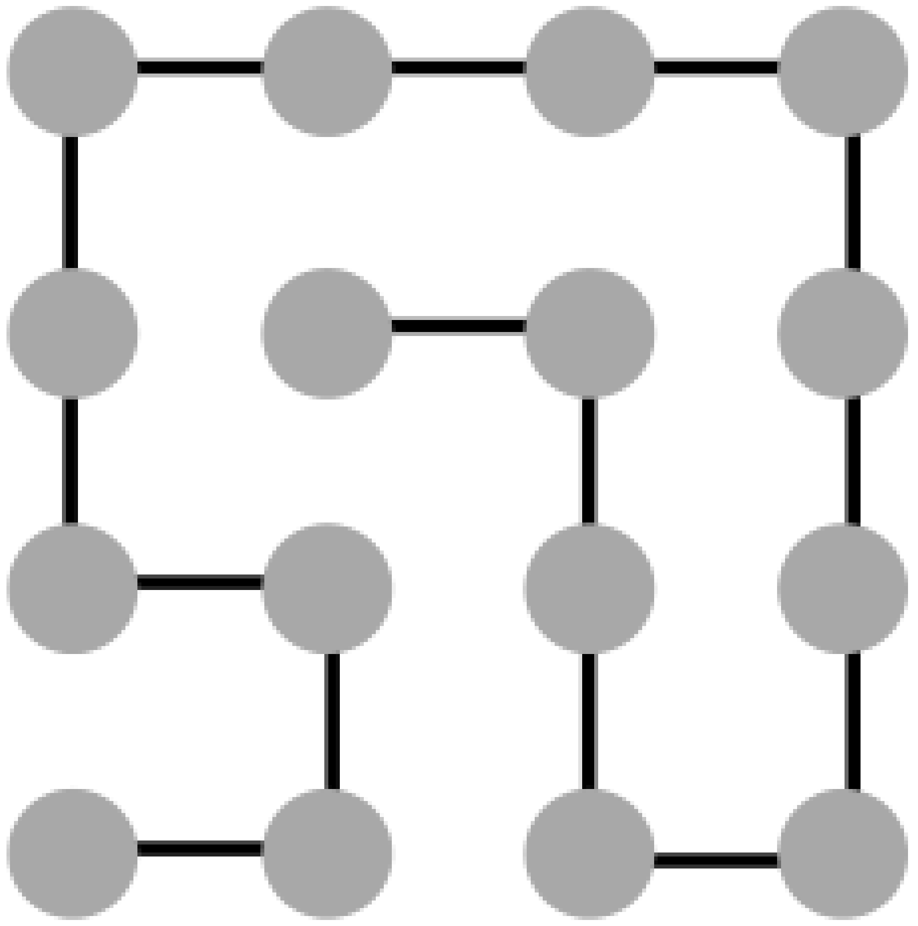
Spanning Tree Integration

Kruskal's Algorithm: $O(E \log E)$

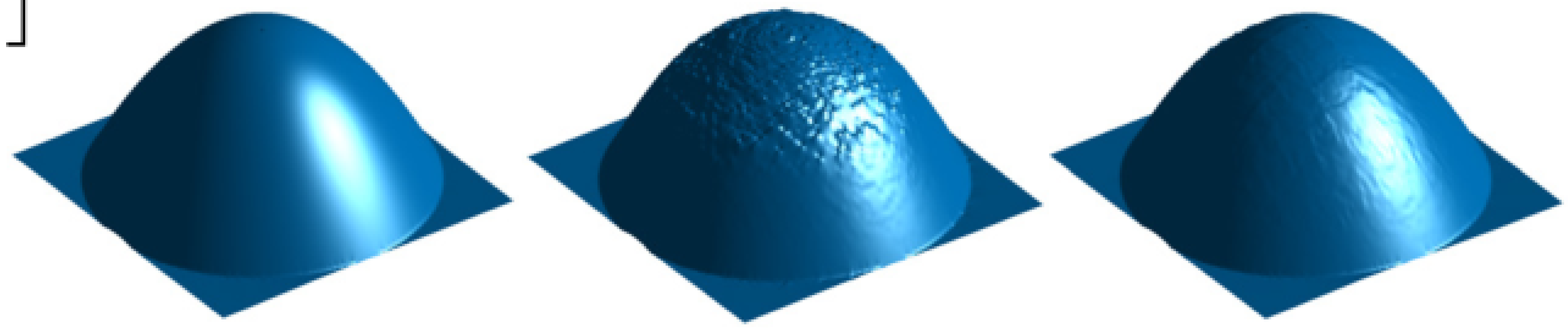
$$\begin{bmatrix} \lambda \mathbf{M} \odot \mathbf{I} \\ \nabla_S^2 \end{bmatrix} \mathrm{VEC}\left(\widehat{\mathbf{D}}\right) = \begin{bmatrix} \lambda \mathrm{VEC}\left(\mathbf{M} \odot \mathbf{D}\right) \\ \nabla_S^T\left(\mathbf{N}^{\mathrm{corr}}\right) \end{bmatrix}$$



Full Gradients



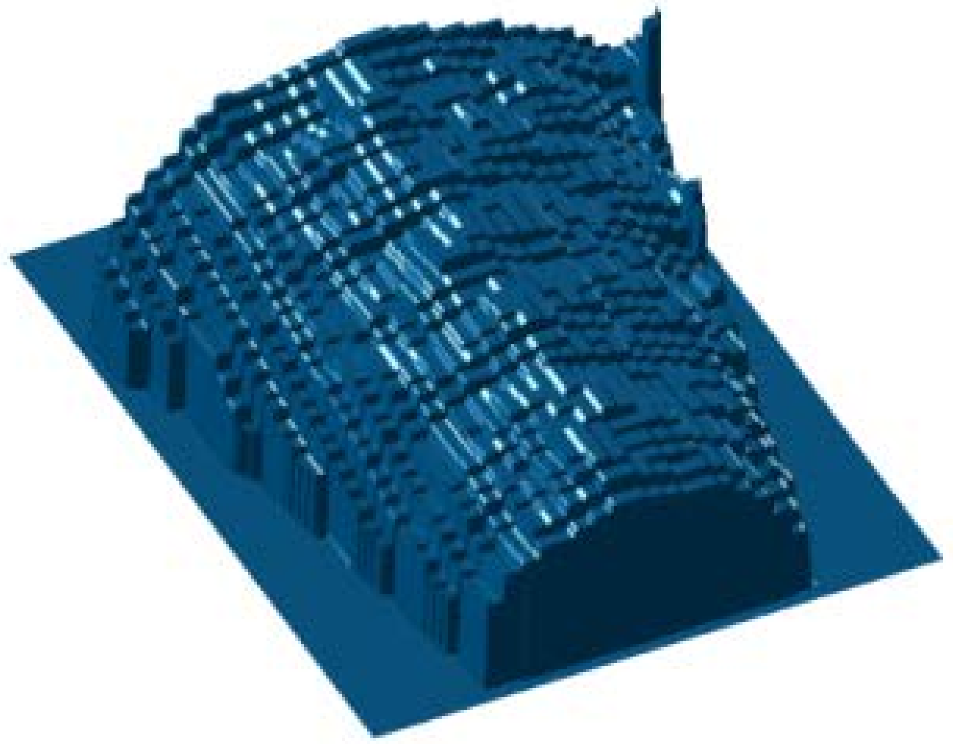
Minimum Spanning Tree



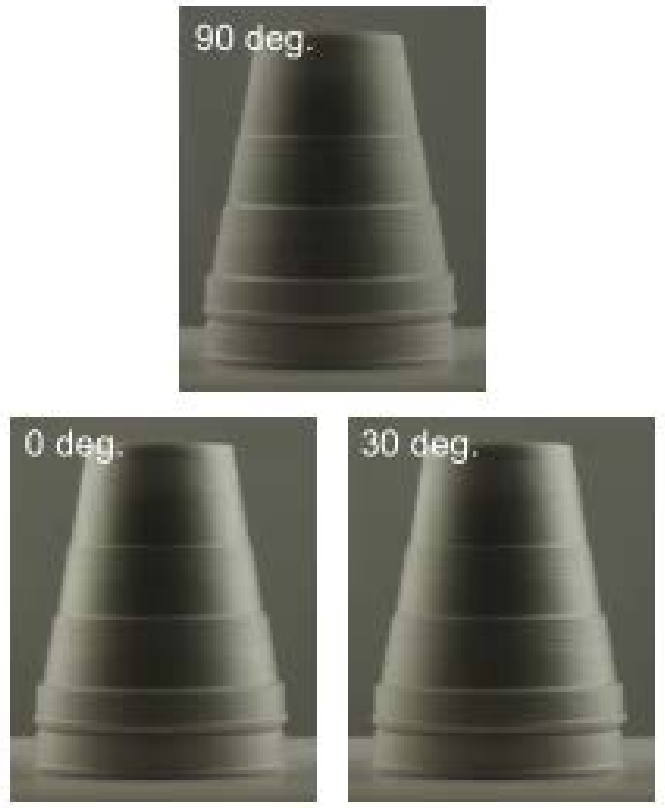
Ground Truth Surface   Full Integration   Spanning Tree Integration

Gradients can be flagged if the polarization signal is too small (e.g. DOLP)

Visual Debugging

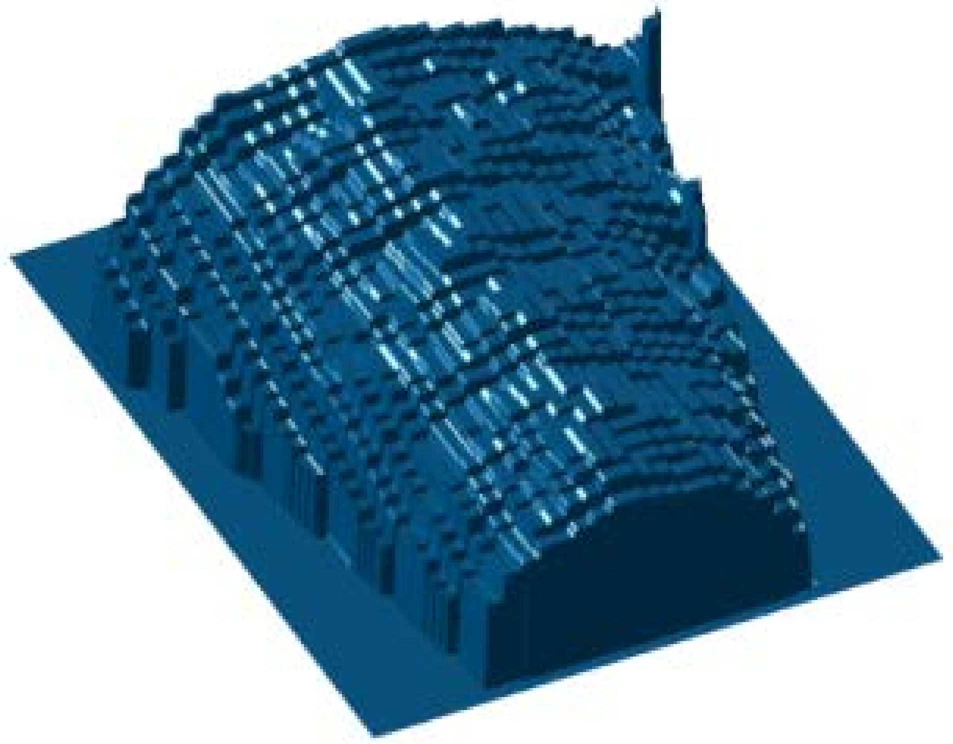


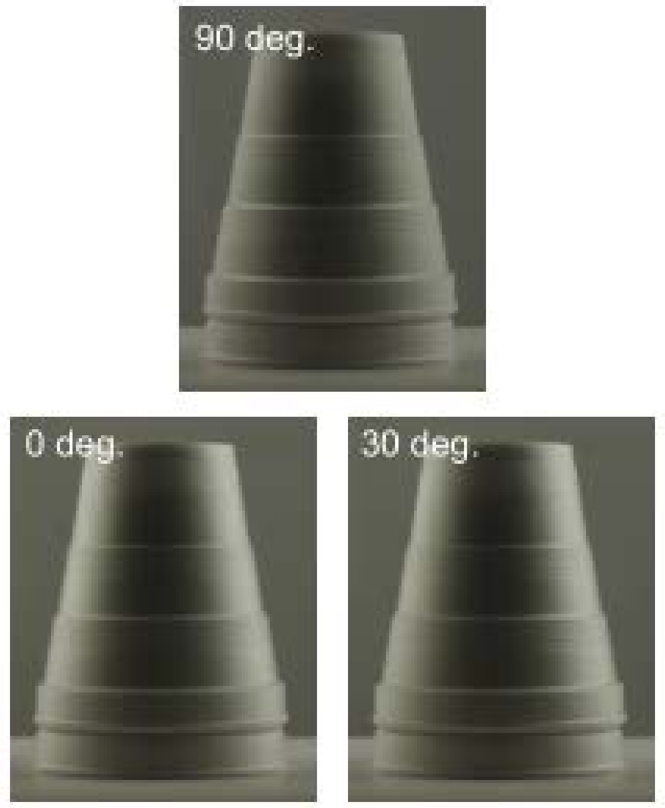
Kinect

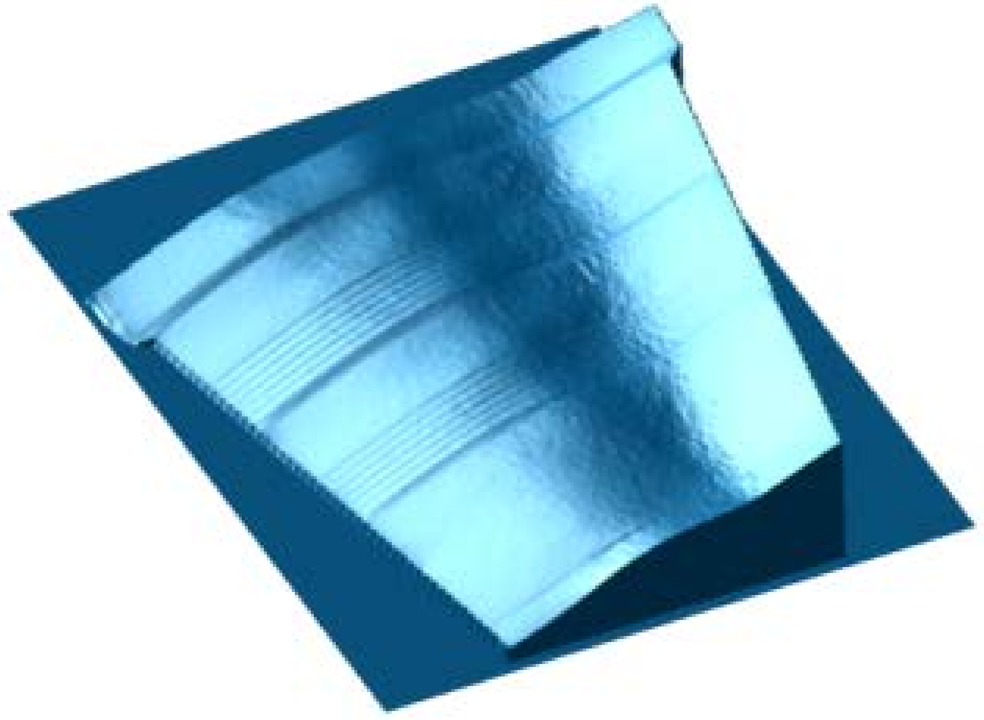


3 Polar Photos

Visual Debugging

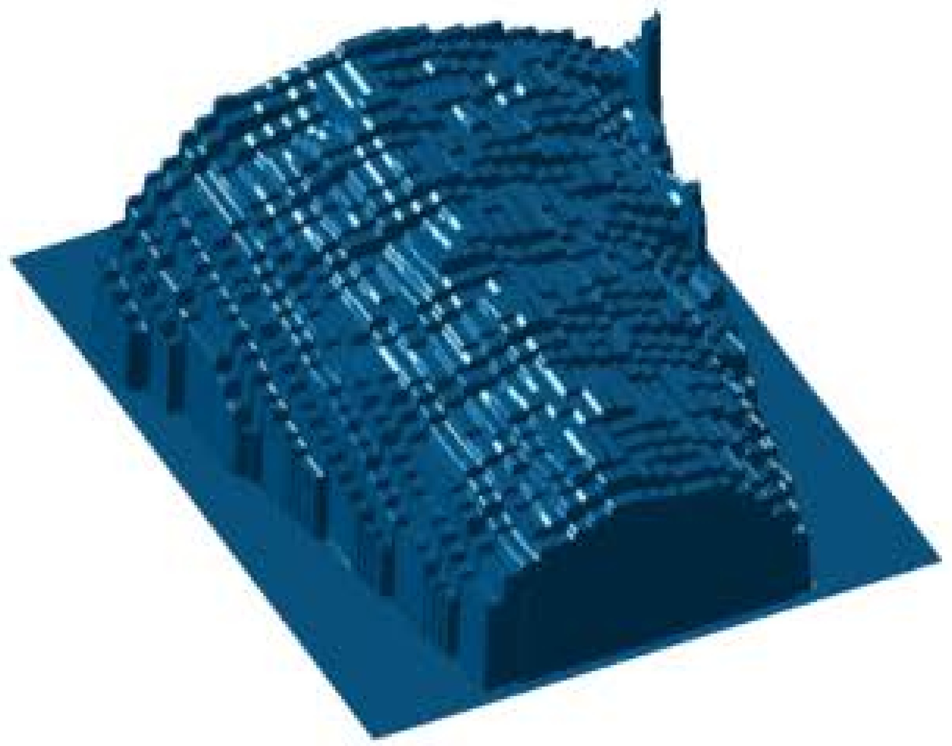




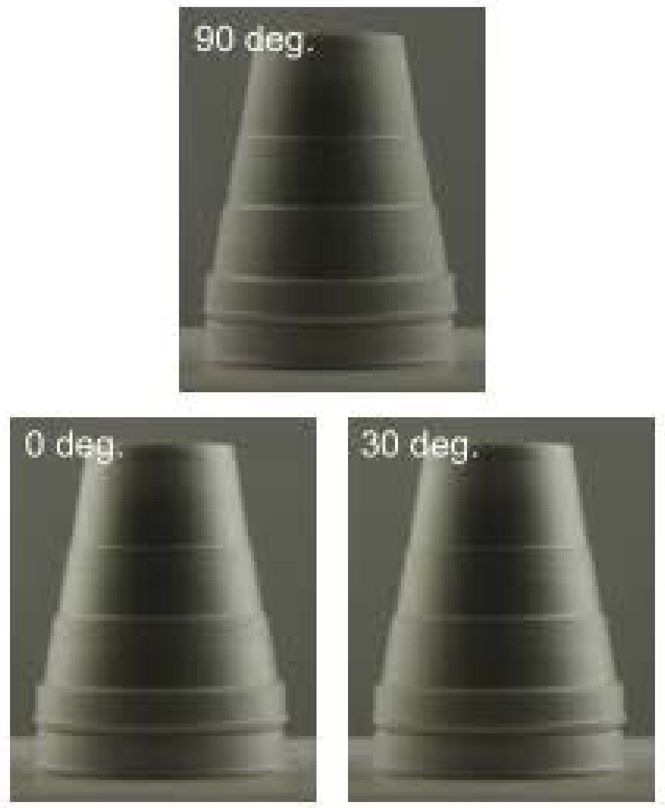


Kinect **3 Polar Photos** **Fresnel**

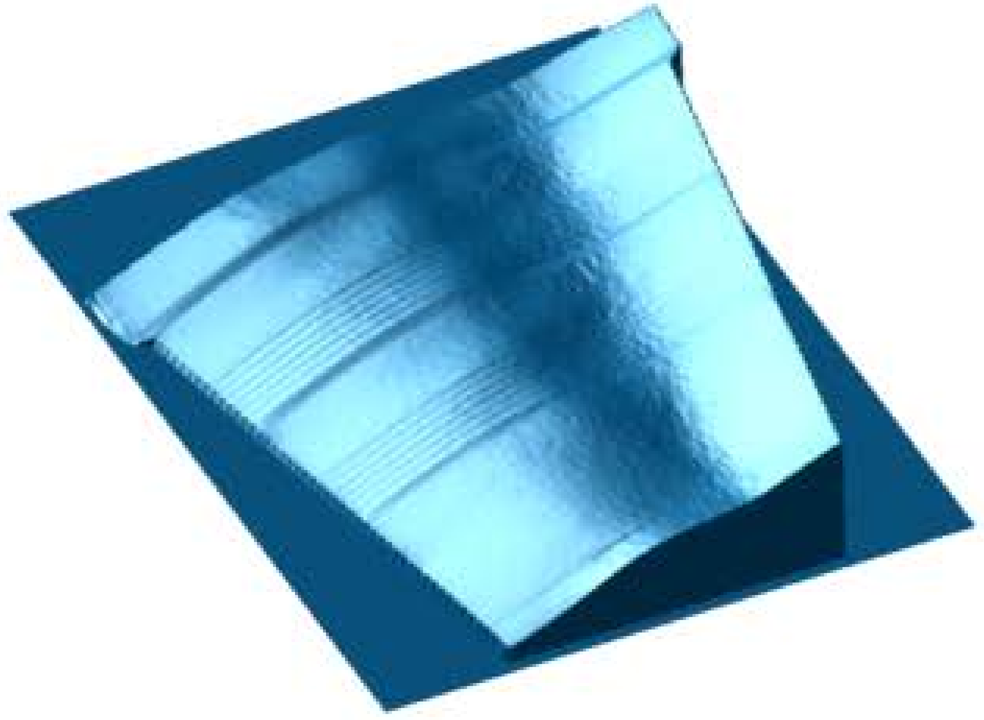
Visual Debugging



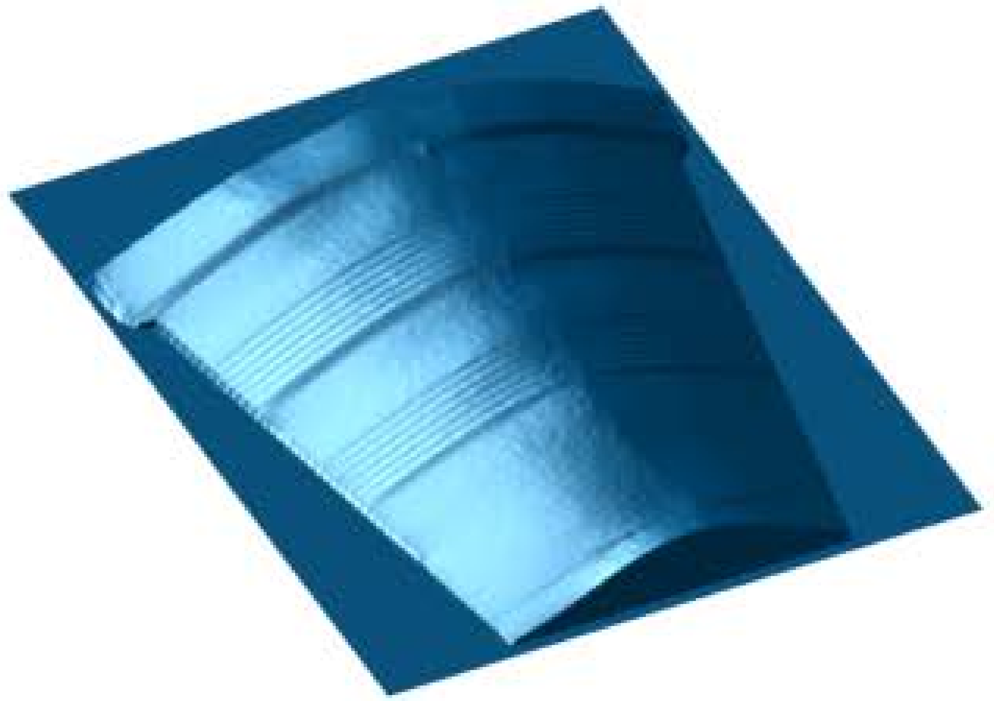
Kinect



3 Polar Photos

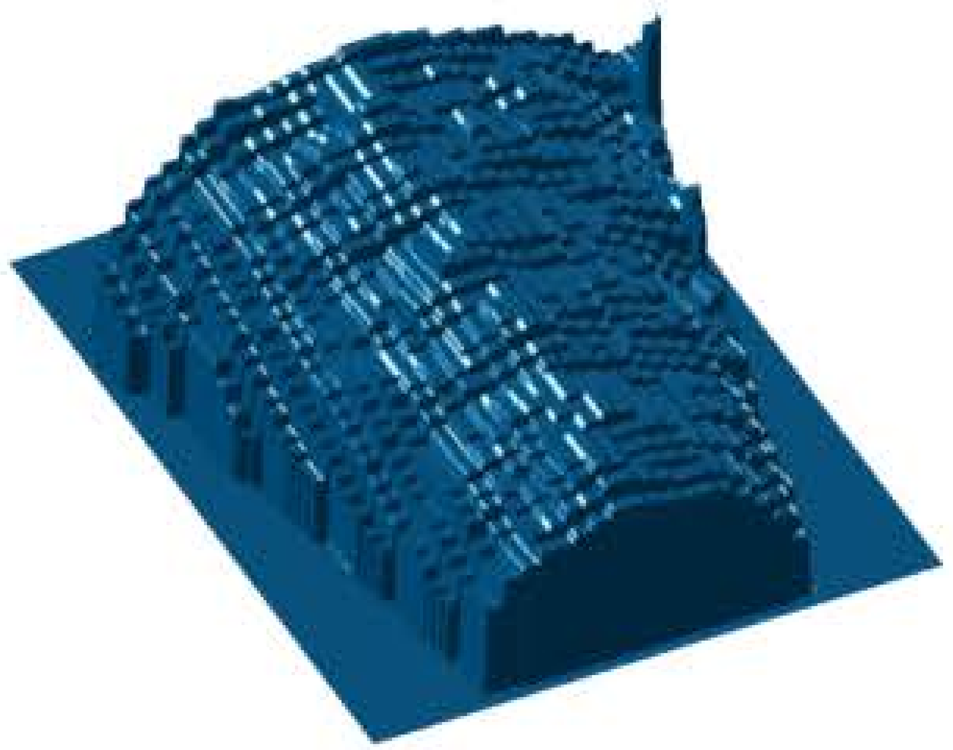


Fresnel

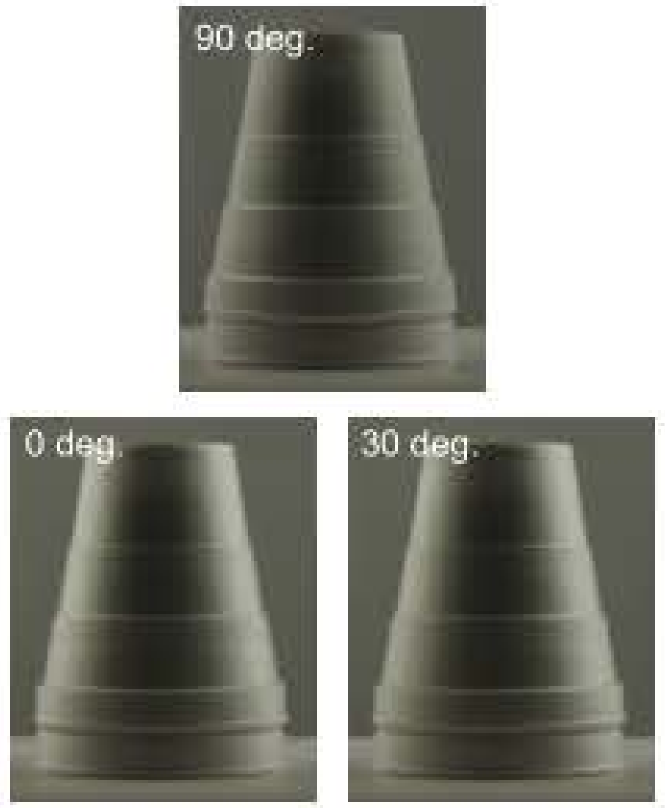


Grad. Corr.

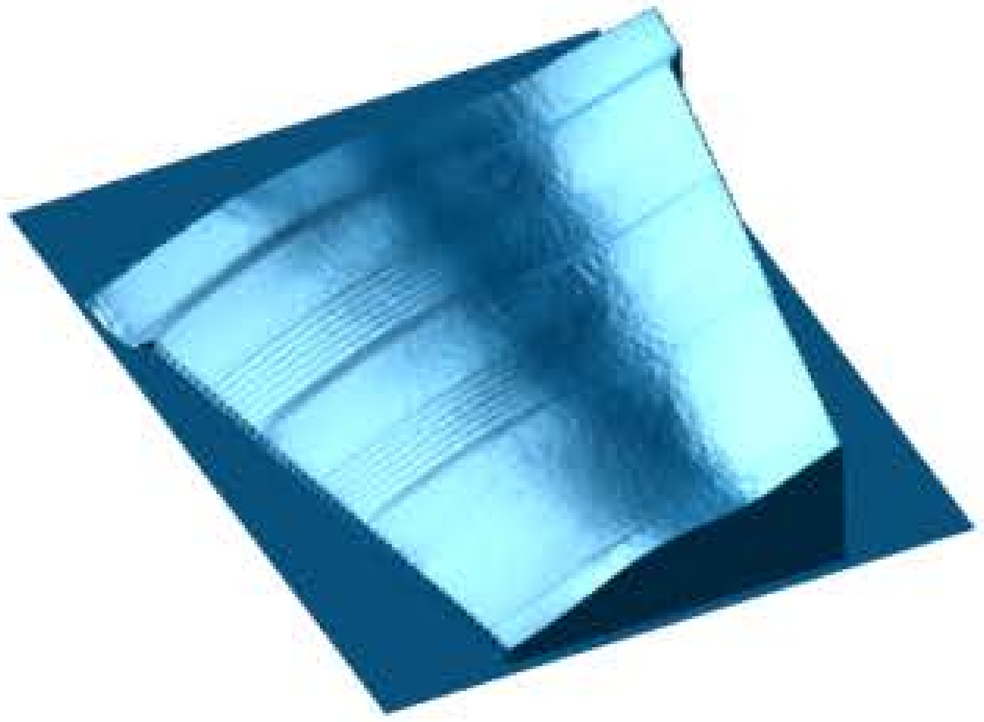
Visual Debugging



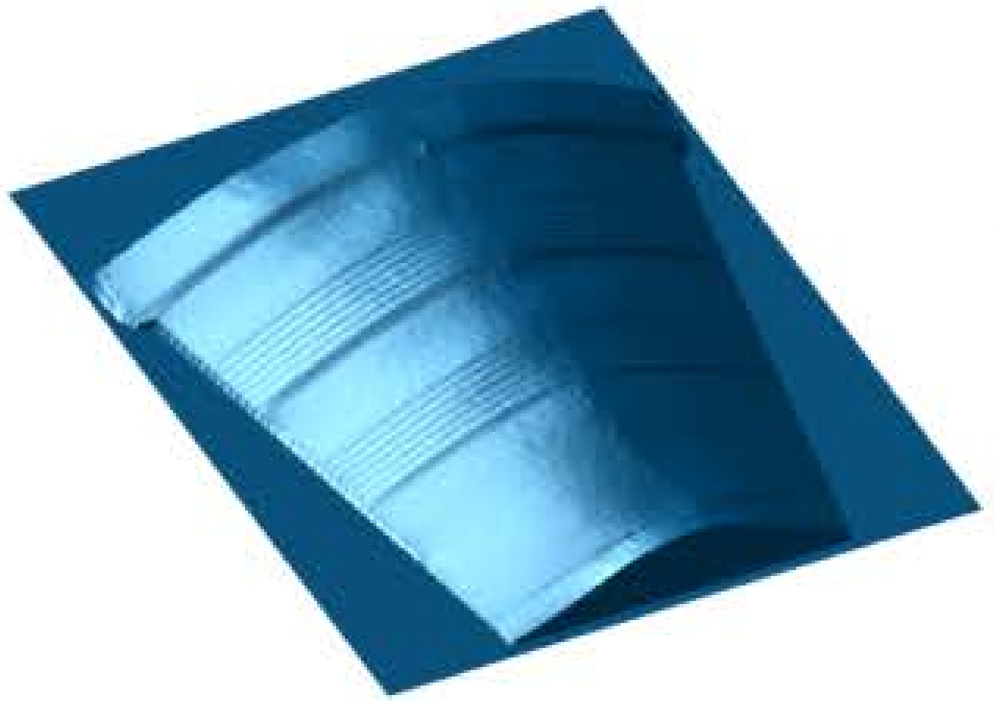
Kinect



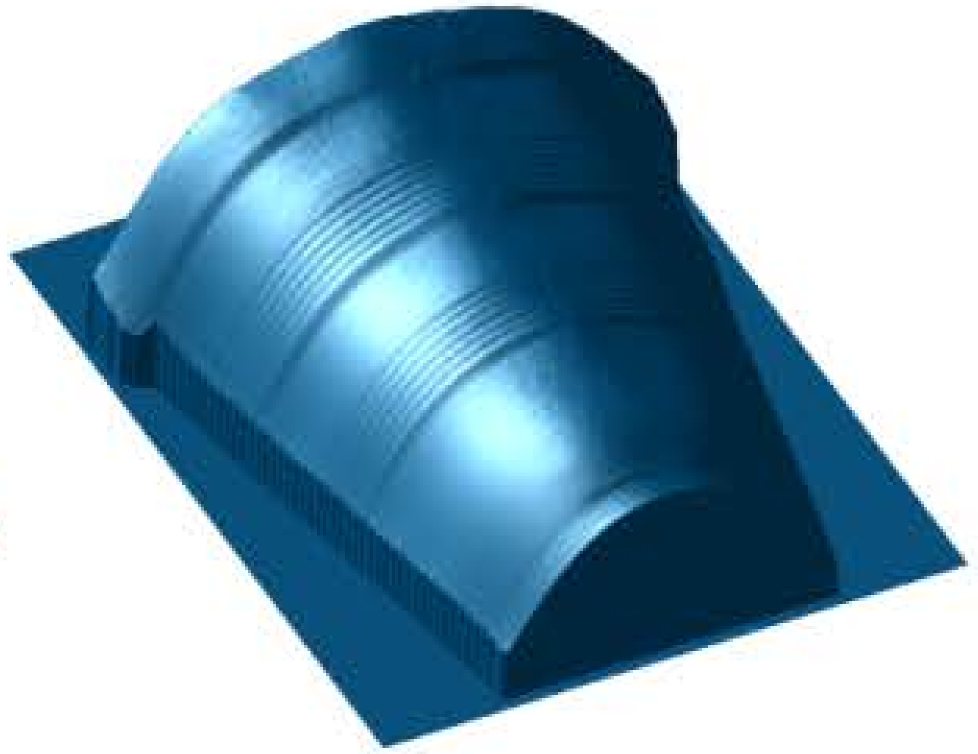
3 Polar Photos



Fresnel

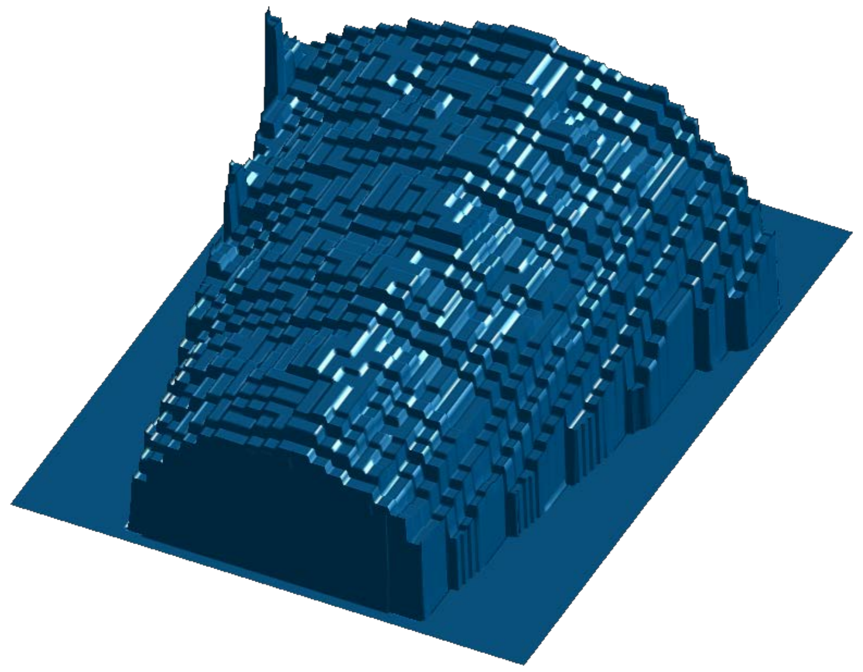


Grad. Corr.



Graph Integ.

Alternate Approaches



Microsoft Kinect ver. 2

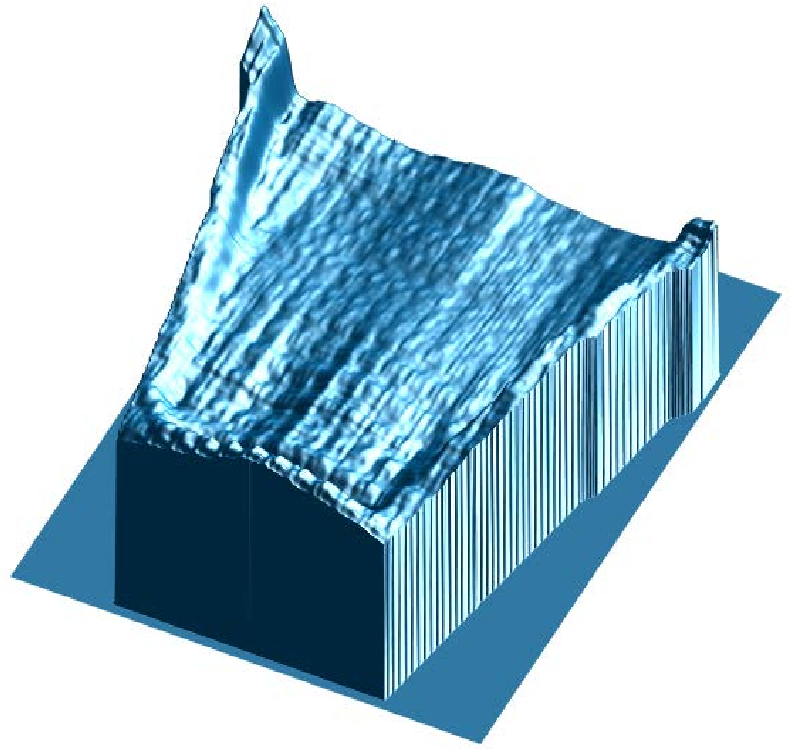
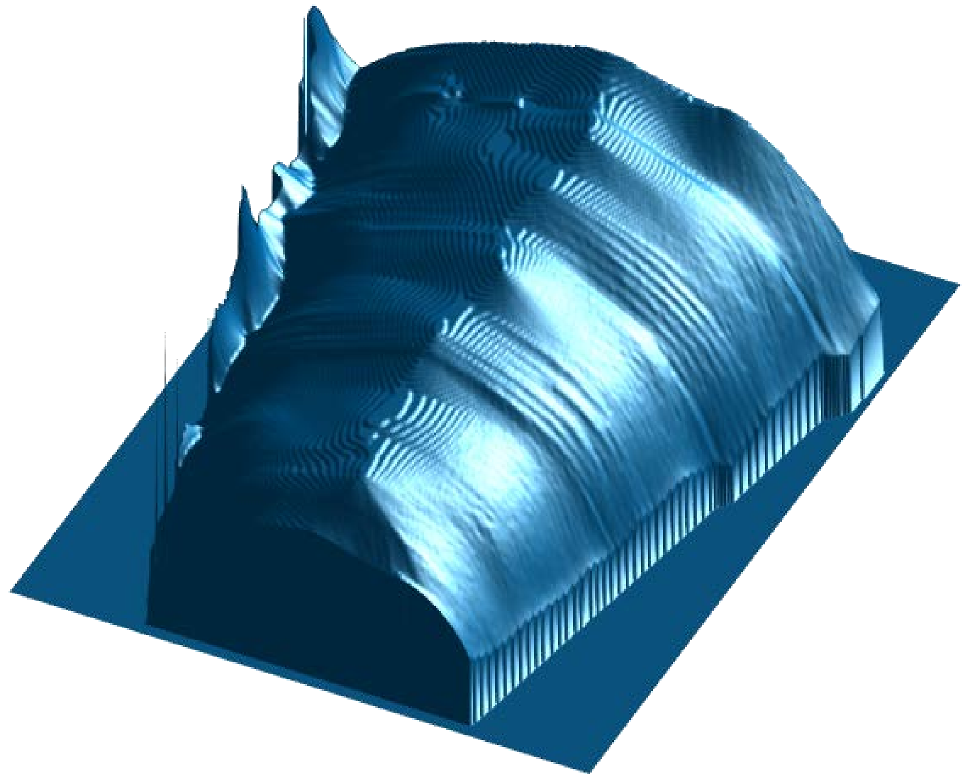
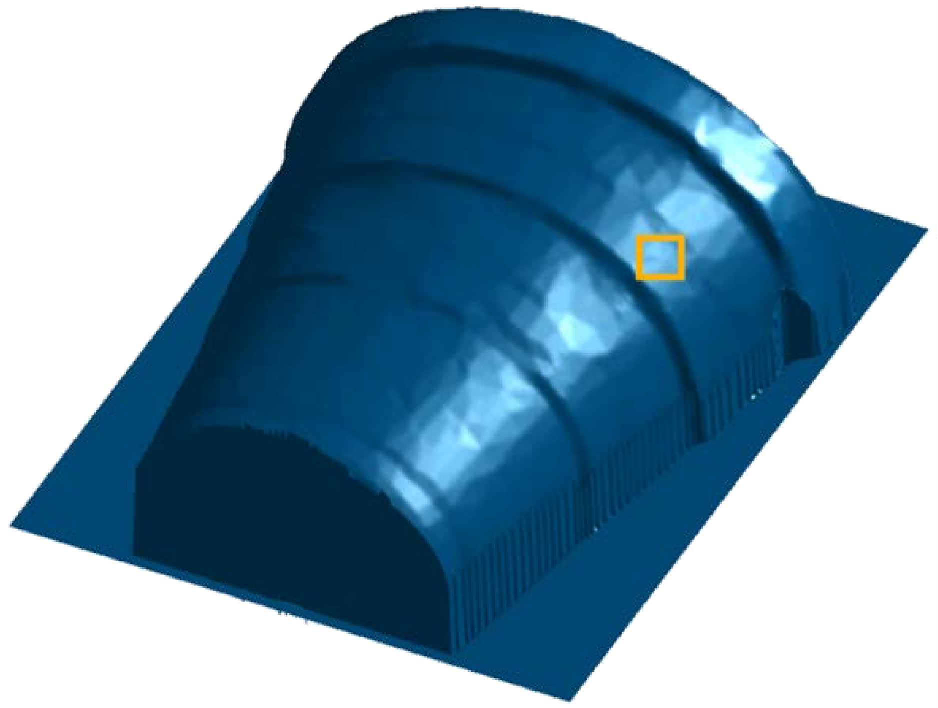


Image-based Machine Learning [Laina16]

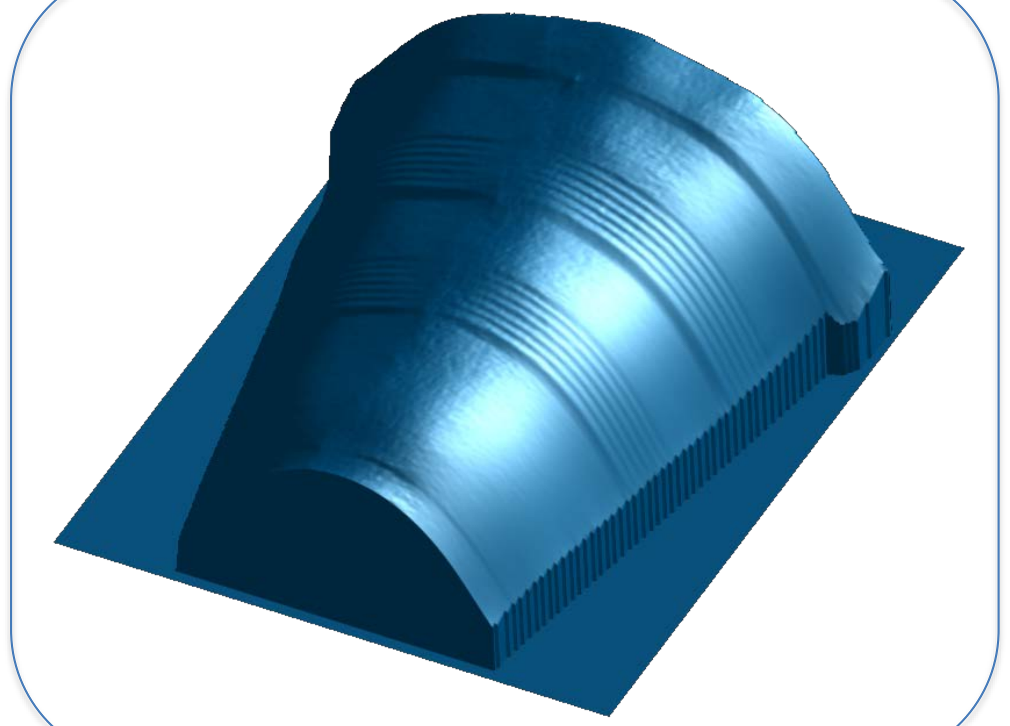
Trained on 3D Database from NYU [Silberman12]



Shading Refinement [Wu14]



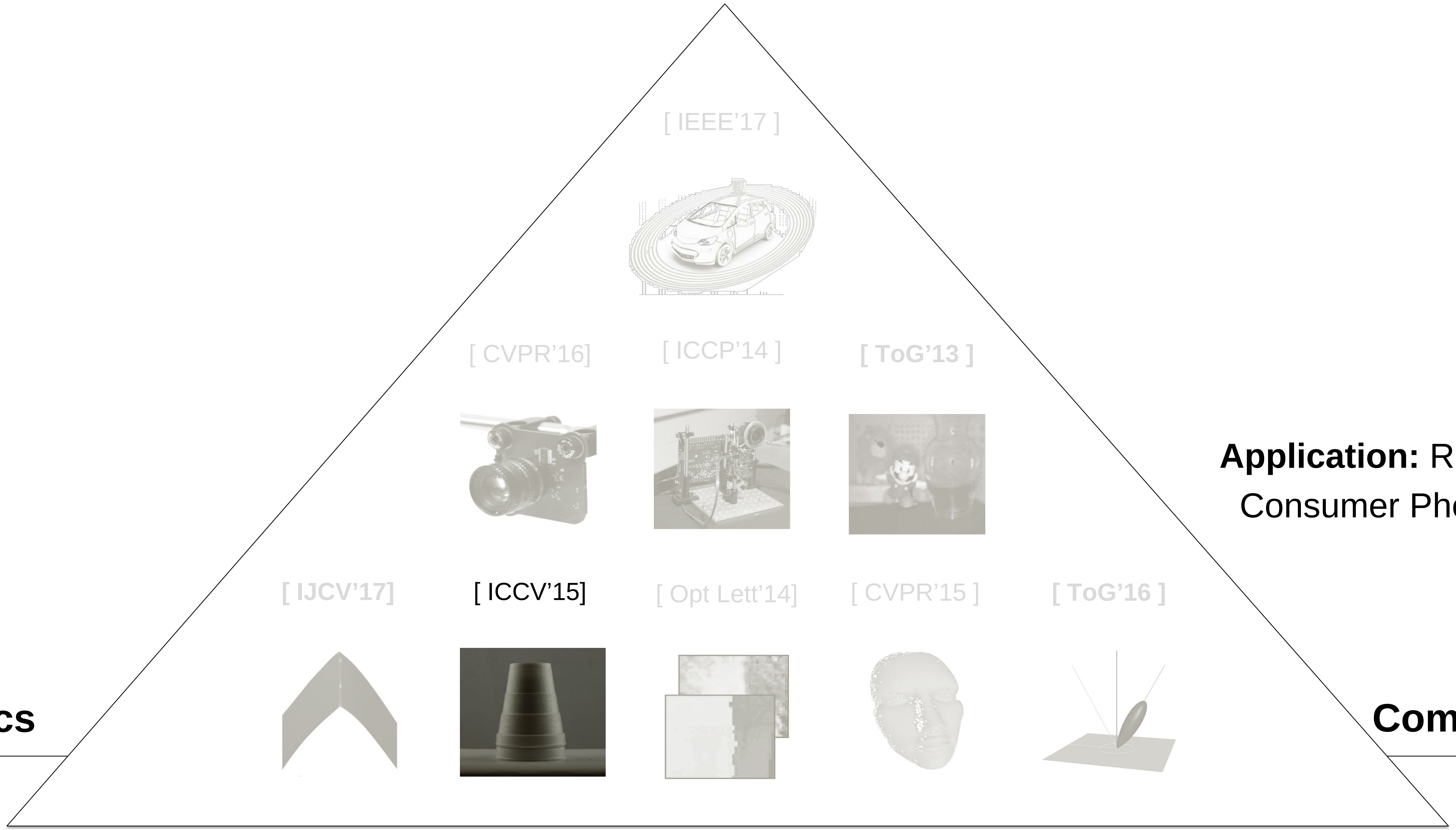
Industry Laser Scanner



Polarization Approach

Physics, Hardware, and Computation

Hardware

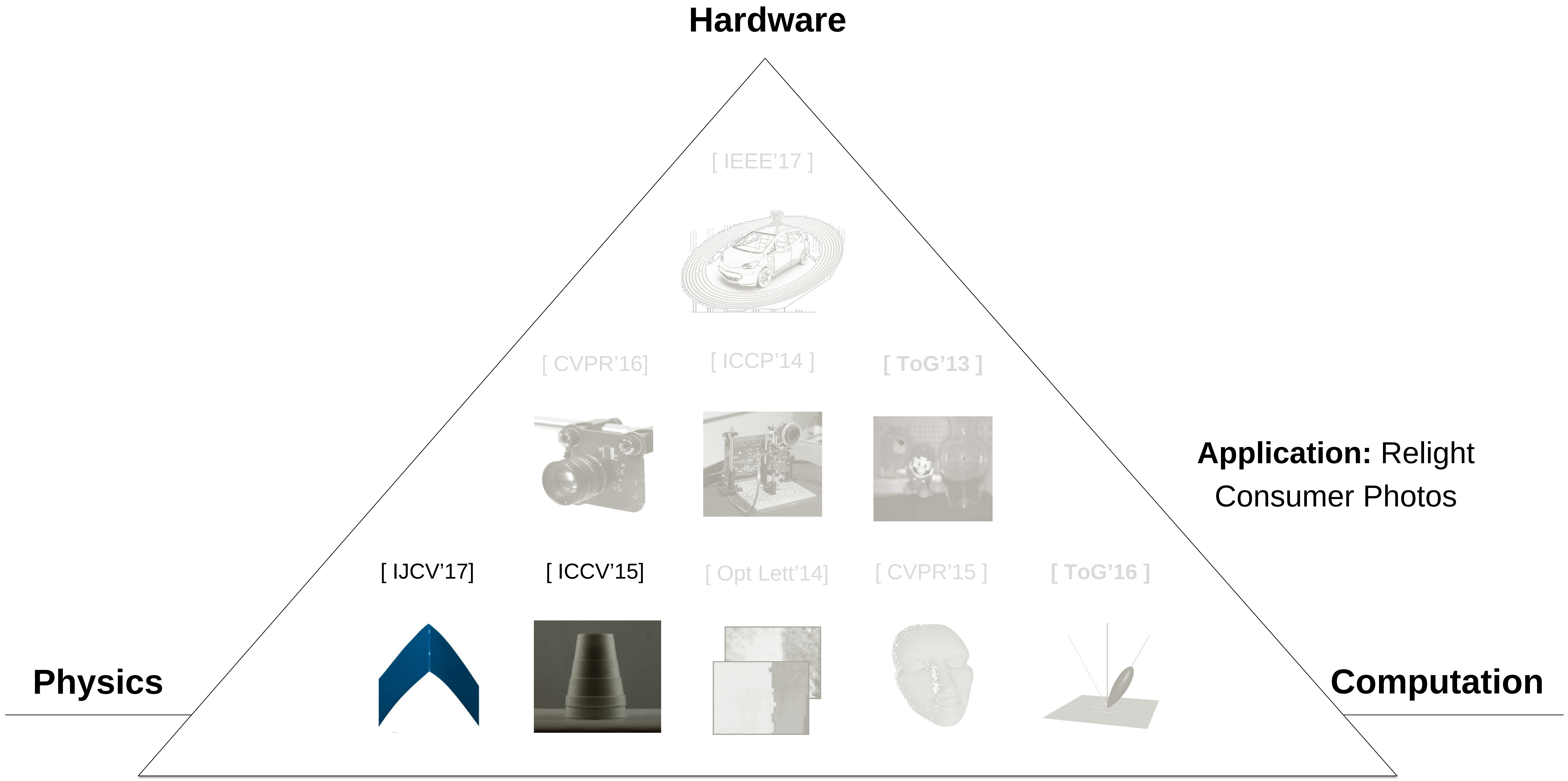


Application: Relight Consumer Photos

Physics

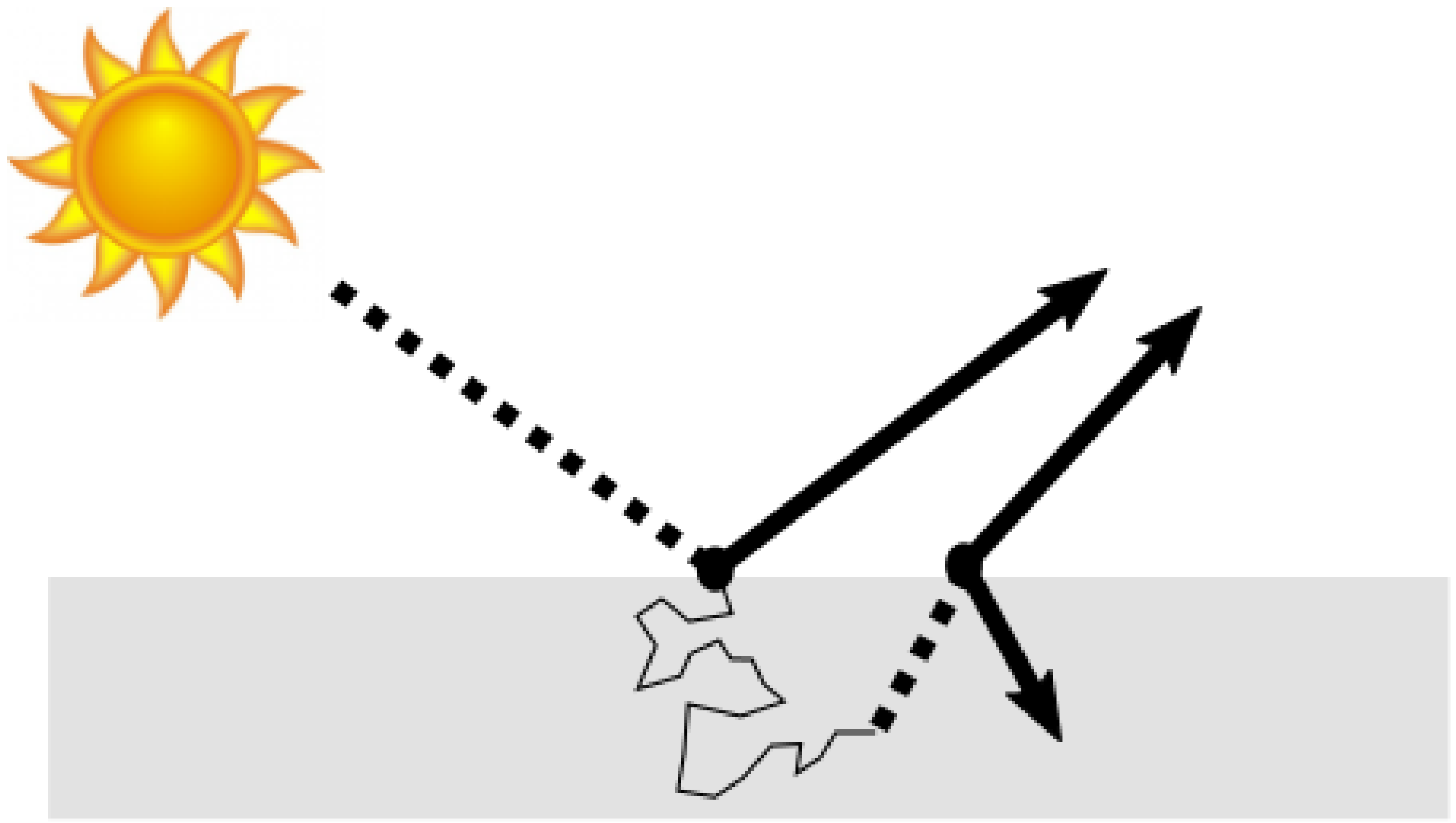
Computation

Physics, Hardware, and Computation



Provable Guarantees on Light Transport

Proposition 1 *Stochastic ambiguities in the azimuthal angle are avoided when polarized reflections are either diffuse or specular dominant.*

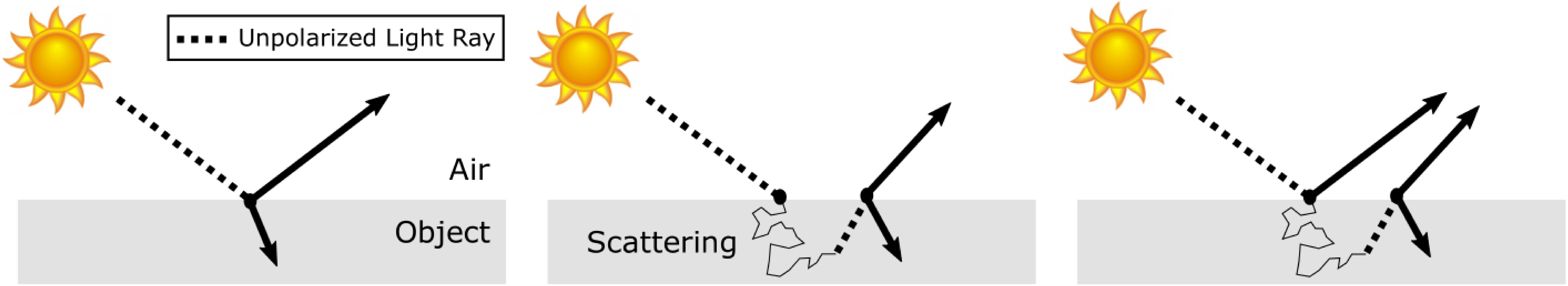


(c) Mixed Reflection

Proposition 2 *Assuming the conditions of Proposition 1 hold, perturbations in zenith angle due to mixed reflections can be corrected by applying the rotation operator $\widehat{\mathscr{R}}$, as described in Eq. 10.*

[Kadambi et al. IJCV 2017]

Surface Assumption



(a) Specular Reflection | (b) Diffuse Reflection | (c) Mixed Reflection

Fresnel Equations

[Fresnel 1819]

"Reversed Fresnel"

[Atkinson et al. 2006]

"Mixed Fresnel"

[Kadambi et al. 2017]

$$\rho^{\text{spec}} = \frac{2n\tan\theta\sin\theta}{\tan^2\theta\sin^2\theta + |n^*|^2}$$

OR

$$\rho = \frac{\left(n-\frac{1}{n}\right)^2\sin^2\theta}{2+2n^2-\left(n+\frac{1}{n}\right)^2\sin^2\theta+4\cos\theta\sqrt{n^2-\sin^2\theta}}$$

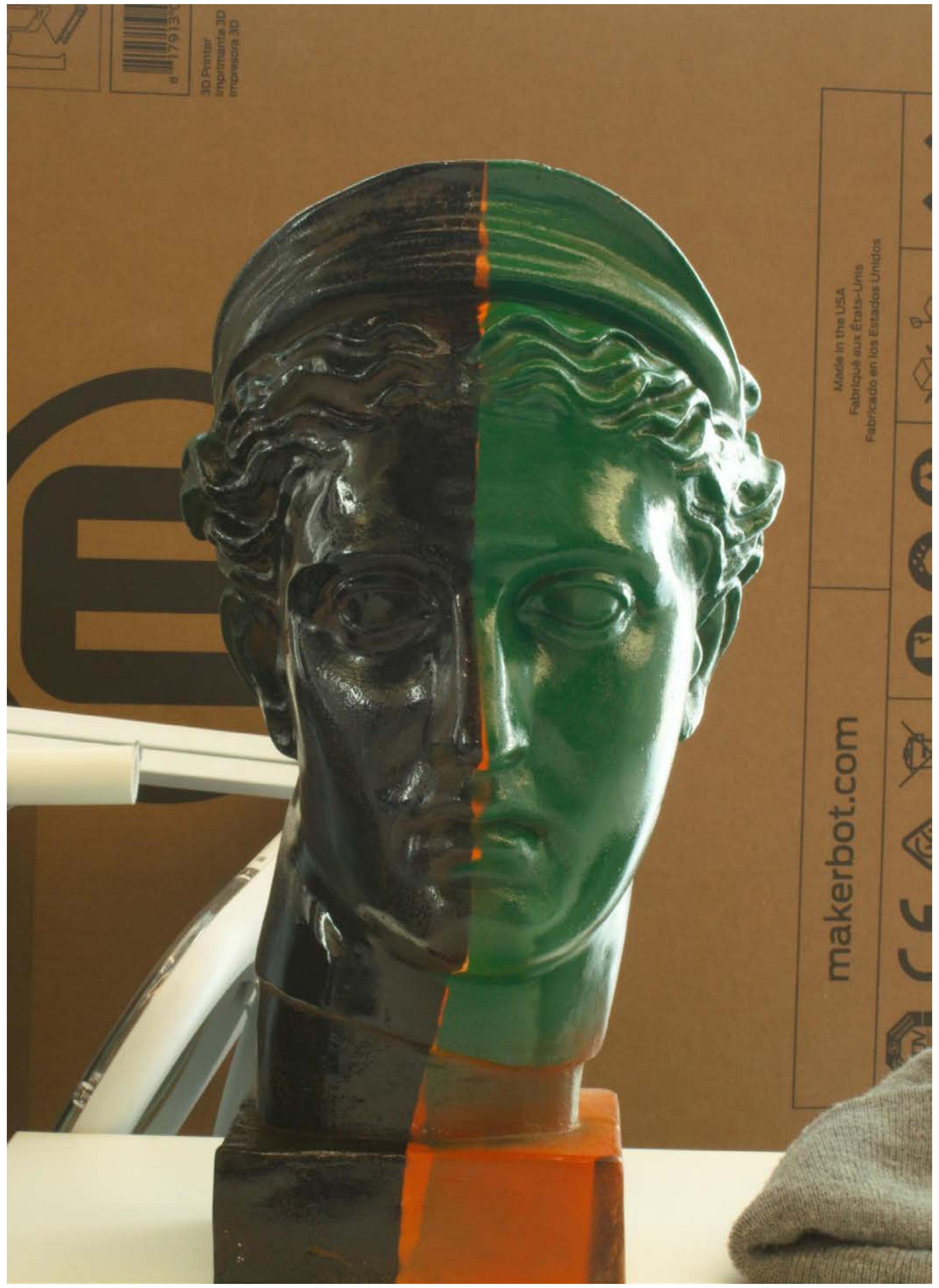
Contribution:
analyze a
mixture model

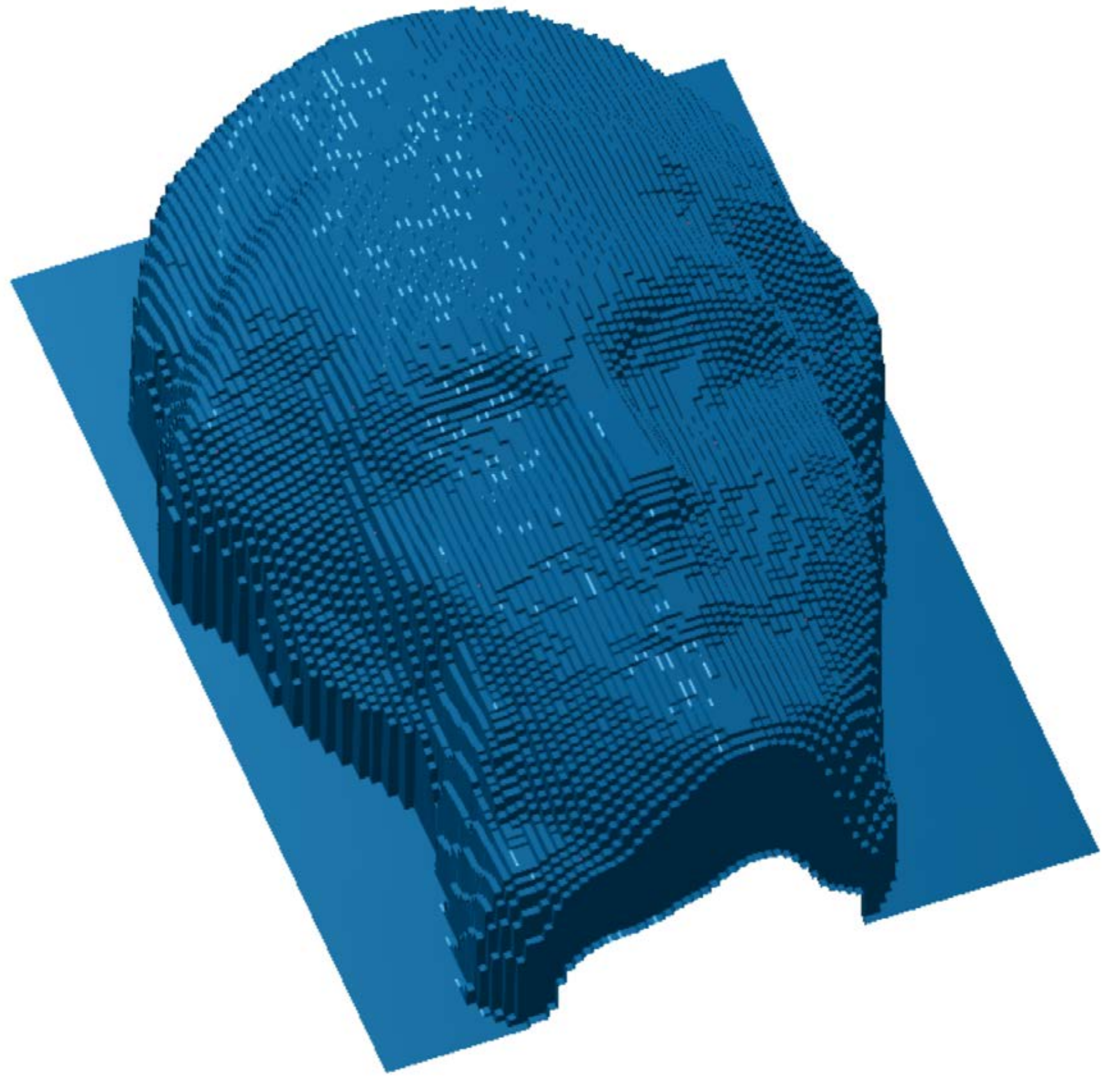
One of the most challenging objects to scan

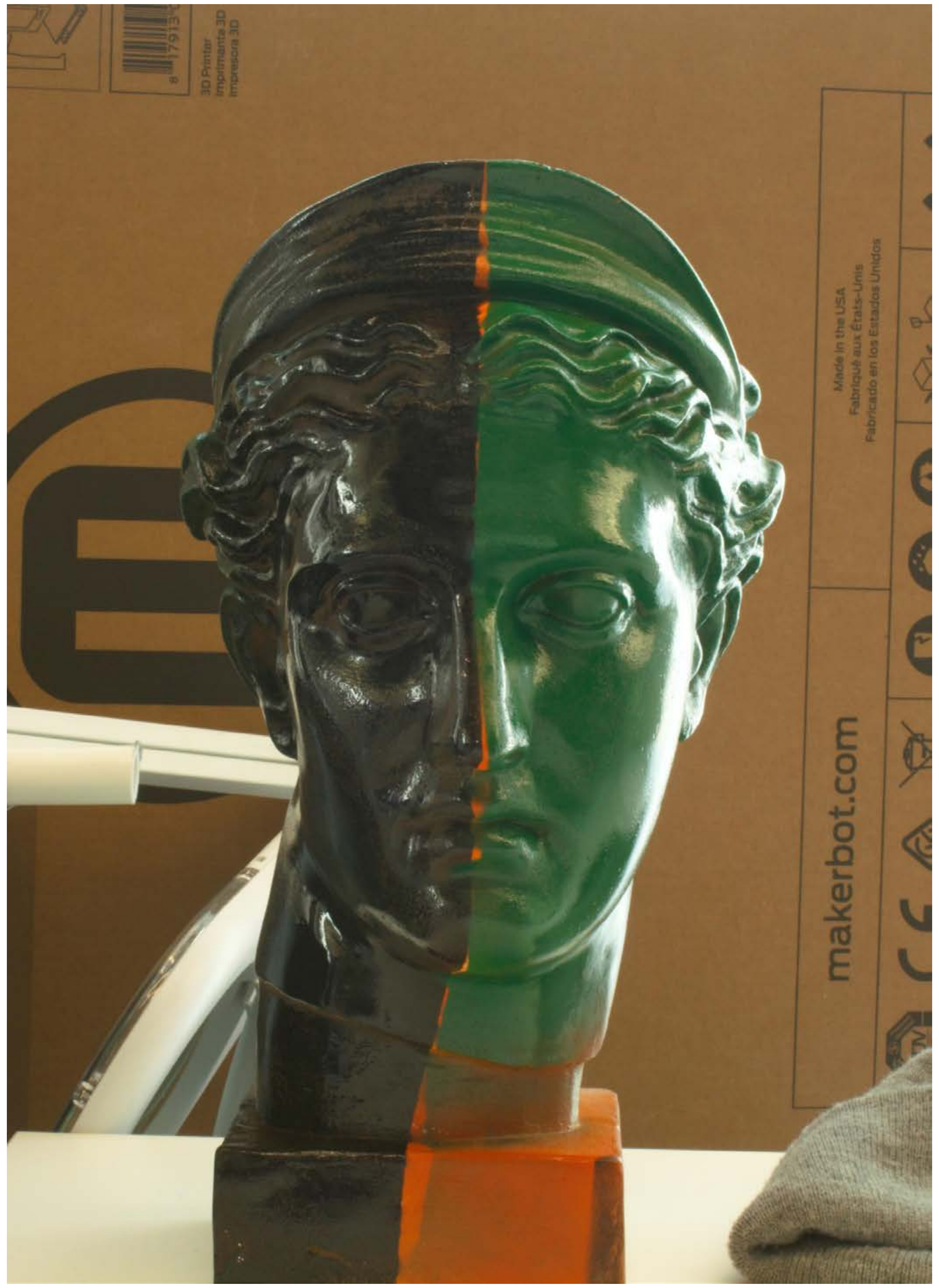
Paints of different colors

Uncontrolled Ambient light
from window

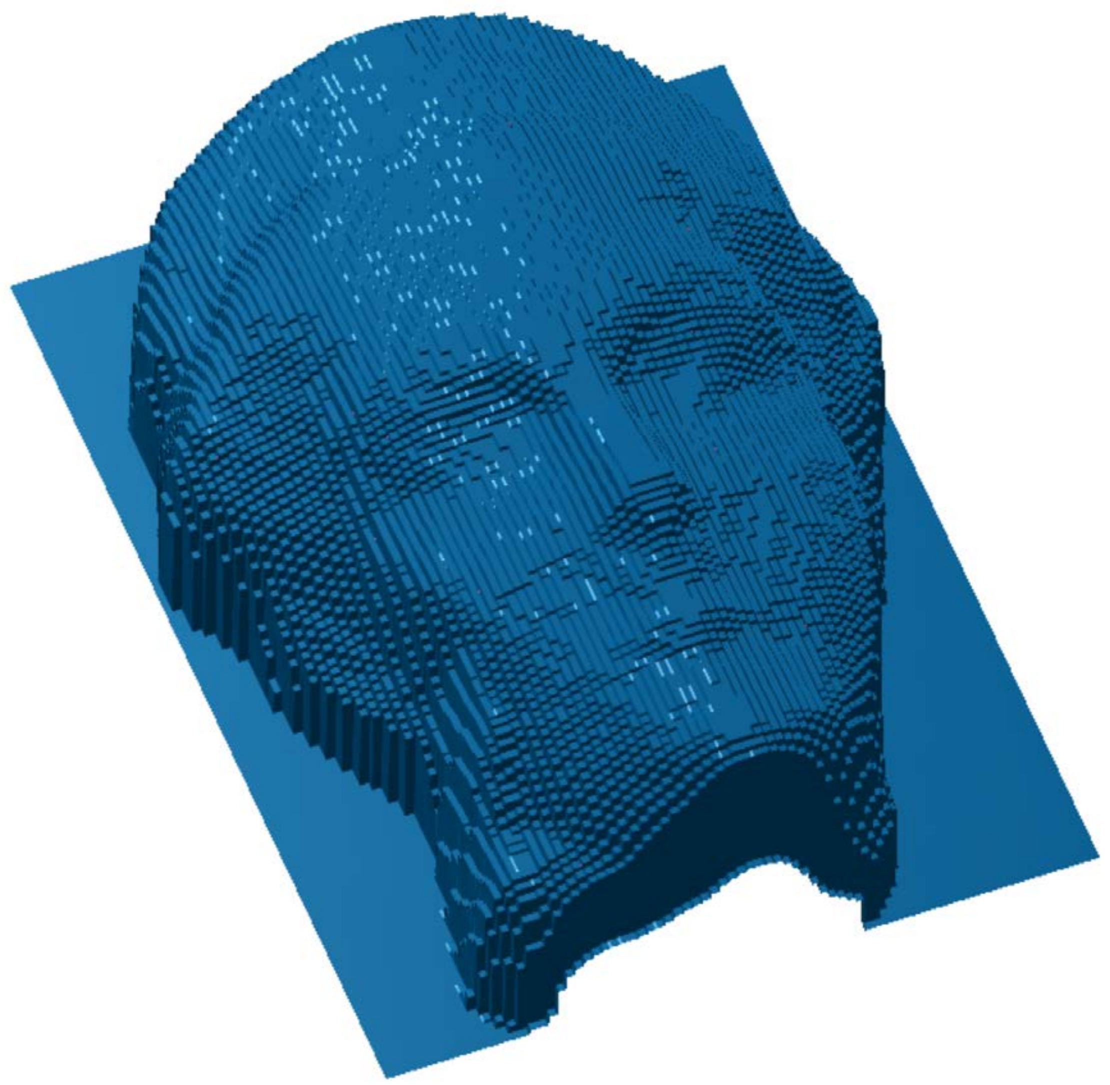
Kinect



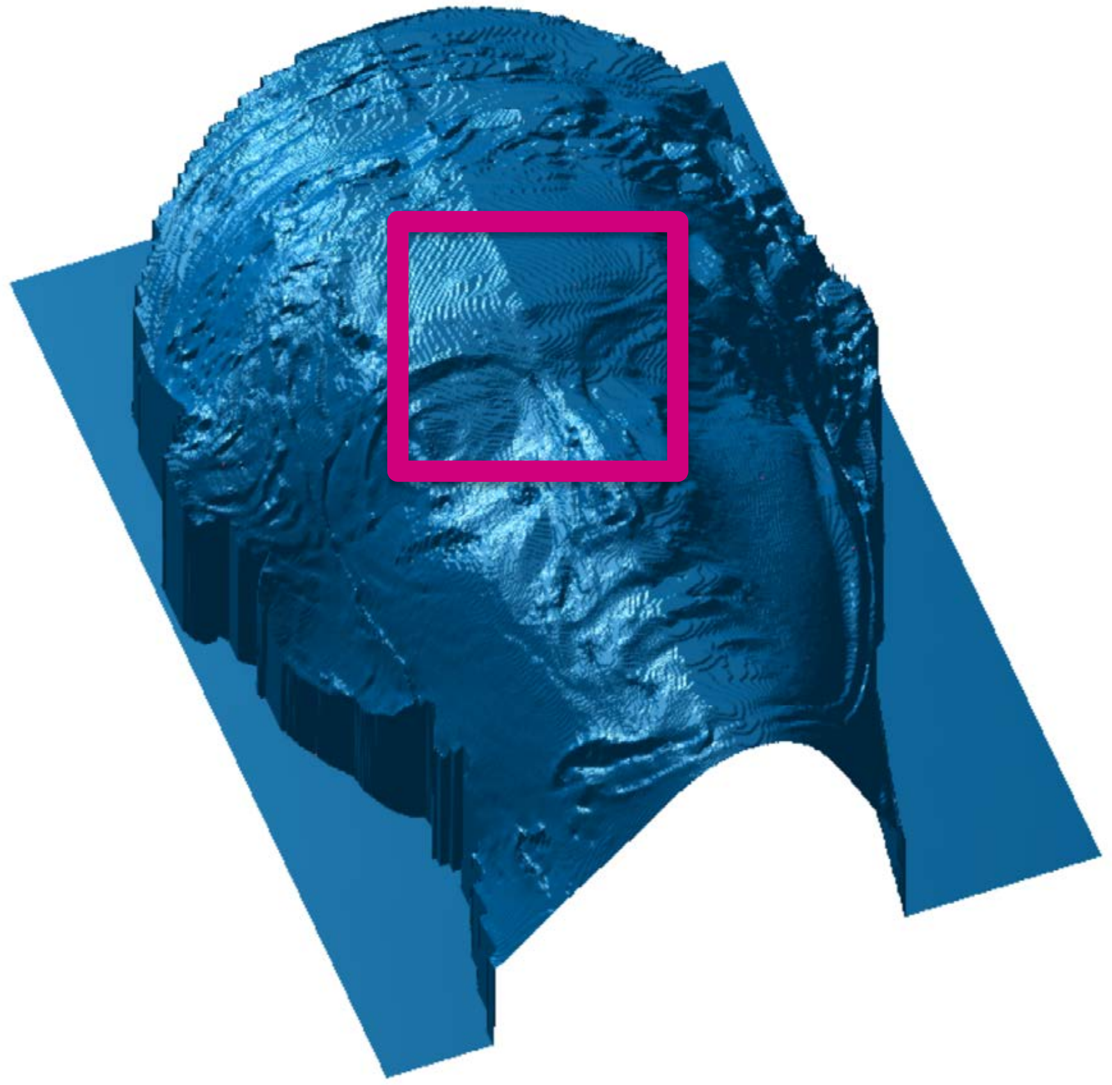




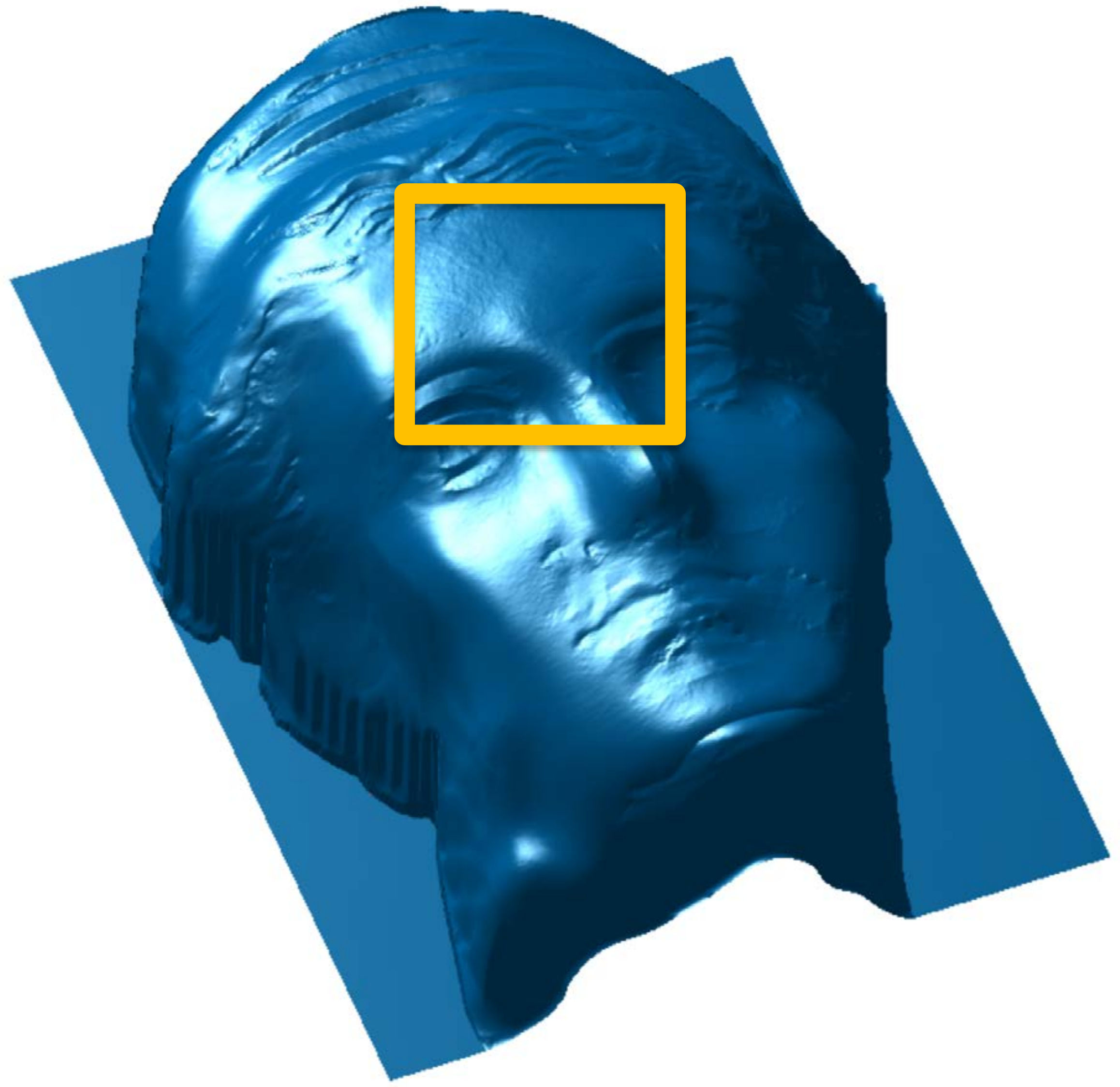
Kinect

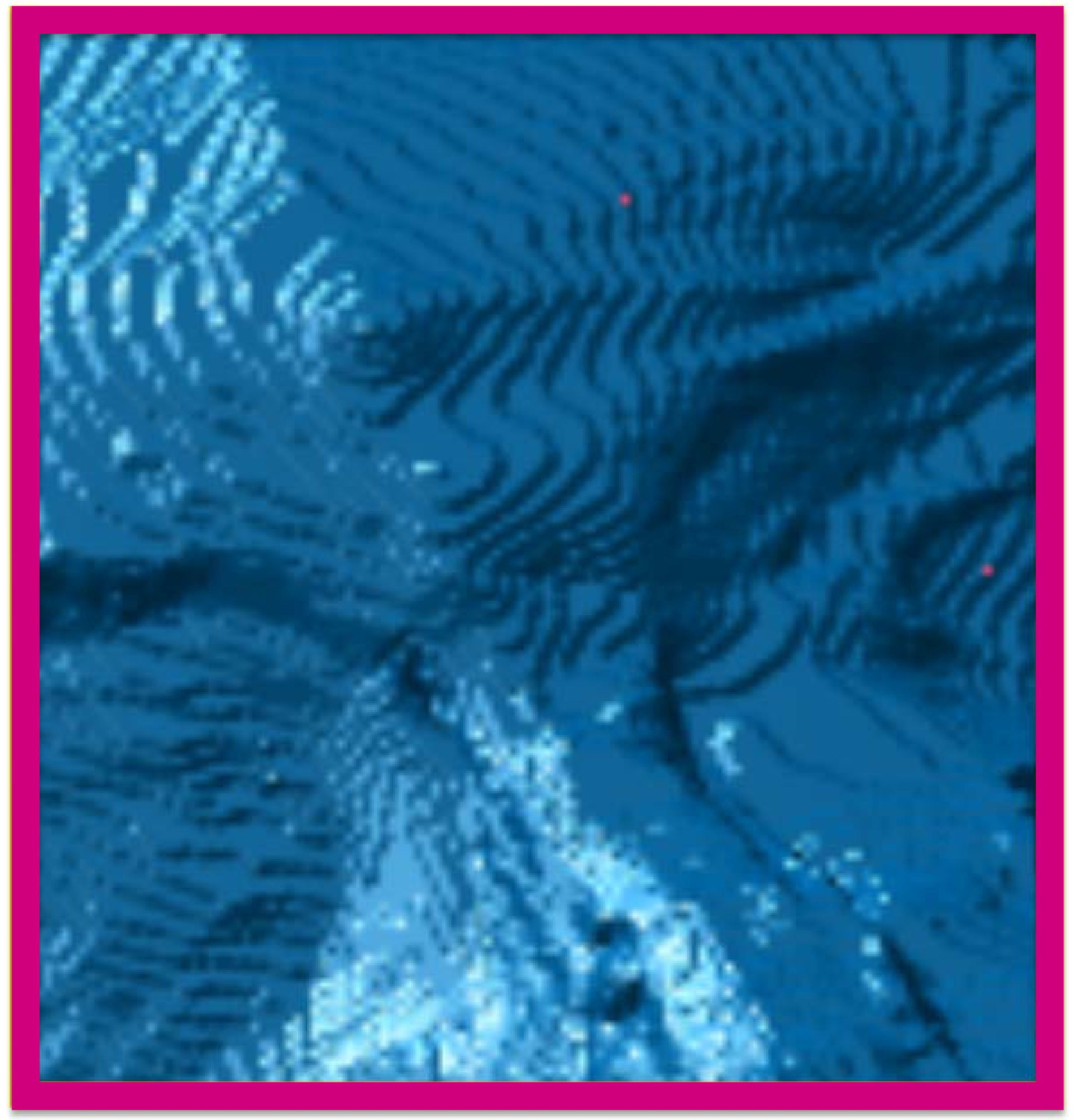


Shading [Wu 14]



Polarized 3D

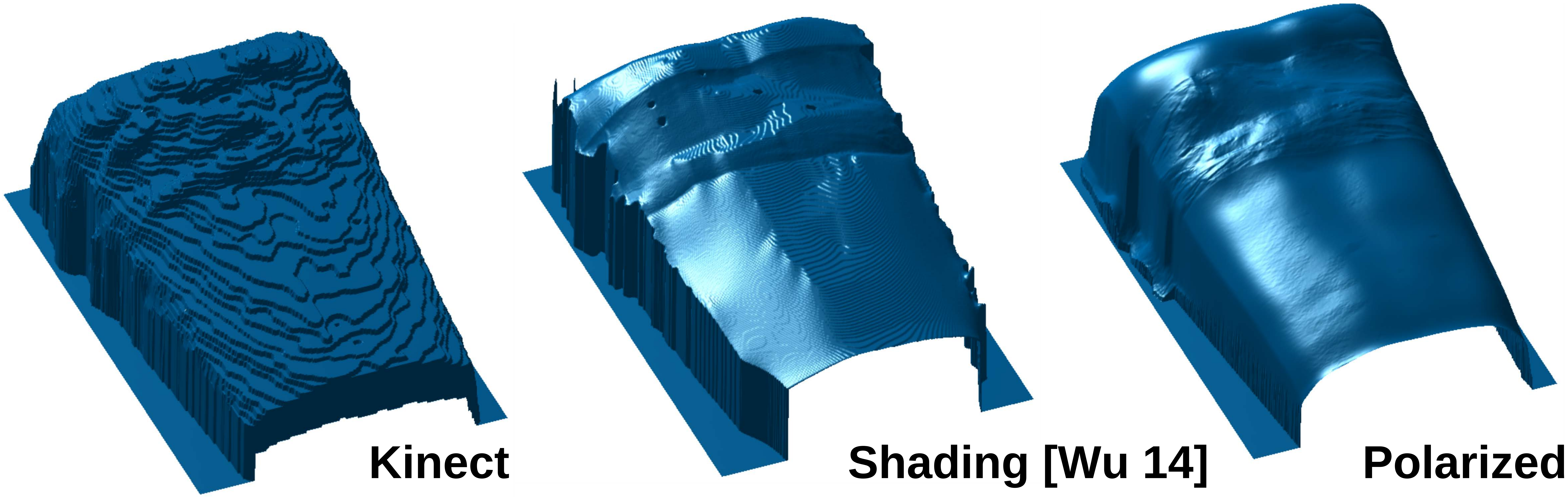




Passive Polarimetric Imaging

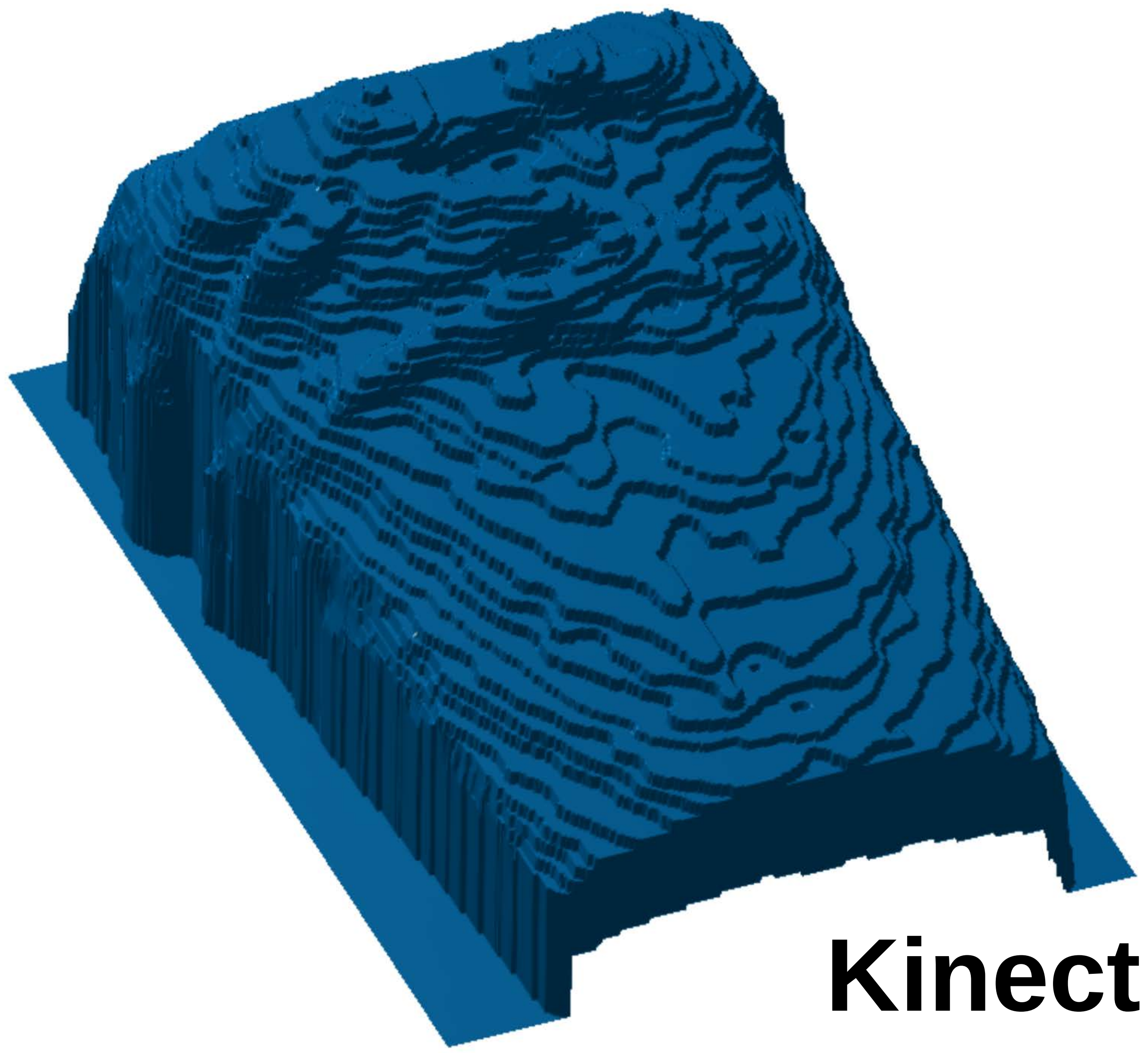
Varying Reflection Class

Passive Polarimetric Imaging

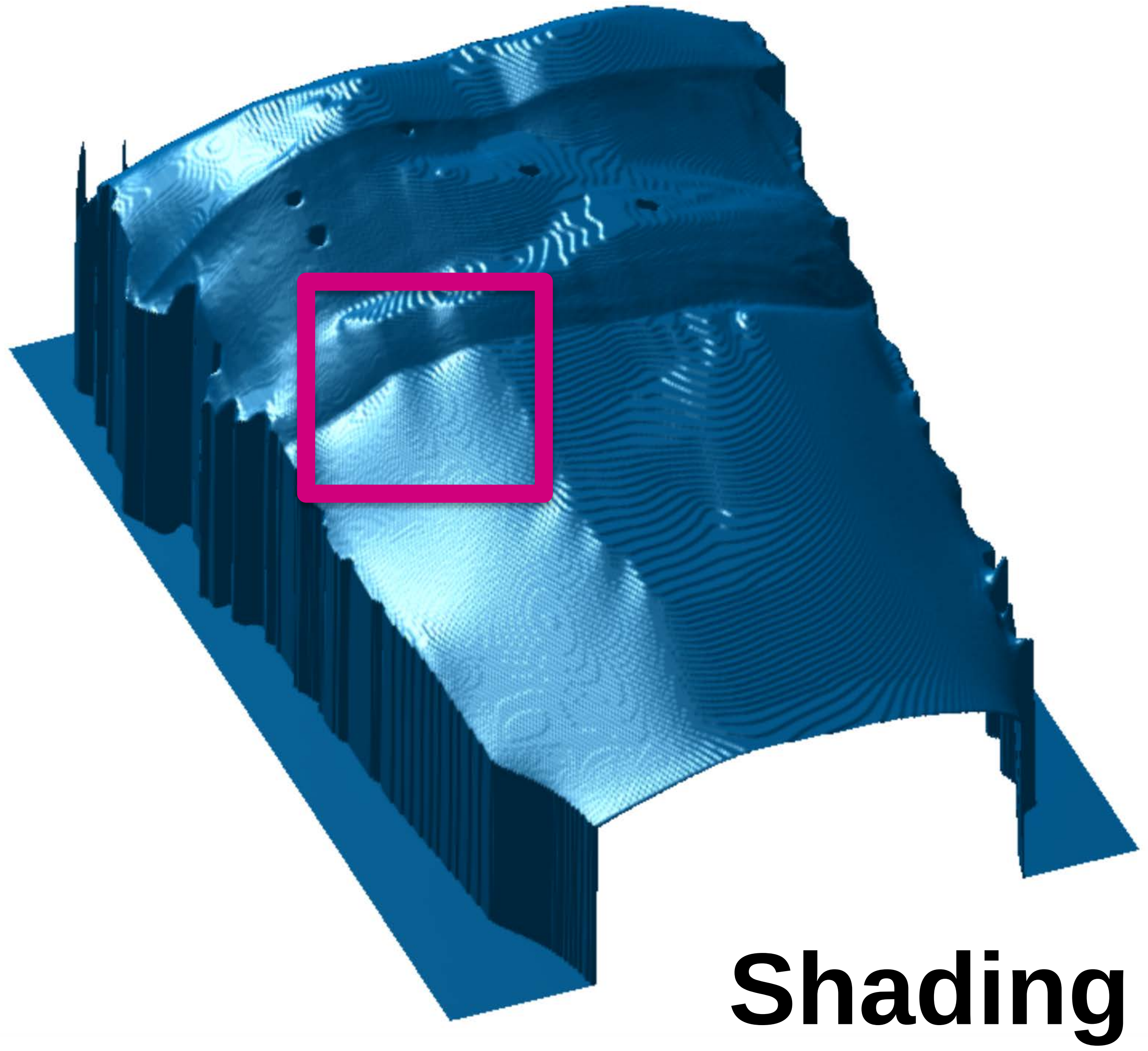


Varying Reflection Class

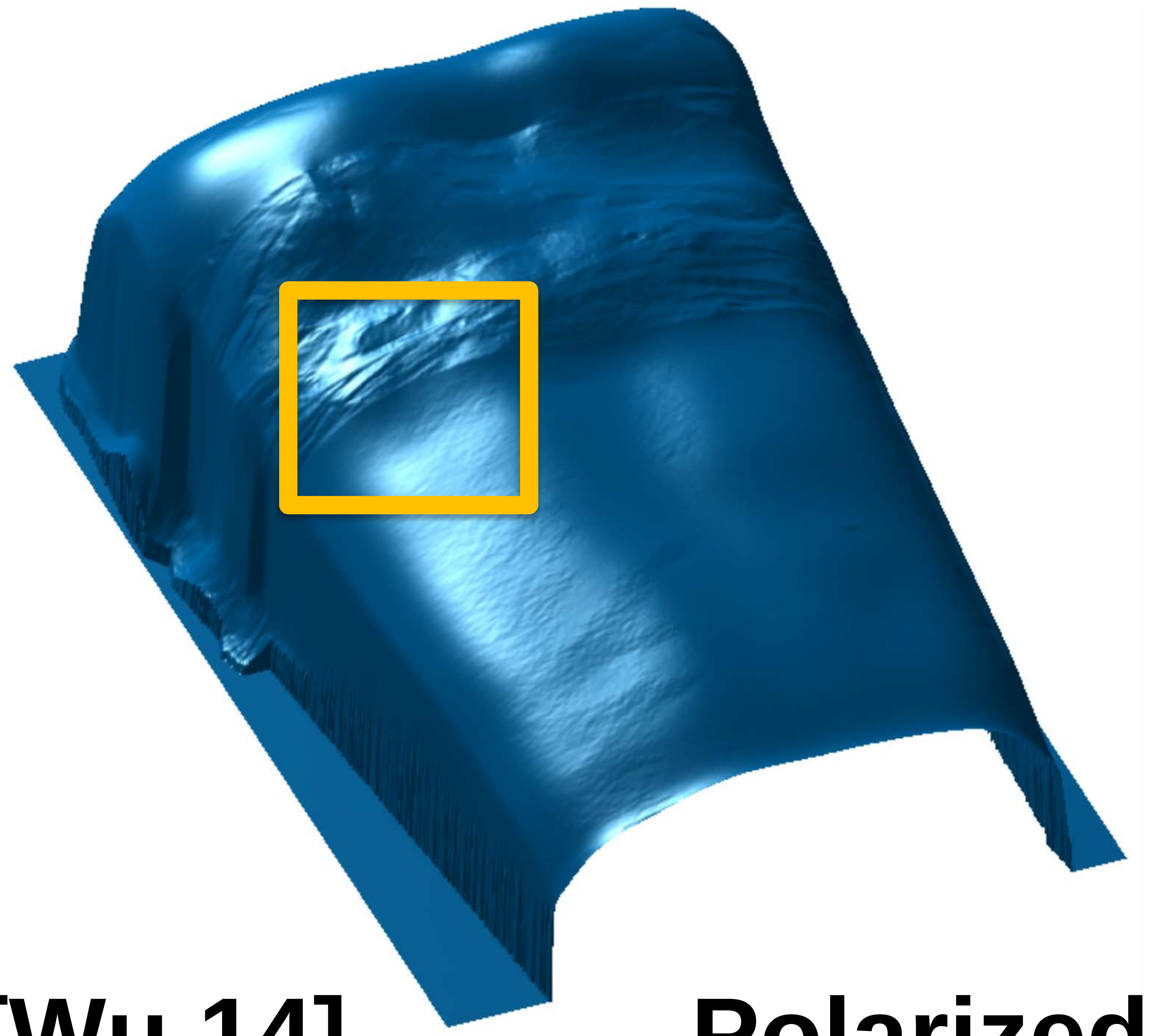
Passive Polarimetric Imaging



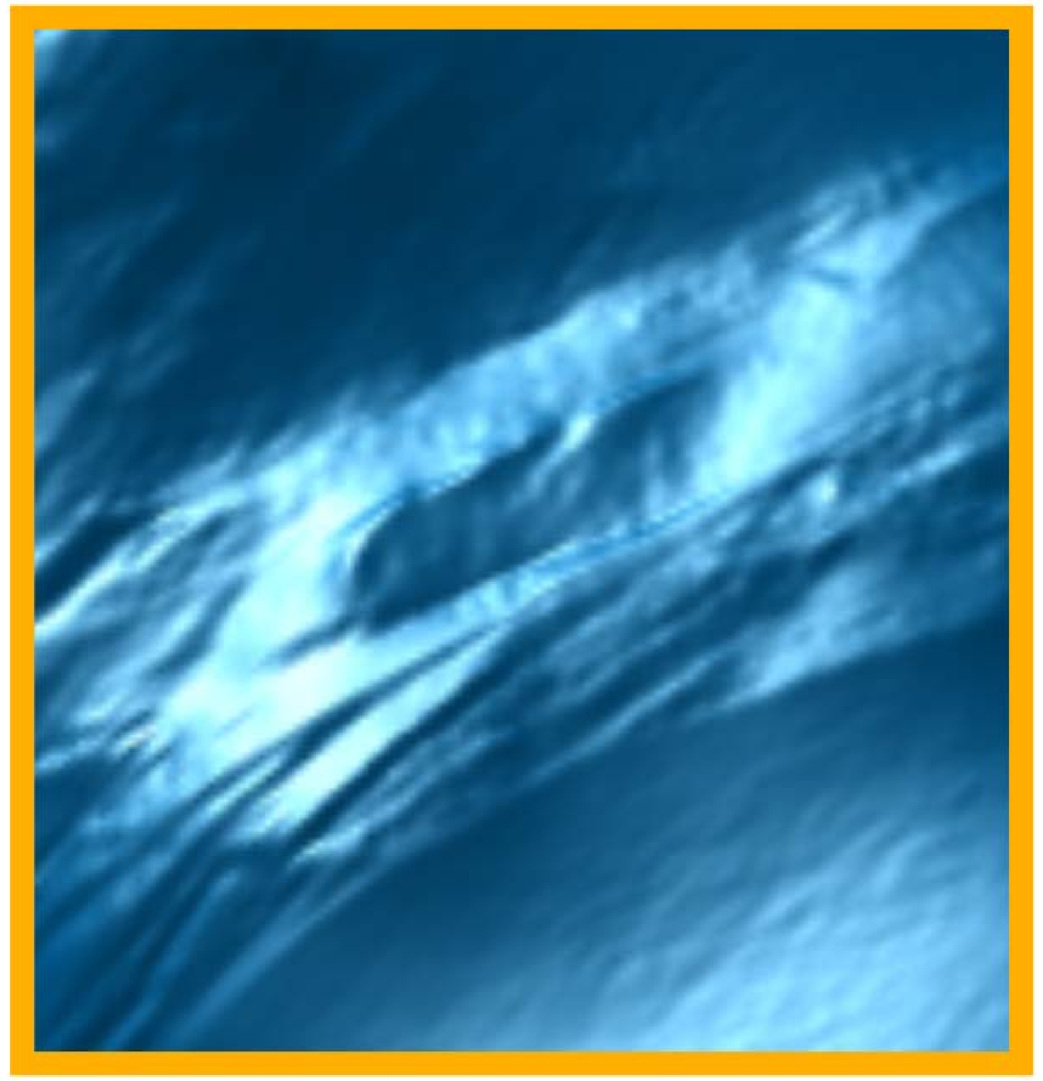
Kinect



Shading [Wu 14]



Polarized 3D

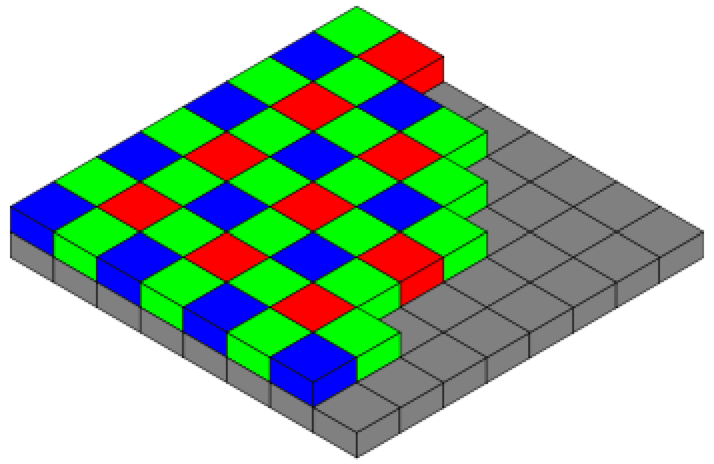


Many lingering challenges!

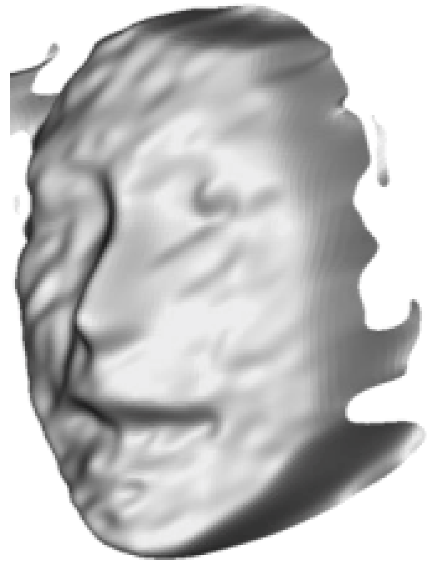
Limitations

Note: we have only scratched surface of just *linear* polarization

Birefringence, circular polarization, etc.



(-) Requires Multiple Images



(-) Requires Coarse Depth

(-) Not real-time (3 sec/frame)

Solutions

Multipolar Camera

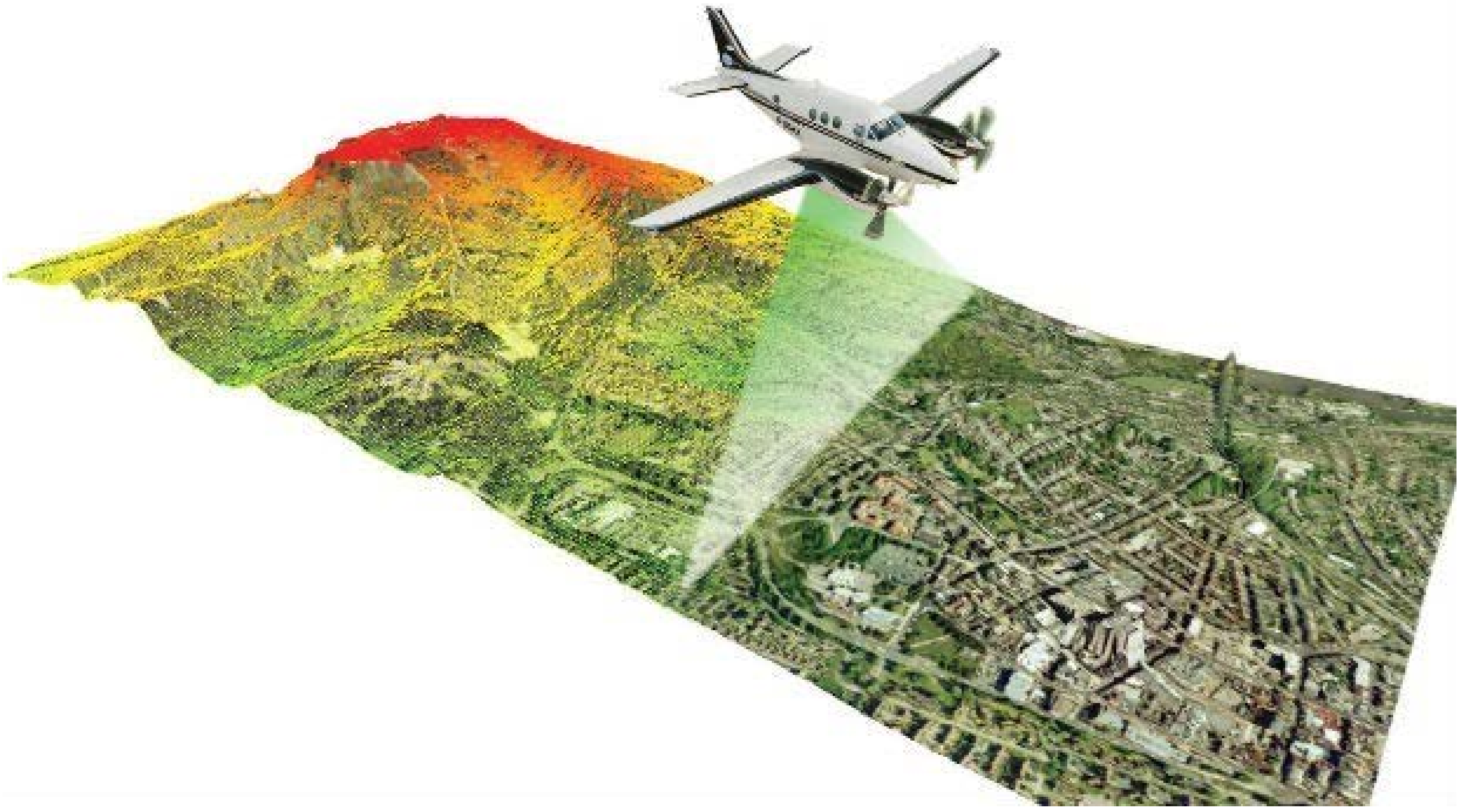
Depth Priors from Machine Learning

GPU or physics-based learning

Future pathways to probe

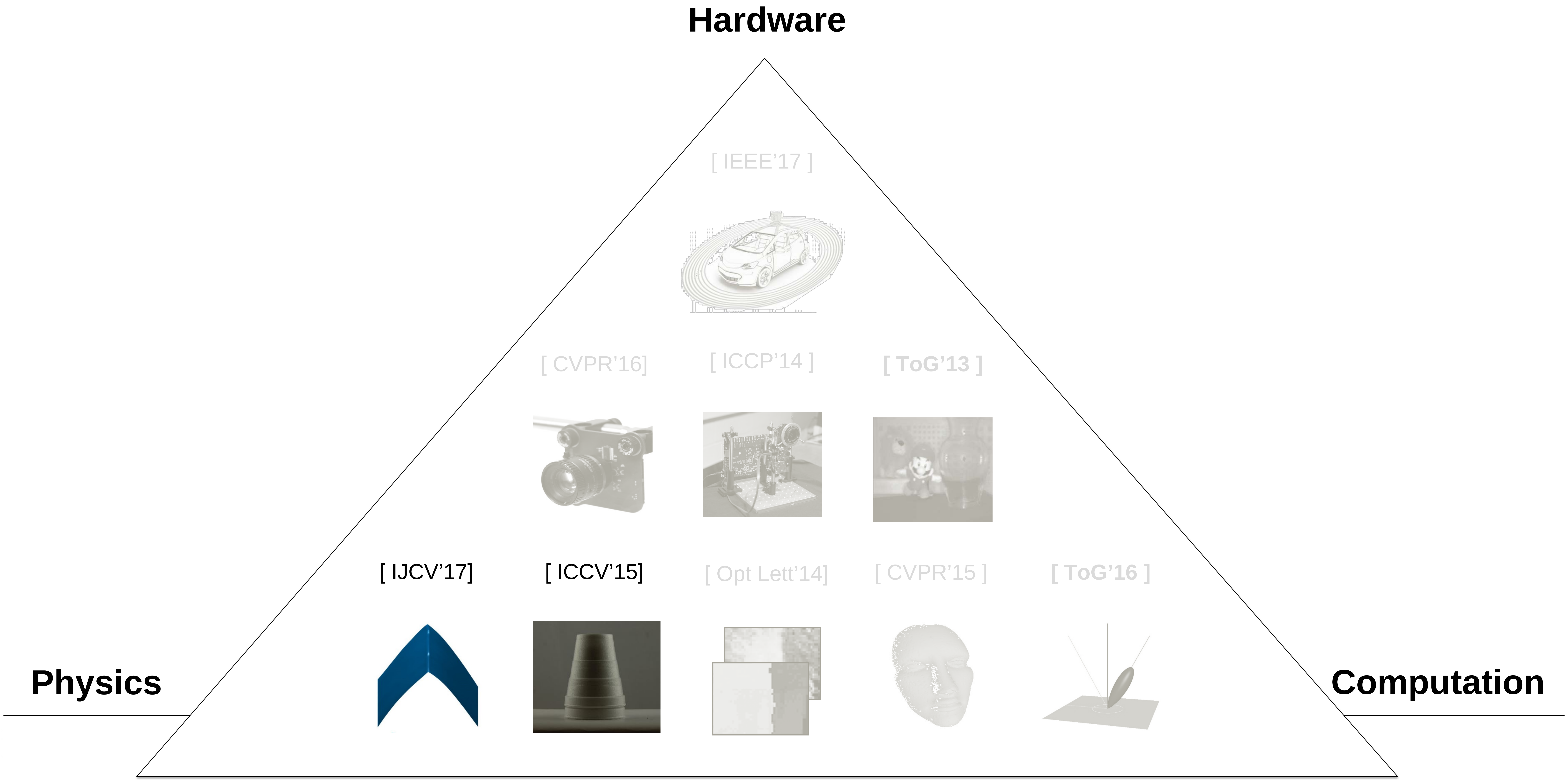
Fine structures for Bioengineering

Smartphone 3D Vision

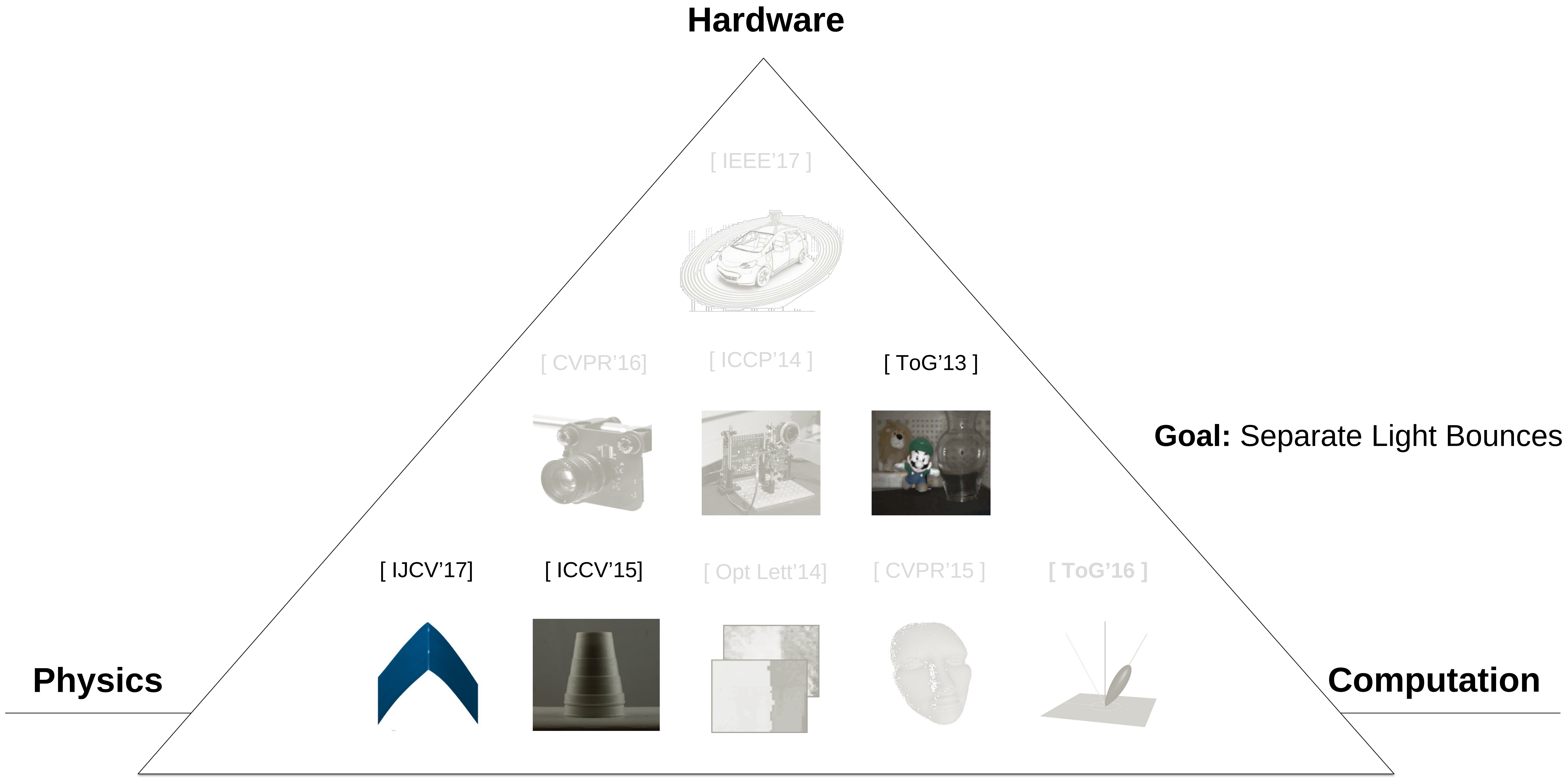


Long-range 3D sensing

Physics, Hardware, and Computation

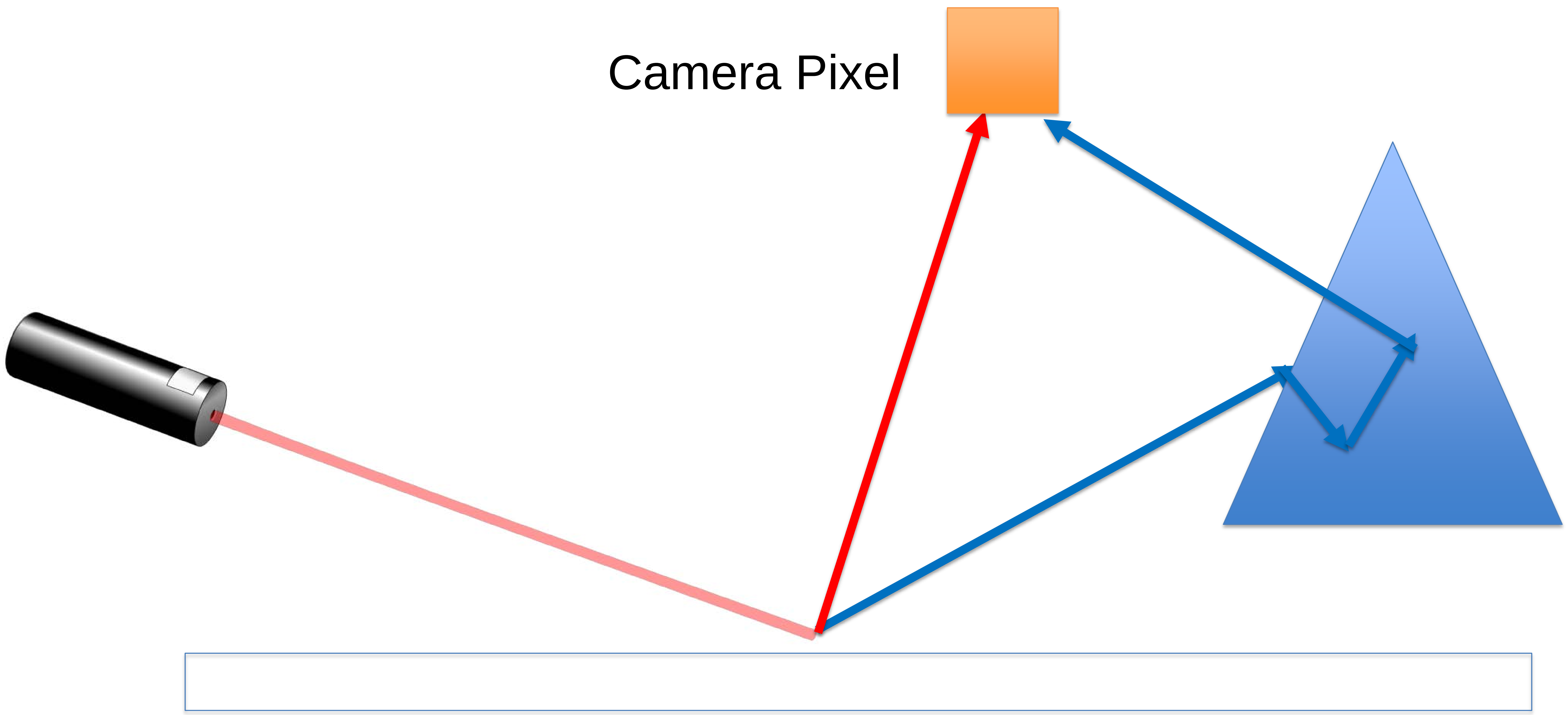


Physics, Hardware, and Computation



MIT Tech Review

Separating Multiple Bounces of Light



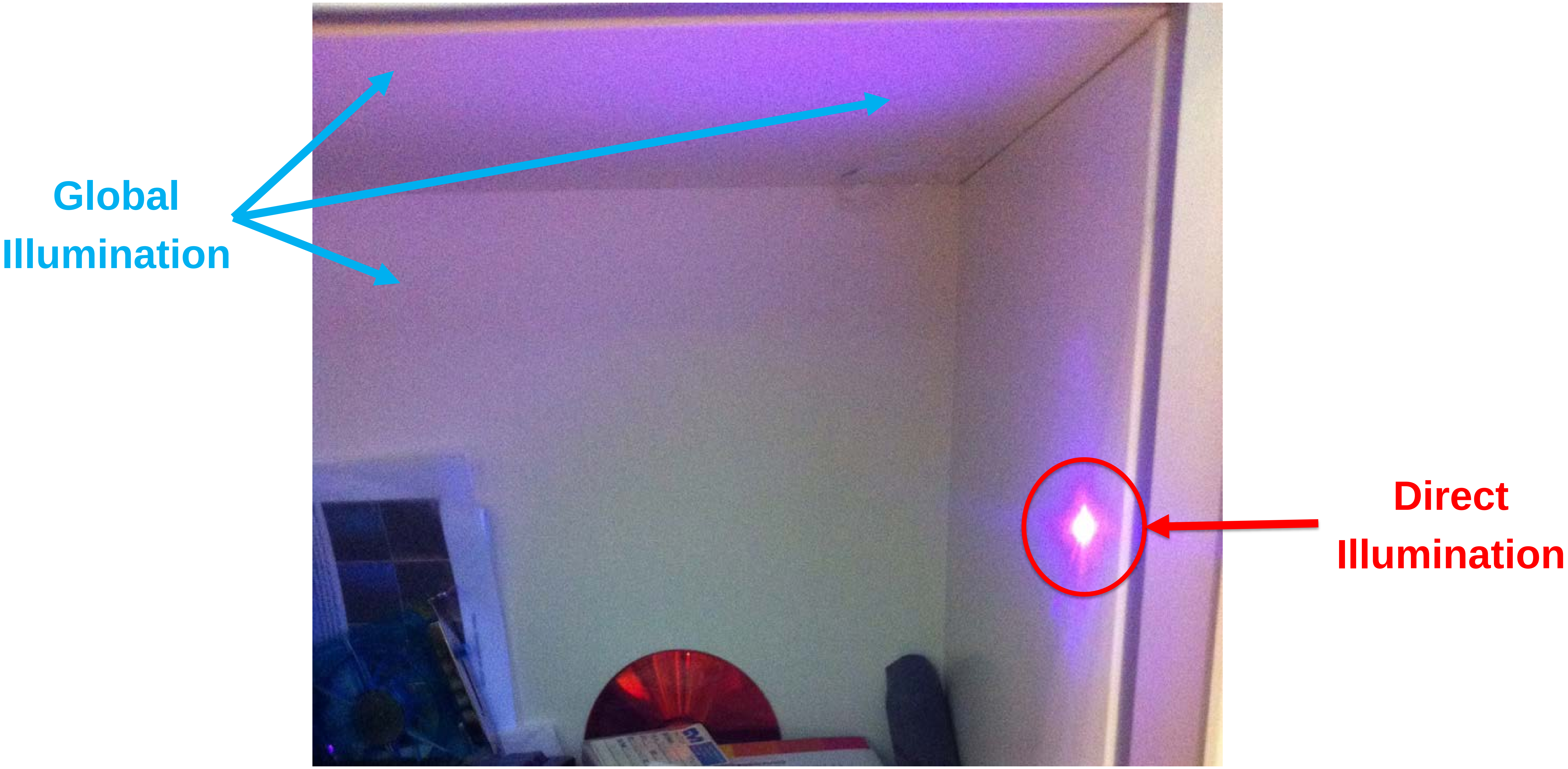
This pixel measures both blue and red paths. Can we split the light?

Ill-posed Problem

$$I = I_A + I_B$$

So the problem needs to be constrained

Previous Work: Smoothness in Space

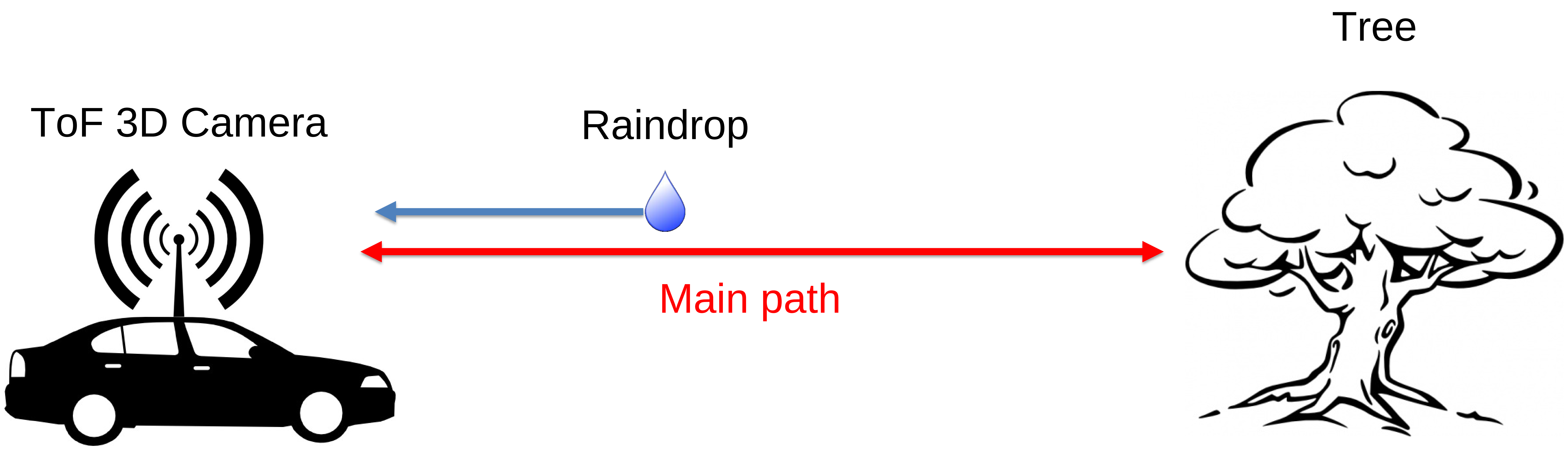


Nayar, Krishnan, Grossberg, Raskar SIGGRAPH 2006

Smoothness a Limiting Assumption

“If a laser beam hits a water drop… the lidar can think it’s an object and slam on the brakes”

– Director of CMU autonomous driving lab



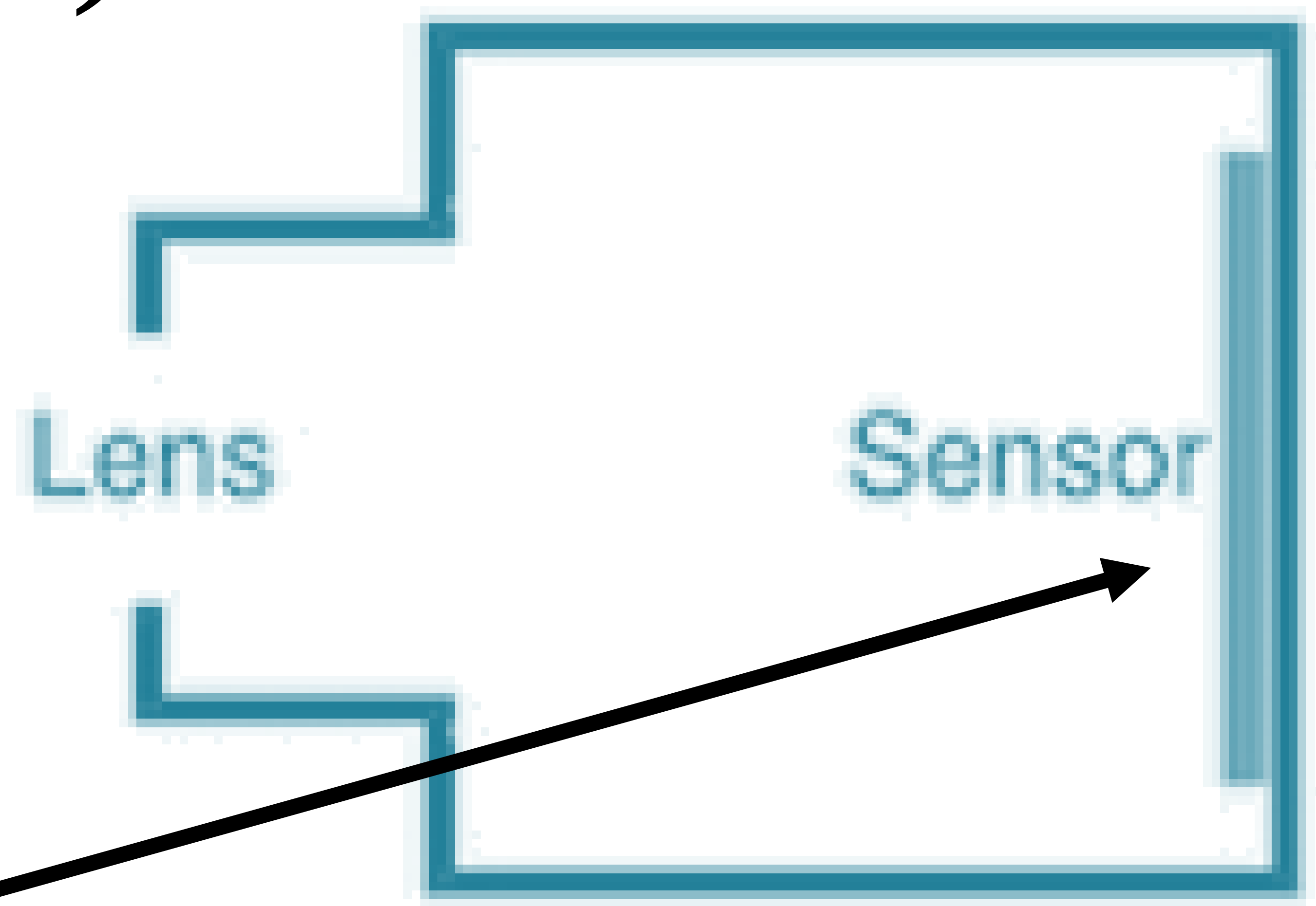
Multipath Interference for CW emitters

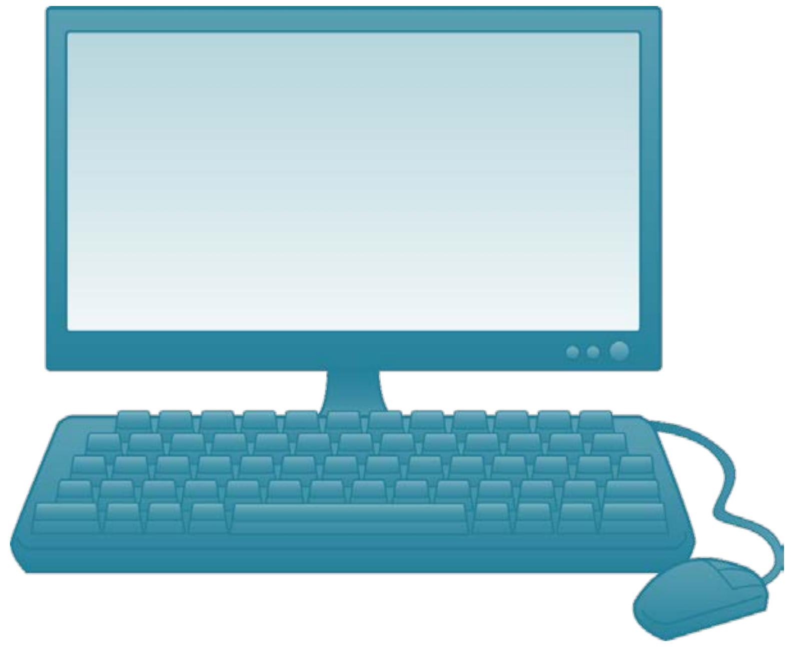
Generalizing the Camera to Systems Thinking

7D Brightness Sampling

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

Measure “t”





Sparse Approximation

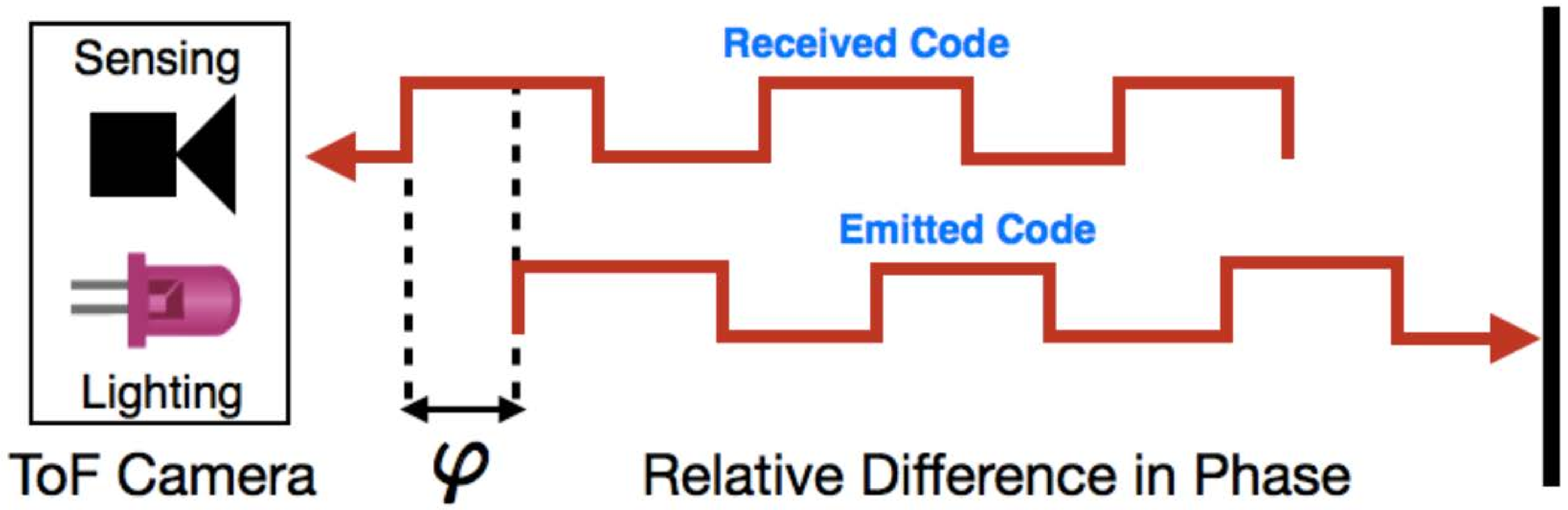
ToF Imaging Sensor

Overview of Time of Flight

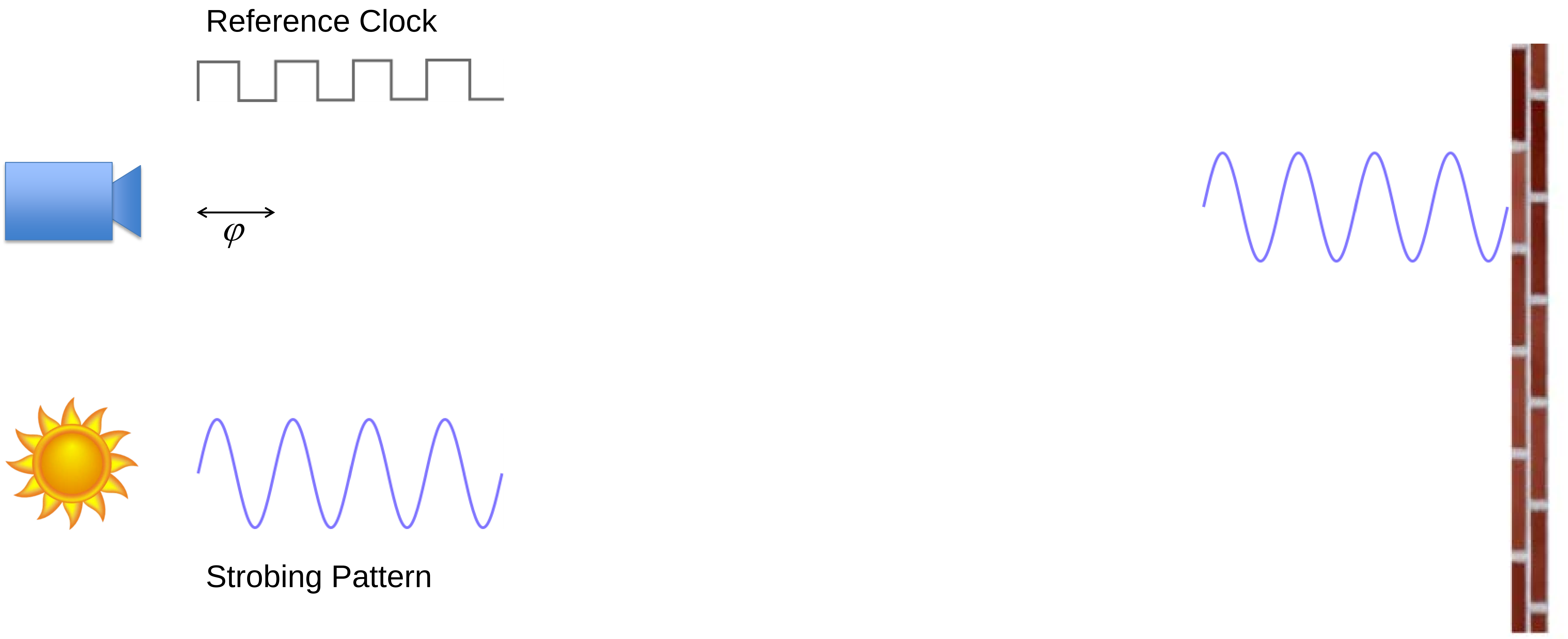
$$d = vt \qquad v = 3 * 10^8\ m/s$$

So, we need a camera to measure time delay.

Example: Microsoft Kinect (ver 2)

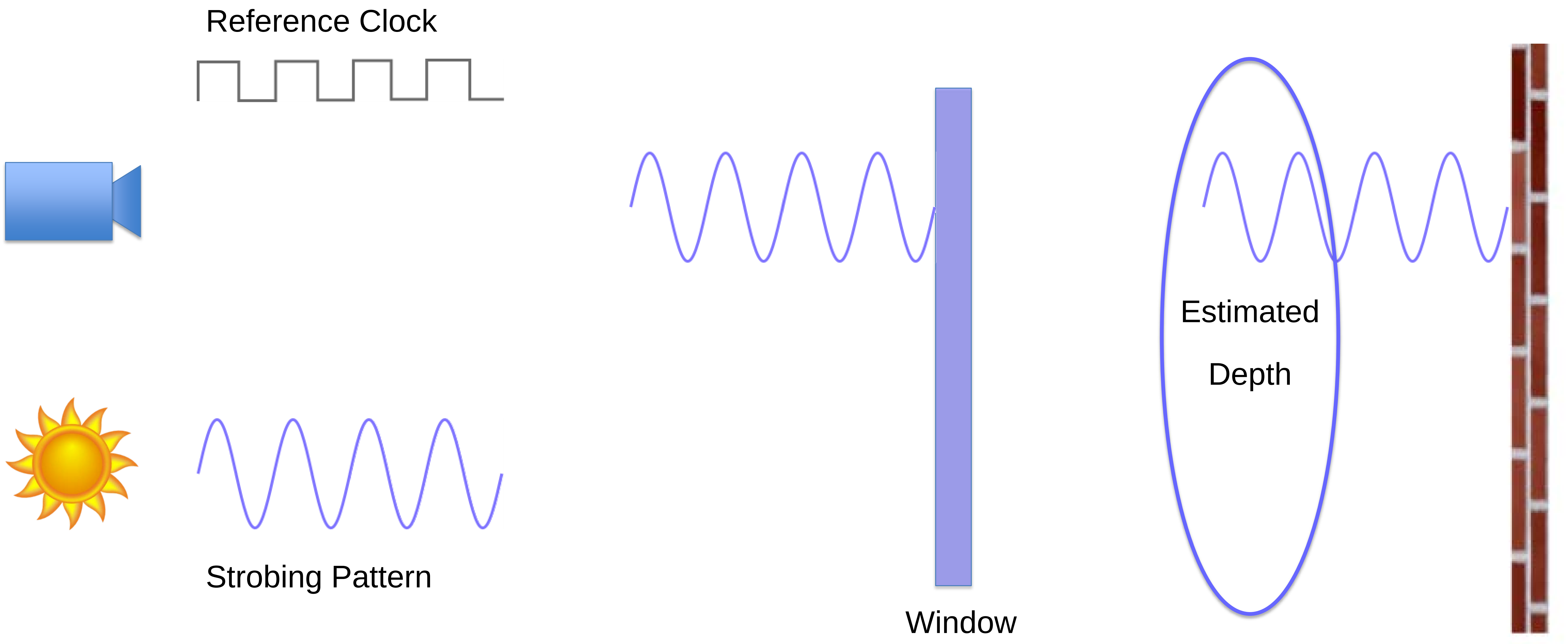


$$z = \frac{c\Phi}{2\pi f_\omega}, \quad c \approx 3\times 10^8\,\mathrm{m/s}$$



Recall: Strobing Pattern is MHz (nanosecond periods)

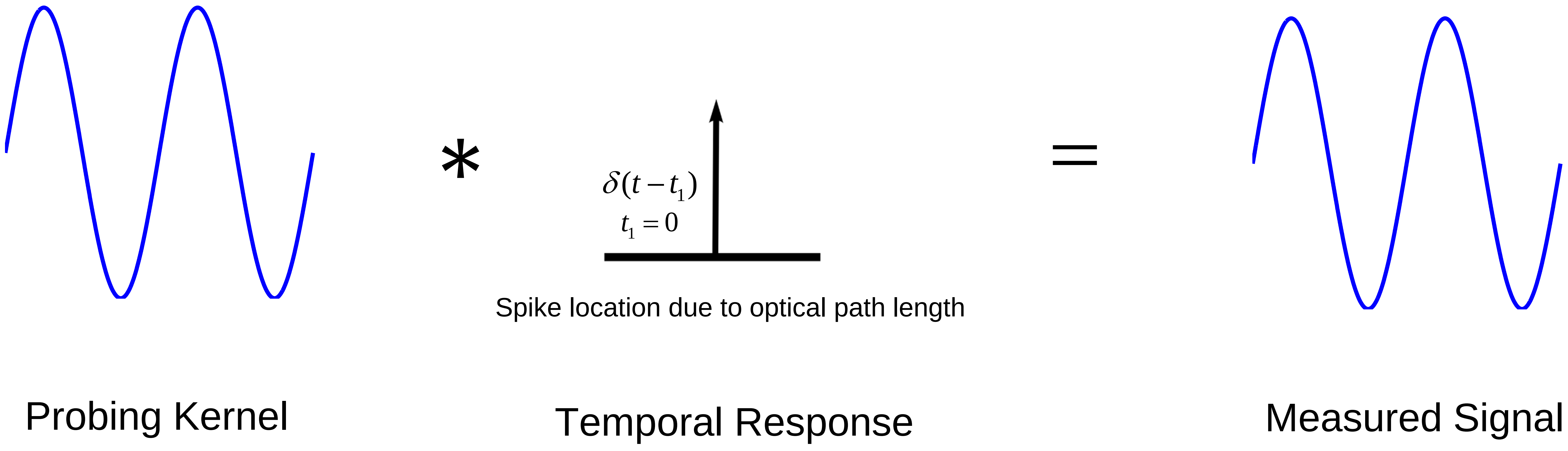
Interference



Measure one Phase that is in between (mod 2 \pi)

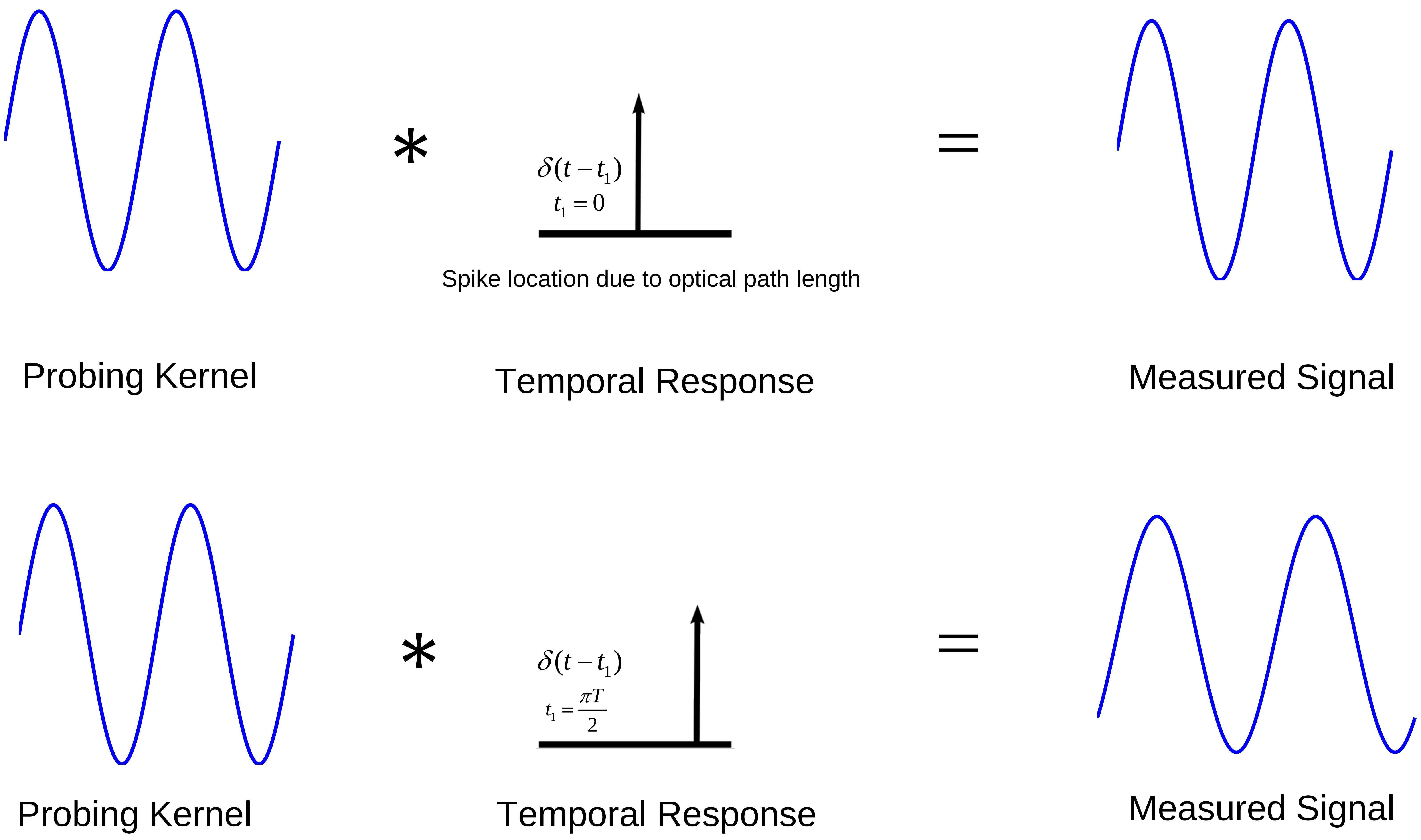
Recall: Strobing Pattern is MHz (nanosecond periods)

Each Pixel Becomes a Linear Time-invariant System



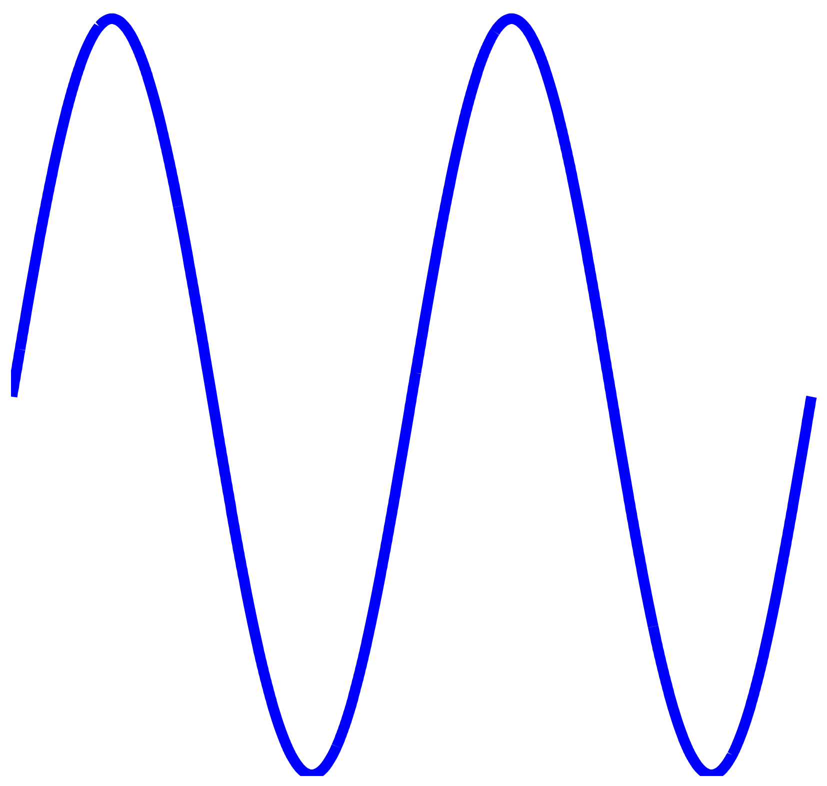
Kadambi et al. ACM Trans. Graphics 2013

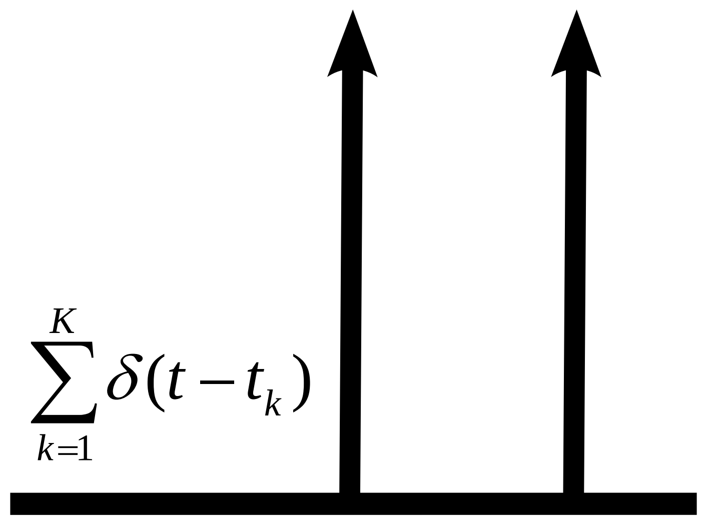
Each Pixel Becomes a Linear Time-invariant System



Kadambi et al. ACM Trans. Graphics 2013

Multipath Interference



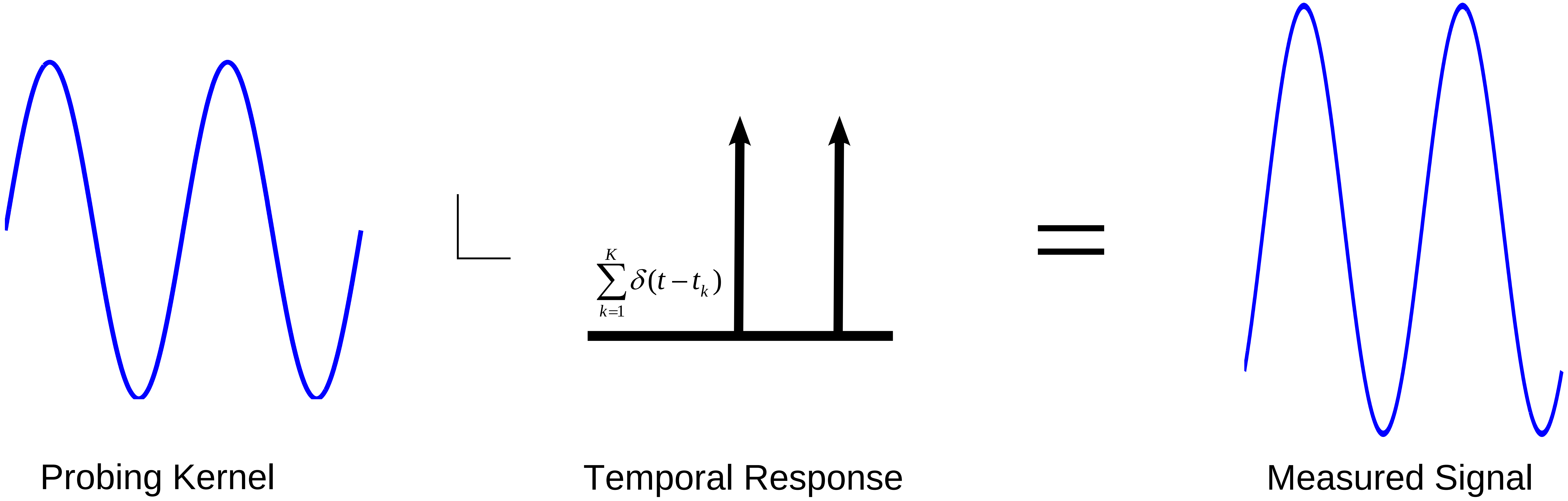


=

Probing Kernel

Temporal Response

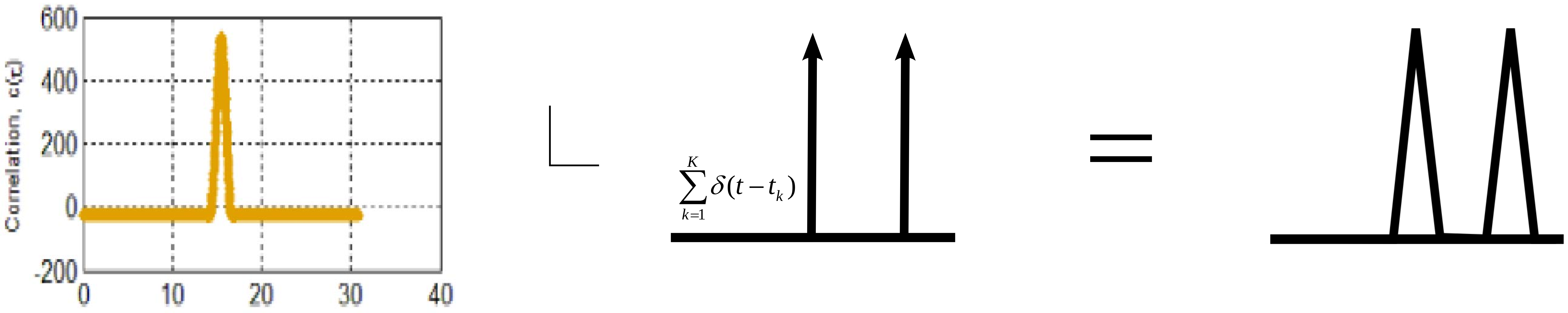
Multipath Interference



Problem of **unicity**: sum of two sines at same frequency but different phase is a single sine wave at a mixed phase

Kadambi et al. ACM Trans. Graphics 2013

Multipath Interference



Probing Kernel

Temporal Response

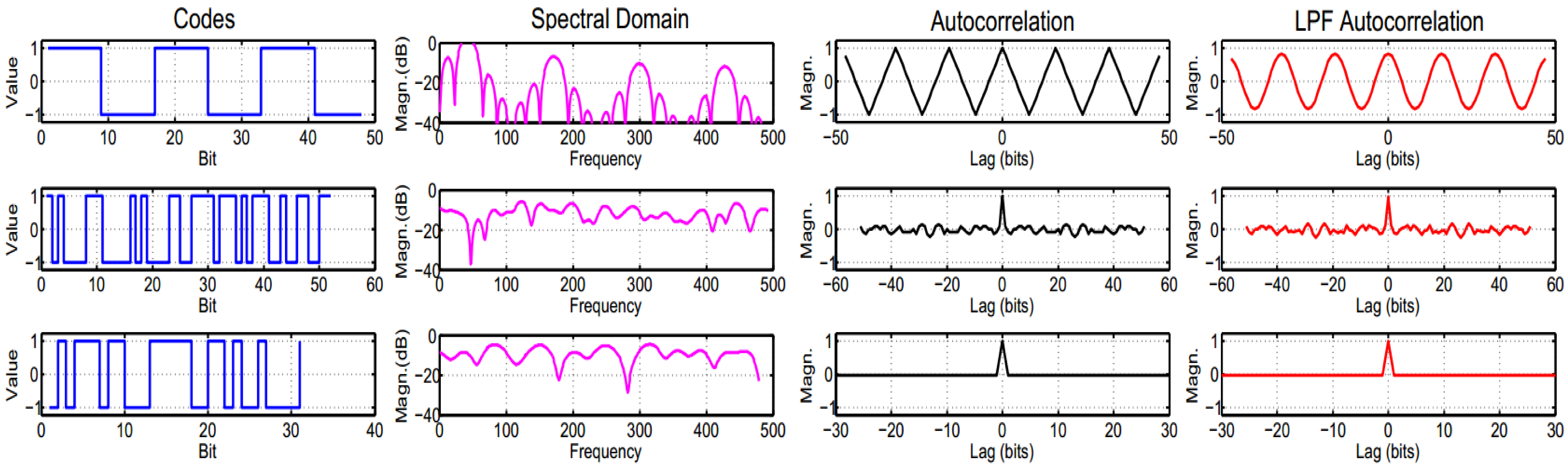
Measured Signal

This is a cartoon

Kadambi et al. ACM Trans. Graphics 2013

What AM modulation is optimal?

Imaging device should be "spread spectrum" → term from telecommunications



Kadambi et al. ACM Trans. Graphics 2013

Prior-based Orthogonal Matching Pursuit

We explore the matching pursuit class of problems which approximate the original l0 program:

$$\arg\min_{\vec{x}} \left\| \vec{y} - \mathbf{H}\vec{x} \right\|_2^2 + \lambda \left\| \vec{x} \right\|_0^2$$

We make two modifications here:
1. Non-negativity constraints (Bruckstein, Elad, and Zibulevsky, ISCCSP 2008).
2. Proximity constraints

Nonnegativity

a) Consider only positive projections when searching for the next atom.
b) When updating the residual use a solver to impose positivity on the coefficients.

Proximity Constraints

$$p(\vec{x}) \in \mathcal{N}(\vec{x};\mu,\sigma)$$

$$\arg\max_{\vec{x}} \, p(\vec{x} \mid \vec{y}) \rightarrow \arg\max_{\vec{x}} \, \underbrace{p(\vec{y} \mid \vec{x})}_{\text{Likelihood}} \, \underbrace{p(\vec{x})}_{\text{Prior}}$$

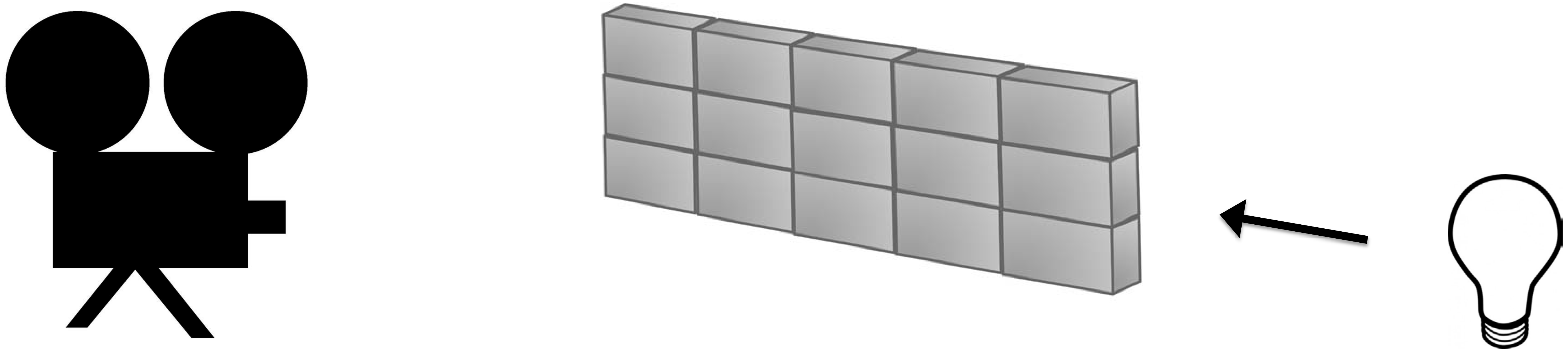
Theory→ Instantiation

Nanophotography: AM modulation with customizable signal encoding

Imaging at 8 Billion Effective FPS

Kadambi et al. ACM Trans. Graphics 2013

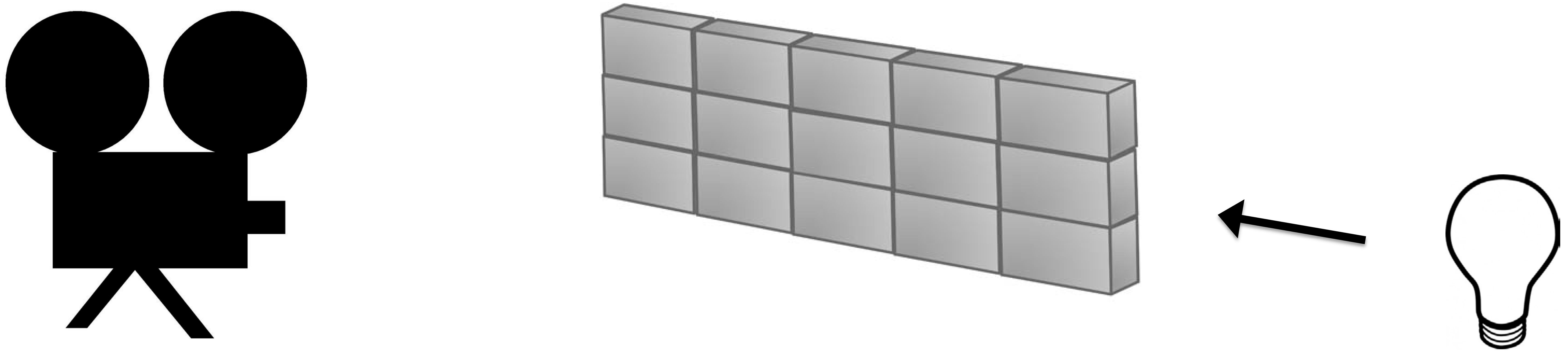
Imaging at 8 Billion Effective FPS



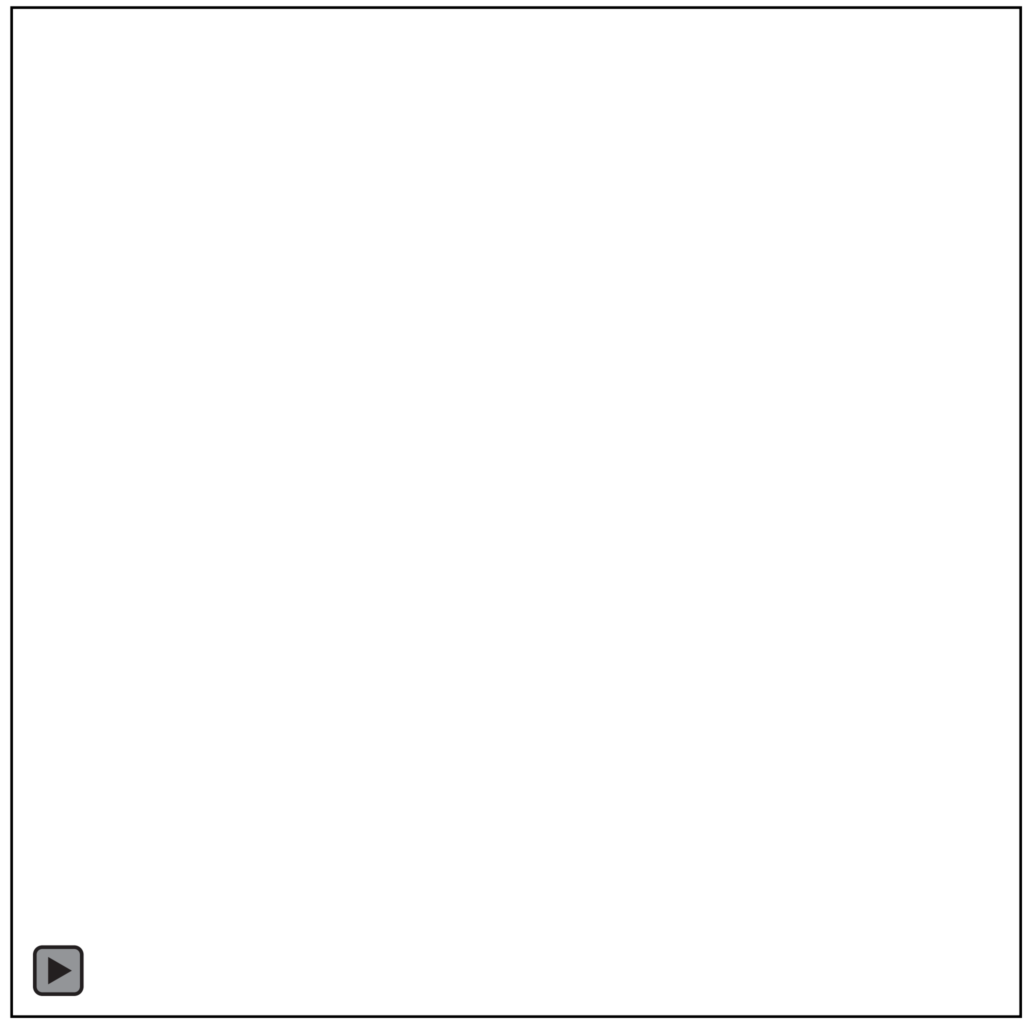
Nanocamera

Kadambi et al. ACM Trans. Graphics 2013

Imaging at 8 Billion Effective FPS

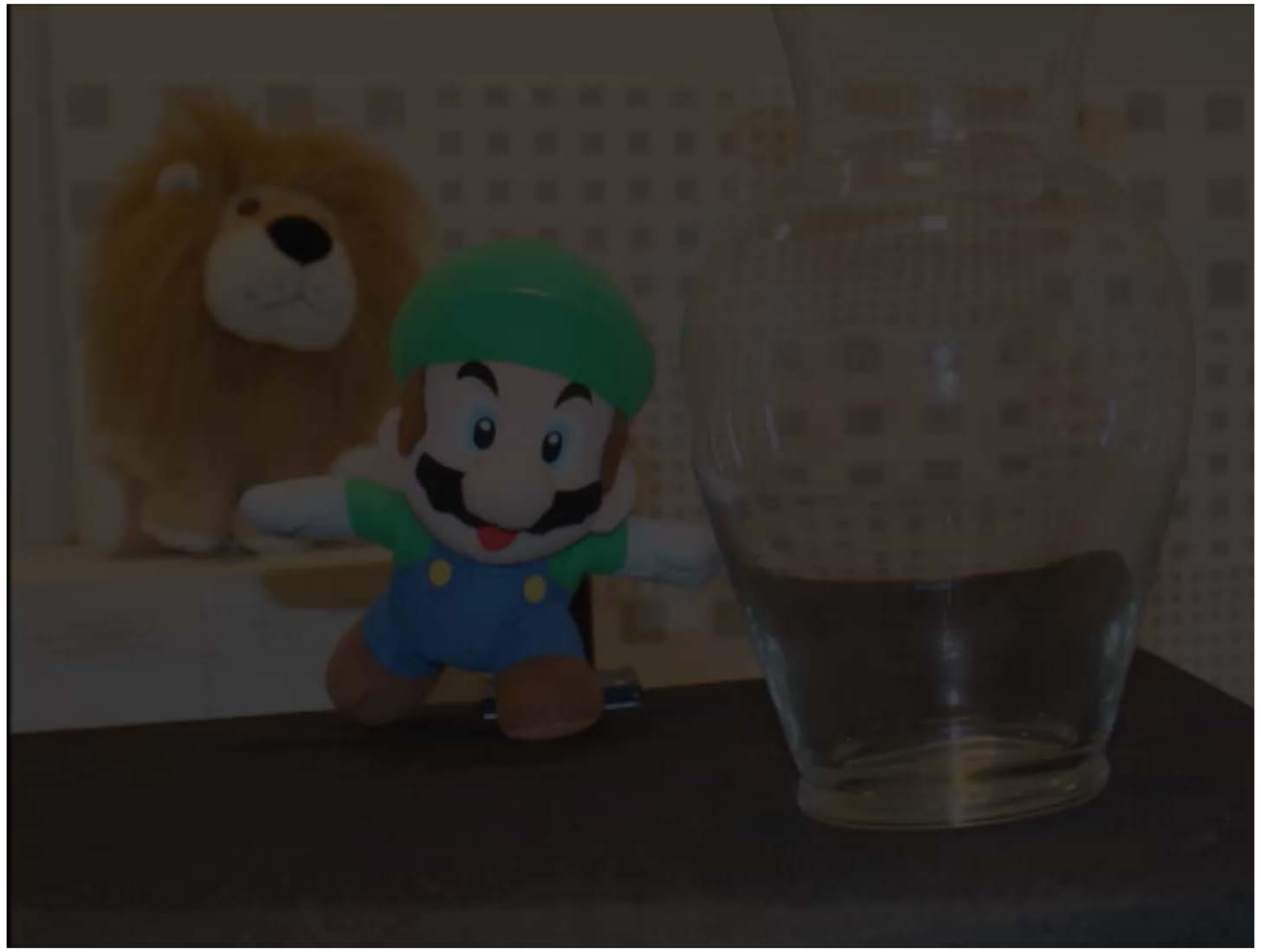


Nanocamera



Captured Data

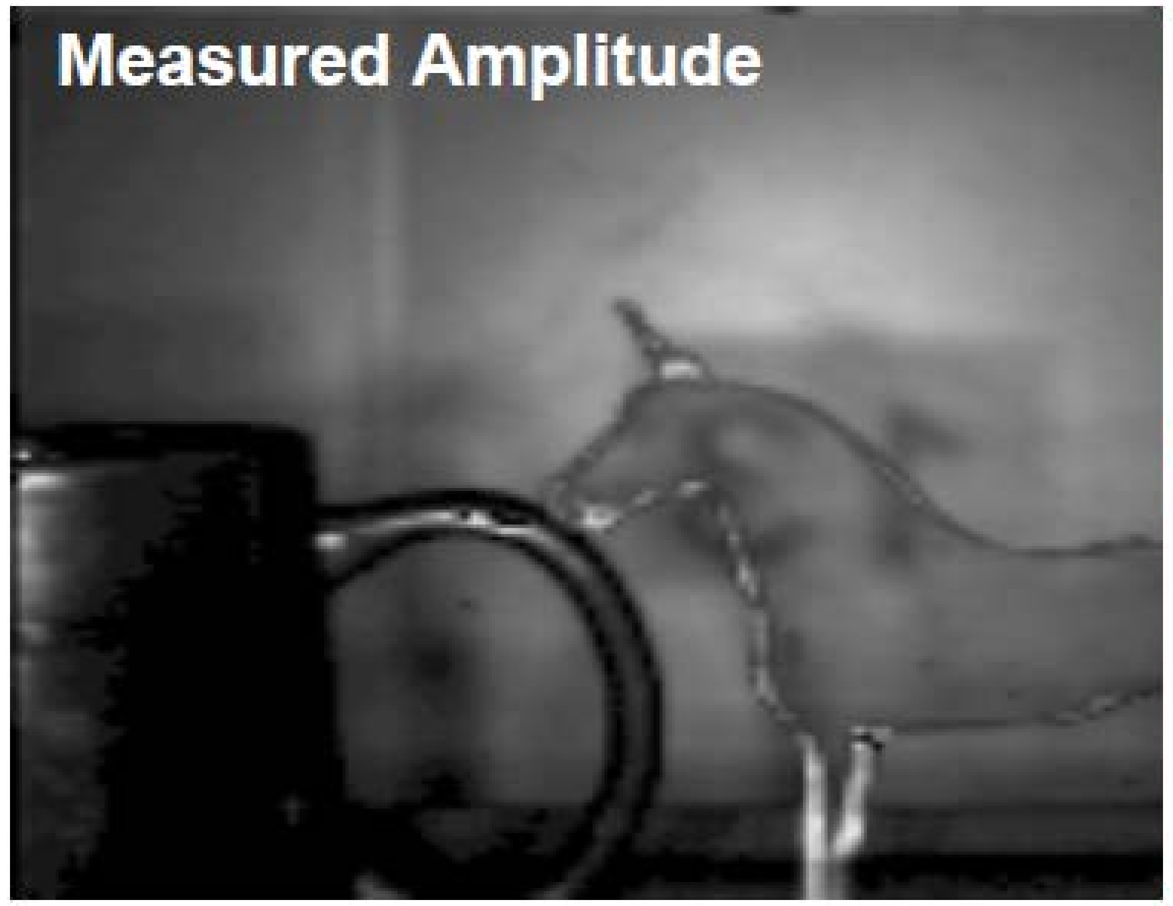
Kadambi et al. ACM Trans. Graphics 2013



[Kadambi et al. SIGGRAPHA13]

Note non-smooth multipath (e.g. Specularities)

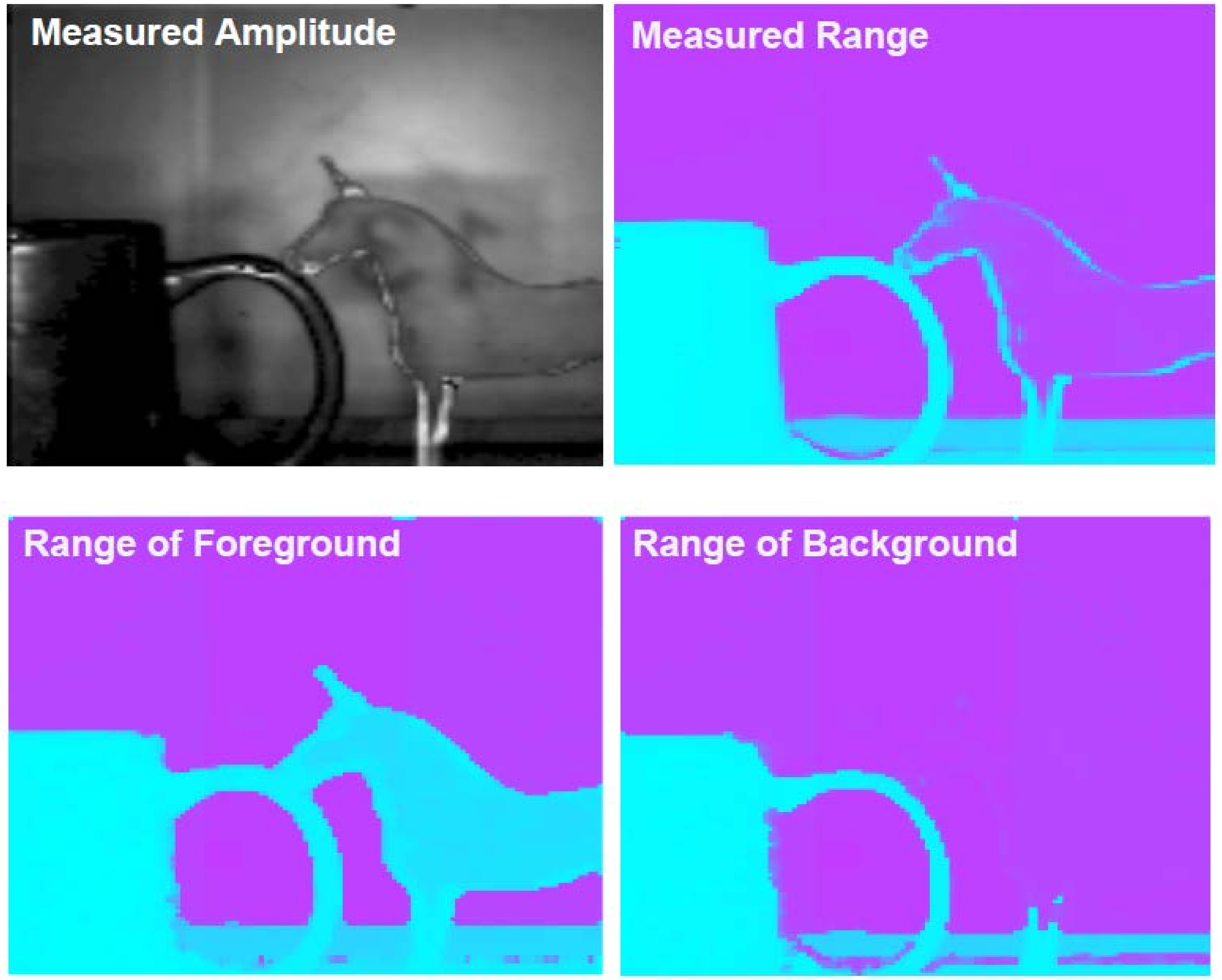
Tool Application: 3D Imaging in Multipath Environments



Contribution: Multi-bounce 3D imaging [Kadambi et al. SIGGRAPH Asia 2013]

Transient imaging tackling Edge Cases in Imaging

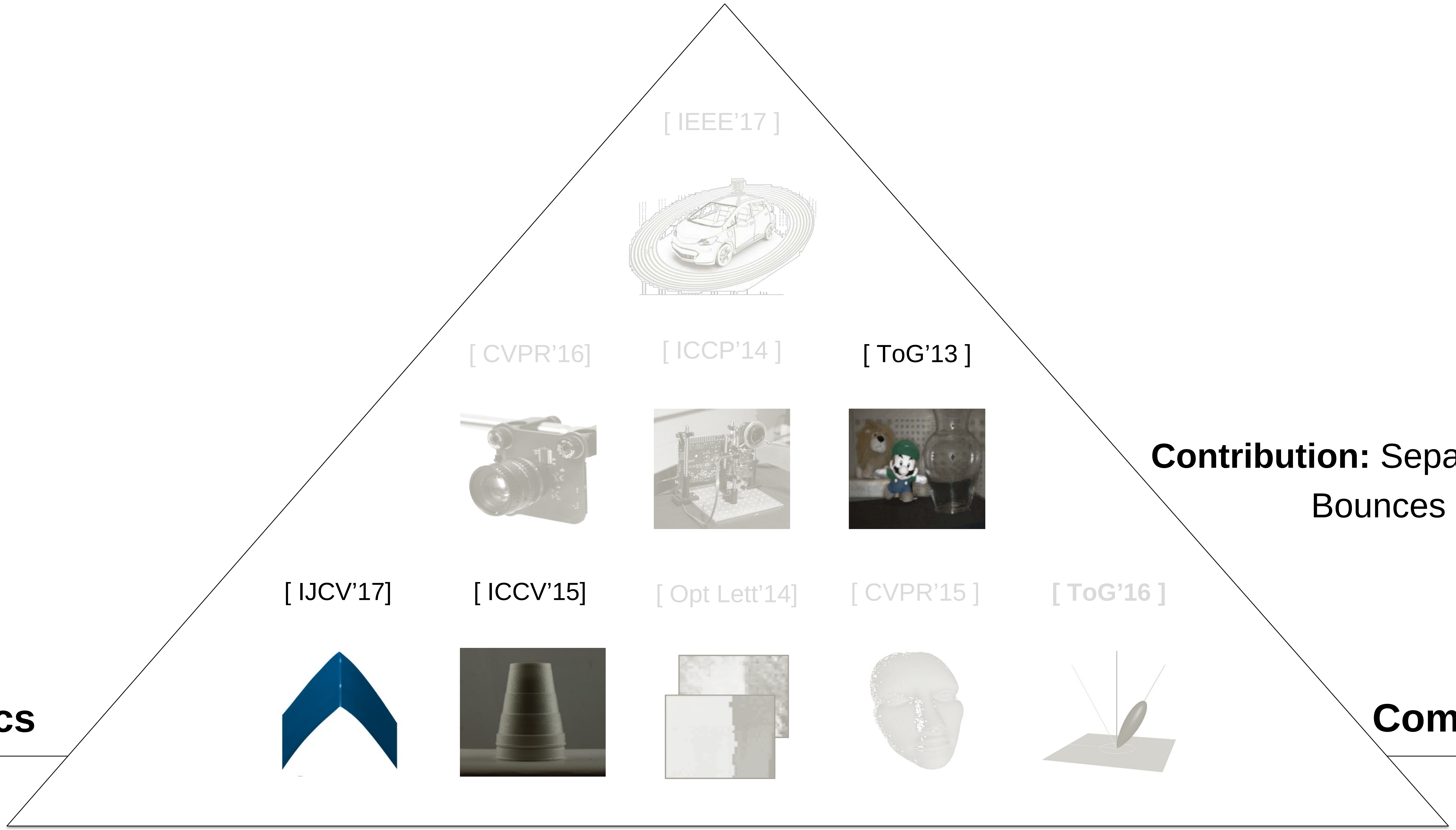
3D Shape of Translucent Objects



Seeing around Corners

Physics, Hardware, and Computation

Hardware

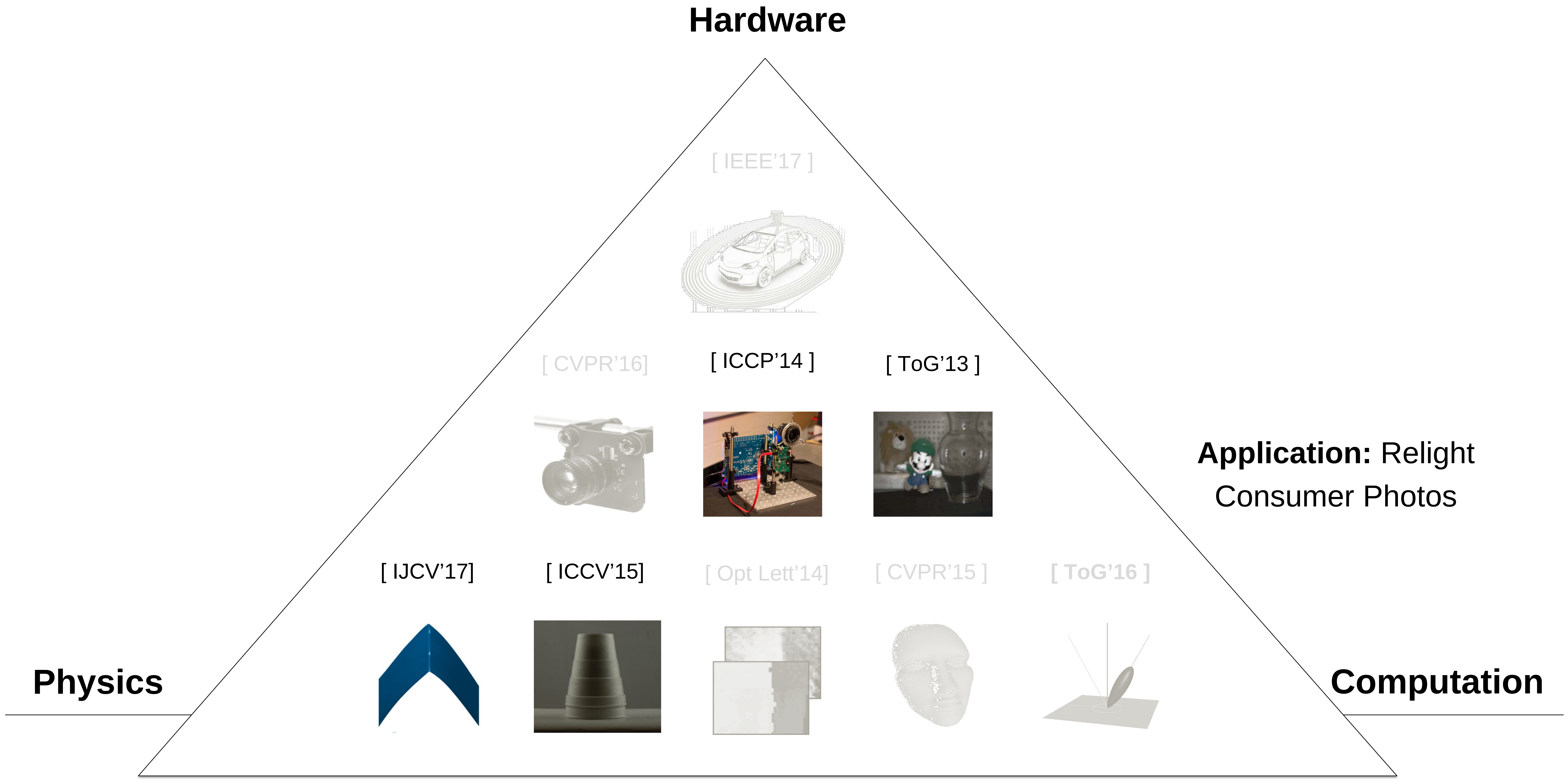


Contribution: Separate Light Bounces

Physics

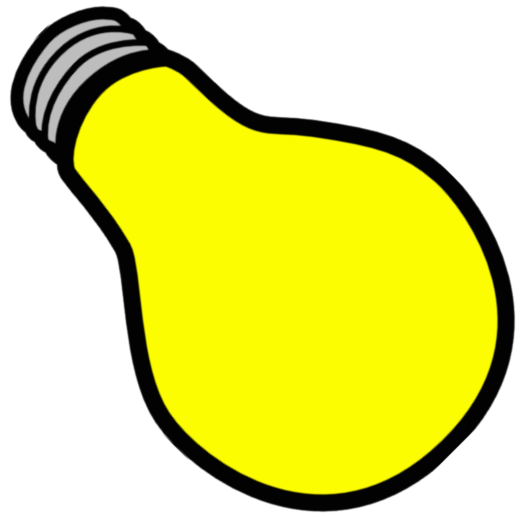
Computation

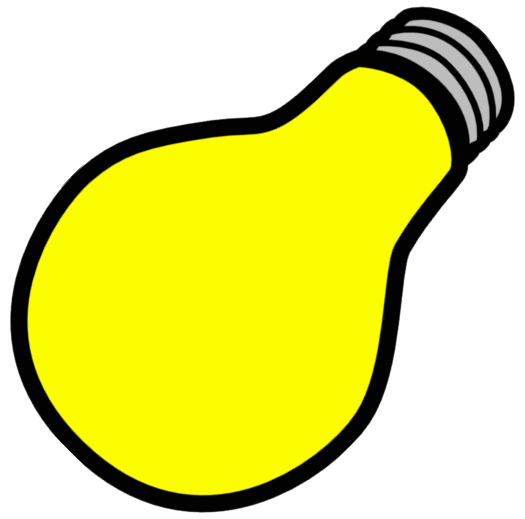
Physics, Hardware, and Computation



Tool Application: Multi-Light Separation

A



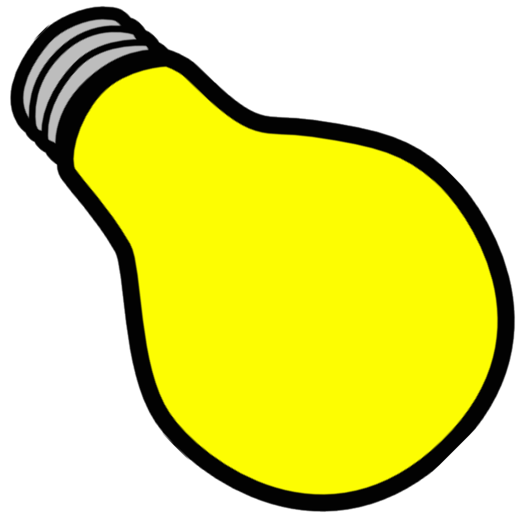


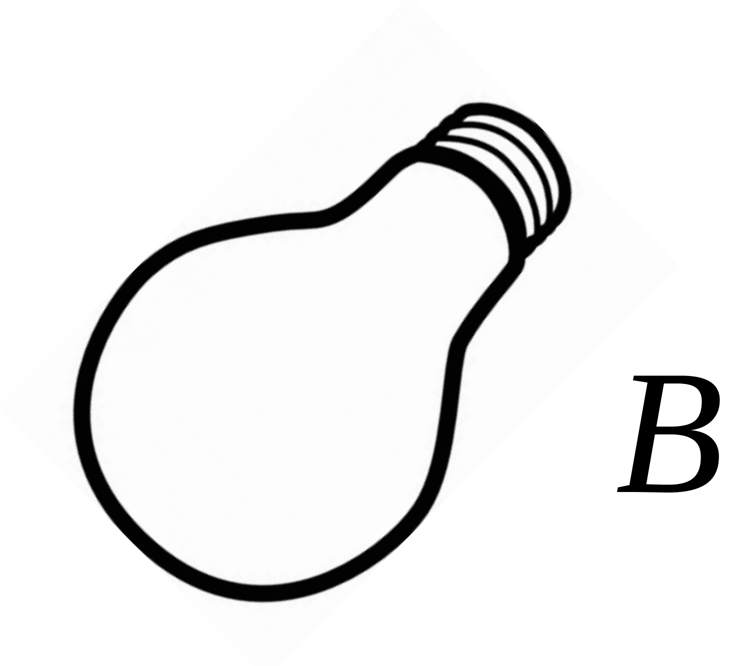
Scene

Tool Application: Multi-Light Separation

Naïve Approach

A





B

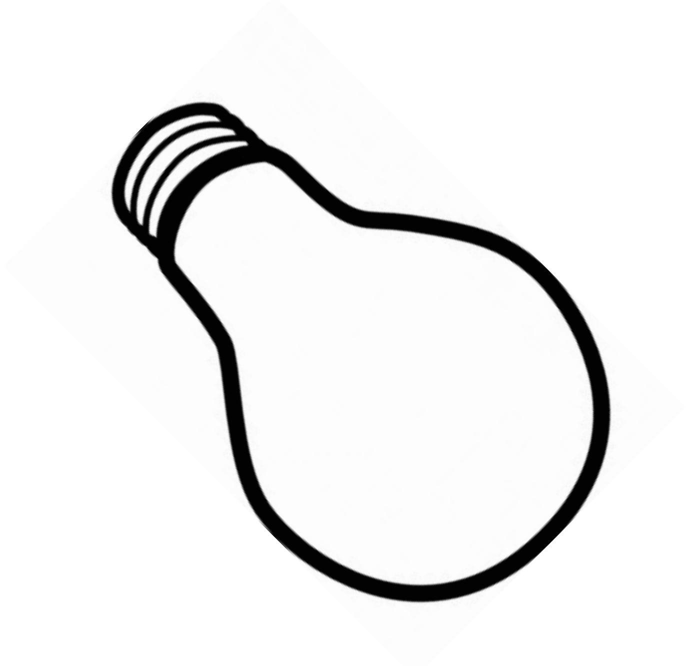
$$I = I_A$$

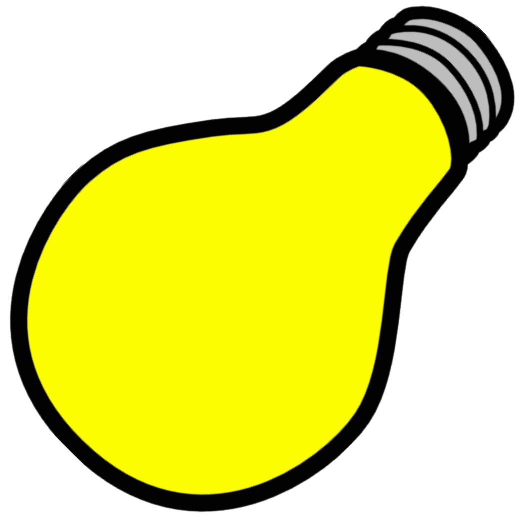
Scene

Tool Application: Multi-Light Separation

Naïve Approach

A



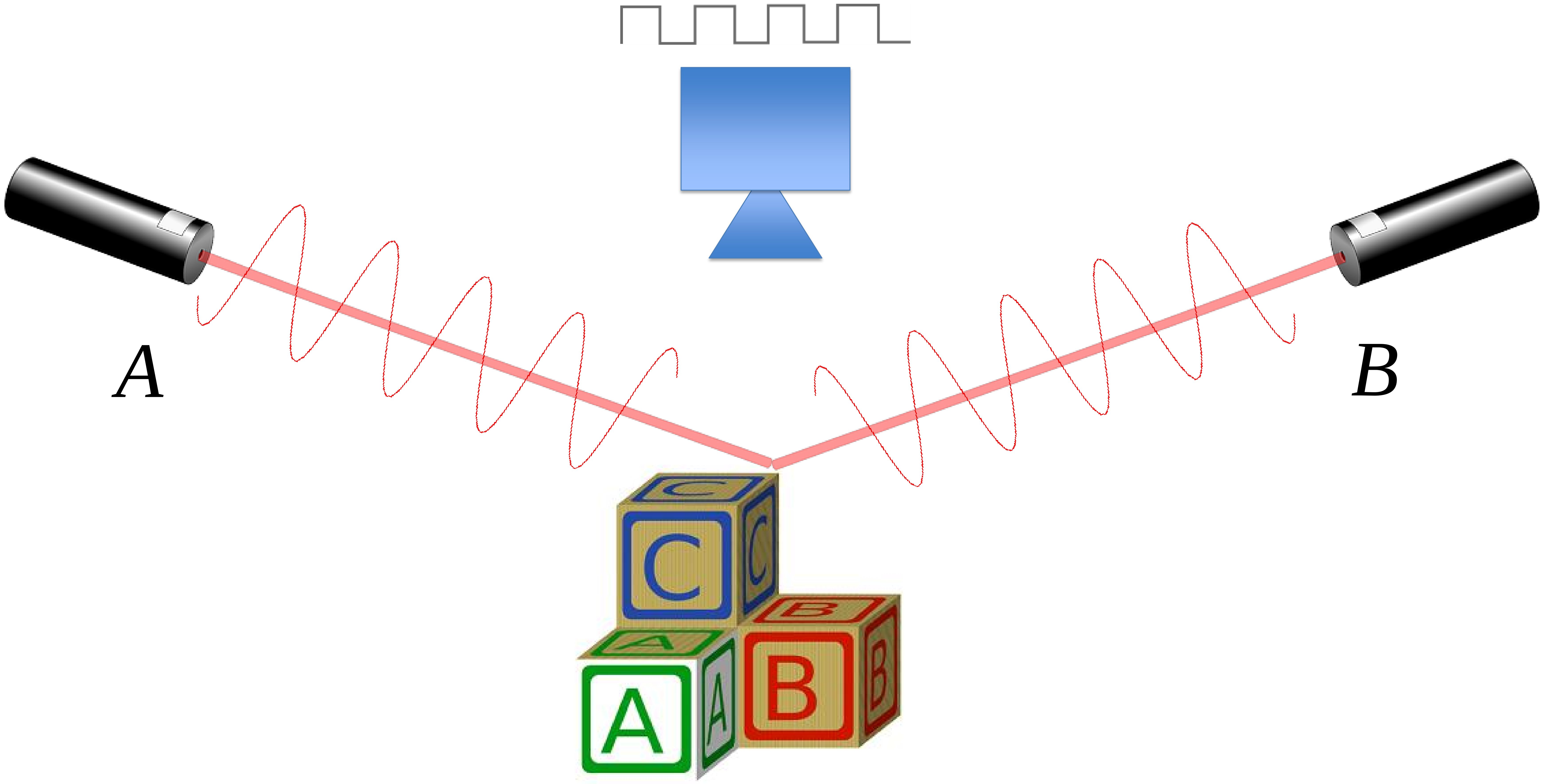


B

Scene

$$I = I_B$$

Tool Application: Multi-Light Separation



Scene

Sense of “Optimal Codes” in context of SNR and power bandwidth

Tool Application: Multi-Light Separation

Kadambi et al. IEEE ICCP 2014

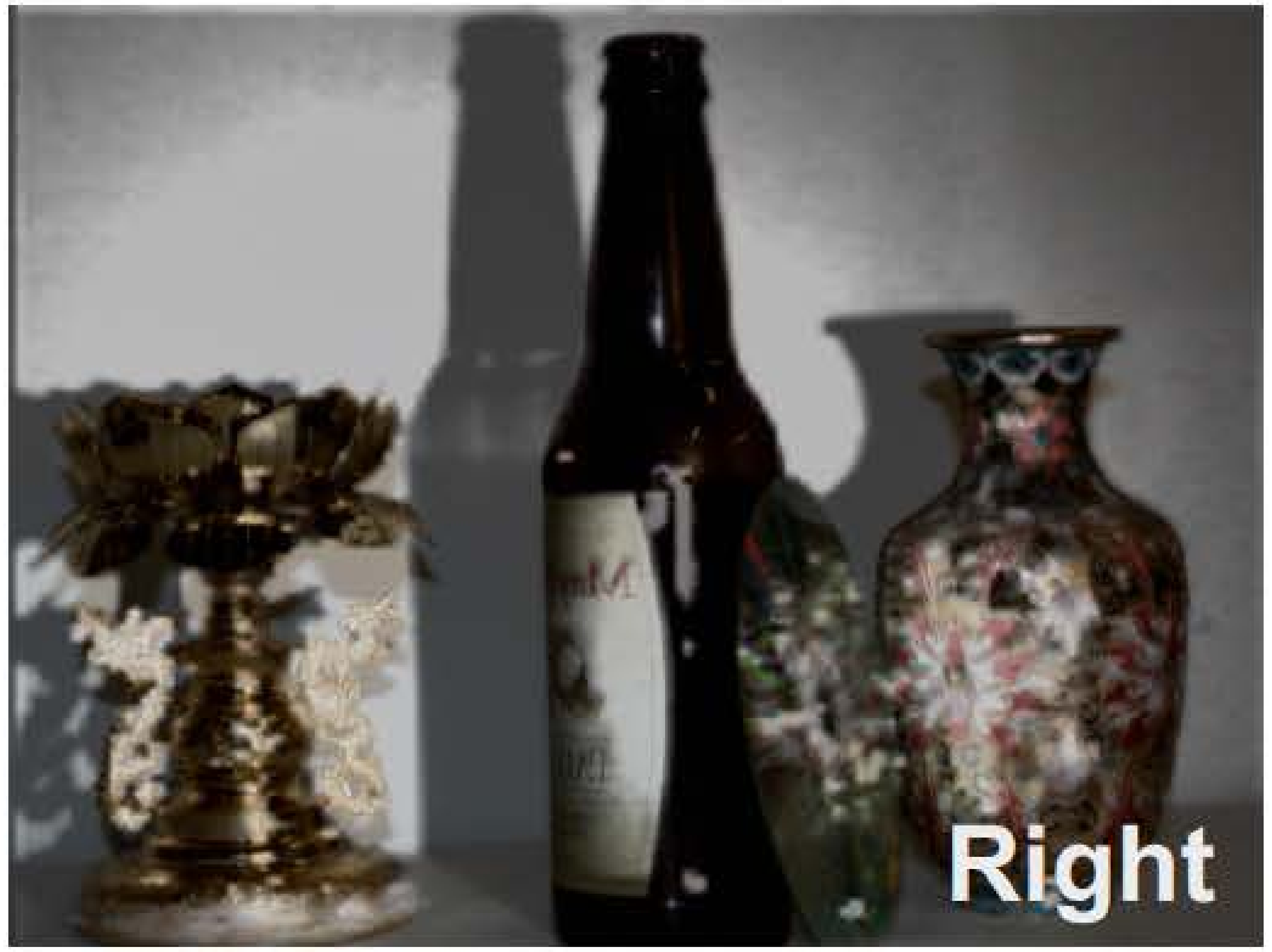
Tool Application: Multi-Light Separation

Tool Application: Multi-Light Separation

Tool Application: Multi-Light Separation

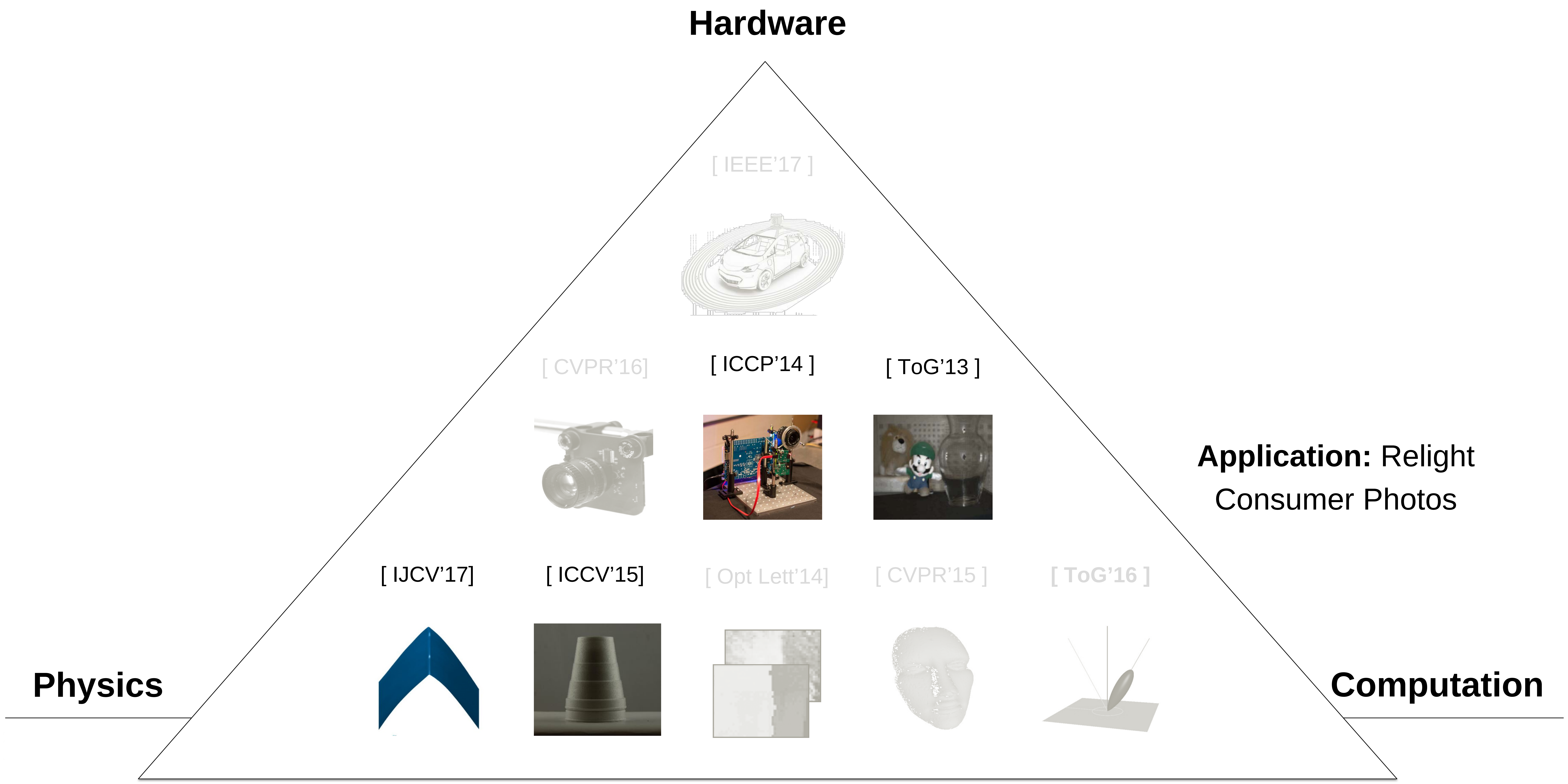
Kadambi et al. IEEE ICCP 2014

Tool Application: Multi-Light Separation

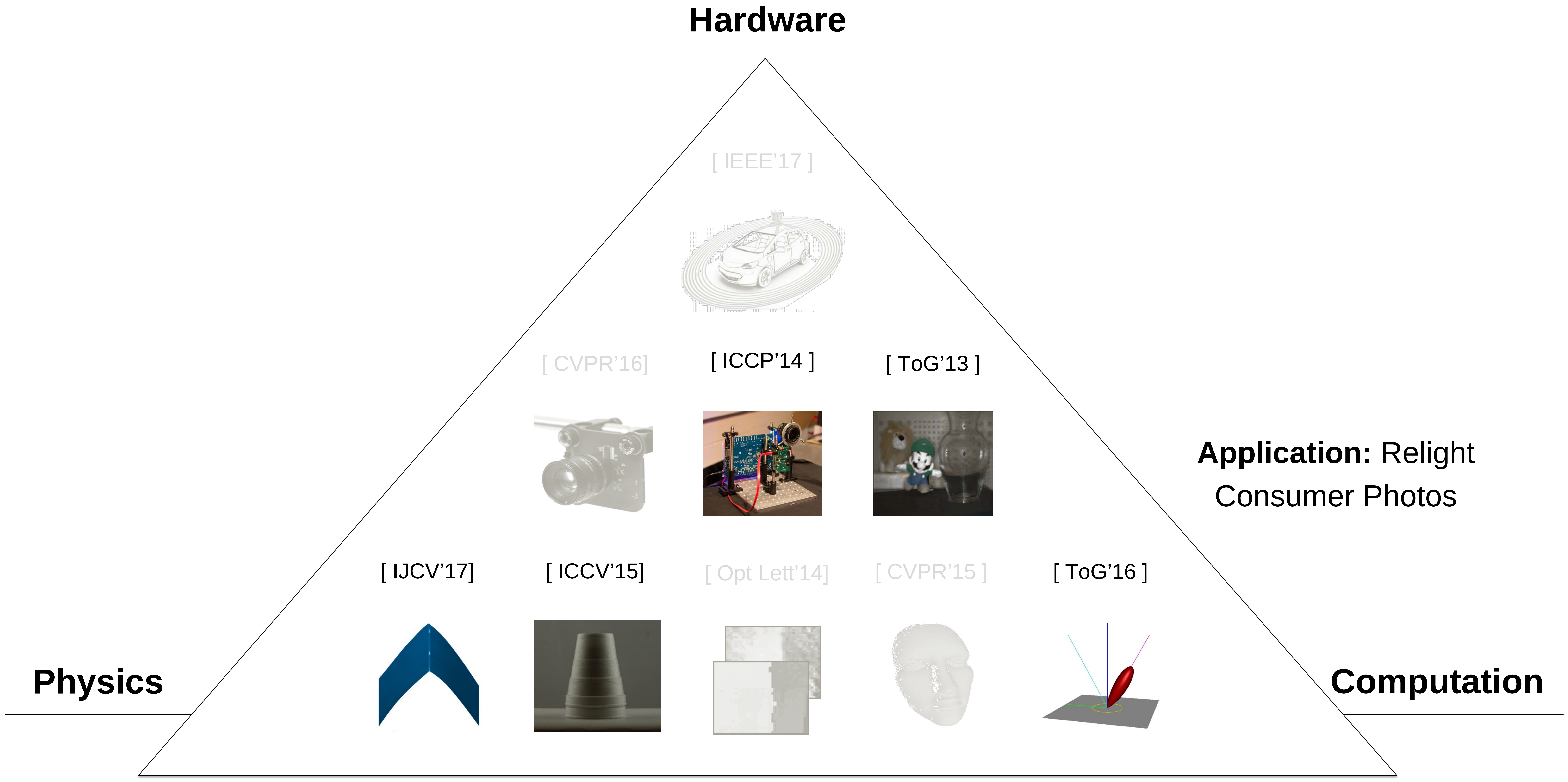


Kadambi et al. IEEE ICCP 2014

Physics, Hardware, and Computation

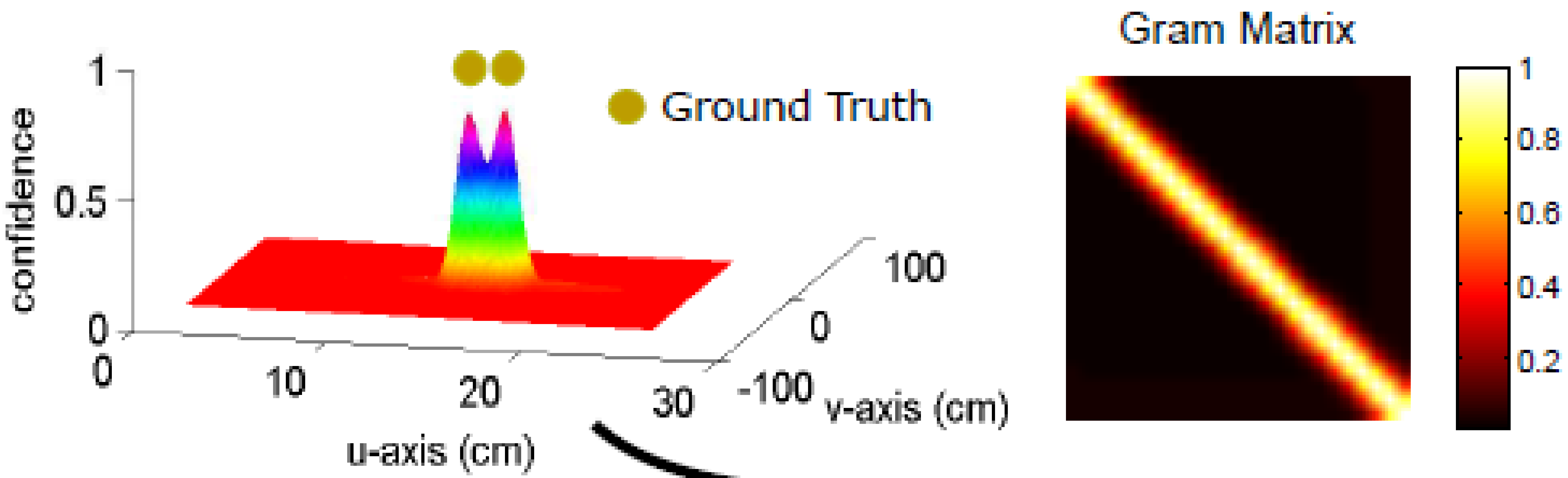


Physics, Hardware, and Computation

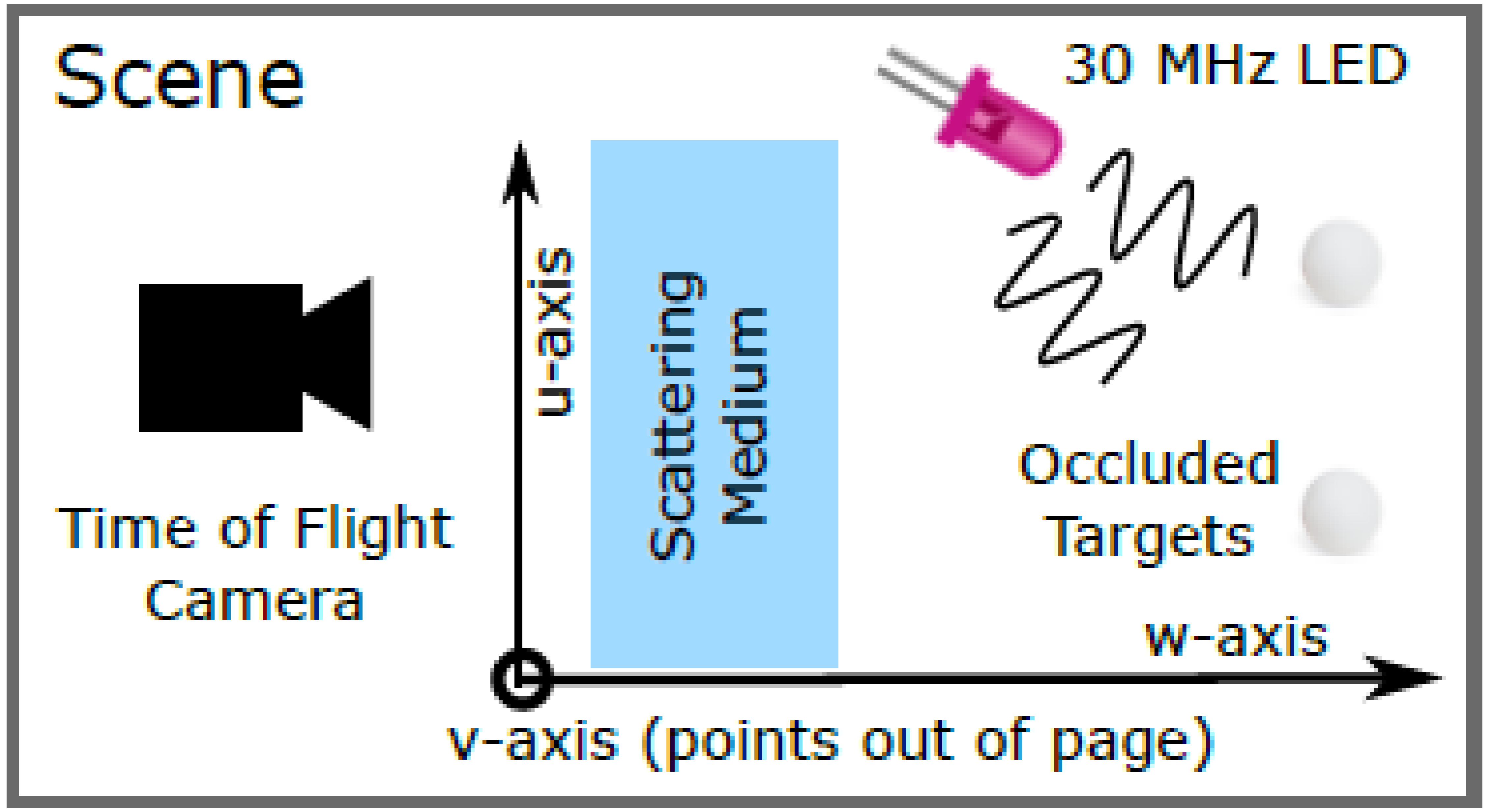


Scattering is not always discrete

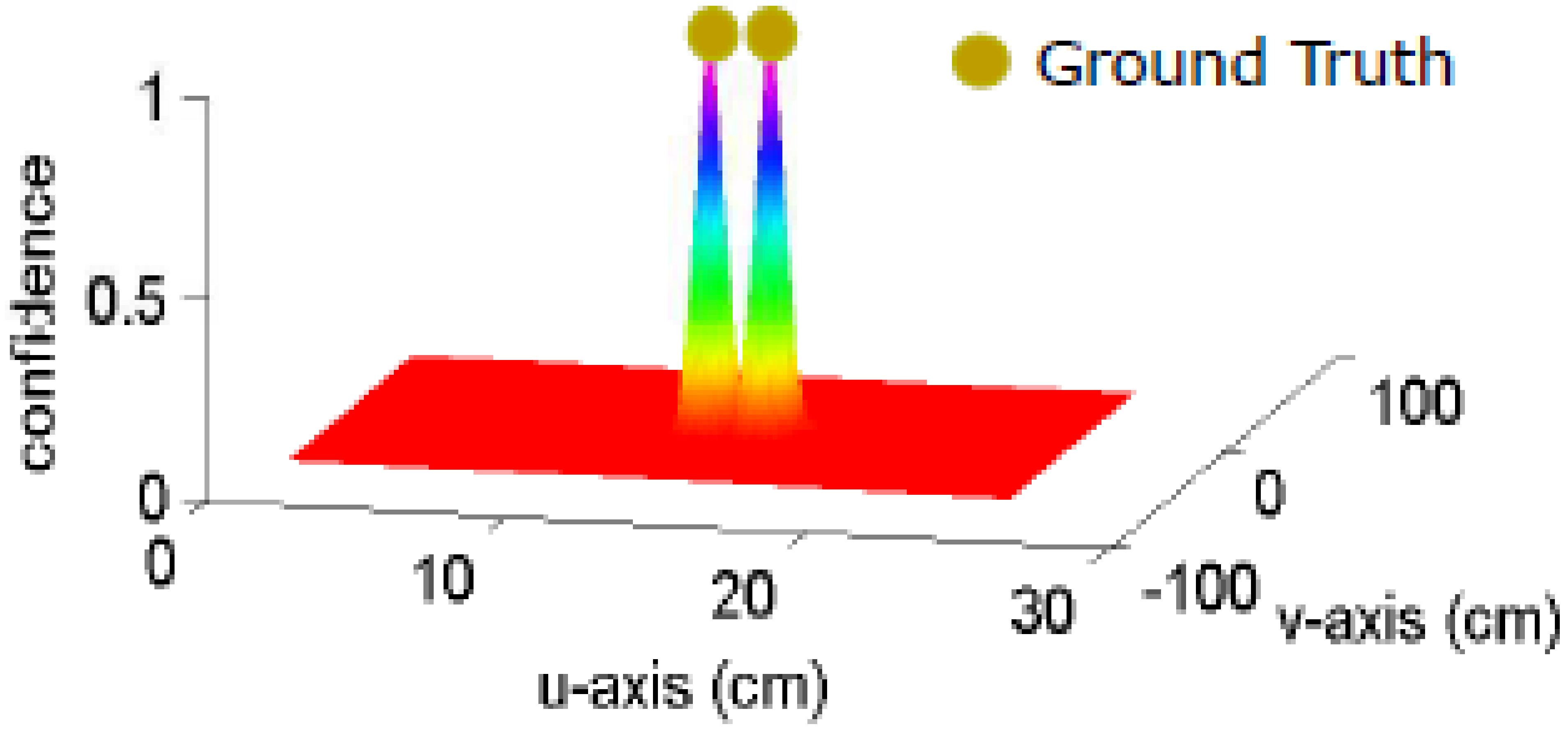

Exploit Space-time Diversity
What’s behind the water?



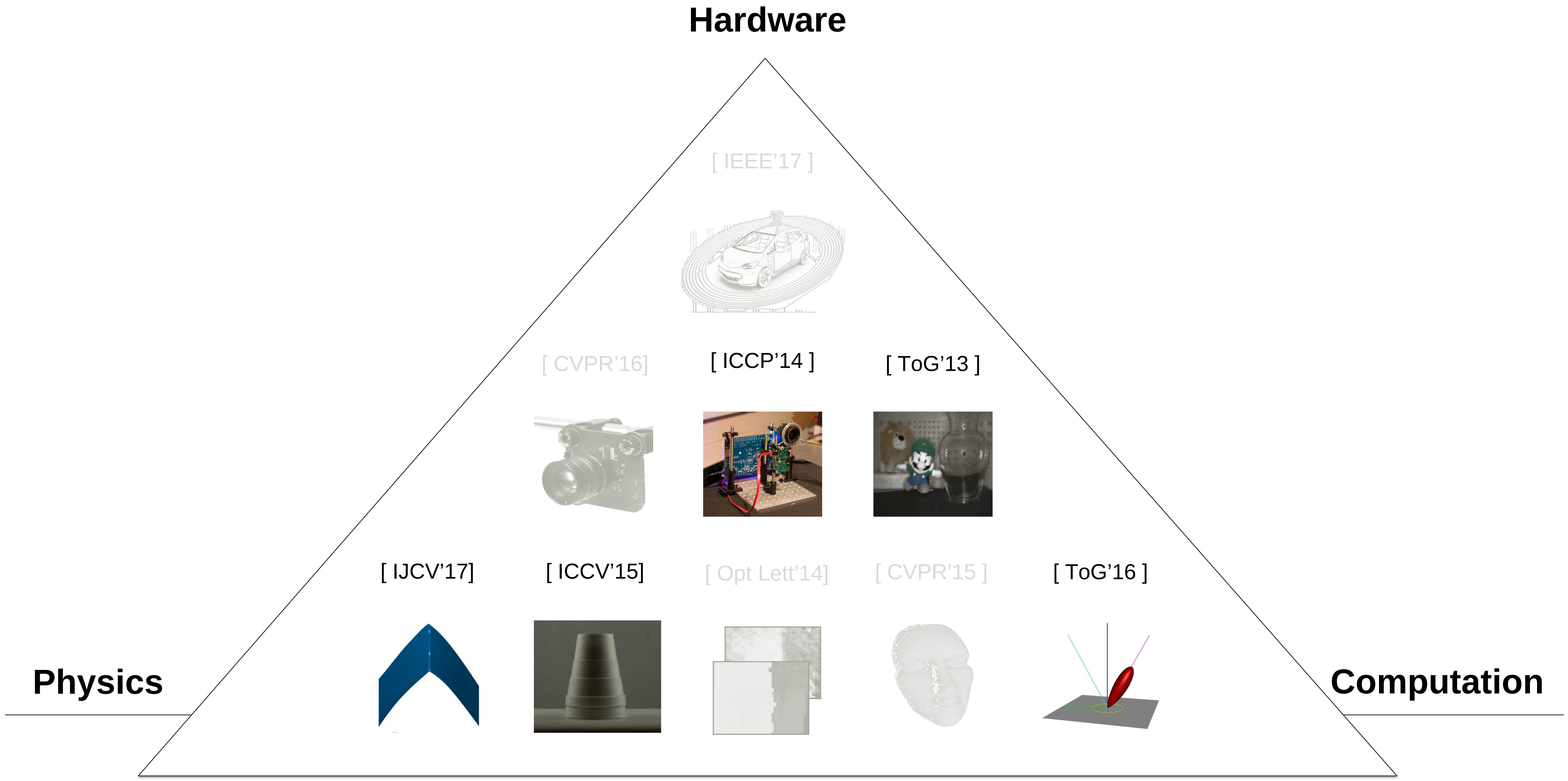
(b) Highly Scattering



With Sparse Reconstruction



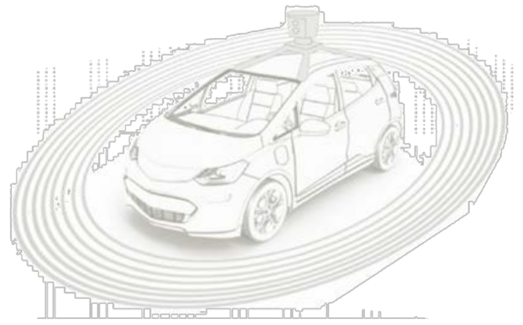
Physics, Hardware, and Computation



Physics, Hardware, and Computation

Hardware

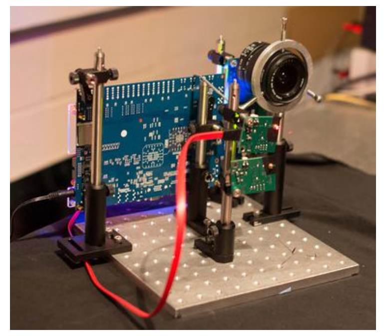
[IEEE'17]



When does the separation work?

[CVPR'16]

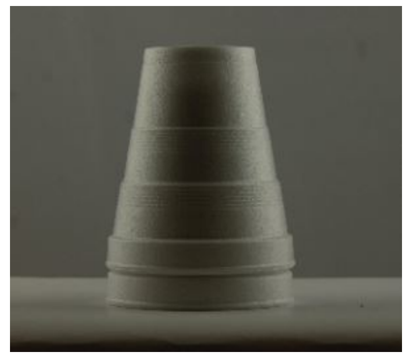
[ICCP'14]



[ToG'13]

[IJCV'17]

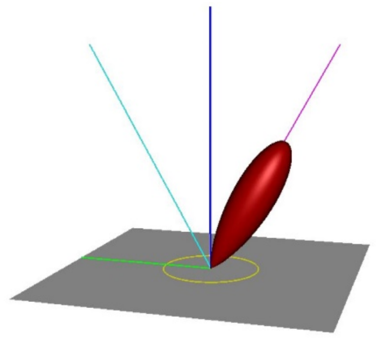
[ICCV'15]



[Opt Lett'14]

[CVPR'15]

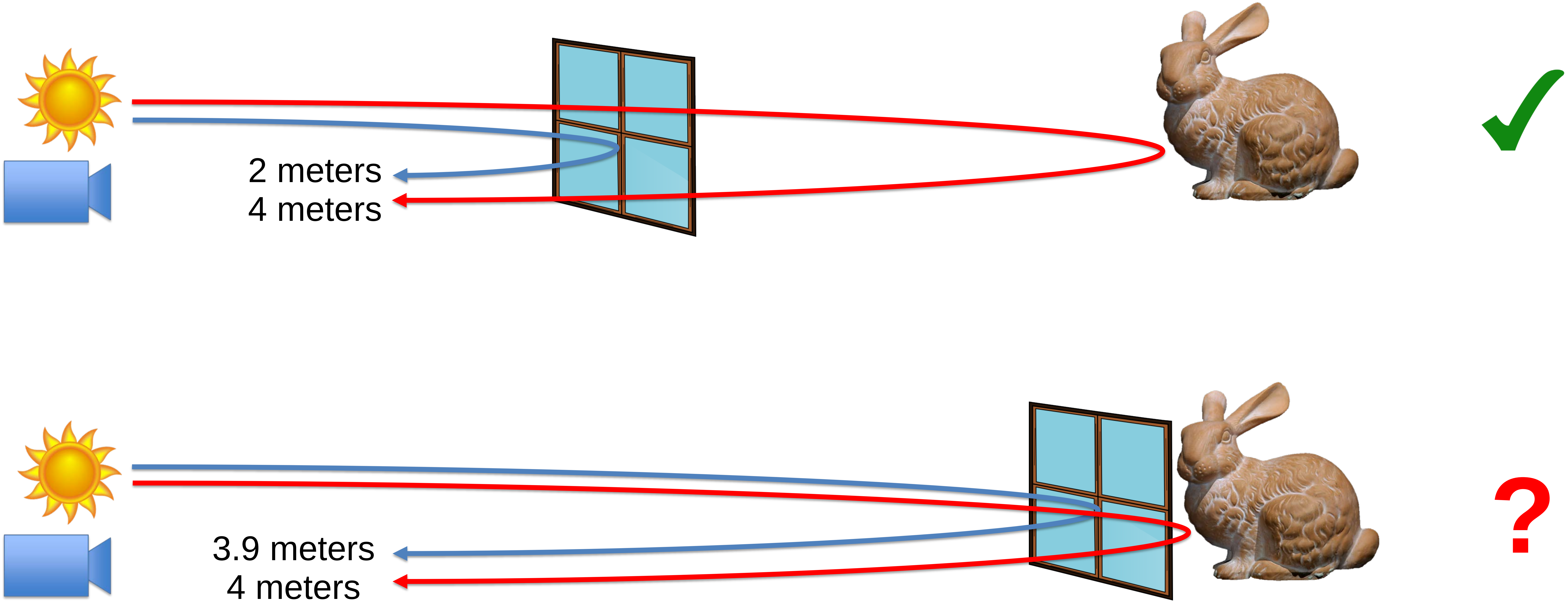
[ToG'16]



Physics

Computation

Intuition



Kadambi et al. IEEE CVPR 2016

A Guarantee on Resolvability of Light Paths

❑ Proposition [Kadambi et al. CVPR16]

Two light-paths of equal amplitude can be separated if the difference in optical path length is greater than:

$$\Delta z > 0.6 \frac{c}{\Delta f_M}$$

Difference in optical path Δz

Camera Frequency Bandwidth Δf_M

Speed of Light c

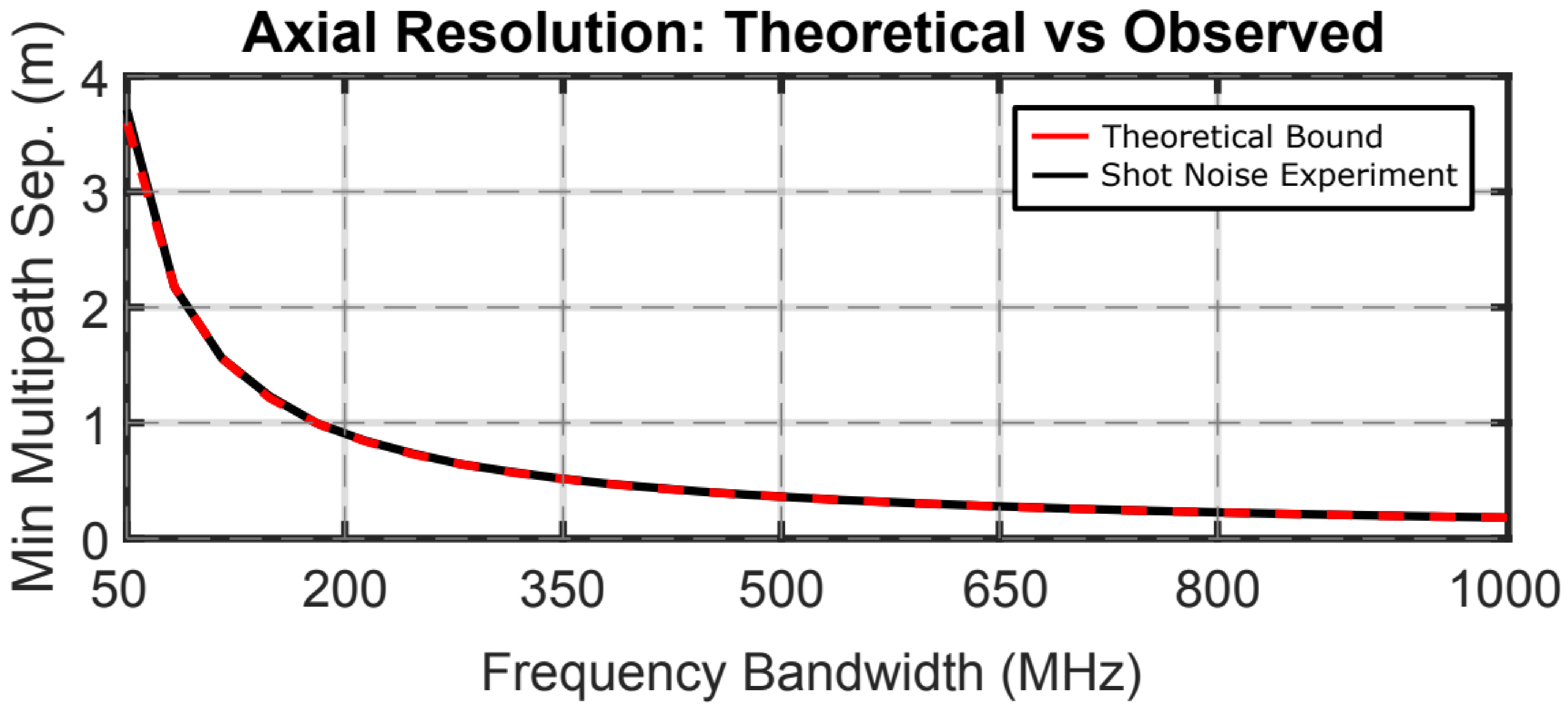
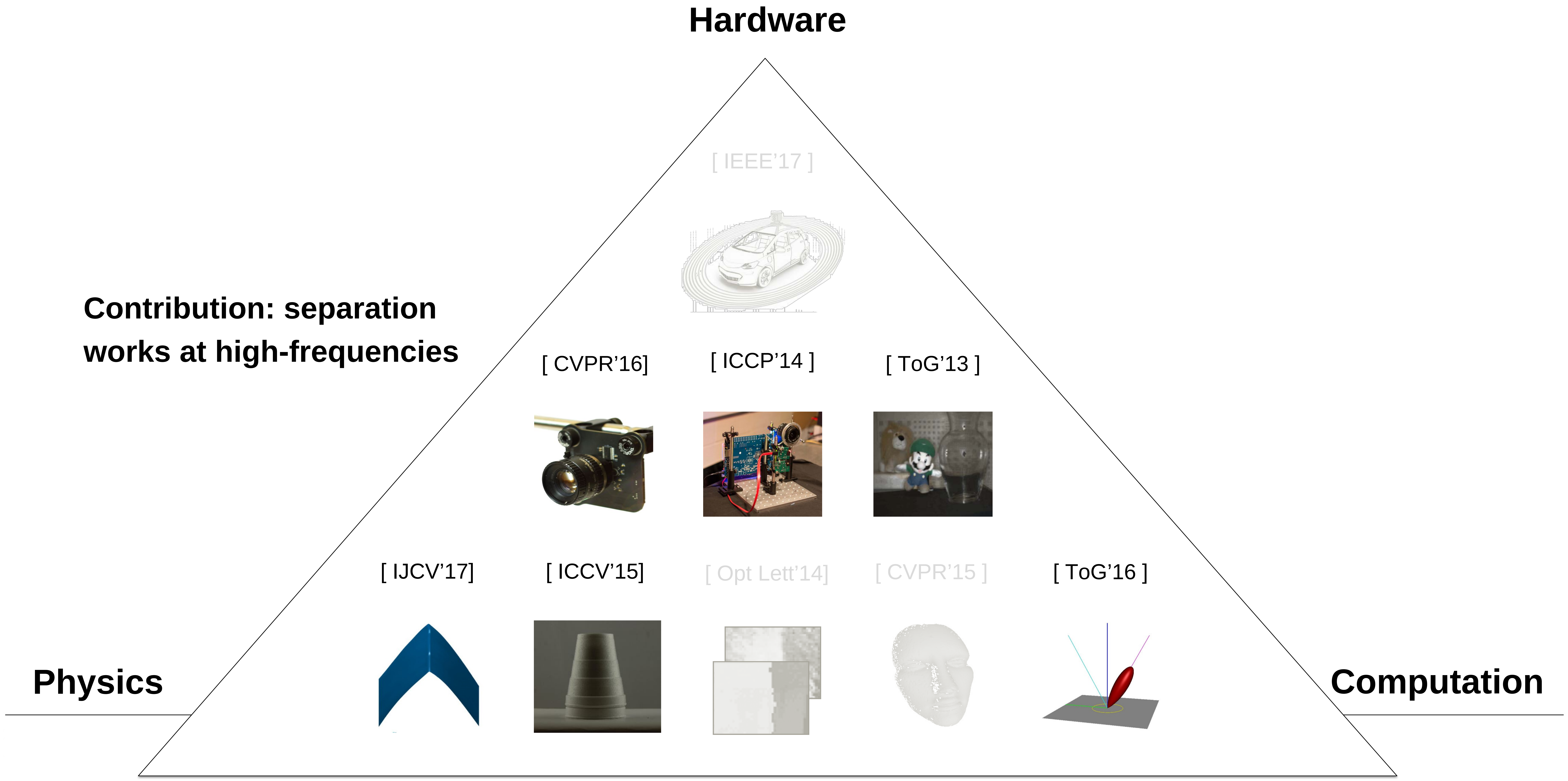


Figure 3. We show that the noiseless bound derived in *Proposition 1* is valid in typical shot noise limited scenarios.

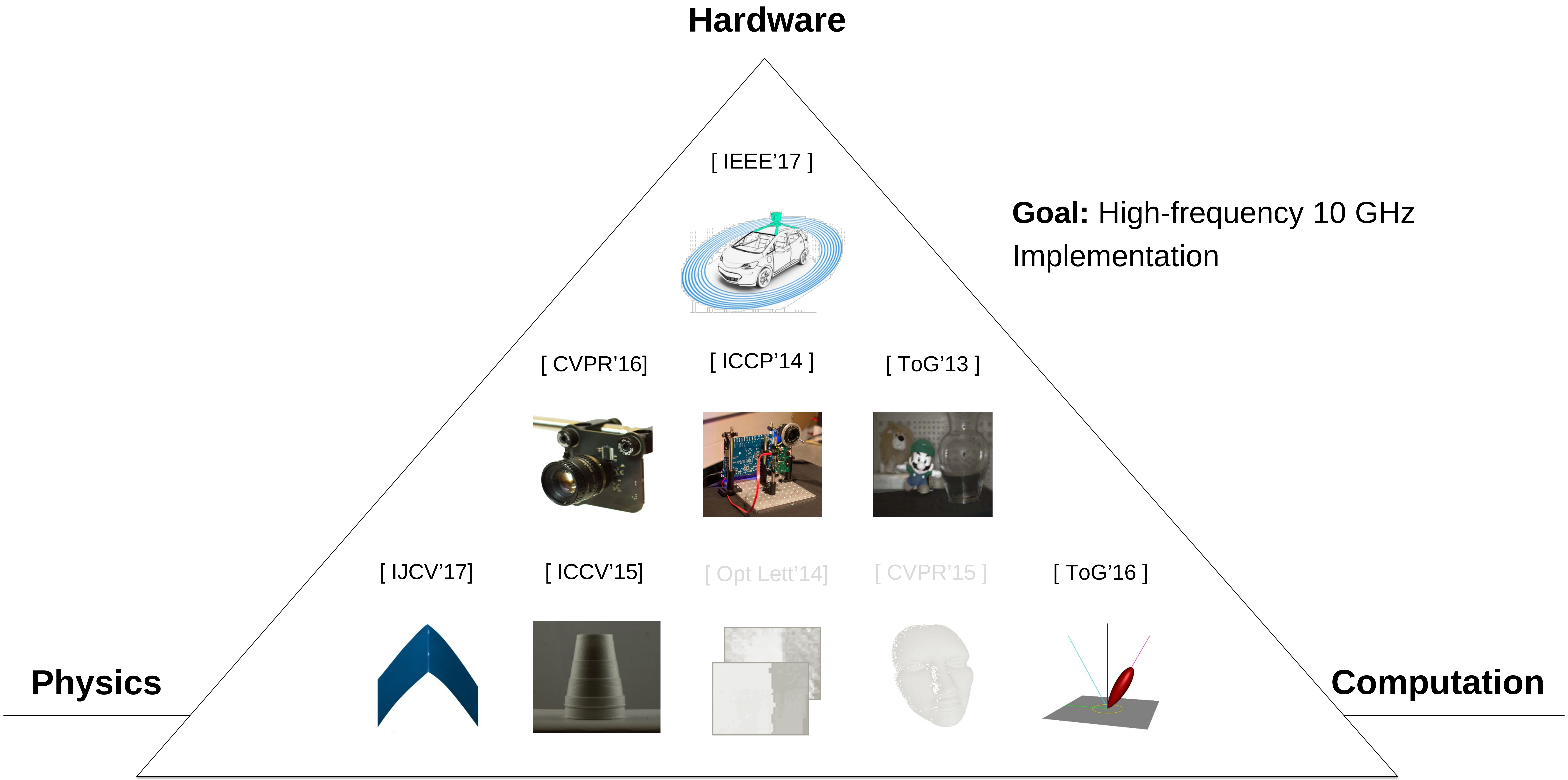
* Valid in shot noise limited cases

Physics, Hardware, and Computation

Contribution: separation works at high-frequencies



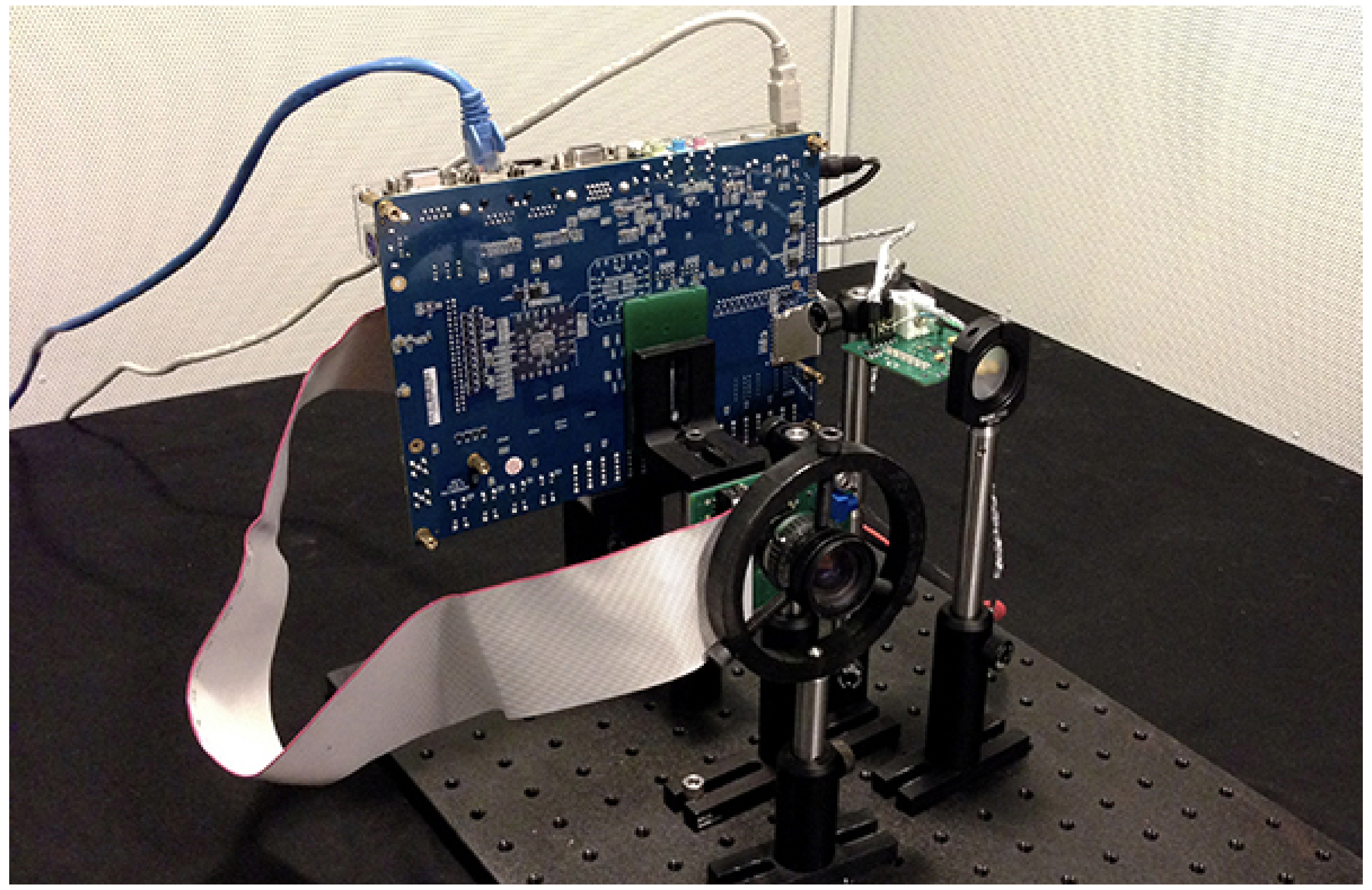
Physics, Hardware, and Computation



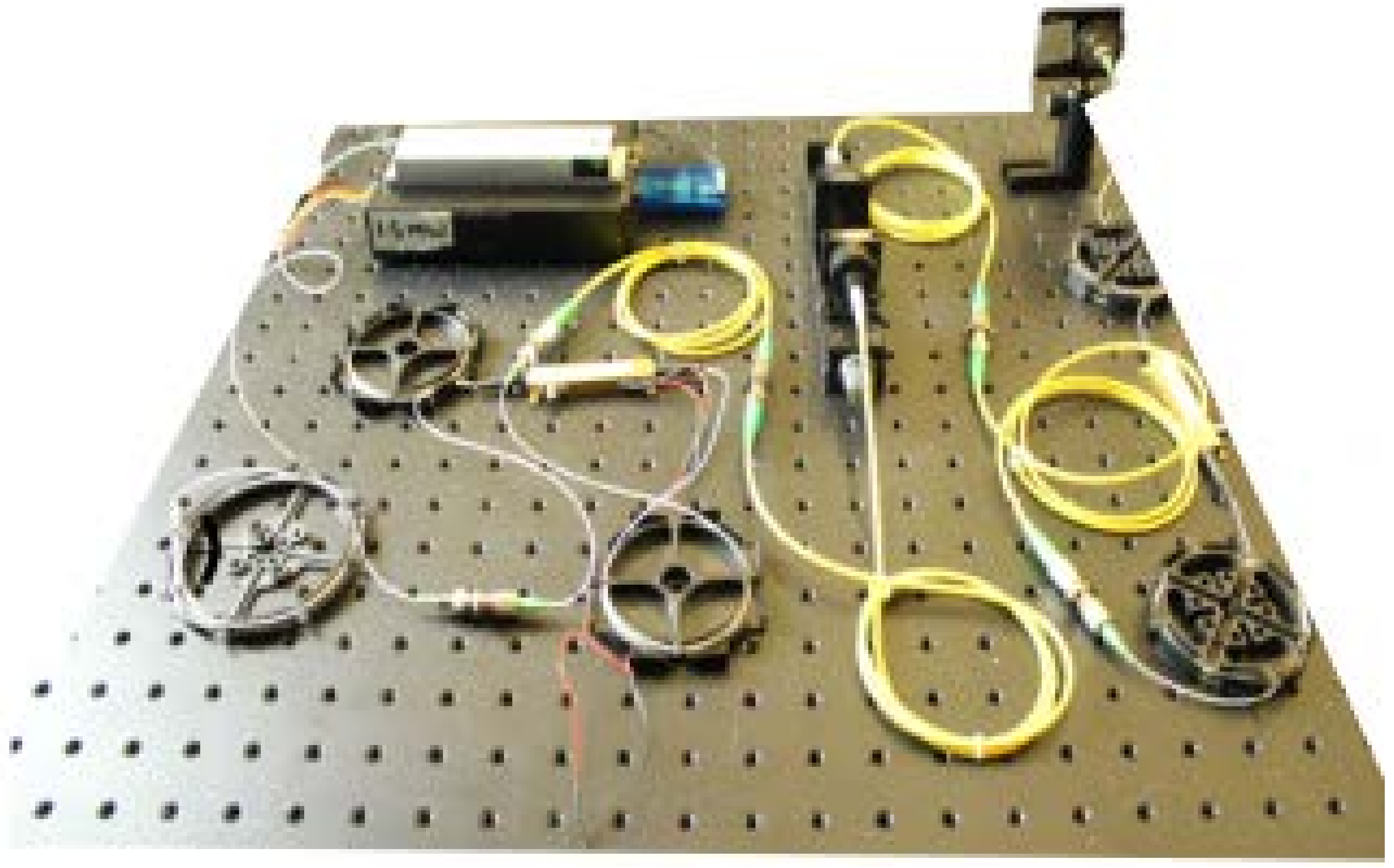
Goal: High-frequency 10 GHz Implementation

New "MicroLIDAR" Project for Descattering

Study optical wave and electronic modulation jointly



CMOS Camera
[Kadambi et al. CVPR16]



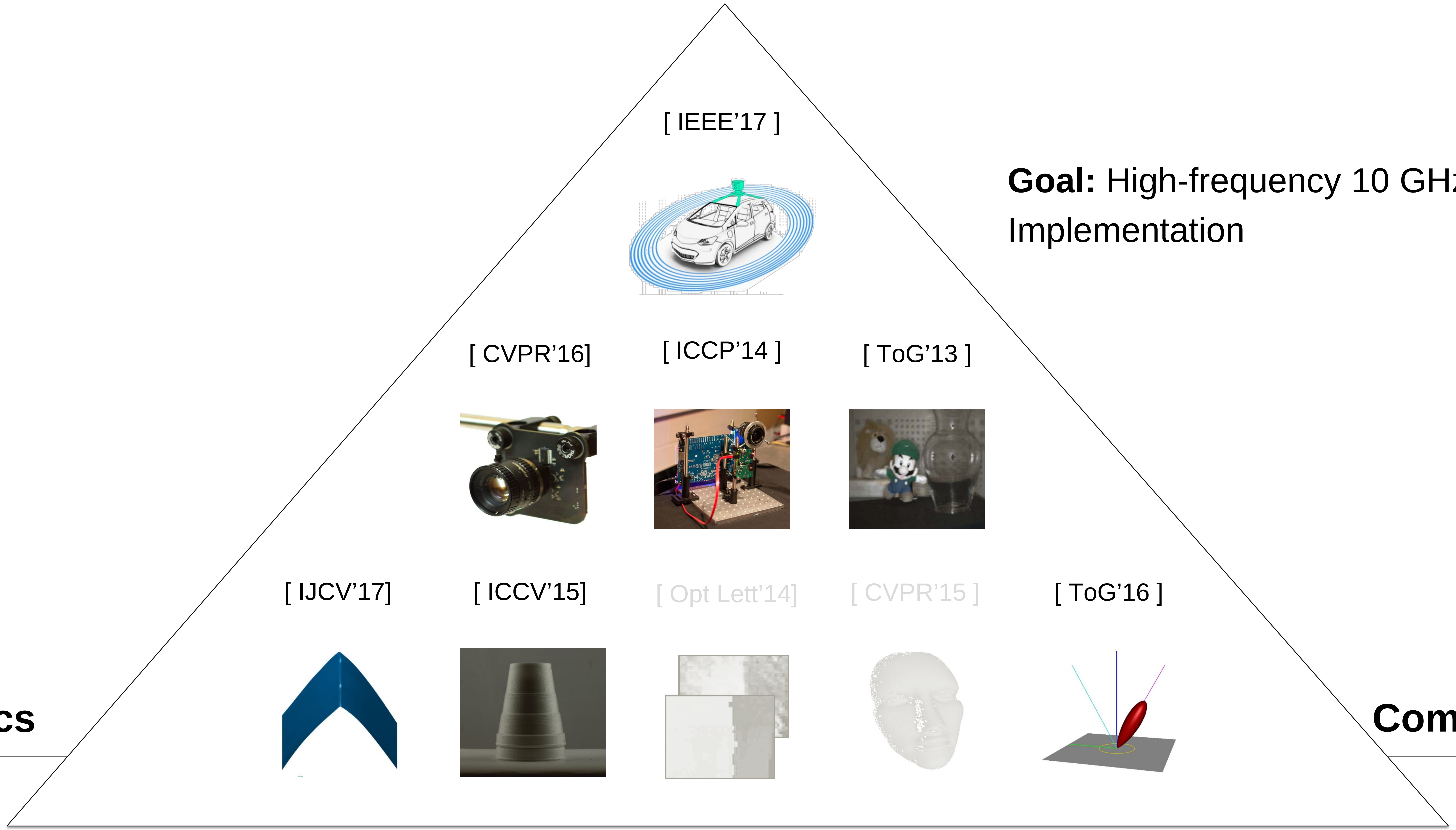
Fiberoptic **MicroLIDAR**
[Kadambi et al. IEEE17]

The MIT Press

Textbook: "Principles of Time-resolved Imaging" (Free in Fall'18)

Physics, Hardware, and Computation

Hardware

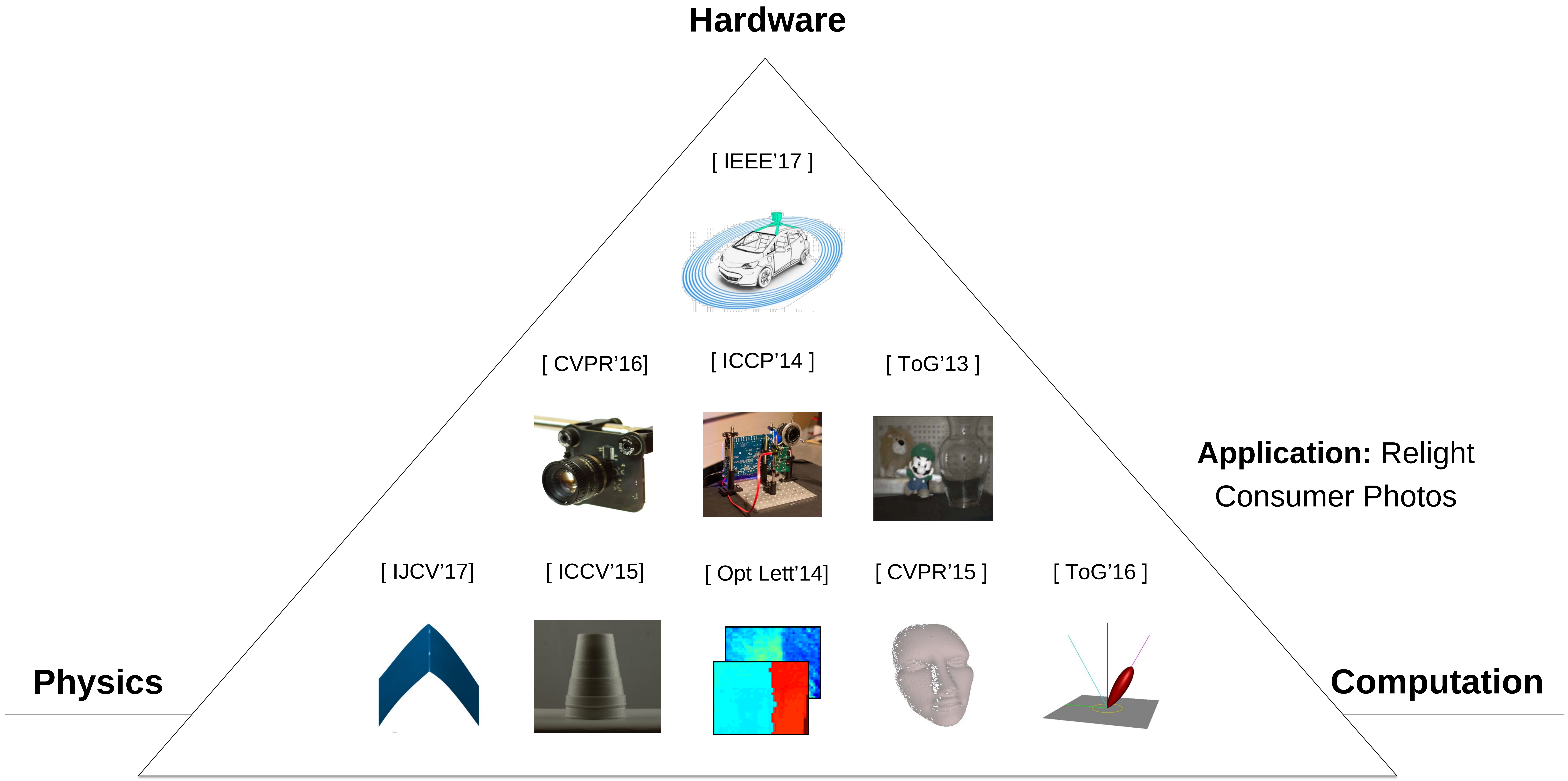


Physics

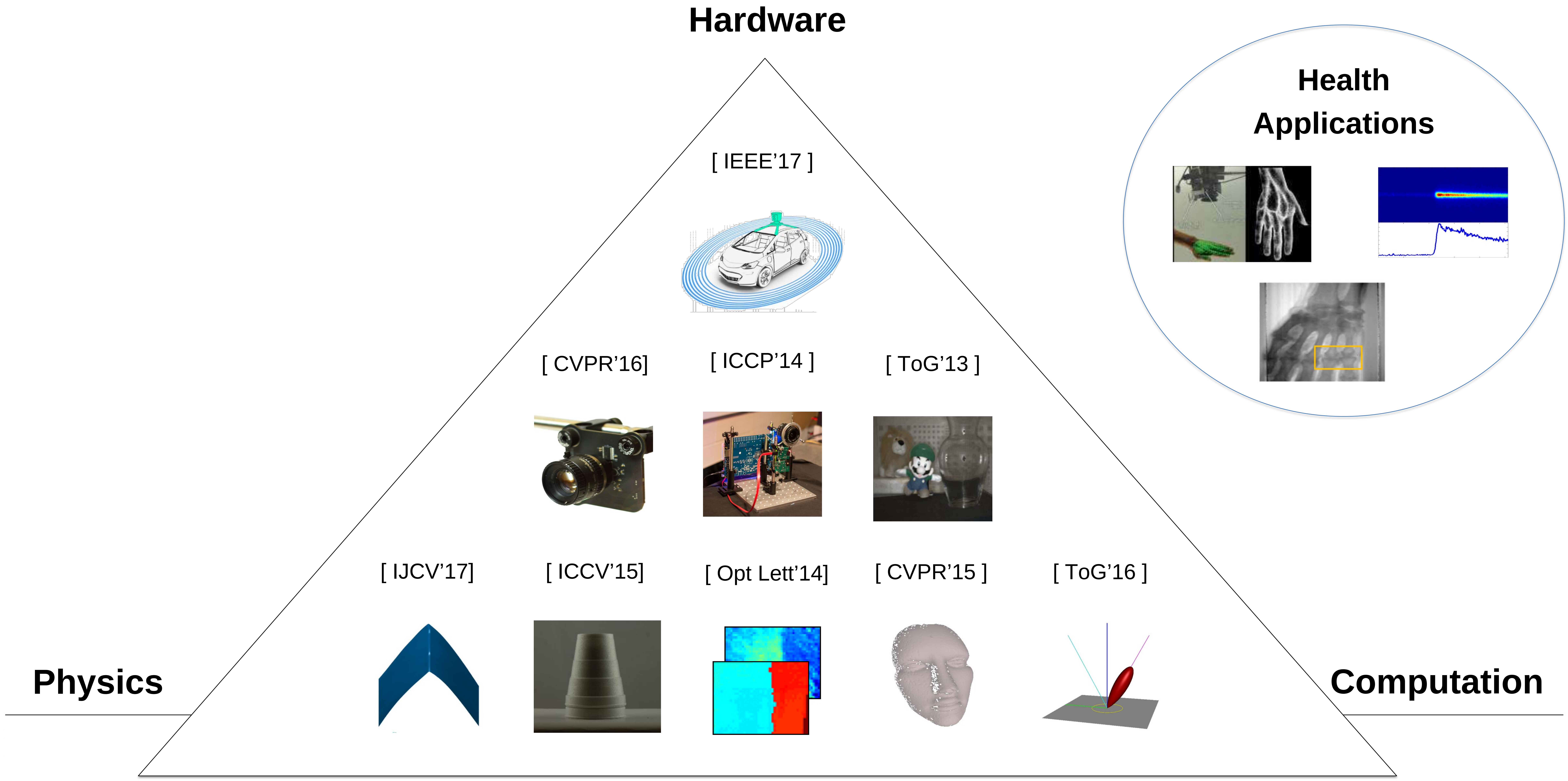
Computation

Goal: High-frequency 10 GHz Implementation

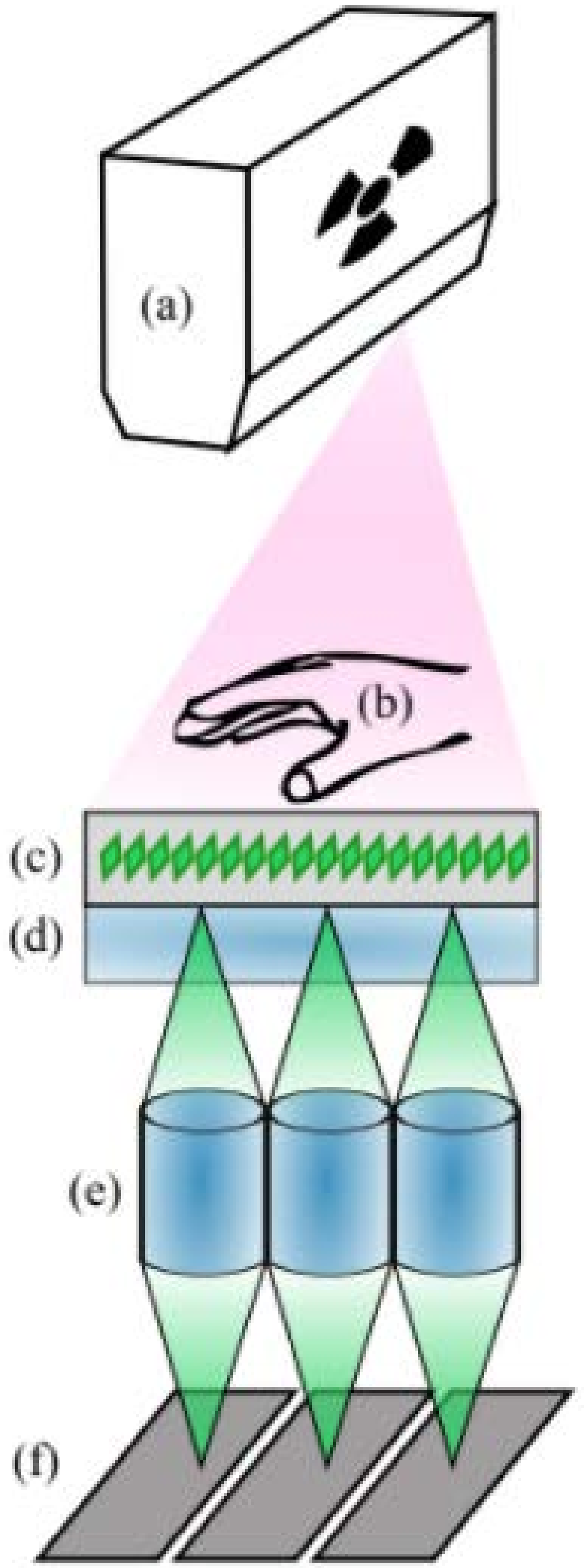
Physics, Hardware, and Computation

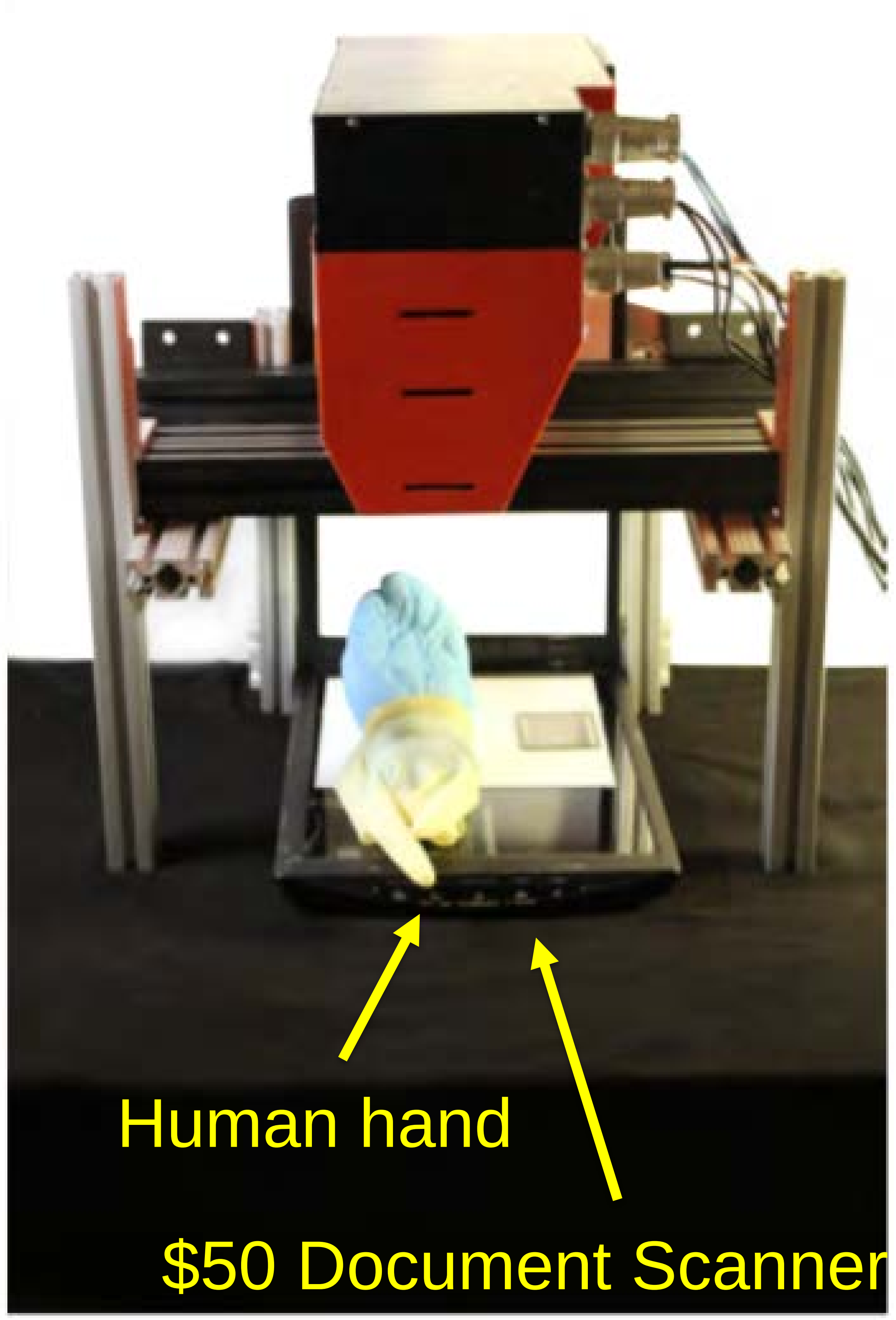


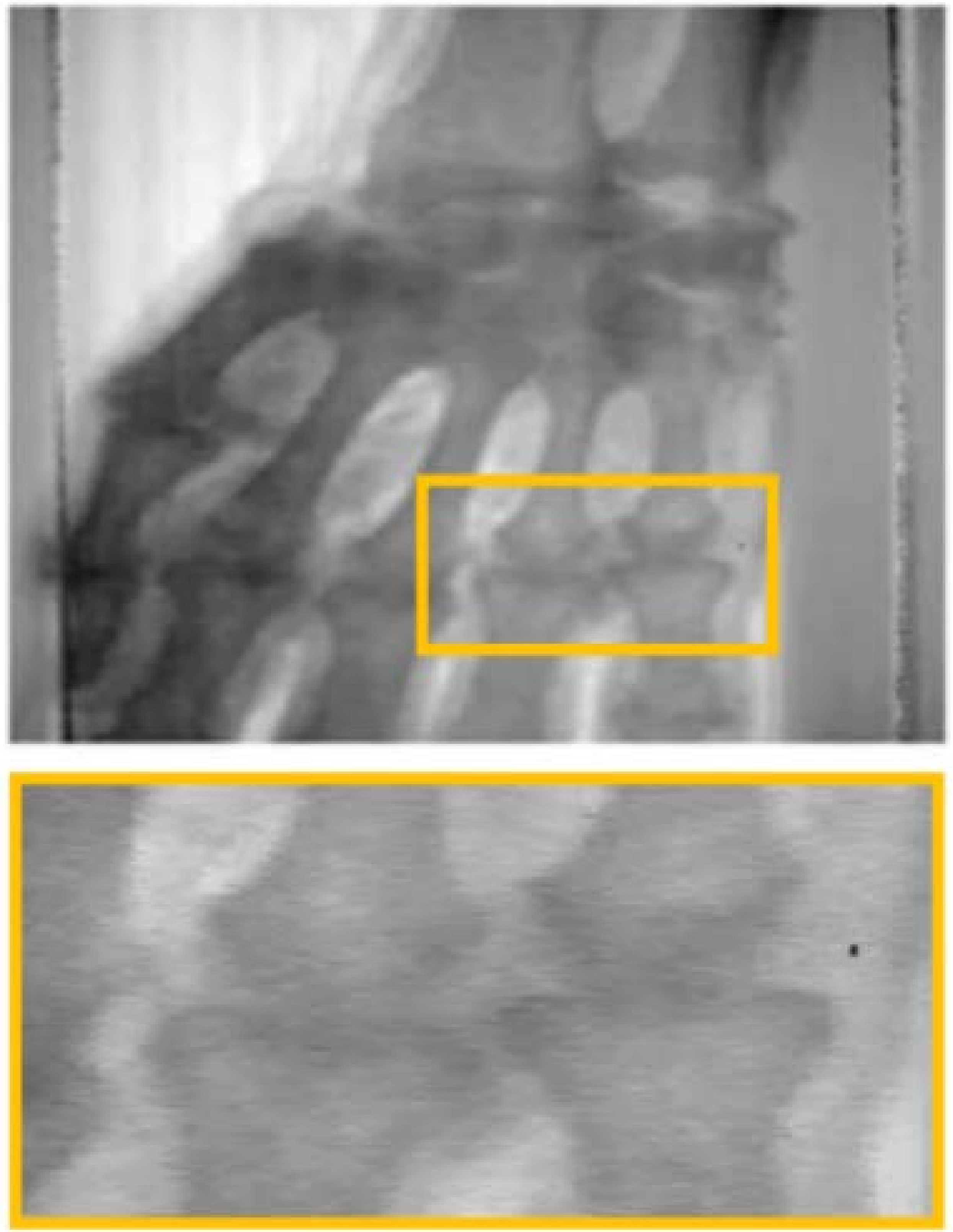
Health Applications



Canon Document Scanner into an X-ray imager?





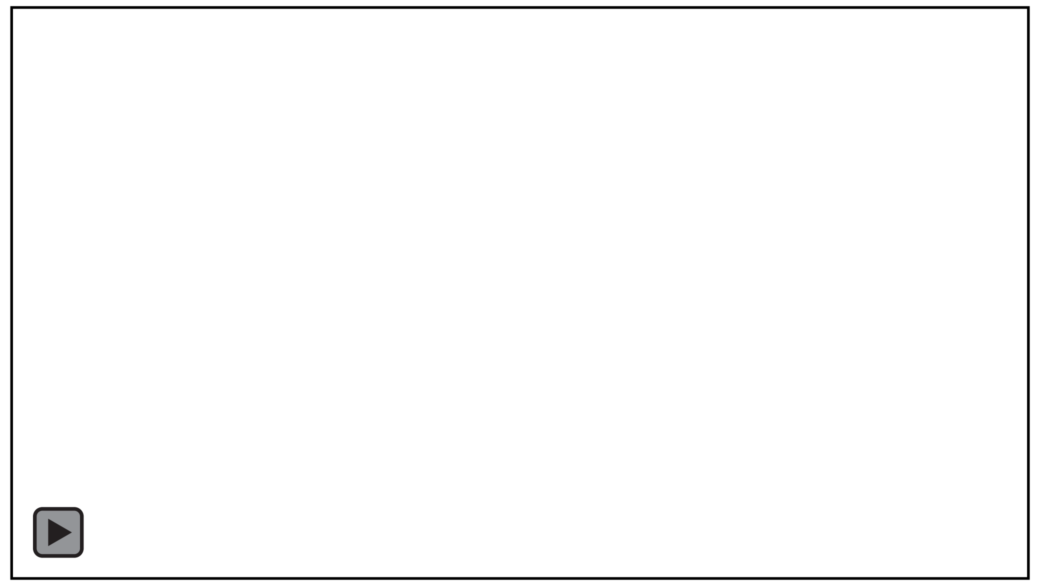


Kadambi et al. 2018

The future of image processing is 7D?

Polarization for 3D

Transient Imaging



Space-Transient Imaging

7D Image Processing

Academic Questions:

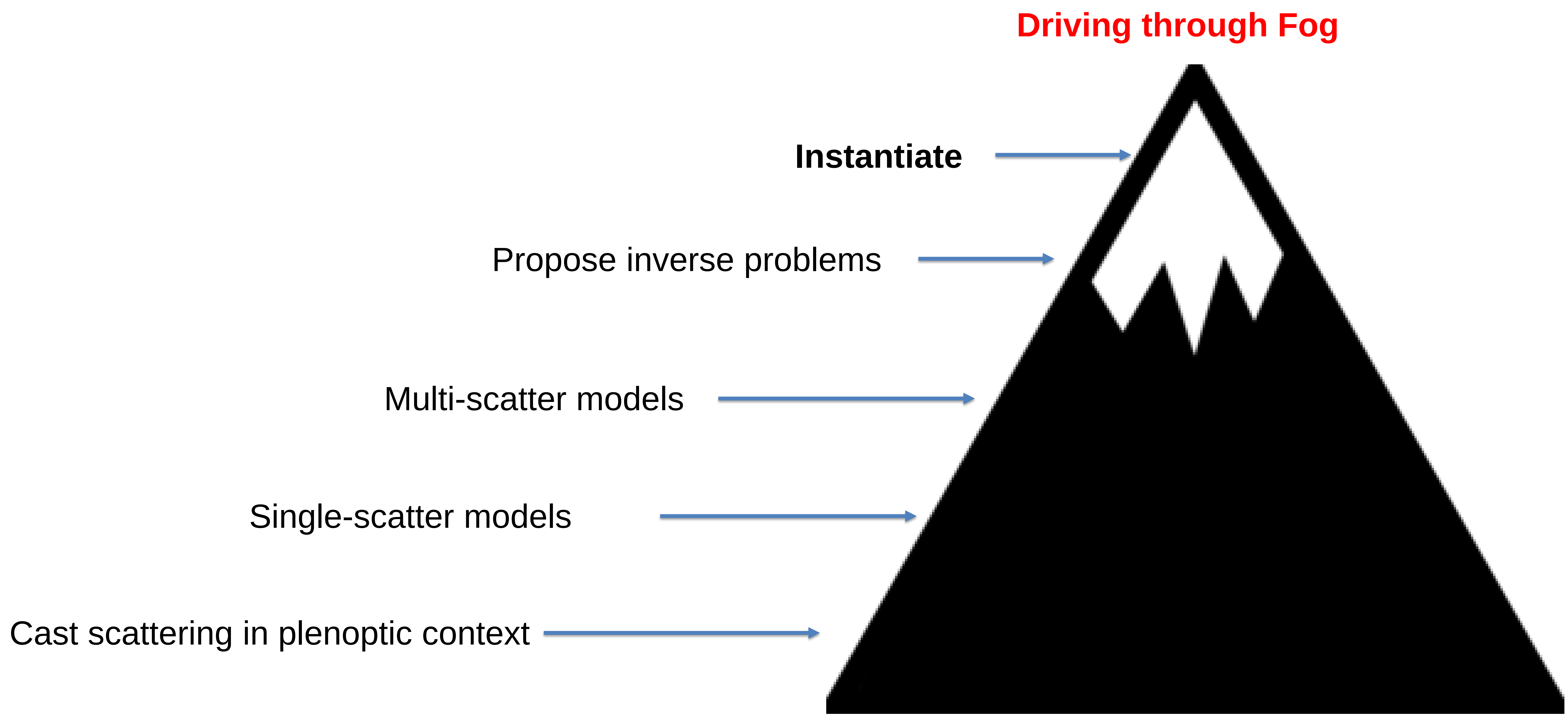
How do multiple bounces relate to polarization?

*How can we overcome **diffraction**?*

*How does **scatter** relate to transience?*

Provable Guarantees of Imaging Correctness?

Driving through Fog: Separate ballistic and scattered photons based on minute axial path delays or polarimetric signal

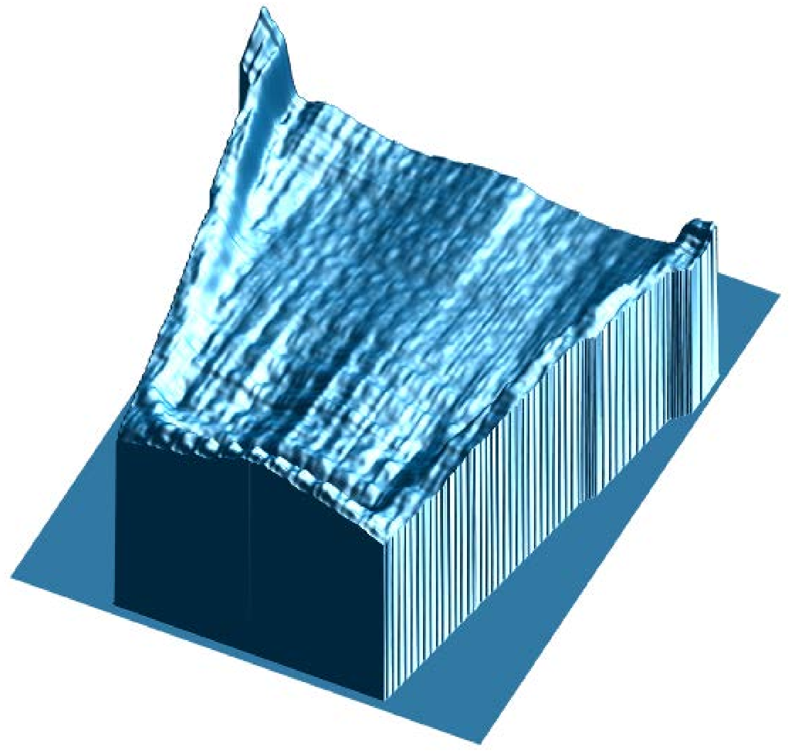


What are other possible mountains?

Future Direction: Physics-based machine learning

Goal: How can we unite physics and learning-based ideas?

Challenges to overcome:
Need specialized datasets
Need specialized CG rendering
Need to rethink algorithms
Need to justify approach



Trained on 3D Database from NYU [Silberman12]

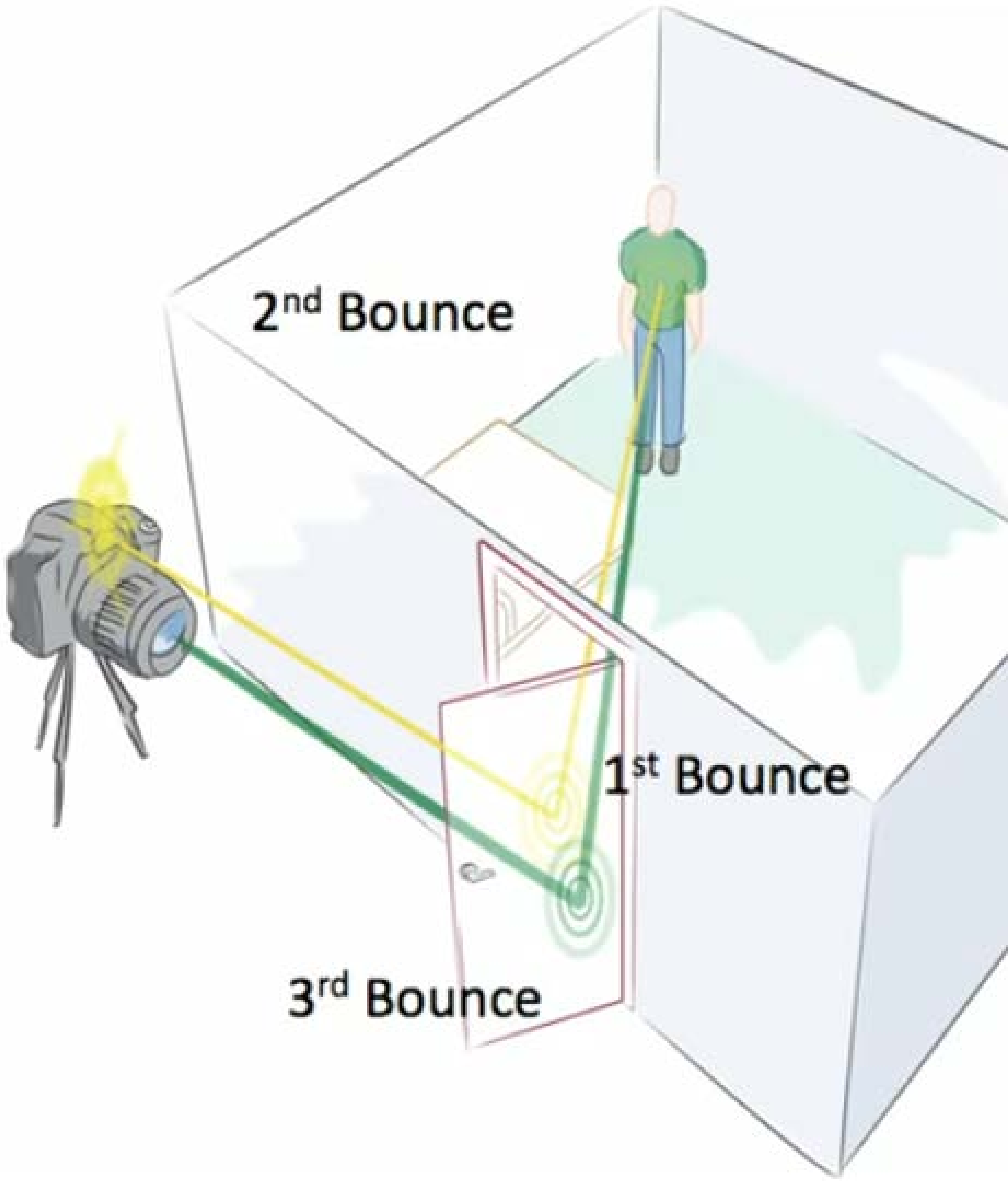
Image-based Machine Learning [Laina16]

Future Direction: Proving “correctness” of an imaging approach

New problems, new bounds – novel problem statements require new, provable bounds

Towards optimality – can we prove analytically that a computational camera is the best possible solution?

New systems, new simulators – e.g. puts pressure on SIGGRAPH and CVPR to evolve.

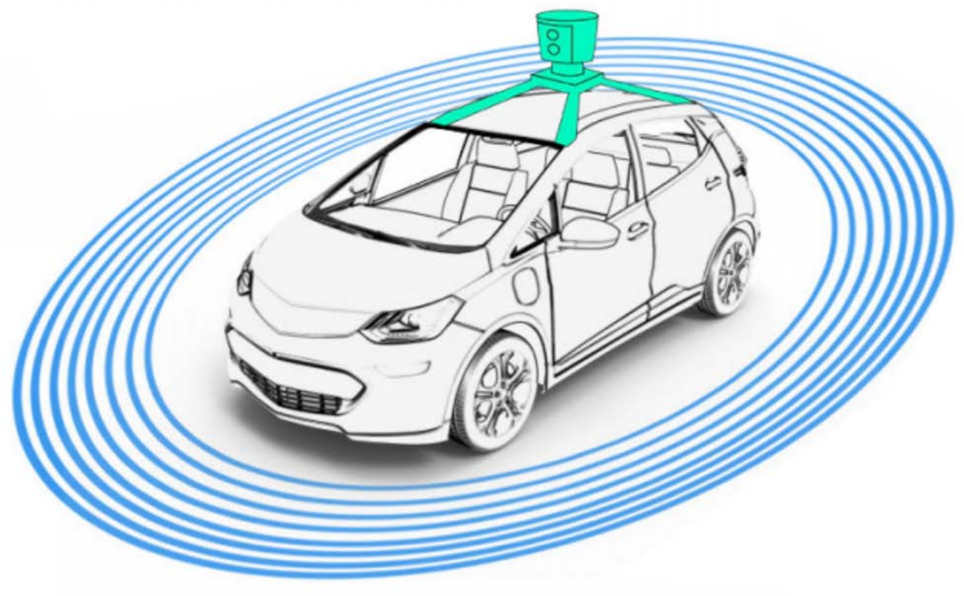


Demand Pressure for New Cameras

Drone Visual Systems

Evolution of Nanoscopes

Image Deeper through Tissue



Autonomous Driving

Mobile Photography

Sound + Light

Course Schedule

http://imagingav.media.mit.edu

13:30 – 13:50	Course Introduction *Ramesh Raskar (MIT)*
13:50 – 15:00	Existing Sensors and Their Limits *Guy Satat (MIT), Achuta Kadambi (UCLA)*
15:00 – 15:10	Break
15:10 – 15:50	Emerging 3D Sensors *Achuta Kadambi (UCLA)*
15:50 – 16:30	Imaging in Bad Weather *Guy Satat (MIT)*
16:30 – 16:40	Break
16:40 – 17:20	Deep Learning-based Computational Imaging *Jan Kautz (NVIDIA)*
17:20 – 17:30	Conclusion and Open Problems