

# Imaging In Challenging Weather Conditions

Guy Satat

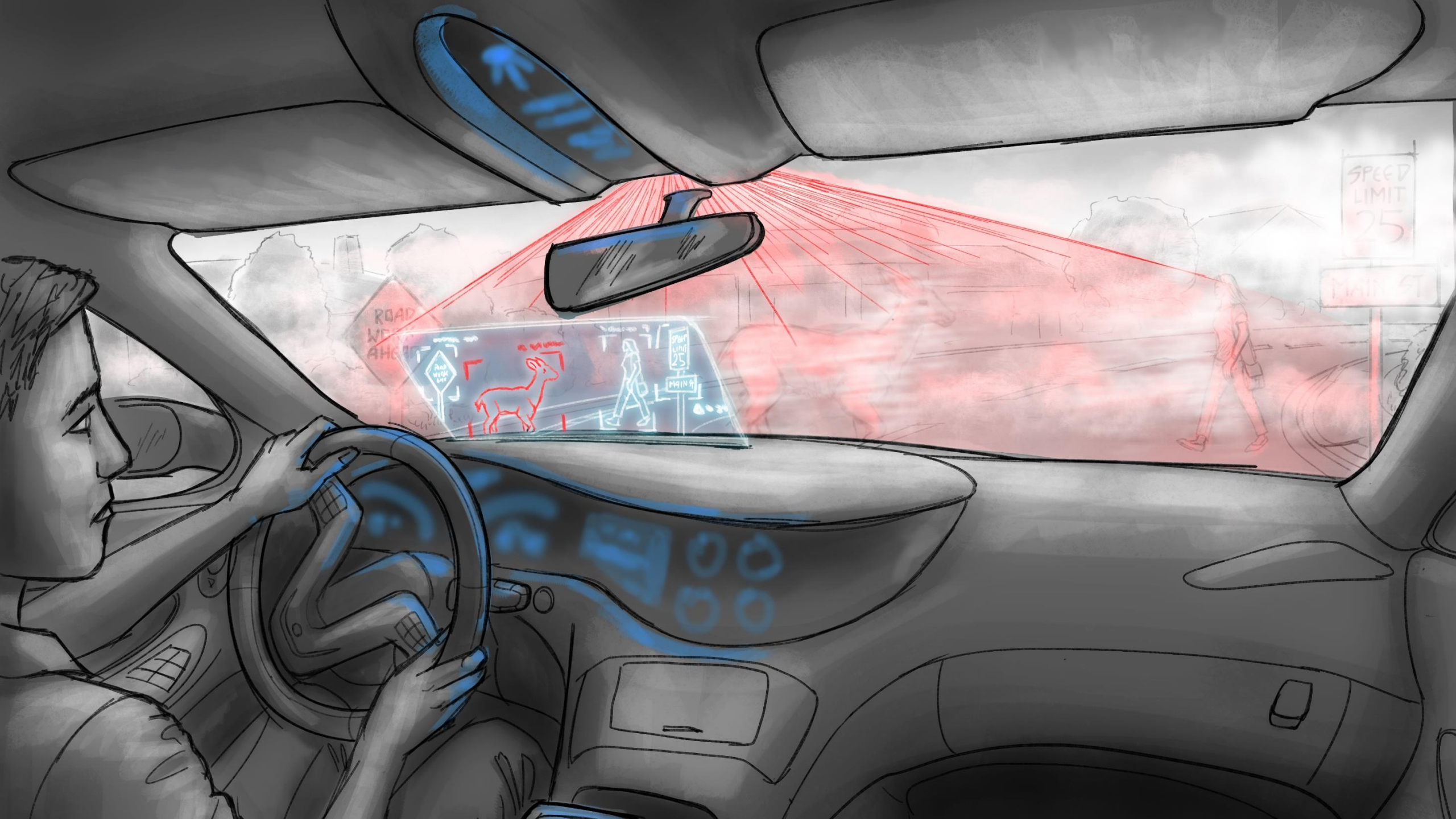
Computational Imaging for Self-Driving Vehicles @ CVPR 2018



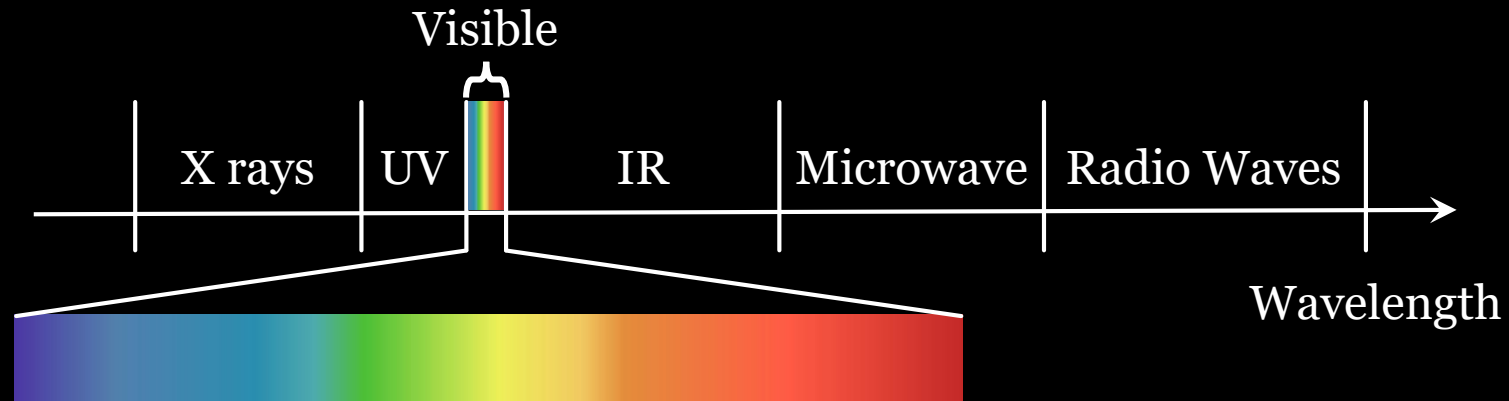


# Imaging Through Fog == Imaging Through Scattering?



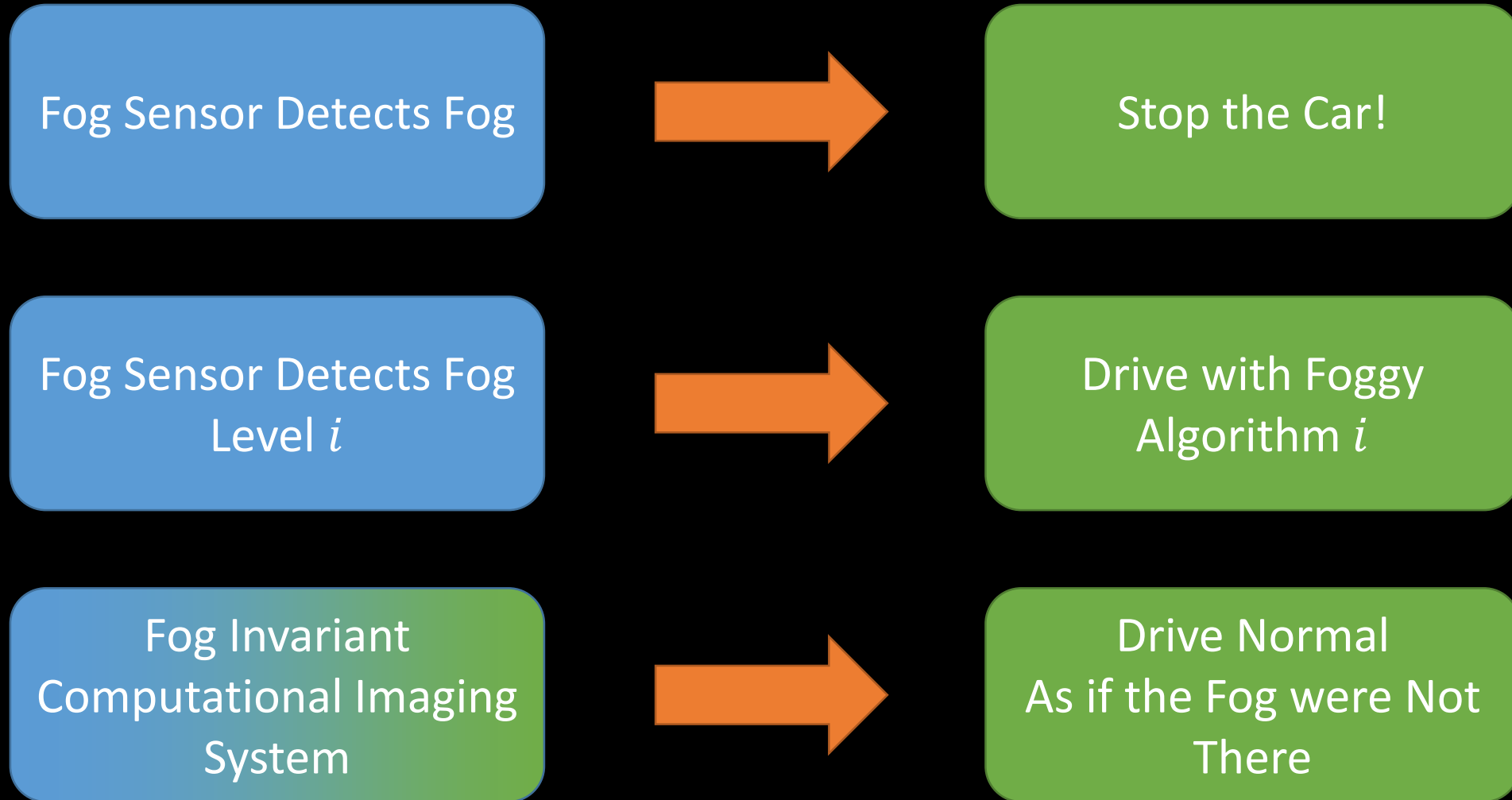


# Why not RADAR ?



- Resolution
- Optical contrast

# Different Strategies to Drive in Fog



Regular Camera

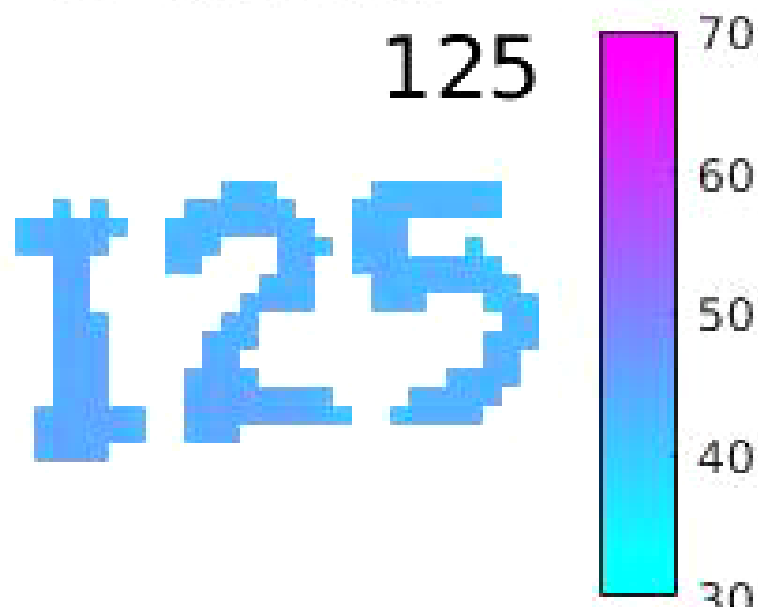


Reflectance



Ours

Depth [cm]



**Estimated visibility: 80 cm**



# Information Carried by Light

- The plenoptic function:

$$I(r, \lambda, t, \theta, P, n, \Phi)$$

Irradiance

Position

Wavelength

Time

Angle

Polarization

Bounce

Phase

# Information Carried by Light

- The plenoptic function:

$$I(r, \lambda, t, \theta, P, n, \Phi)$$

Irradiance

Position

Wavelength

Time

Angle

Polarization

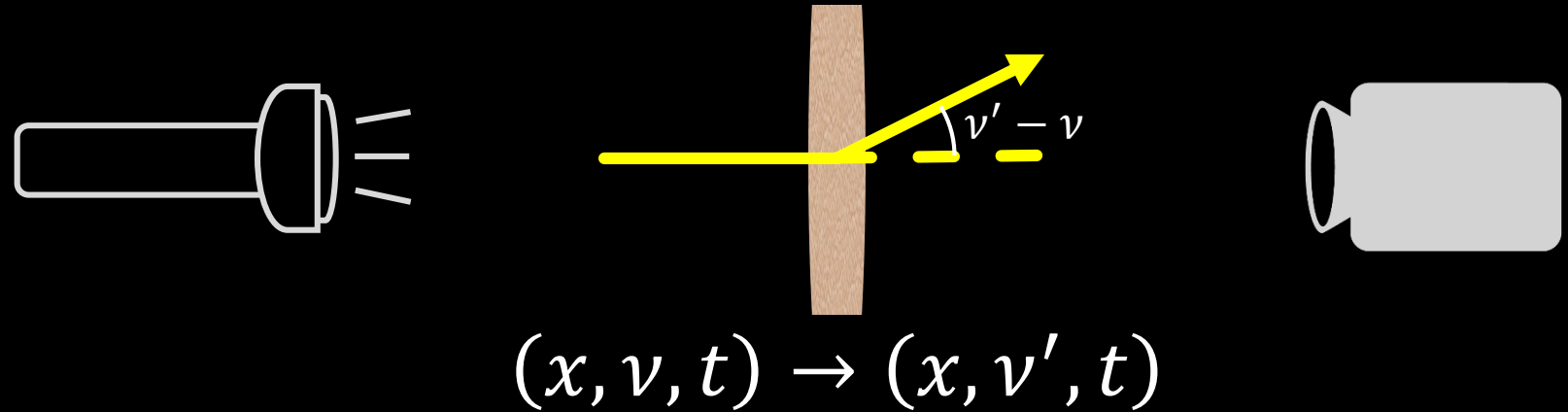
Bounce

Phase

# Scattering Types

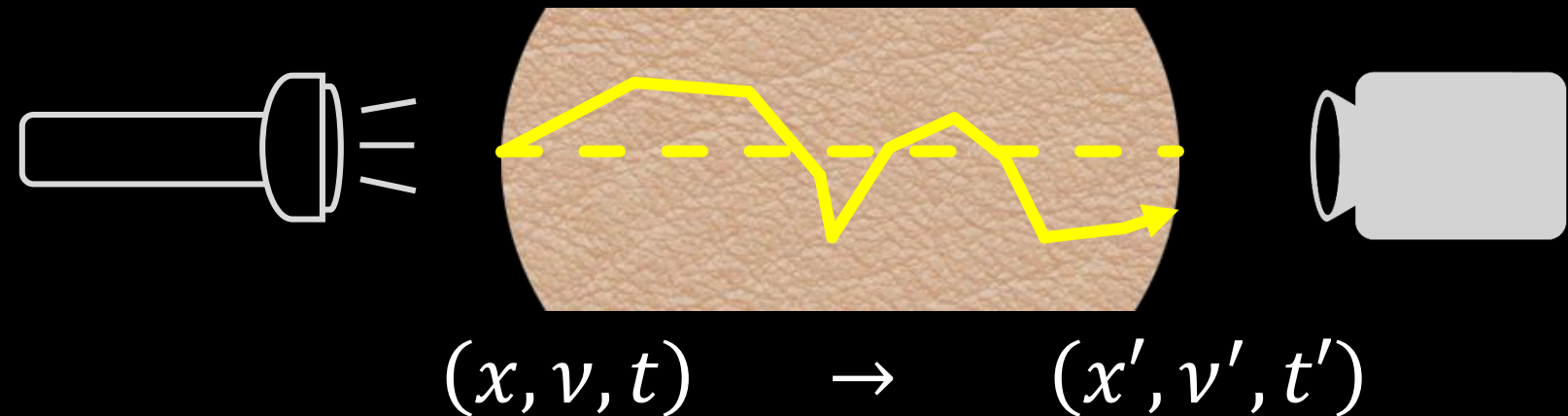
## Sparse Scattering

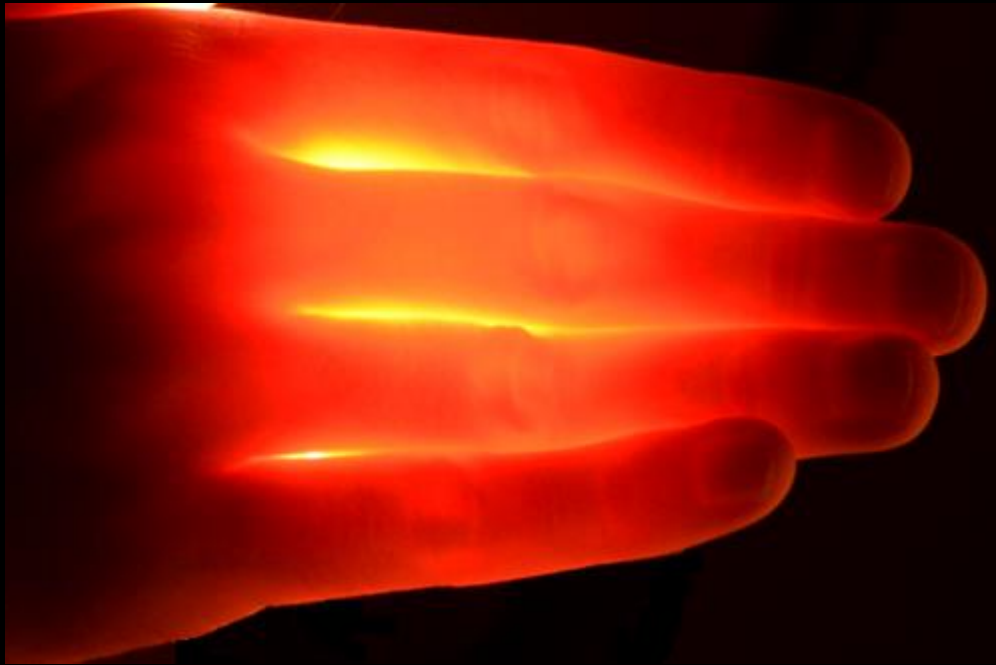
- Milky glass
- Paper
- Lensless imaging



## Volumetric Scattering

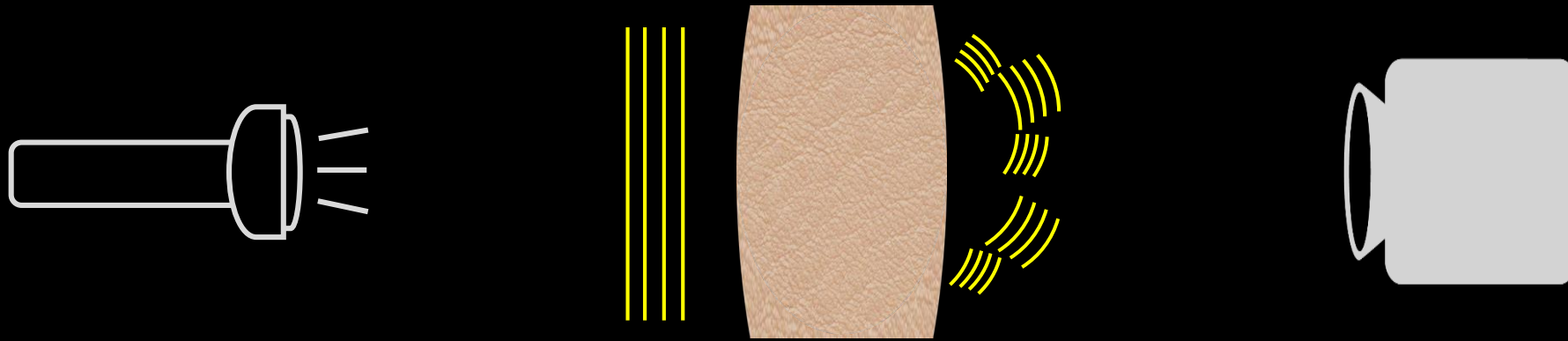
- Tissue
- Fog



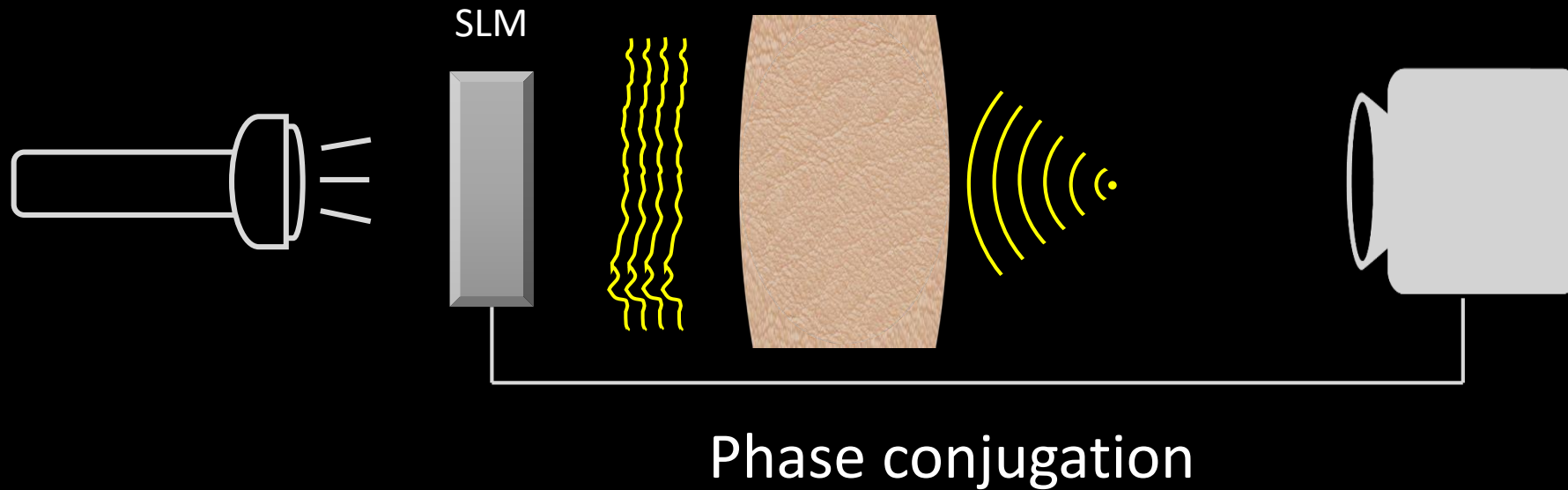


# Lessons learned from seeing into the body

# Phase Conjugation



# Phase Conjugation



**Long iterative process  
Requires Guide Star**

# Diffuse Optical Tomography

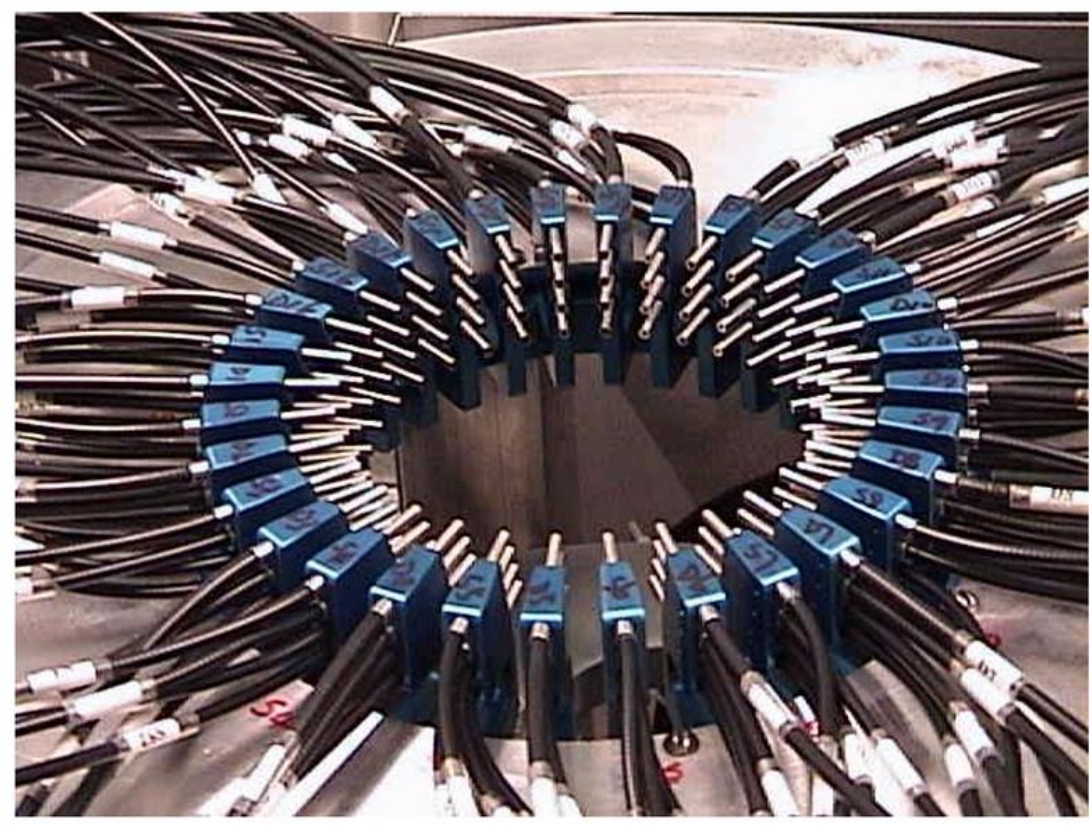
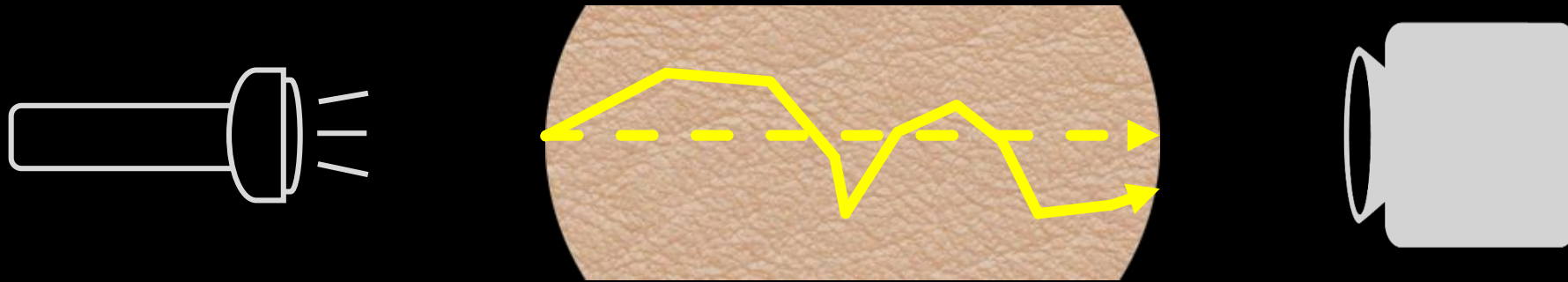


Photo credit: Wikipedia

Constrained  
Imaging Geometry

# Descattering with Photon Gating



Angle

Time

Polarization

Coherence

**Not enough photons**  
**Doesn't reject all scattered light**  
**No computation**



# Constrained Imaging Geometry



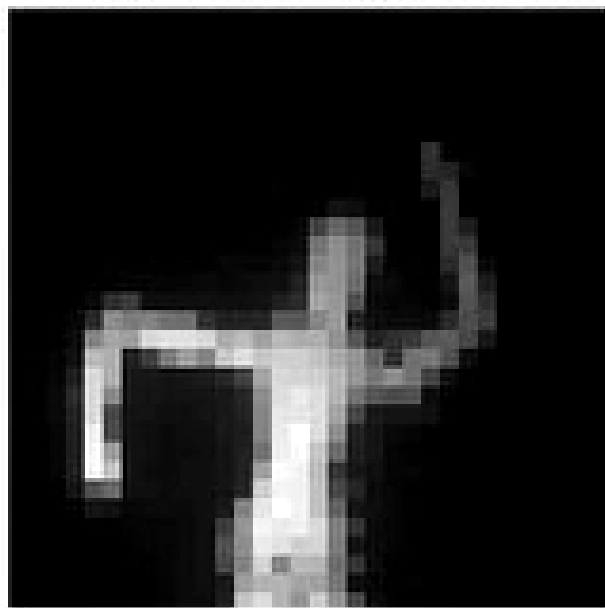
Continuum of possible densities  
Patchy (heterogeneous)  
Moving platform

# Towards Photography Through Realistic Fog

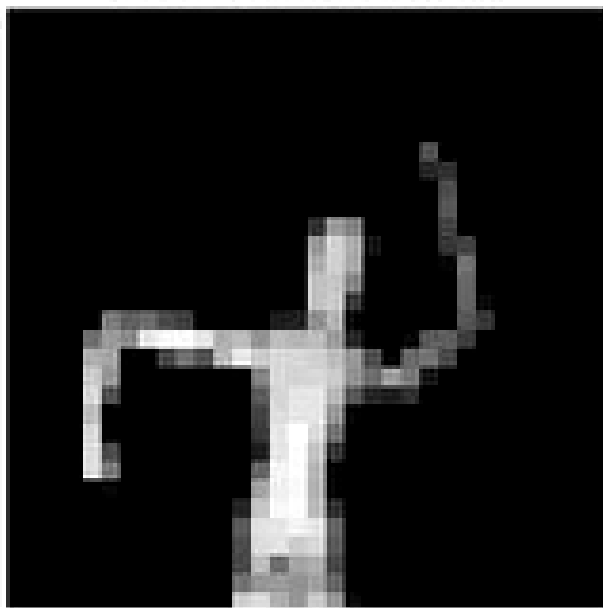
Guy Satat, Matthew Tancik, Ramesh Raskar

ICCP 2018

**Regular Camera**

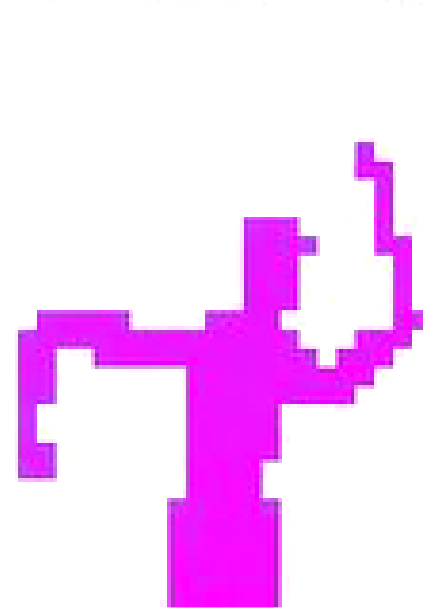


**Reflectance**



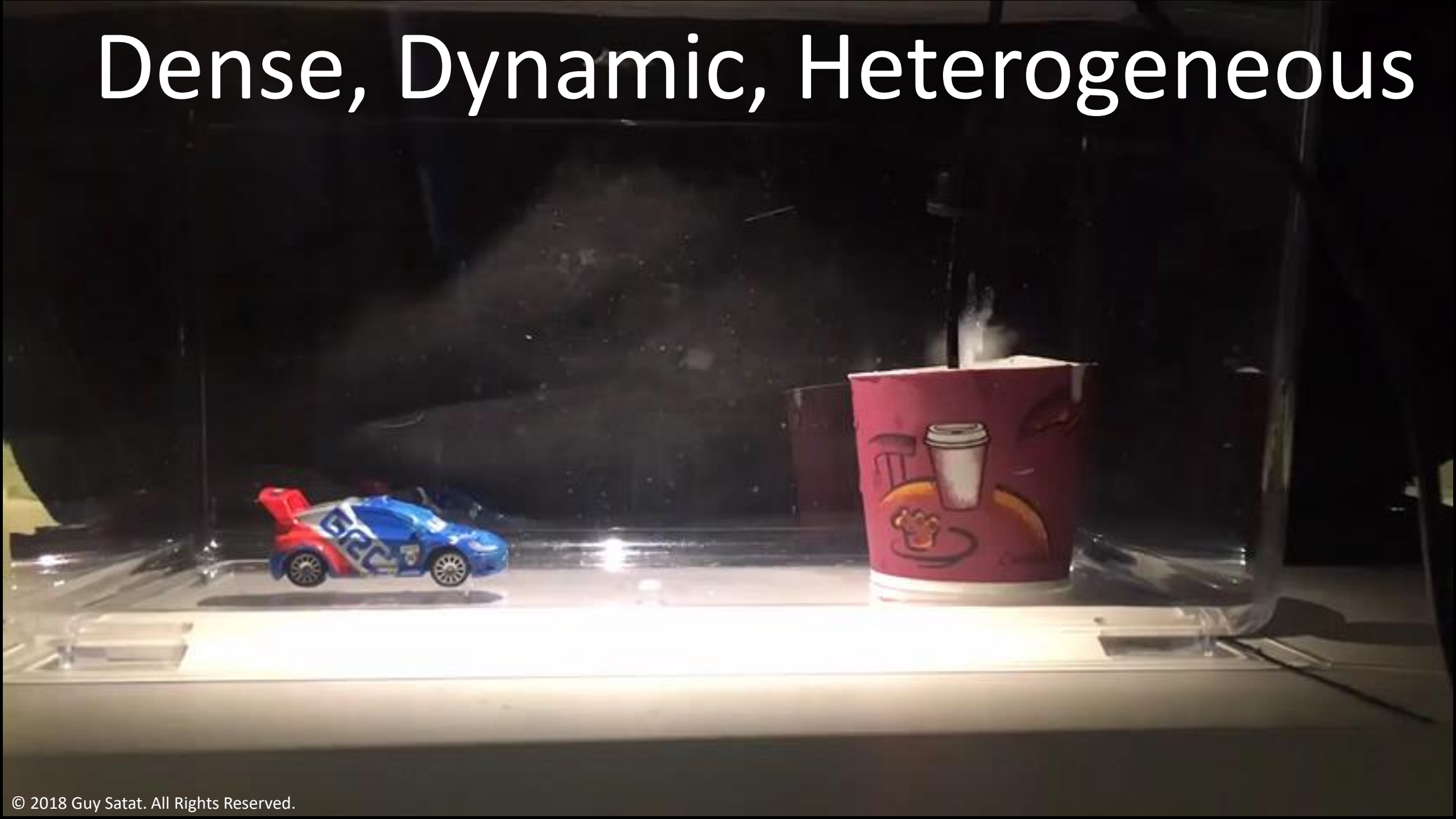
**Ours**

**Depth [cm]**



**Estimated visibility: 80 cm**

# Dense, Dynamic, Heterogeneous

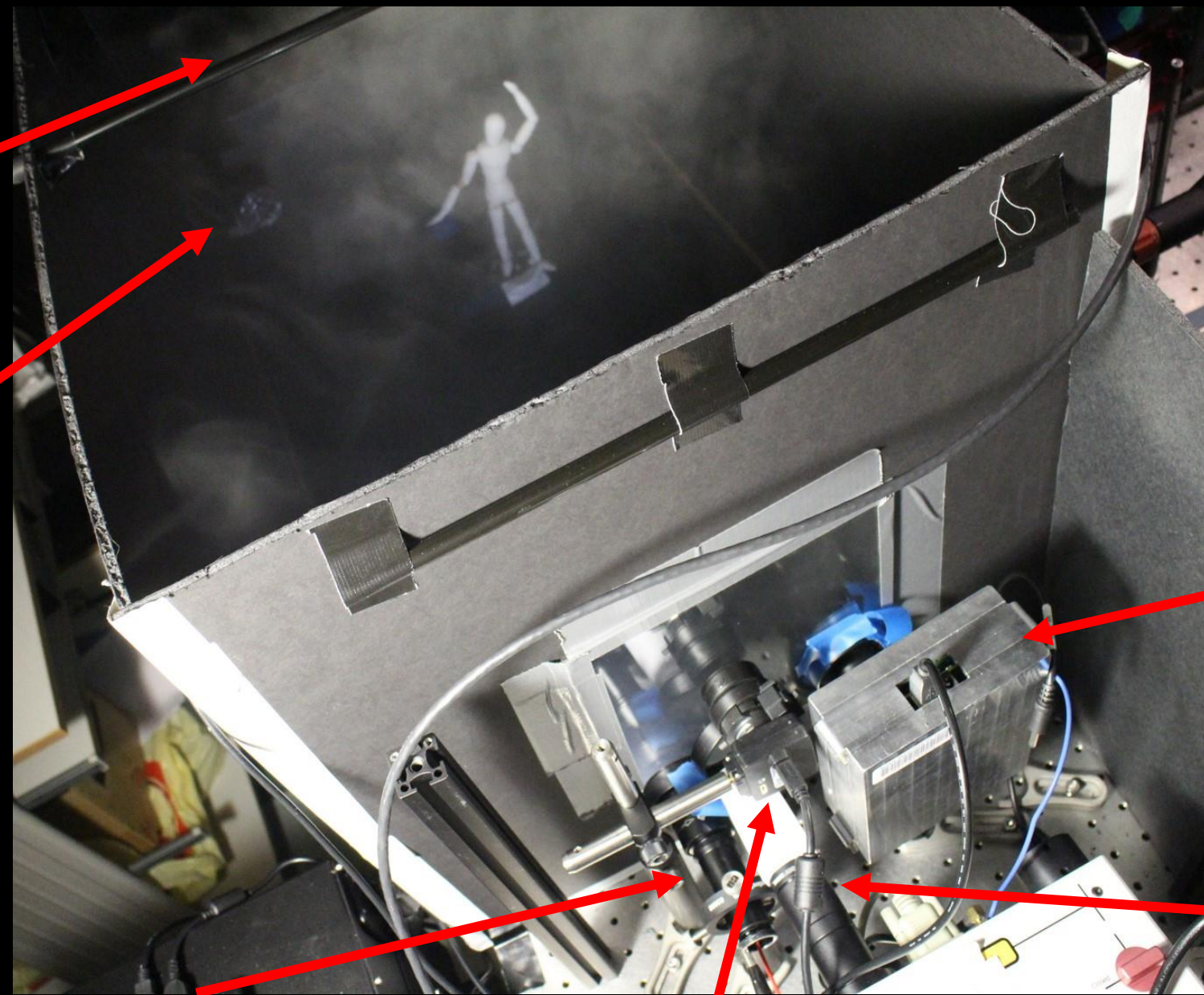


# Key Idea

- Observation:
  - Photons reflected from fog and those reflected from target obey different statistics
- Solution:
  - A probabilistic technique to reject the backreflected photons

Fog  
Generator

Power  
Meter



SPAD  
Camera

Diffused  
Pulsed  
Laser

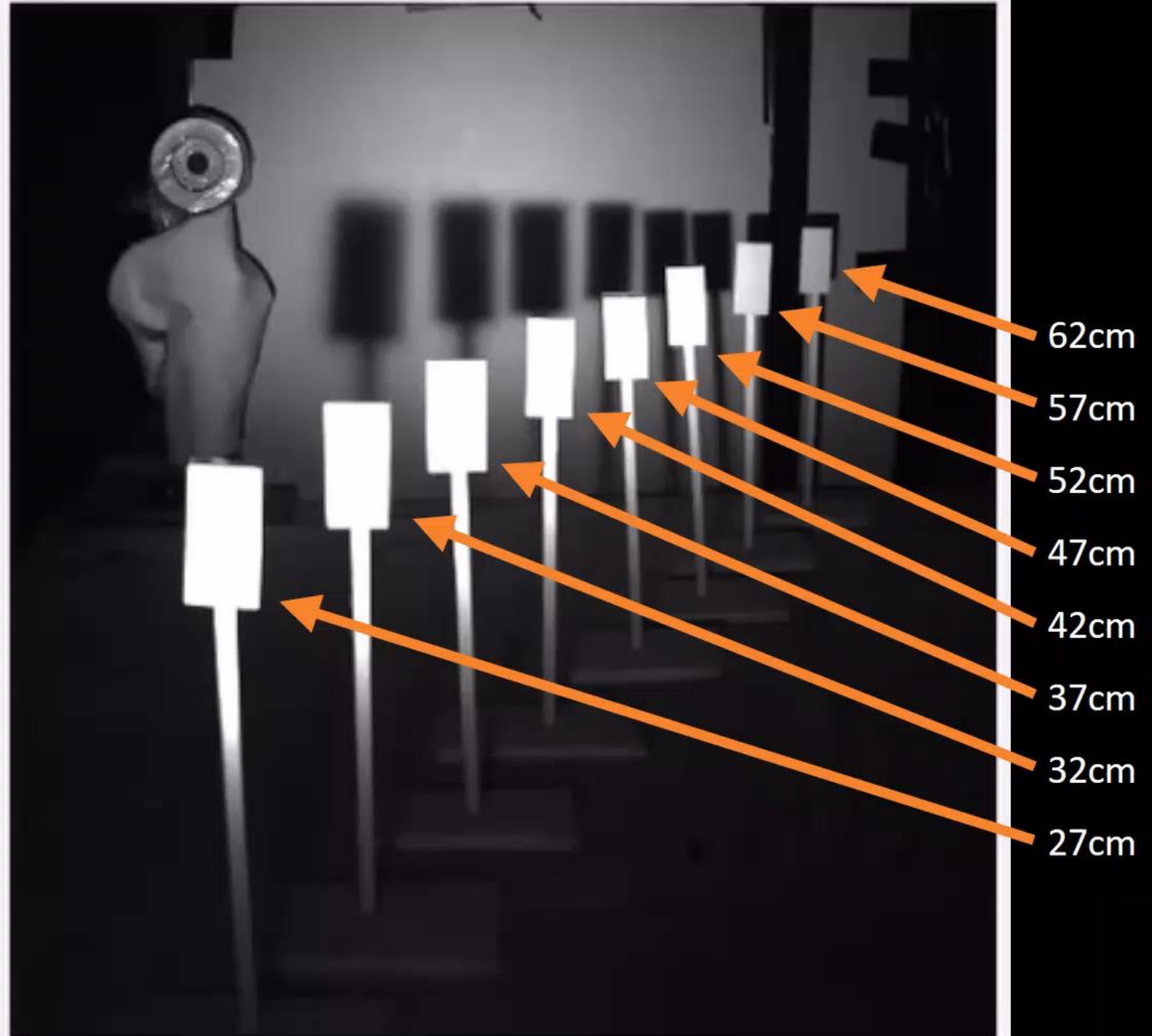
IR flashlight

Regular Camera

Optical Thickness:

$$OT_t = -\log\left(\frac{P_0}{P_t}\right)$$

Optical Thickness: 0.04



62cm

57cm

52cm

47cm

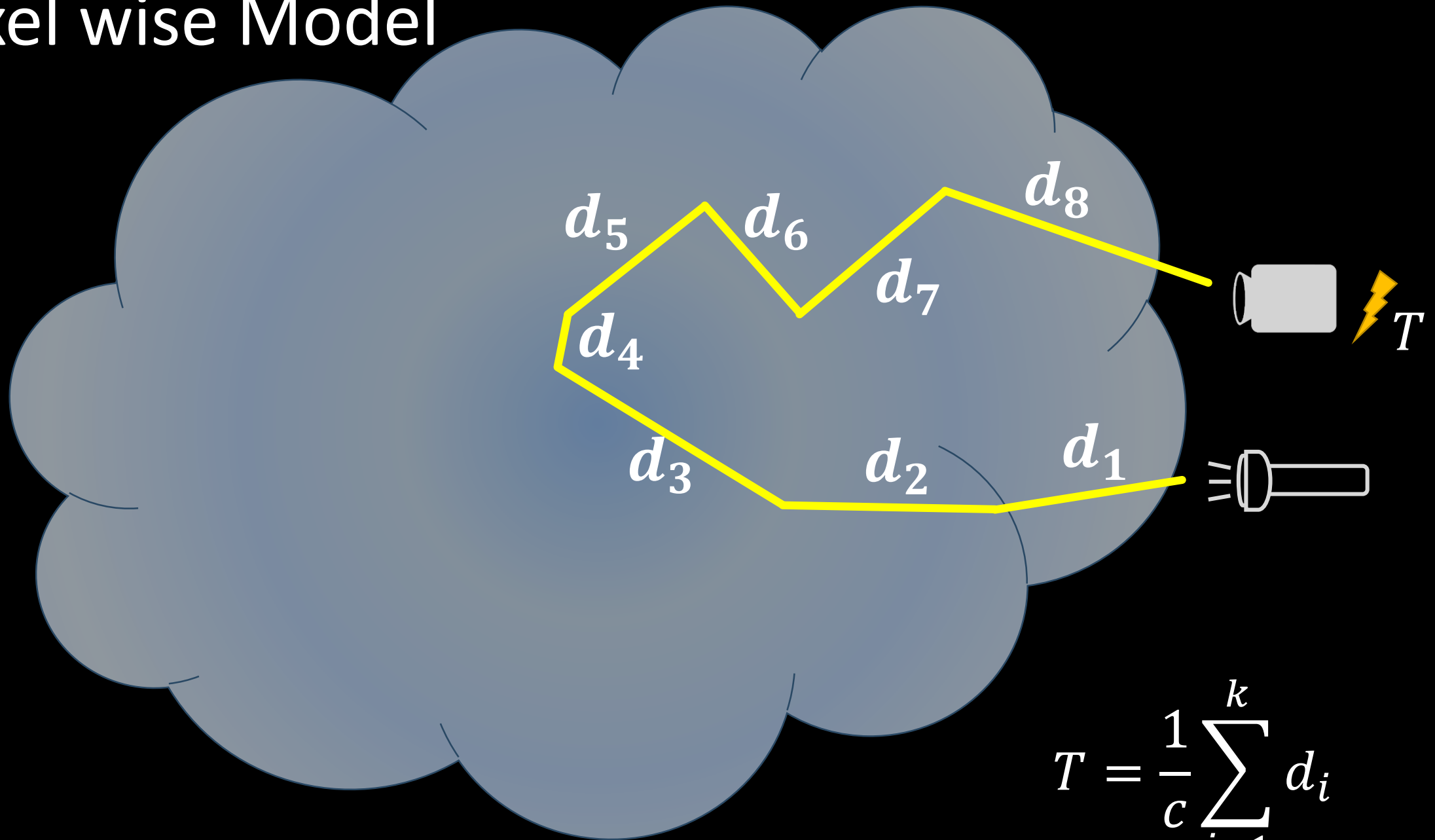
42cm

37cm

32cm

27cm

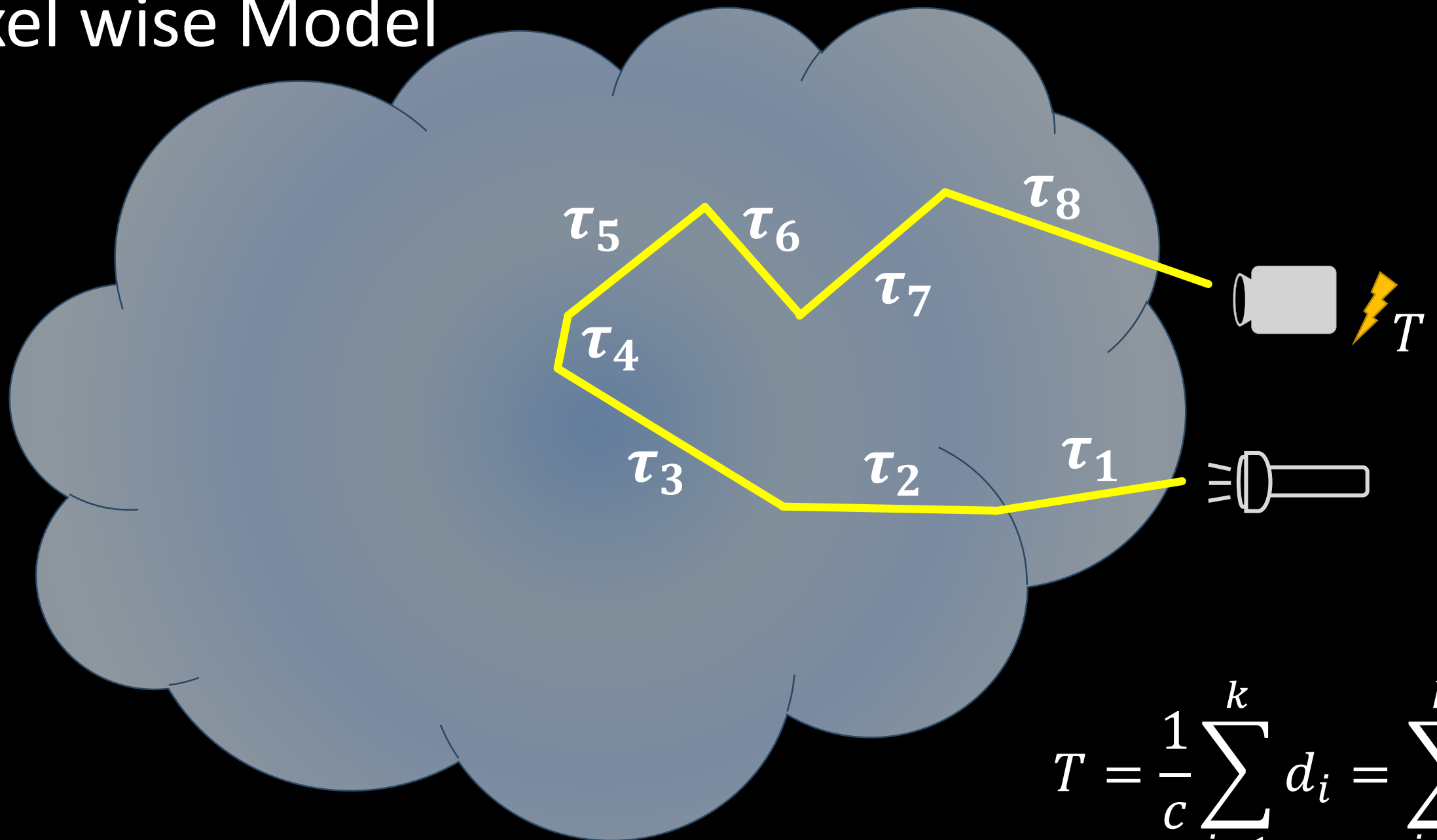
# Pixel wise Model



$$T = \frac{1}{c} \sum_{i=1}^k d_i$$

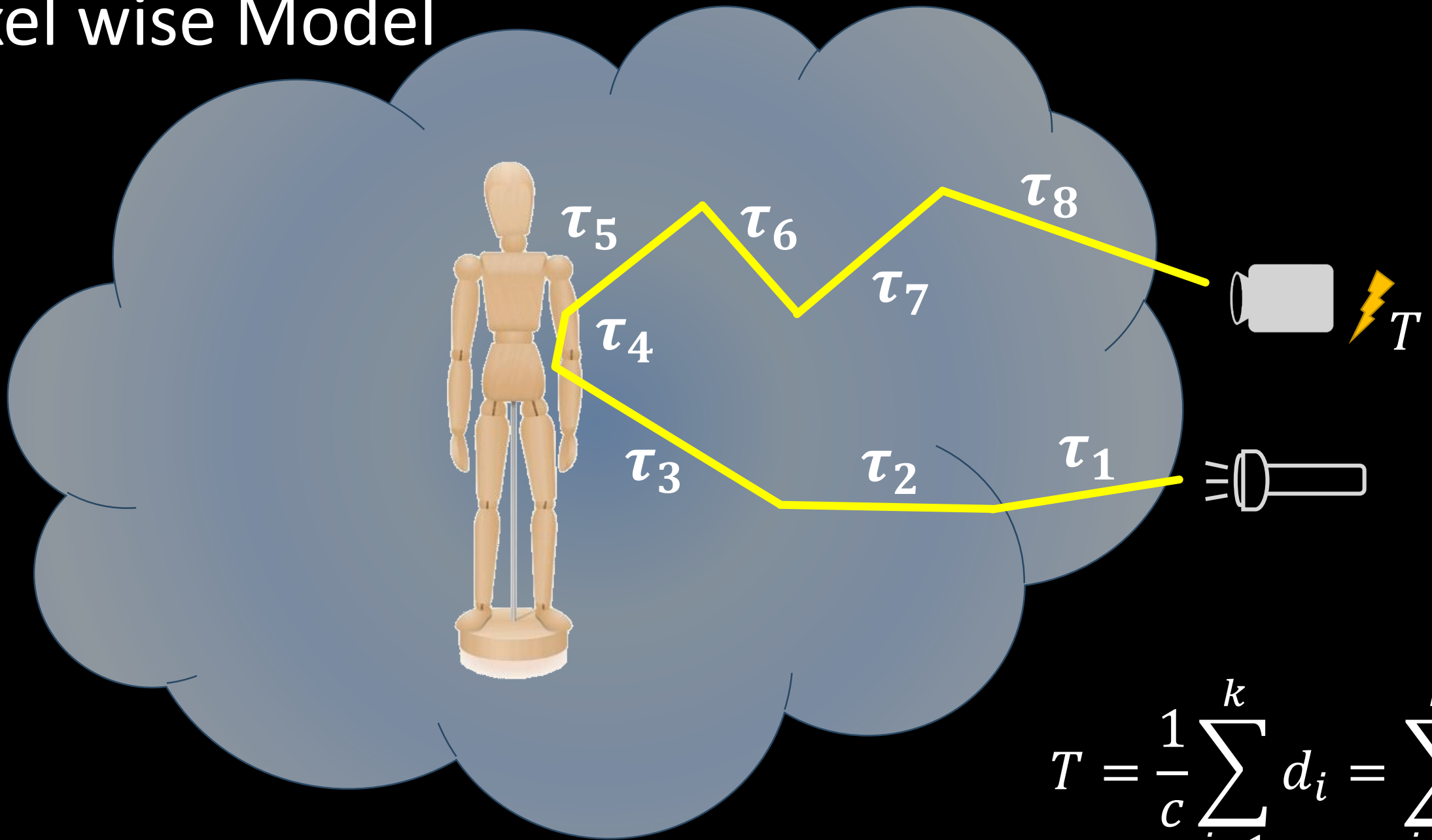


# Pixel wise Model



$$T = \frac{1}{c} \sum_{i=1}^k d_i = \sum_{i=1}^k \tau_i$$

# Pixel wise Model



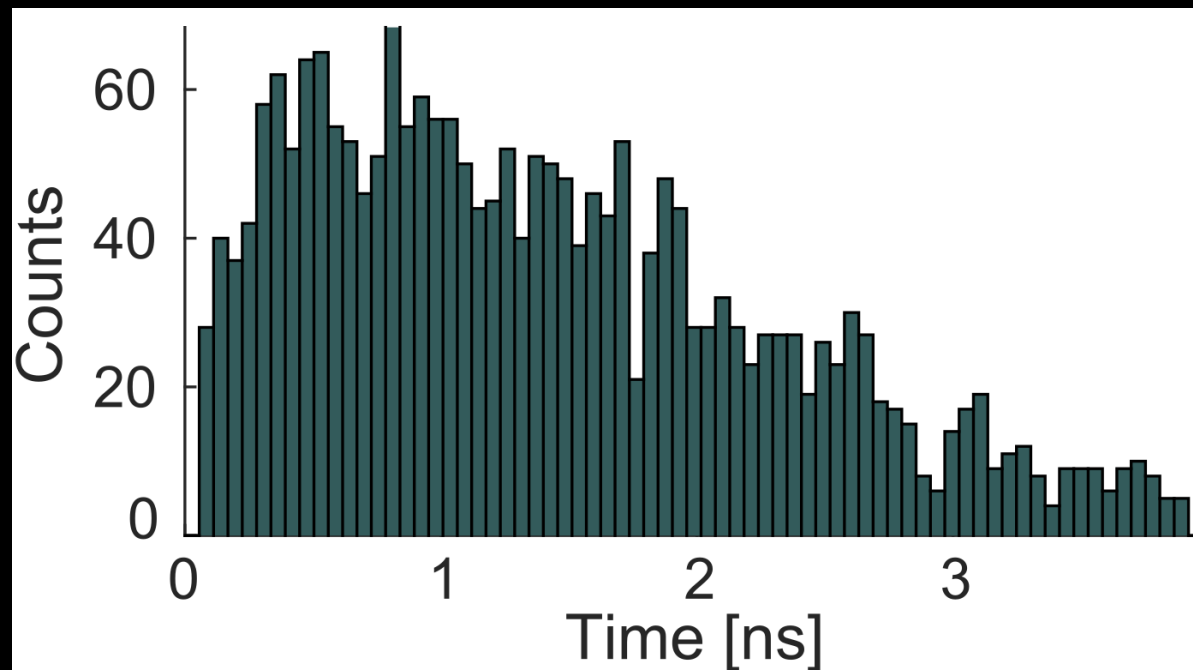
$$T = \frac{1}{c} \sum_{i=1}^k d_i = \sum_{i=1}^k \tau_i$$

# Photon Classes

Background

Signal

Dark Count



# Fog Model

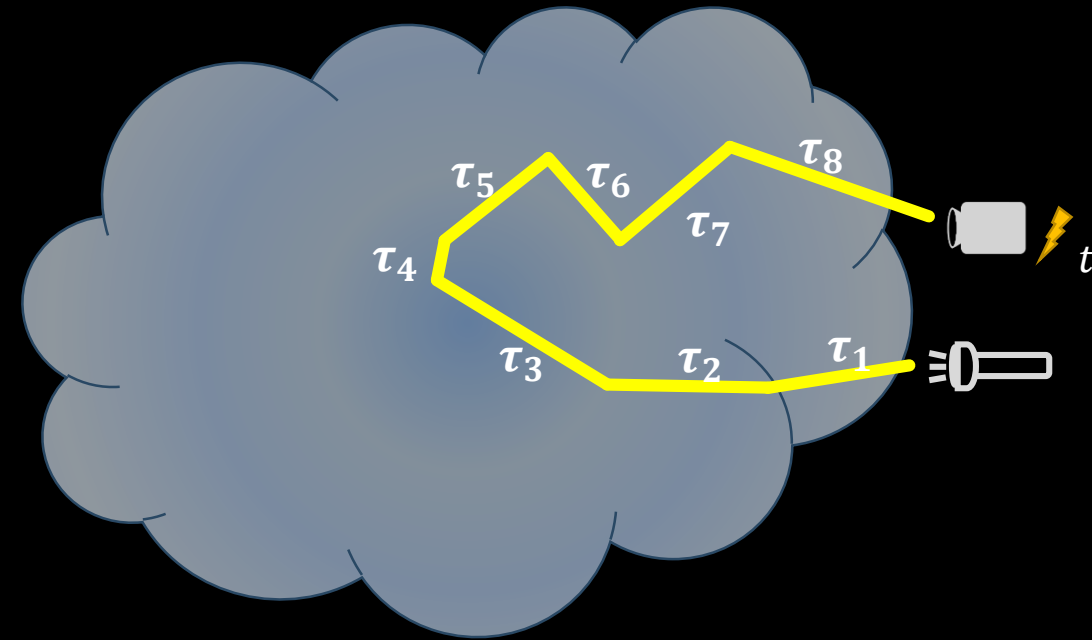
- $T = \sum_{i=1}^k \tau_i$

- $\tau_i \sim \text{Exp}\{\mu_s\}$

- $1/\mu_s$  - mean time between scattering events

- $T \sim \text{Gamma}\{\mu_s, k\}$

- $f_T(t|B) = \frac{\mu_s^k}{\Gamma(k)} t^{k-1} \exp\{-\mu_s t\}$



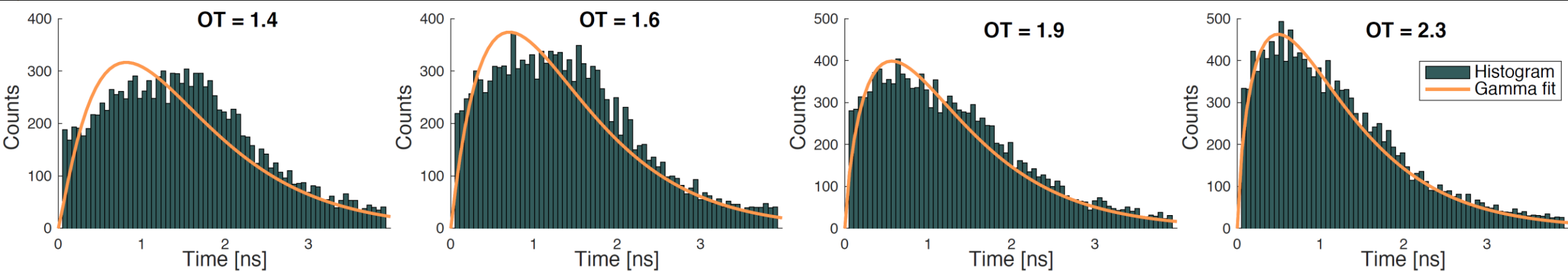
# Fog Model

$$T = \sum \tau_i$$

$$\tau_i \sim \text{Exp}\{\mu_s\}$$

$$T \sim \text{Gamma}\{\mu_s, k\}$$

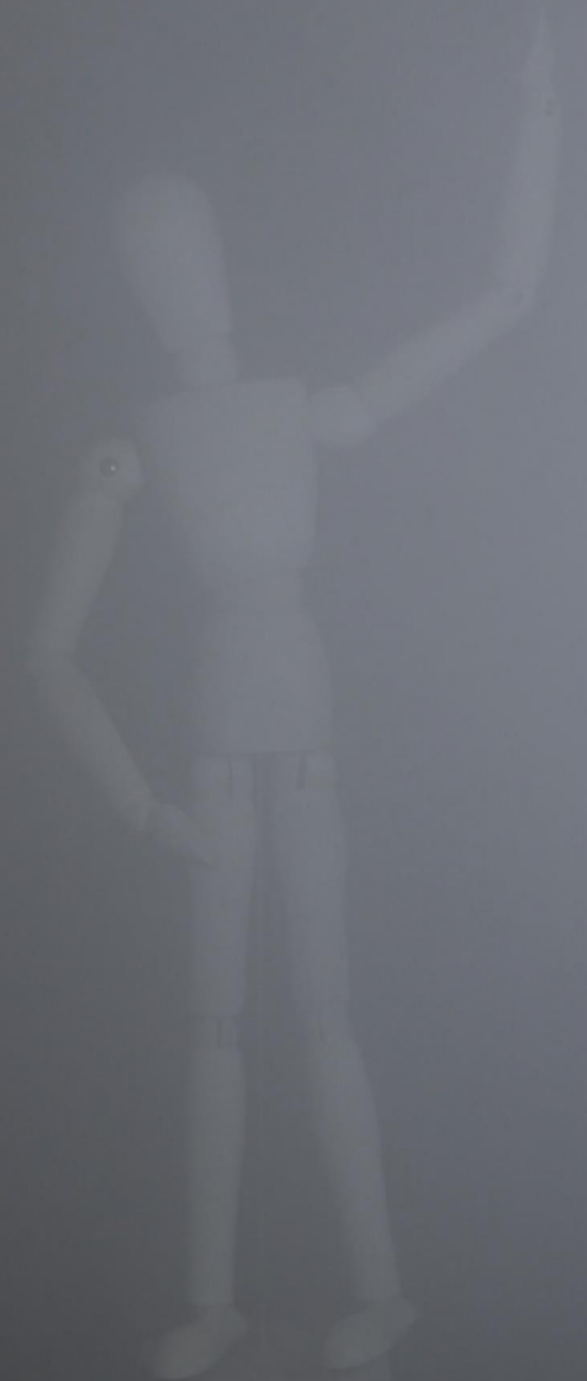
$$f_T(t|B) = \frac{\mu_s^k}{\Gamma(k)} t^{k-1} \exp\{-\mu_s t\}$$



# Signal Model

- Another Gamma?

- $f_T(t|S) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{(t-\mu)^2}{\sigma}\right\}$



# Measurement Model

$$f_T(t) = P(B)f_T(t|B) + P(S)f_T(t|S)$$

Probability to measure a photon at time  $t$

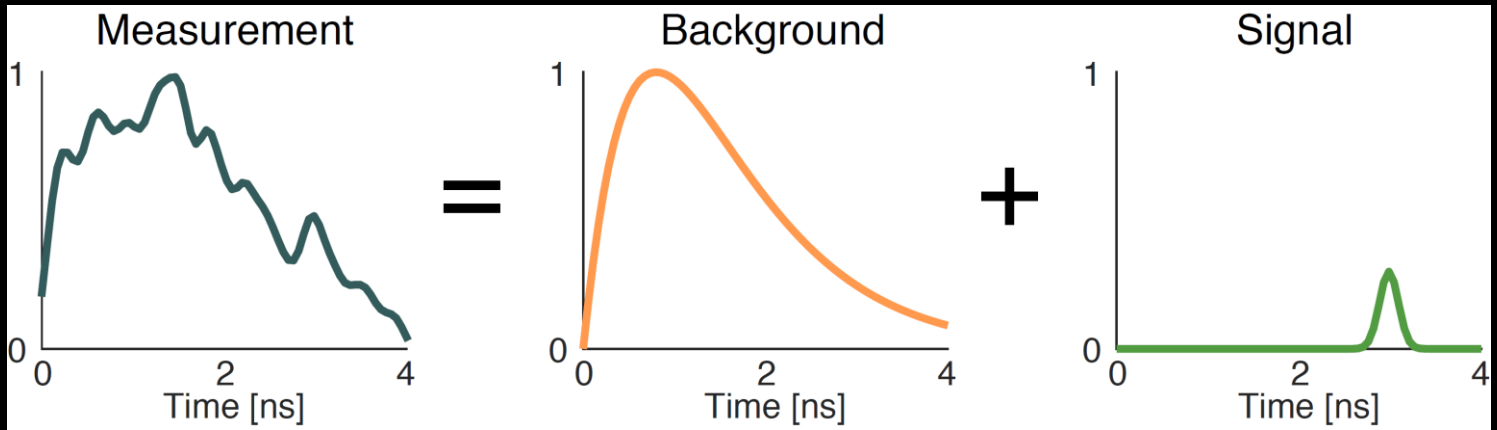
Probability to measure a background photon

Gamma distribution

Probability to measure a signal photon

Normal distribution

Encodes the target depth and reflectance



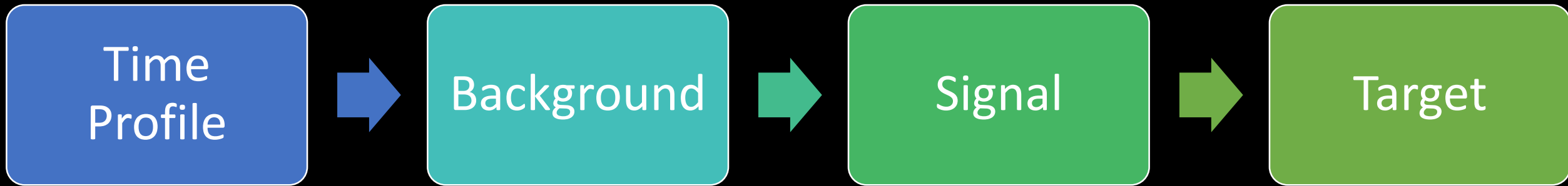
# Model Estimation

$$f_T(t) = \underbrace{P(B)f_T(t|B)}_{\text{Fog}} + \underbrace{P(S)f_T(t|S)}_{\text{Signal}}$$



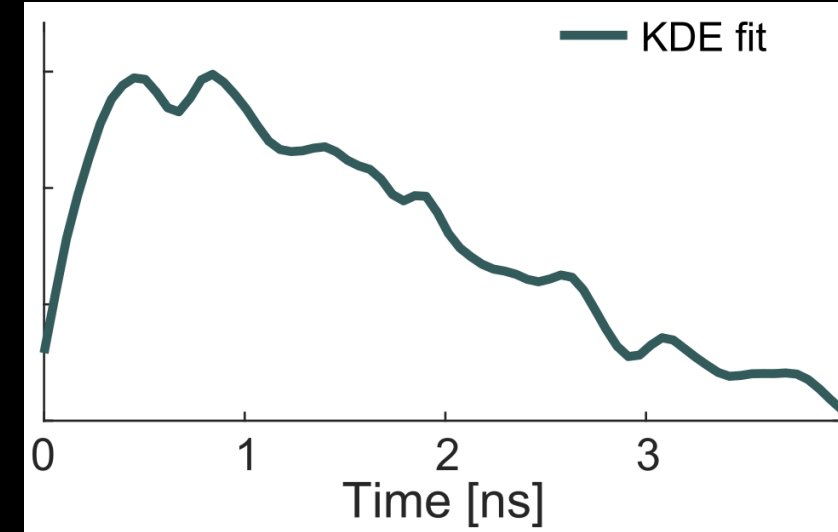
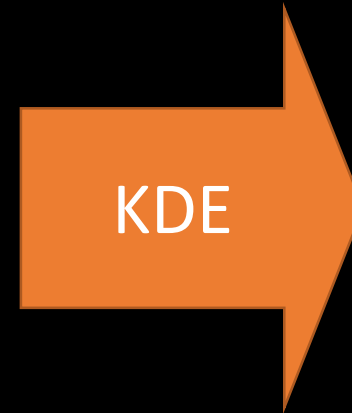
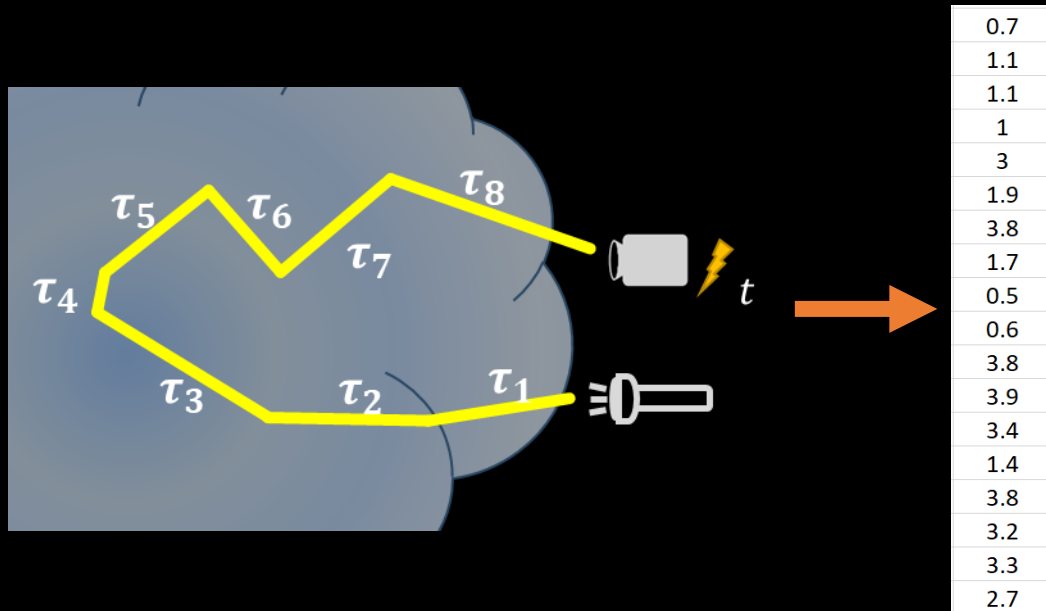
# Model Estimation

$$f_T(t) = \underbrace{P(B)f_T(t|B)}_{\text{Fog}} + \underbrace{P(S)f_T(t|S)}_{\text{Signal}}$$



$$f_T(t) = \underbrace{P(B)f_T(t|B)}_{\text{Fog}} + \underbrace{P(S)f_T(t|S)}_{\text{Signal}}$$

# Time Profile Estimation

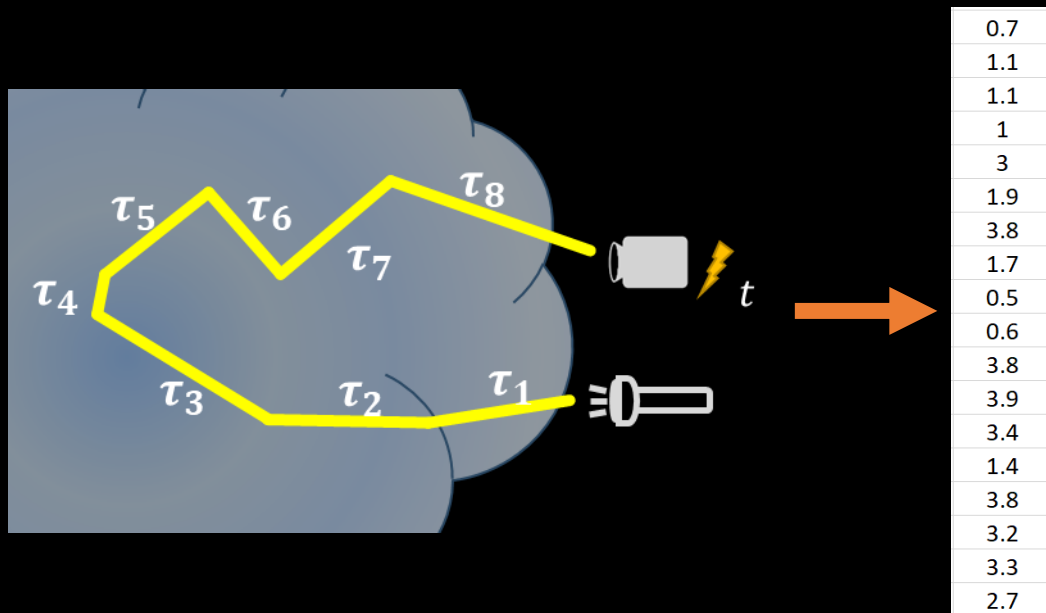


KDE (Kernel Density Estimator):

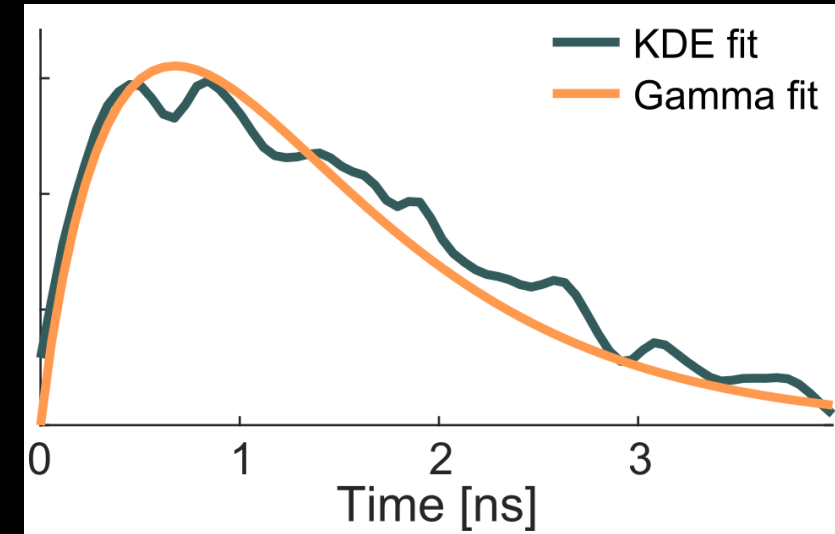
- Works well with a few sampling points

# Background Estimation

$$f_T(t) = \underbrace{P(B)f_T(t|B)}_{\text{Fog}} + \underbrace{P(S)f_T(t|S)}_{\text{Signal}}$$

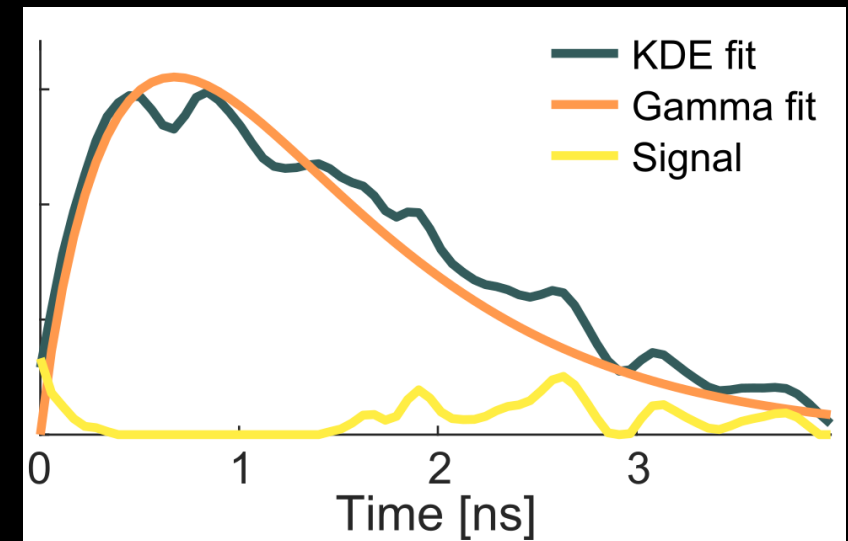
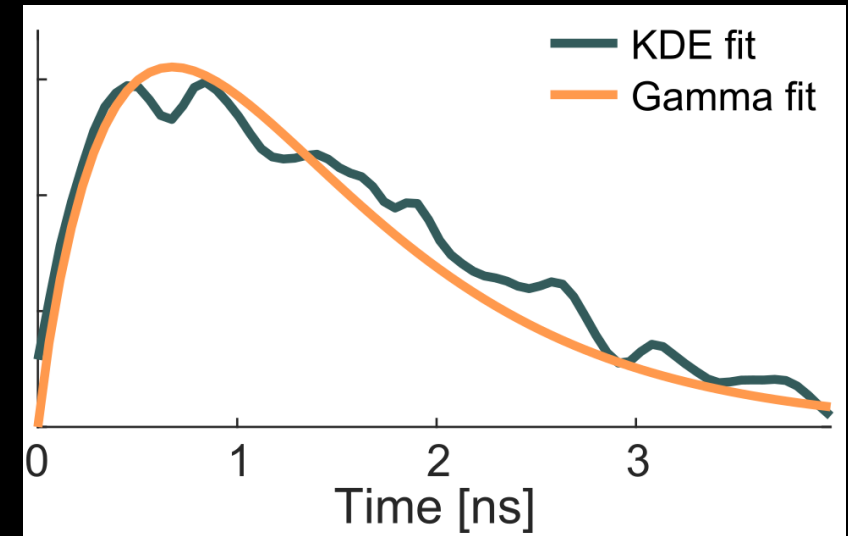
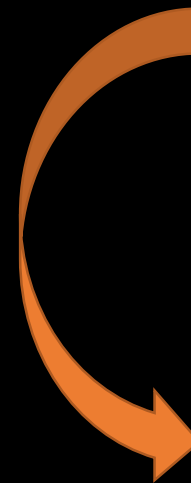
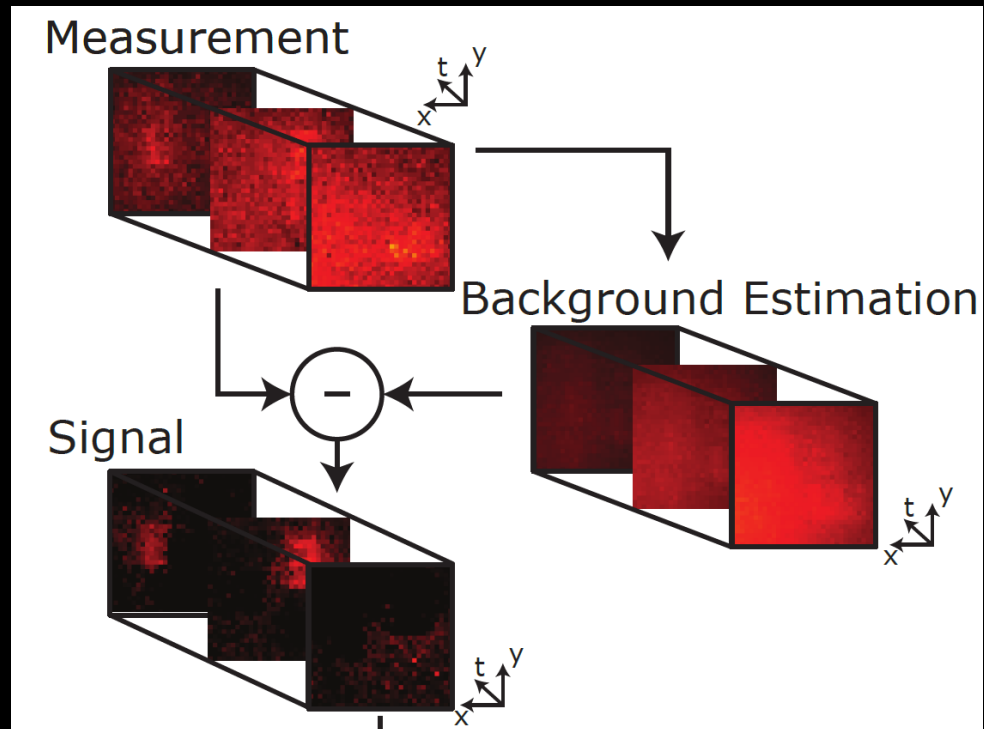


Gamma fit



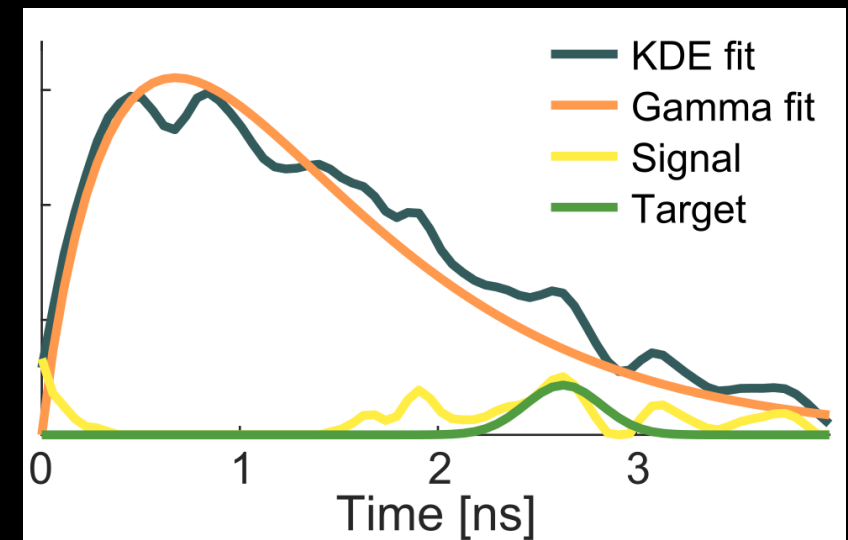
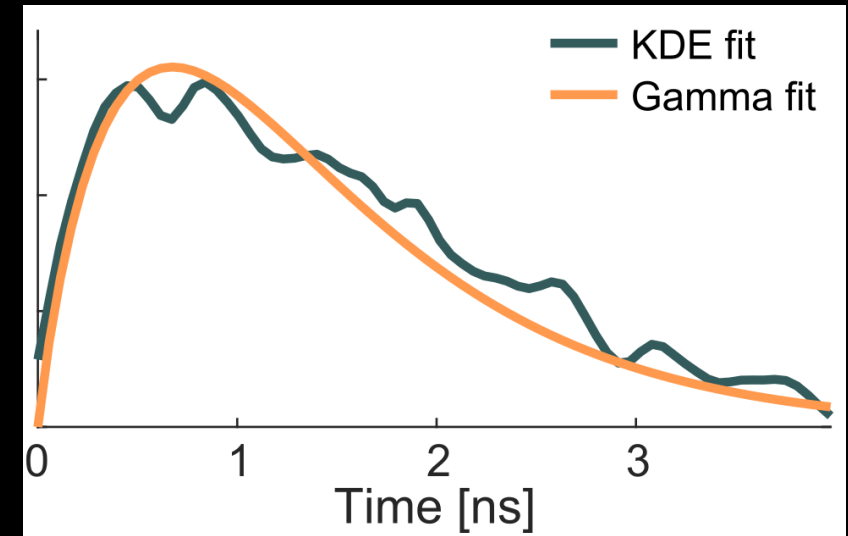
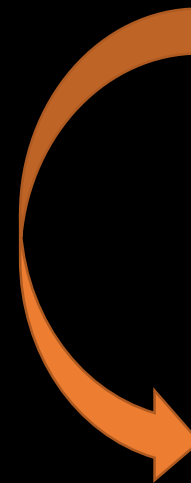
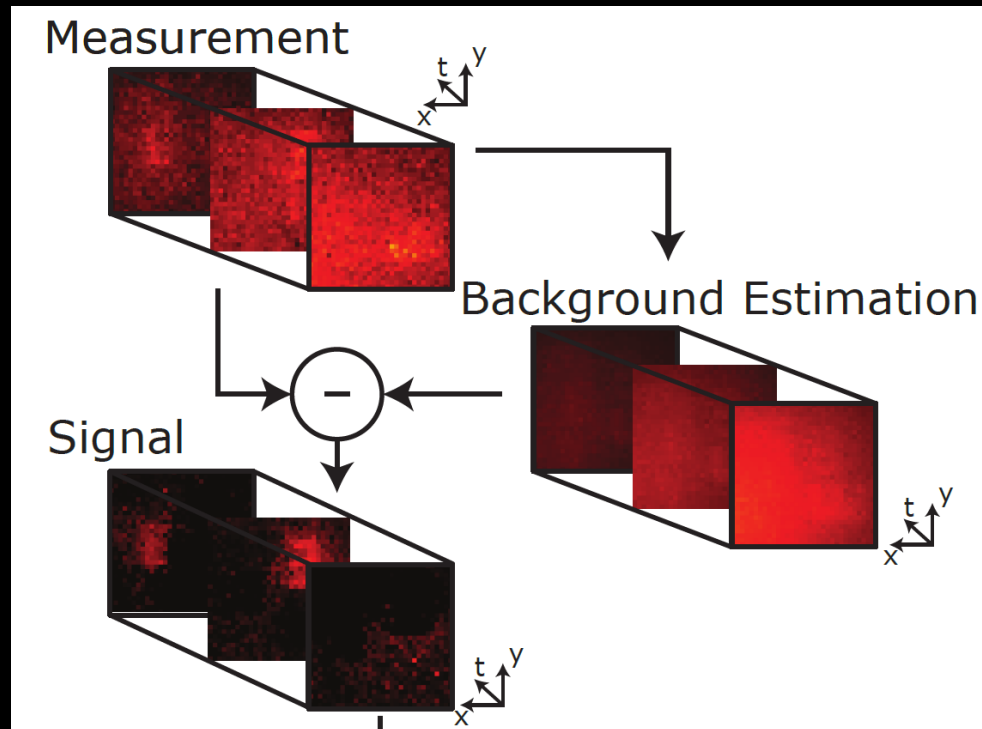
# Signal Estimation

$$f_T(t) = \underbrace{P(B)f_T(t|B)}_{\text{Fog}} + \underbrace{P(S)f_T(t|S)}_{\text{Signal}}$$



# Signal Estimation

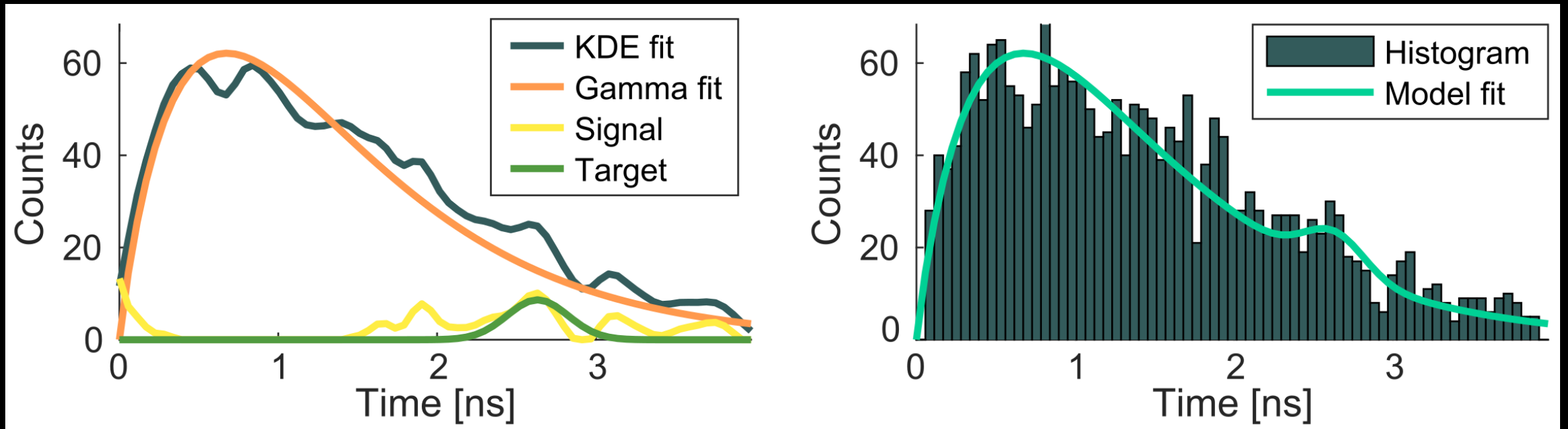
$$f_T(t) = \underbrace{P(B)f_T(t|B)}_{\text{Fog}} + \underbrace{P(S)f_T(t|S)}_{\text{Signal}}$$



$$f_T(t) = \underbrace{P(B)f_T(t|B)}_{\text{Fog}} + \underbrace{P(S)f_T(t|S)}_{\text{Signal}}$$

# Signal Estimation

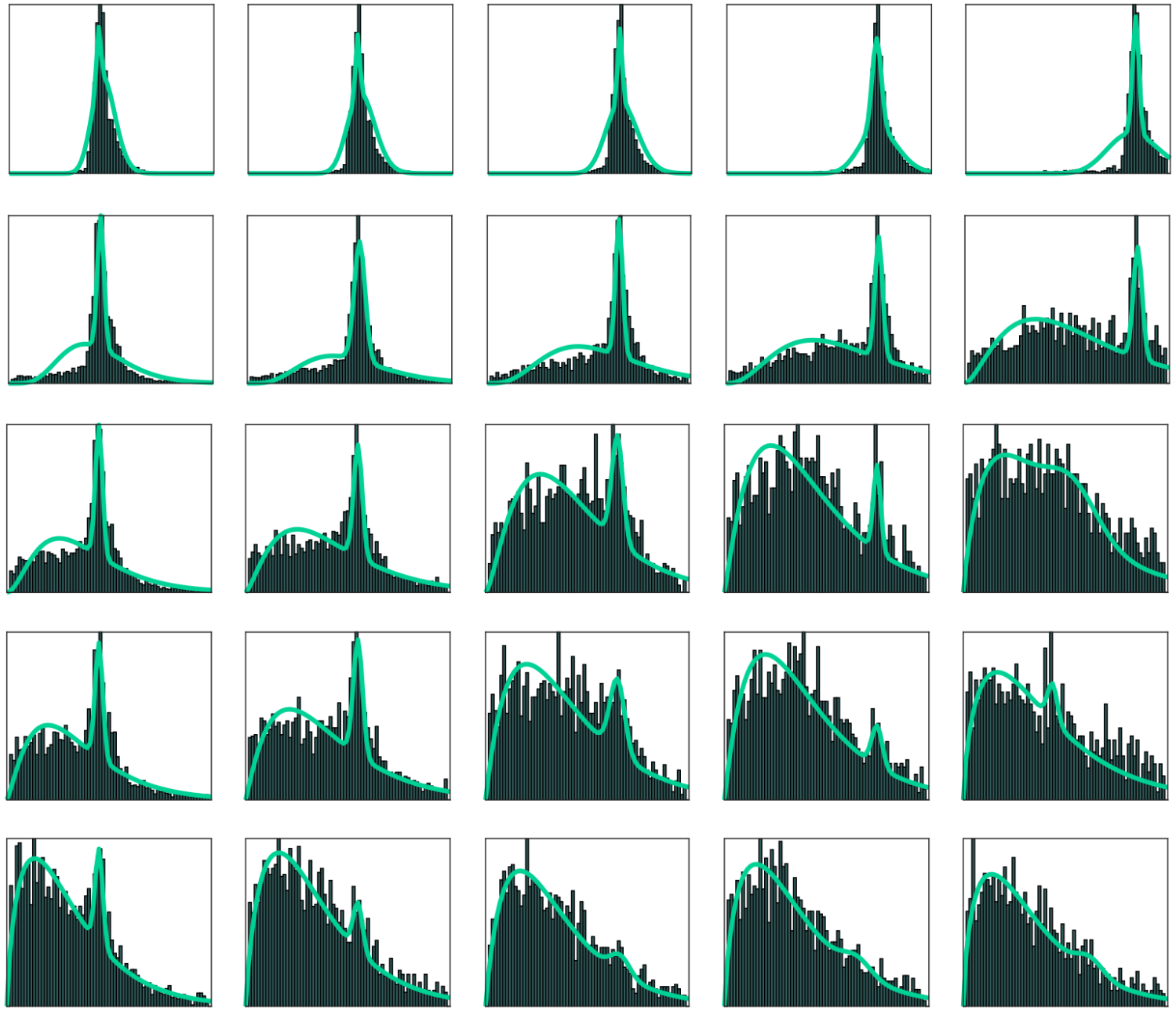
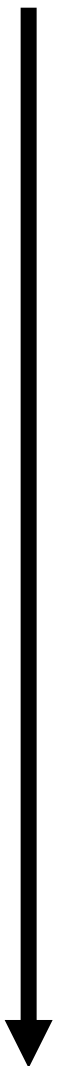
$$[\hat{P}(S), \hat{P}(B)] = \underset{[P(S), P(B)]}{\operatorname{argmin}} \sum_t [P(B)\hat{f}_T(t|B) + P(S)\hat{f}_T(t|S) - \hat{f}_T(t)]^2$$



Target Distance



Fog Density



Histogram  
Model Fit

$$f_T(t) = P(B)f_T(t|B) + P(S)f_T(t|S)$$

# Target Recovery

- $P(S)f_T(t|S) = P(S) \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{(t-\mu)^2}{\sigma}\right\}$

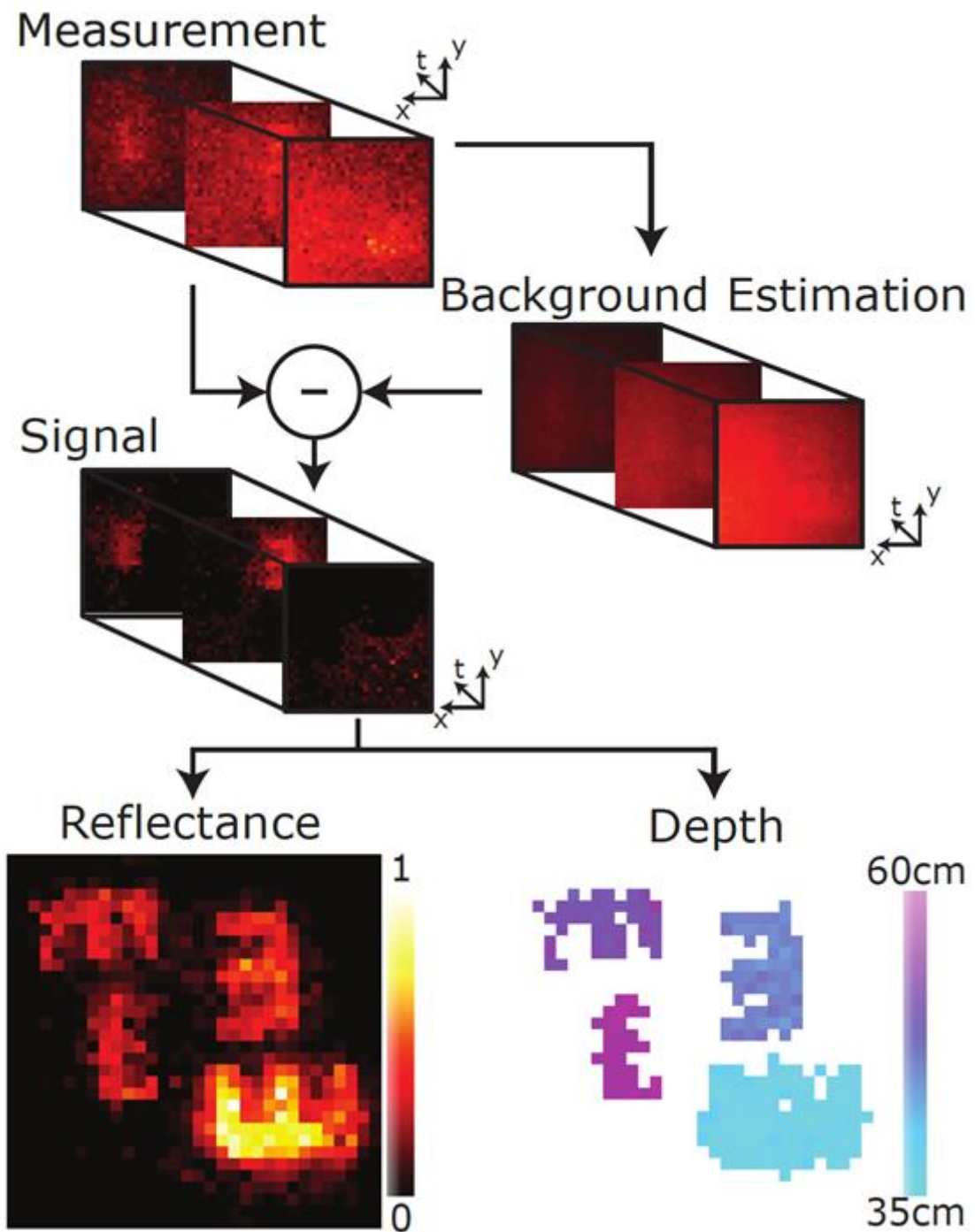
Reflectance



Depth







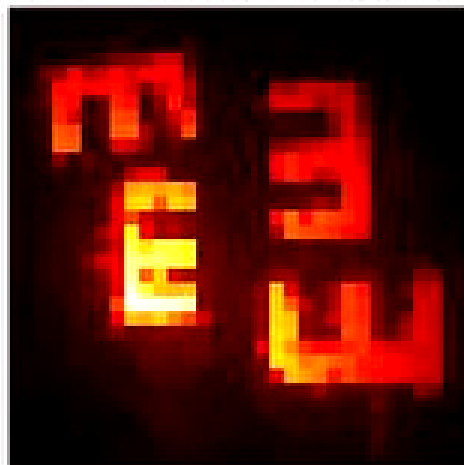
**OT=0.02**

**Regular Camera**



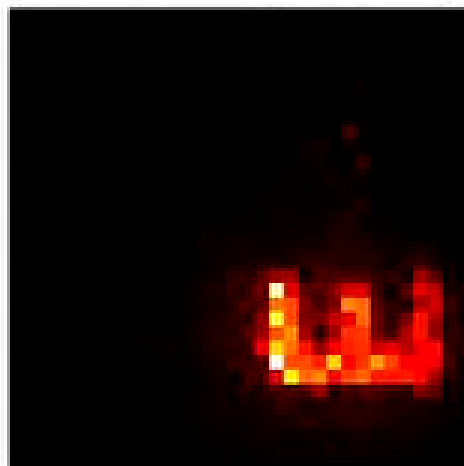
SSIM=1  
PSNR=Inf

**SPAD Photon Counting**



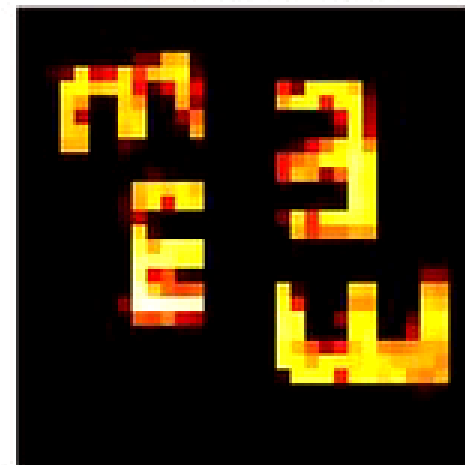
SSIM=1  
PSNR=Inf

**SPAD Time Gating**



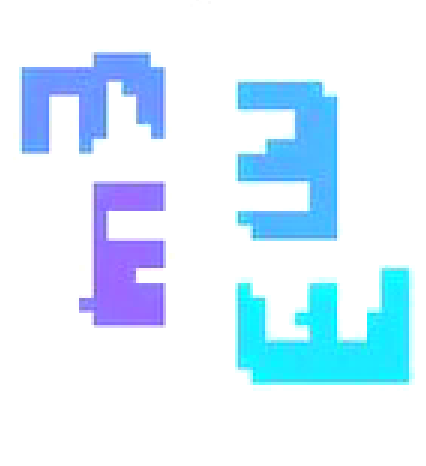
SSIM=0.36  
PSNR=14.32

**Ours**  
**Reflectance**

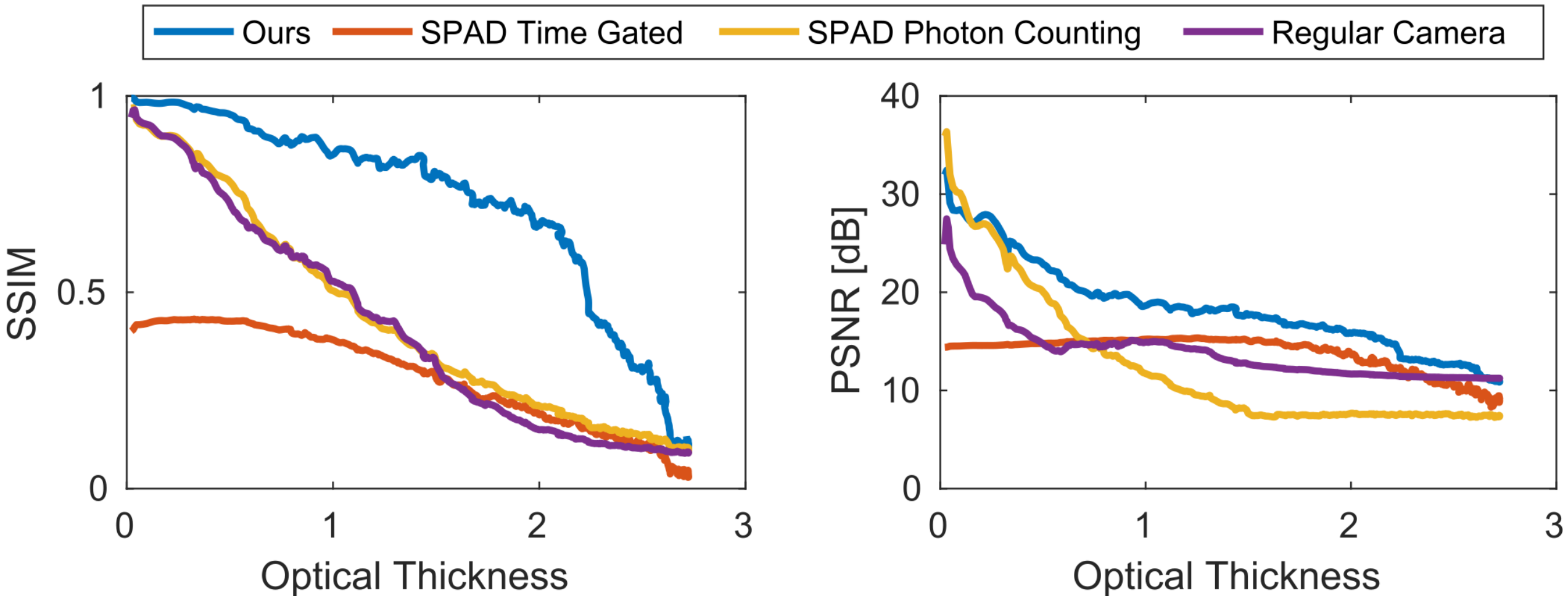


SSIM=1  
PSNR=Inf

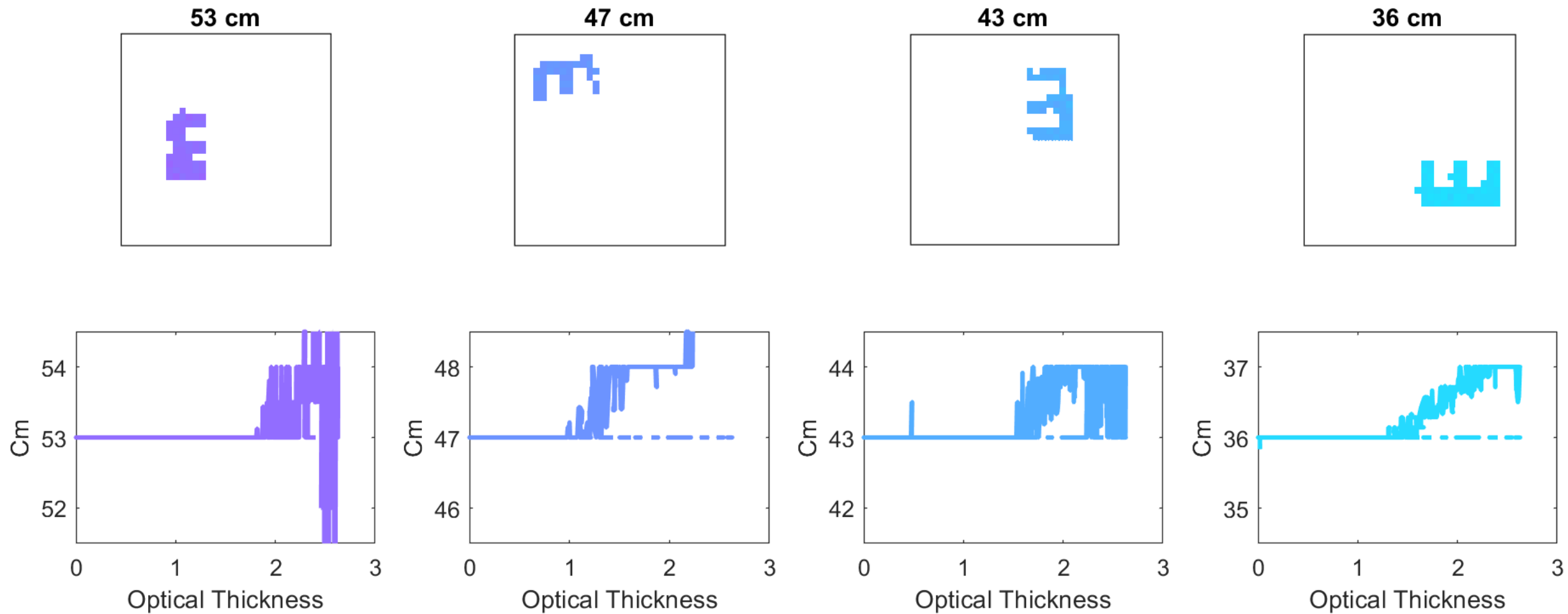
**Depth**



# Reflectance Recovery Error



# Depth Recovery Error



**OT=0.01**

**Regular Camera**



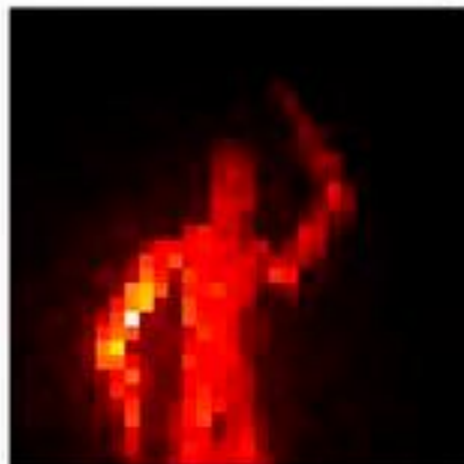
SSIM=1  
PSNR=Inf

**SPAD Photon Counting**



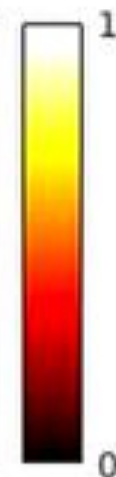
SSIM=1  
PSNR=Inf

**SPAD Time Gating**



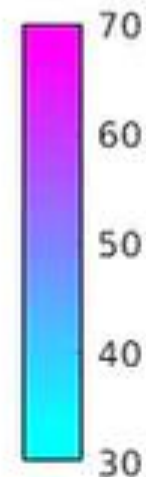
SSIM=0.8  
PSNR=18.17

**Ours**  
**Reflectance**

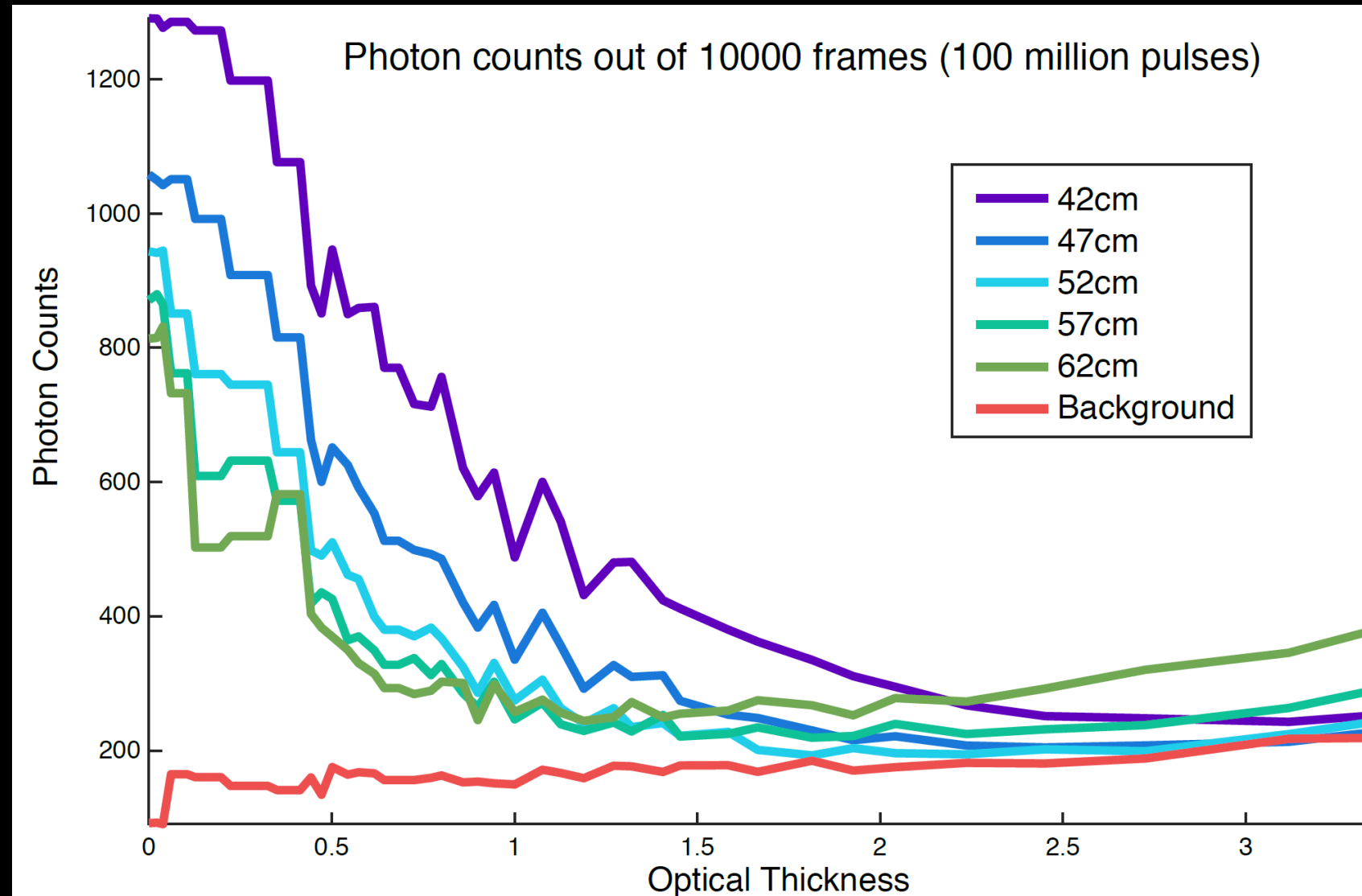


SSIM=1  
PSNR=Inf

**Depth**



# How Many Photons?



# Limitations

Ignores spatial  
nature of scattering

- Impose priors
- Deblur

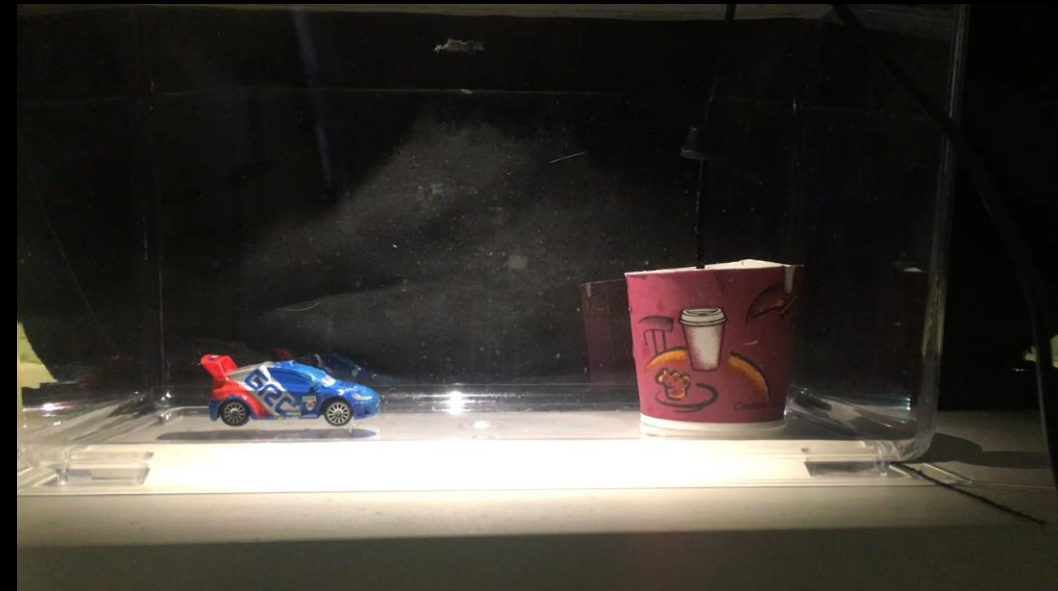


# Limitations

Ignores spatial  
nature of scattering

Photon efficiency

- Current hardware efficiency is  $\sim 1:10^6$
- Algorithm efficiency could improve





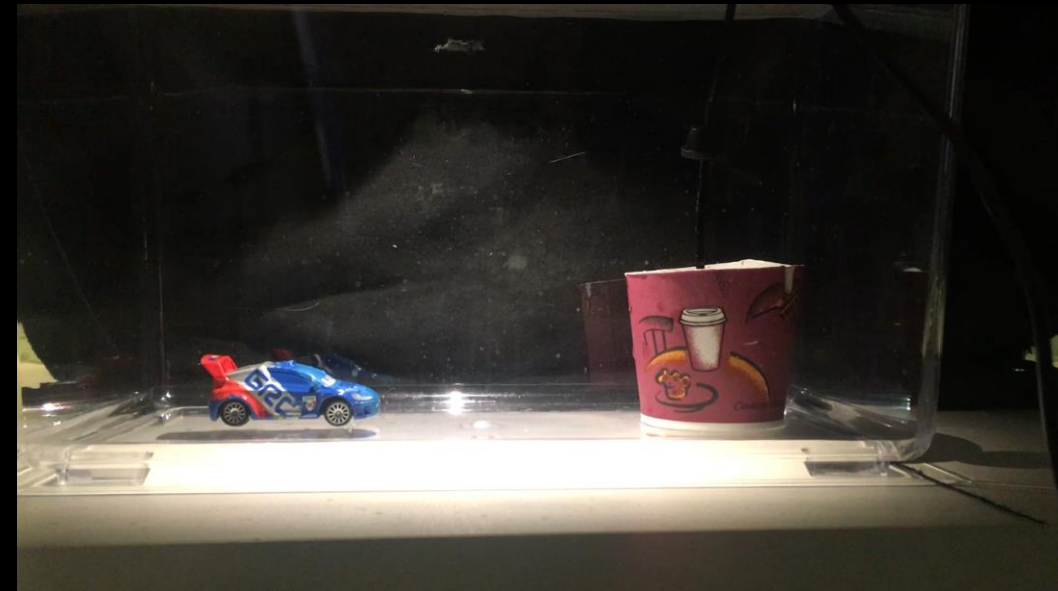
# Limitations

Ignores spatial  
nature of scattering

Photon efficiency

Acquisition time

- New frame every  $100\mu s$
- Currently use constant window of  $20K$  frames  $\rightarrow 2s$
- Dynamic window based of fog estimate



# Limitations

Ignores spatial  
nature of scattering

Photon efficiency

Acquisition time

Scale

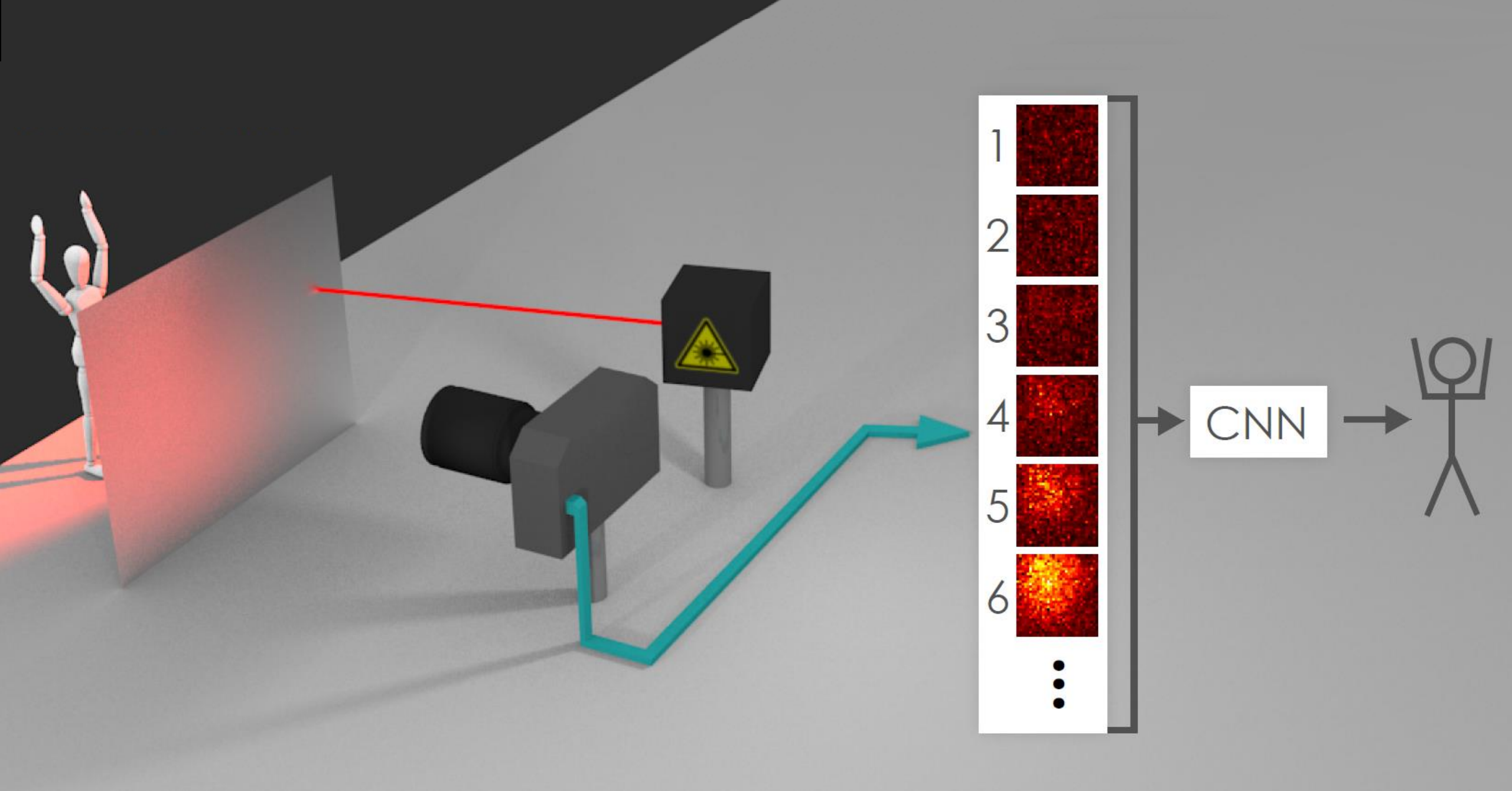
- Optical thickness is unitless
- Larger scenes → relaxed requirement for time resolution
- More dependency on spatial scattering?



# Object Classification through Scattering Media with Deep Learning

Guy Satat, Matthew Tancik, Otkrist Gupta, Barmak Heshmat, Ramesh Raskar

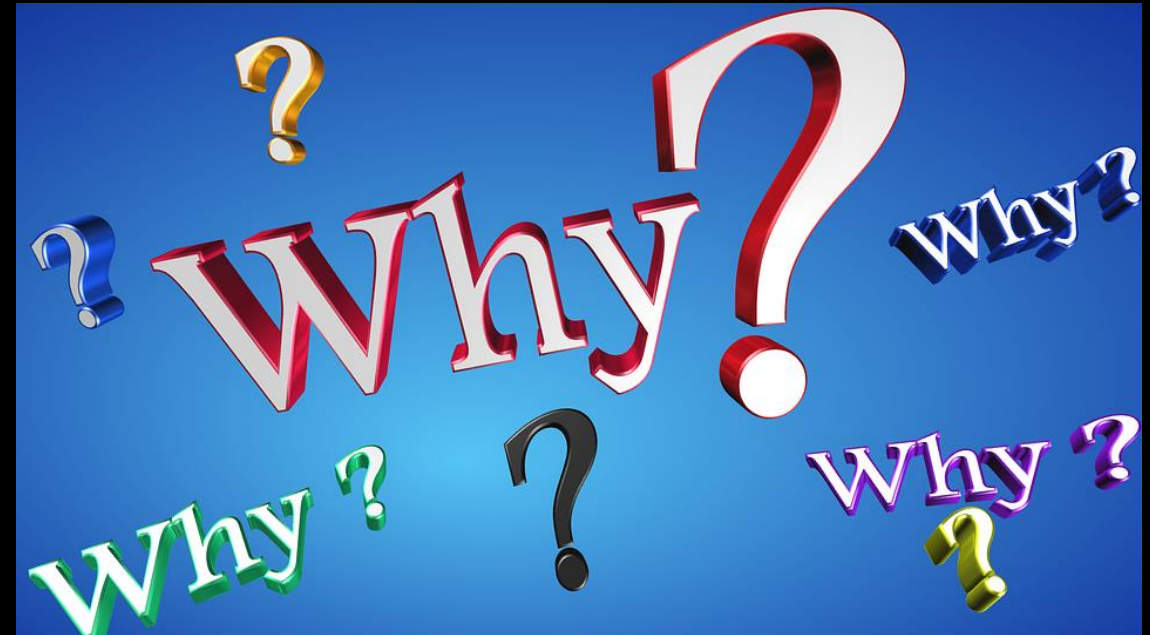
Optics Express (2017)



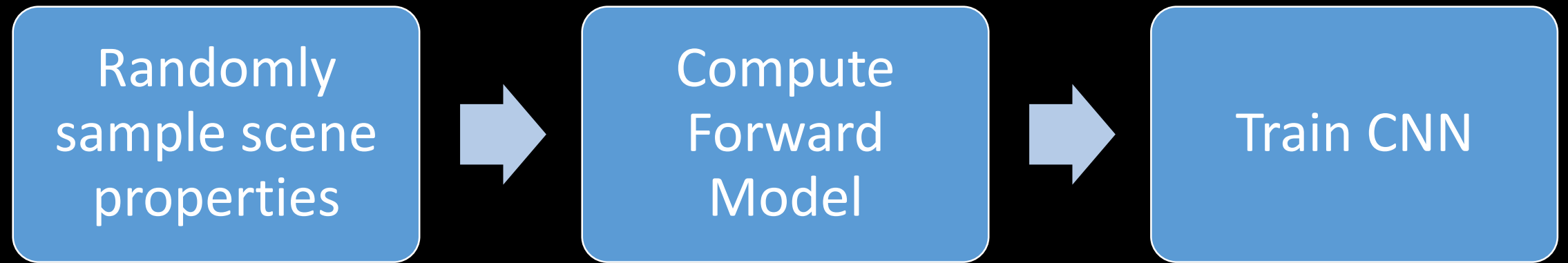
# We Have to Calibrate

# Why Deep Learning?

## Can learn invariants



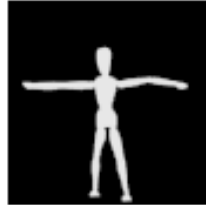





# Learning Invariant to Calibration Parameters

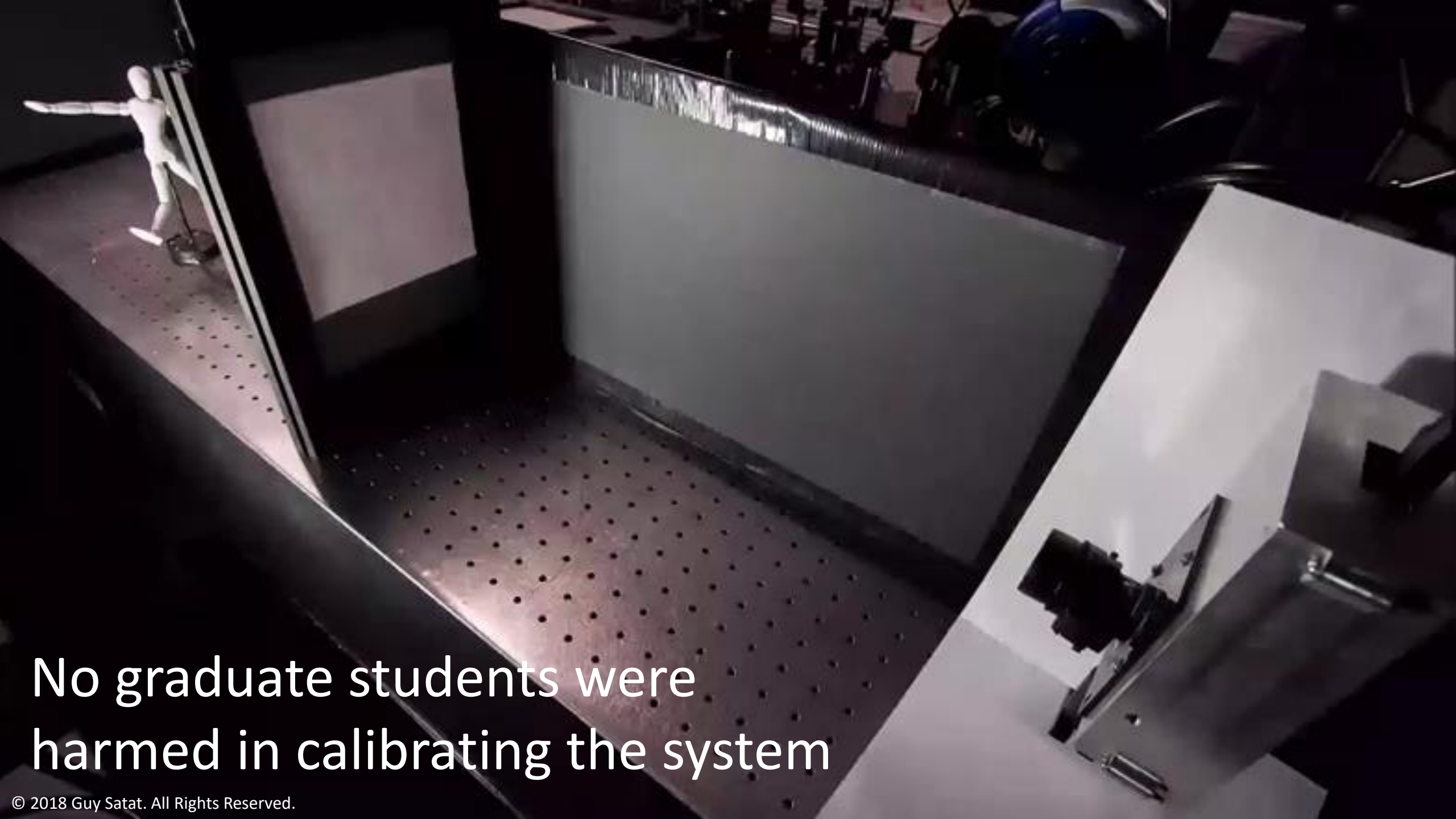


# Train on Synthetic Data

## Test on Lab Measurement

			
	<b>0.9</b>	<b>0.0</b>	<b>0.1</b>
	<b>0.3</b>	<b>0.7</b>	<b>0.0</b>
	<b>0.1</b>	<b>0.2</b>	<b>0.7</b>





No graduate students were  
harmed in calibrating the system

# Summary

- Variety of weather conditions
- Imaging through fog ~ Imaging through scattering
  - Wide range of fog conditions:
    - Dense, dynamic, heterogeneous
    - Calibration free
  - No raster scan
- Probabilistic Computational Imaging
- Data Driven Computational Imaging

