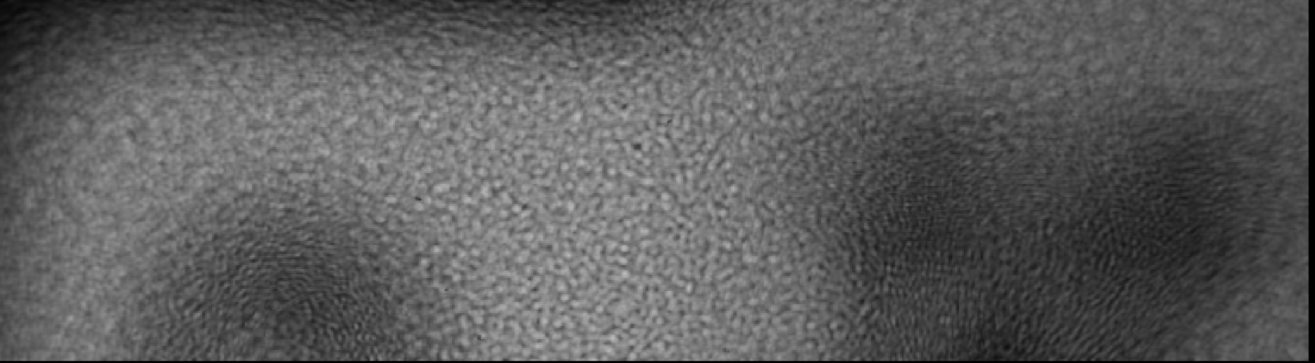
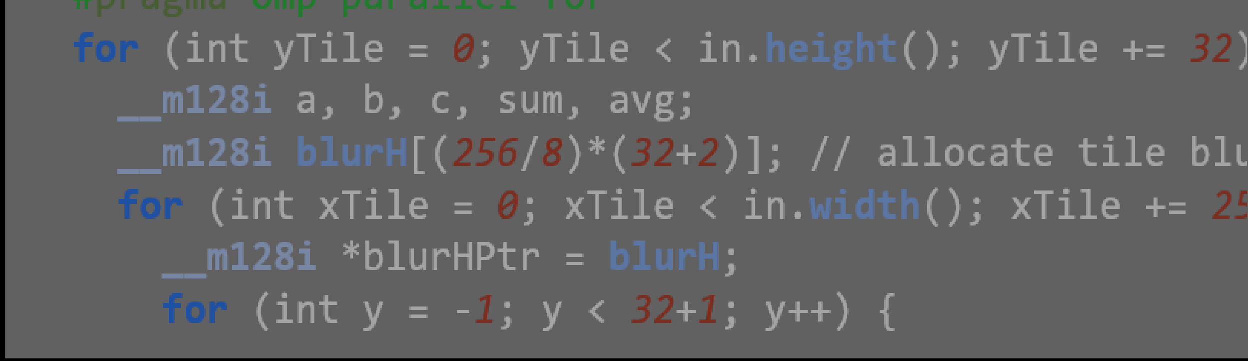




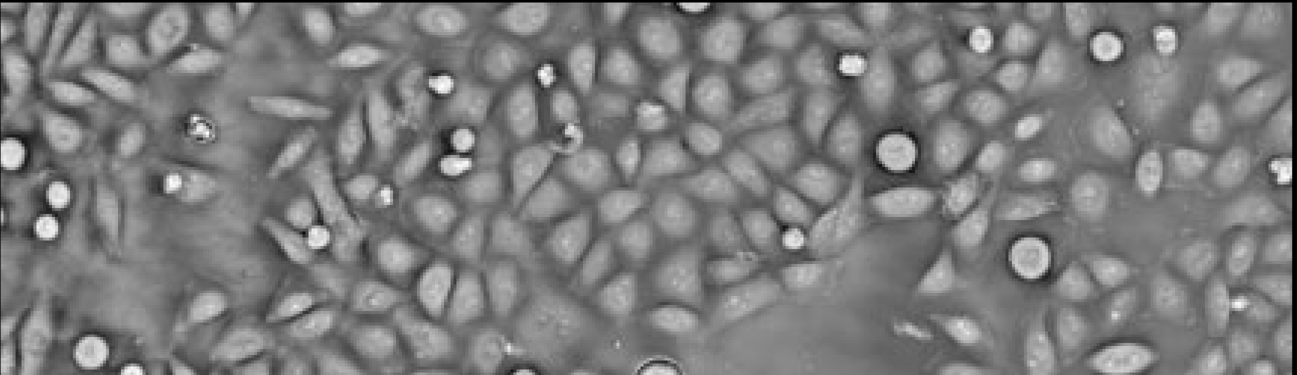
Computational Microscopy with Scattering

Laura Waller

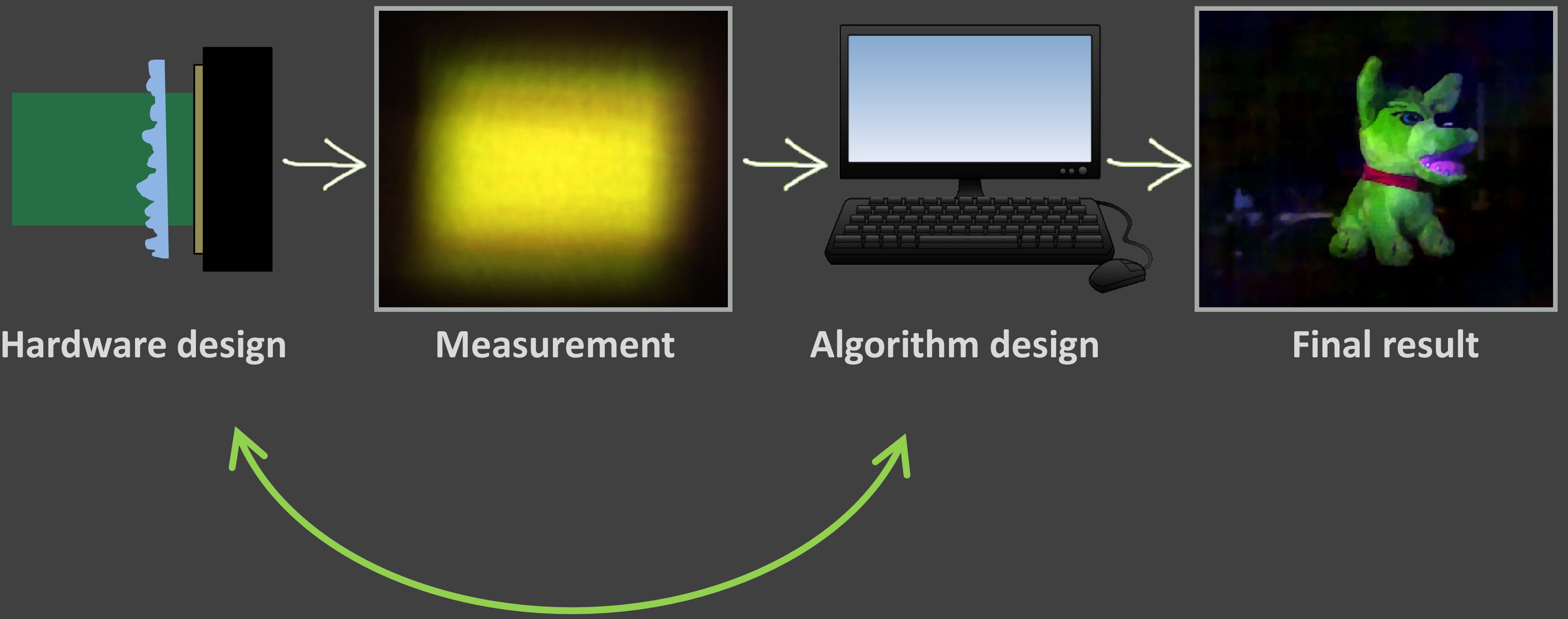
Professor

Electrical Engineering and Computer Sciences

UC Berkeley



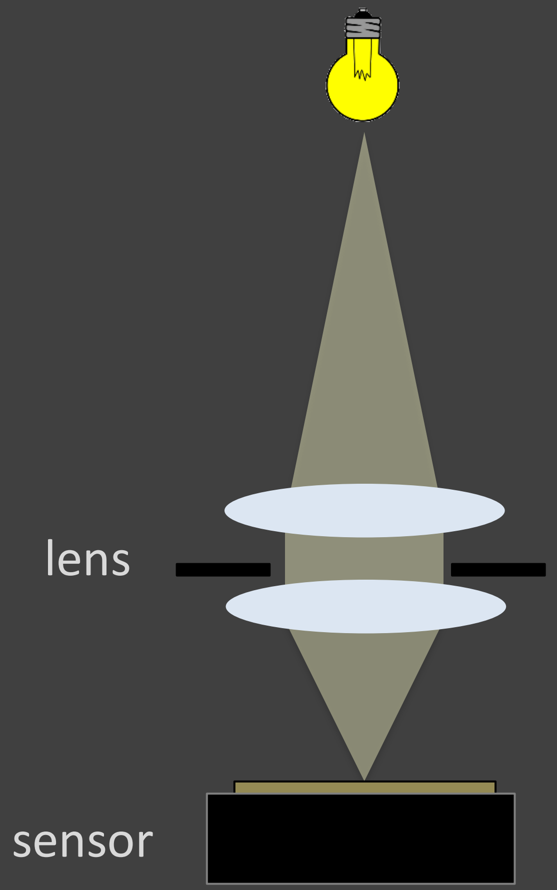
Computational imaging pipeline



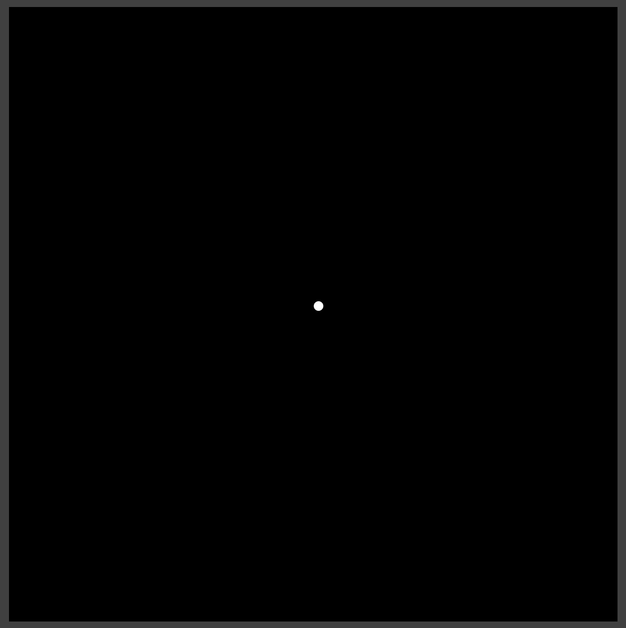
My Research


Atomic resolution 3D TEM
Coded detection microscope
Coded illumination microscope
DiffuserCam
system model
Data-driven system design
backprop
Neuron photostimulation
Large-scale superresolution

Lenses map points to points

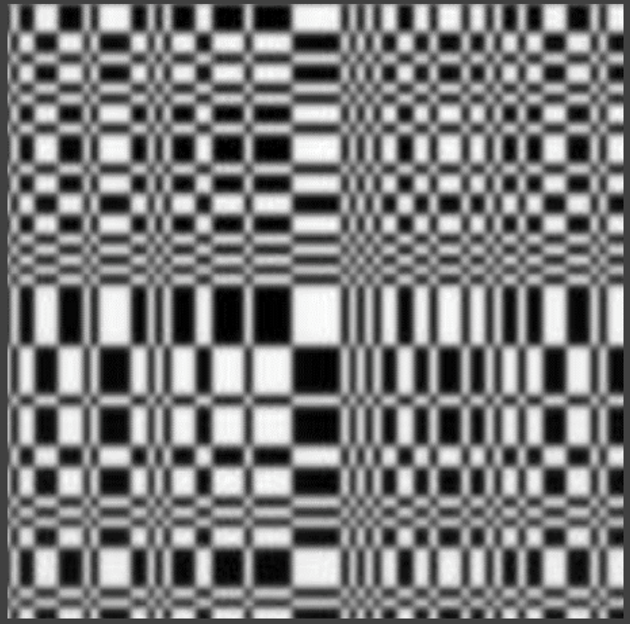


Point Spread Function (PSF)



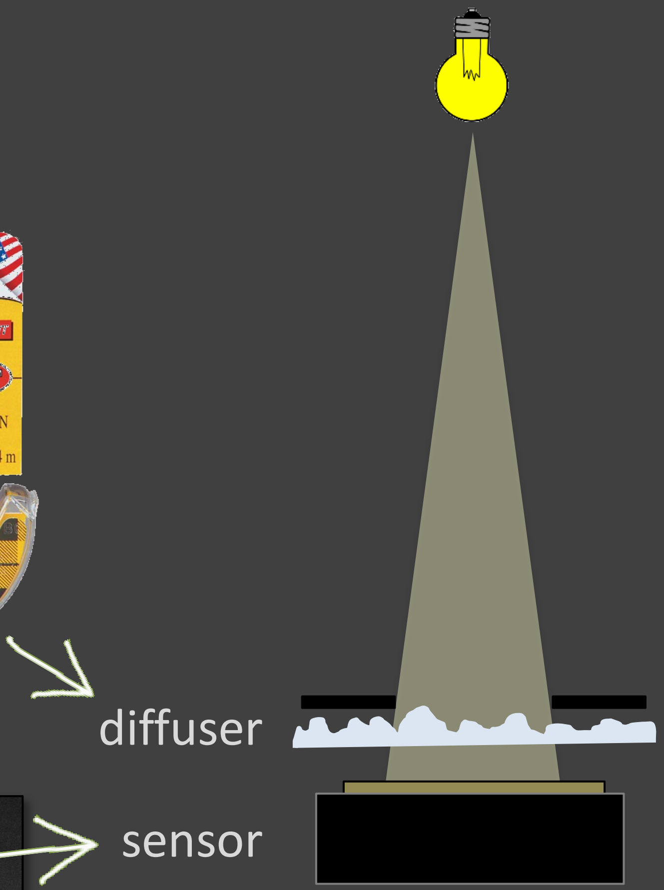
Mask-based cameras multiplex

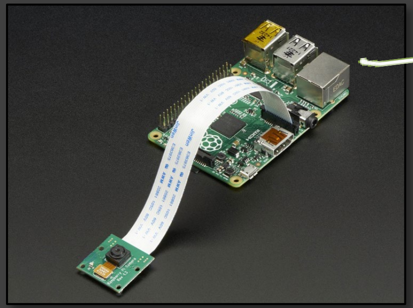
Point Spread Function (PSF)



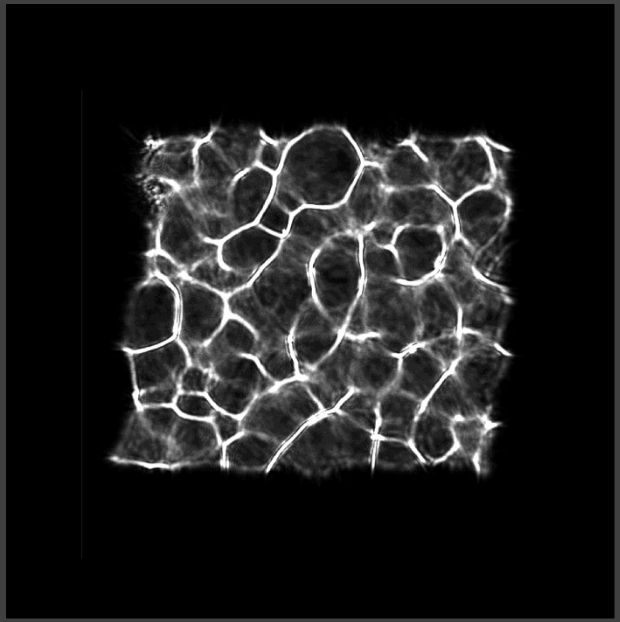
M. S. Asif, et al. *ICCVW* (2015)
J. Tanida, et al. *Applied optics* (2001)
K. Tajima, et al. *ICCP* (2017)
D. G. Stork, et al. *Int. J. Adv. Systems and measurements* (2014)

DiffuserCam: stick a scatterer on a sensor





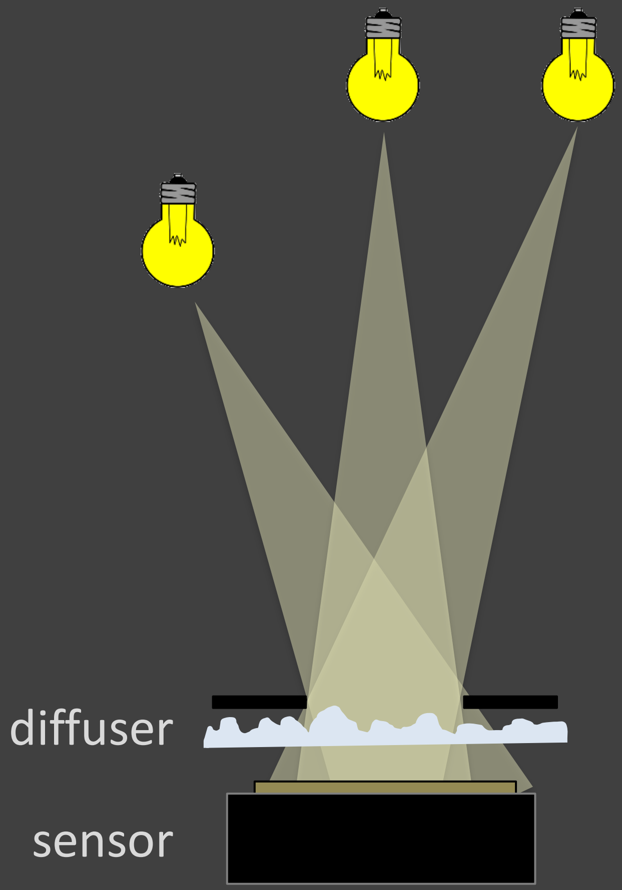
Point Spread Function (PSF)

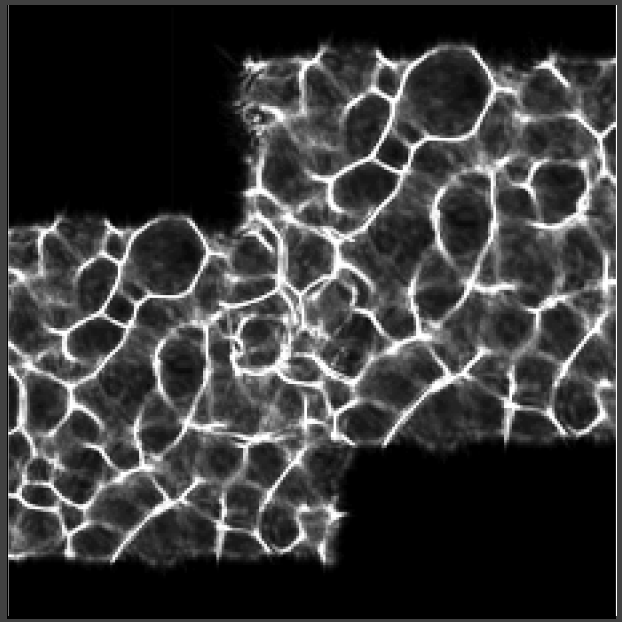


Camille Biscarrat
Shreyas Parthasarathy

https://laurawaller.com/opensource

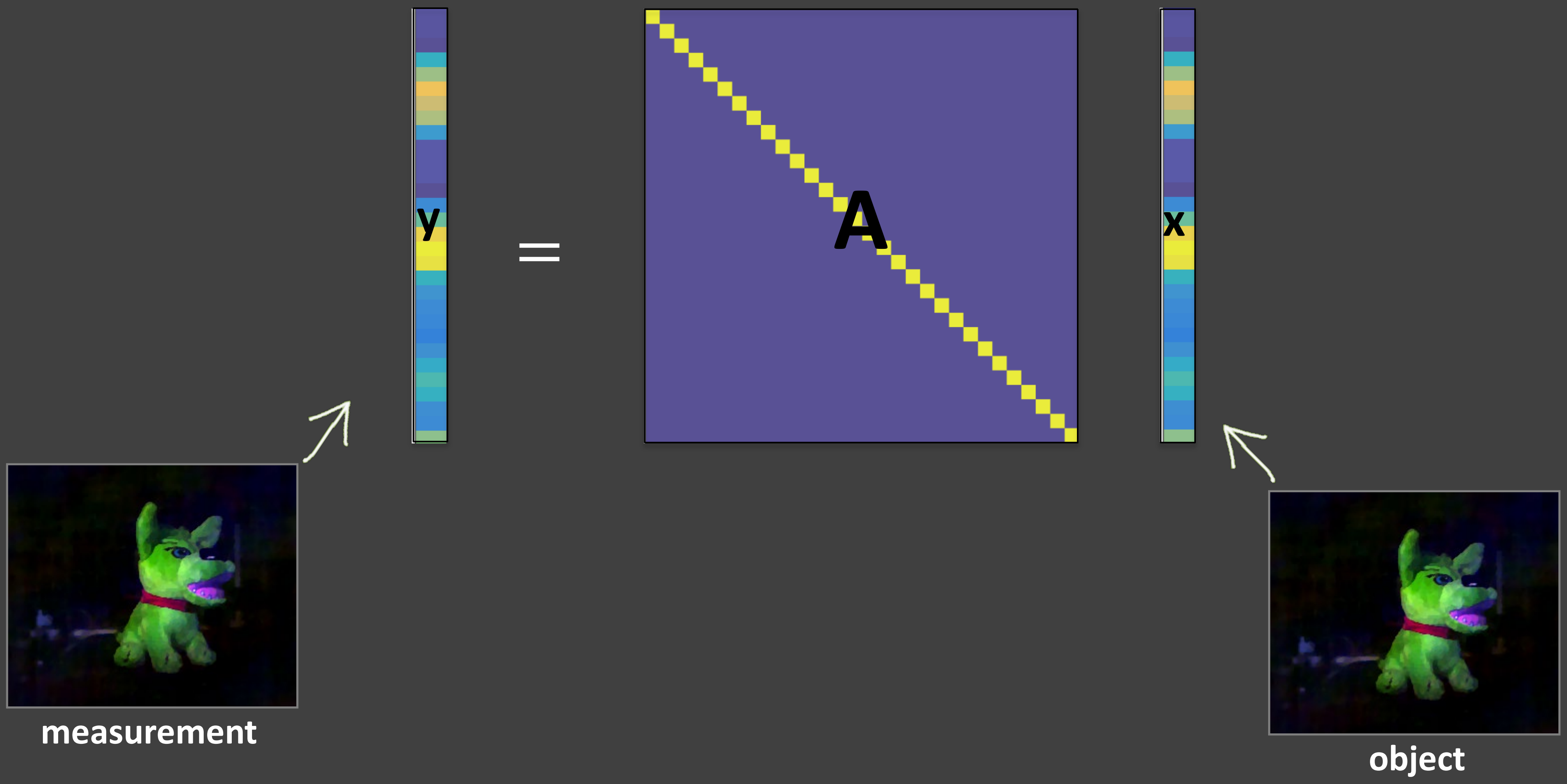
DiffuserCam: stick a scatterer on a sensor



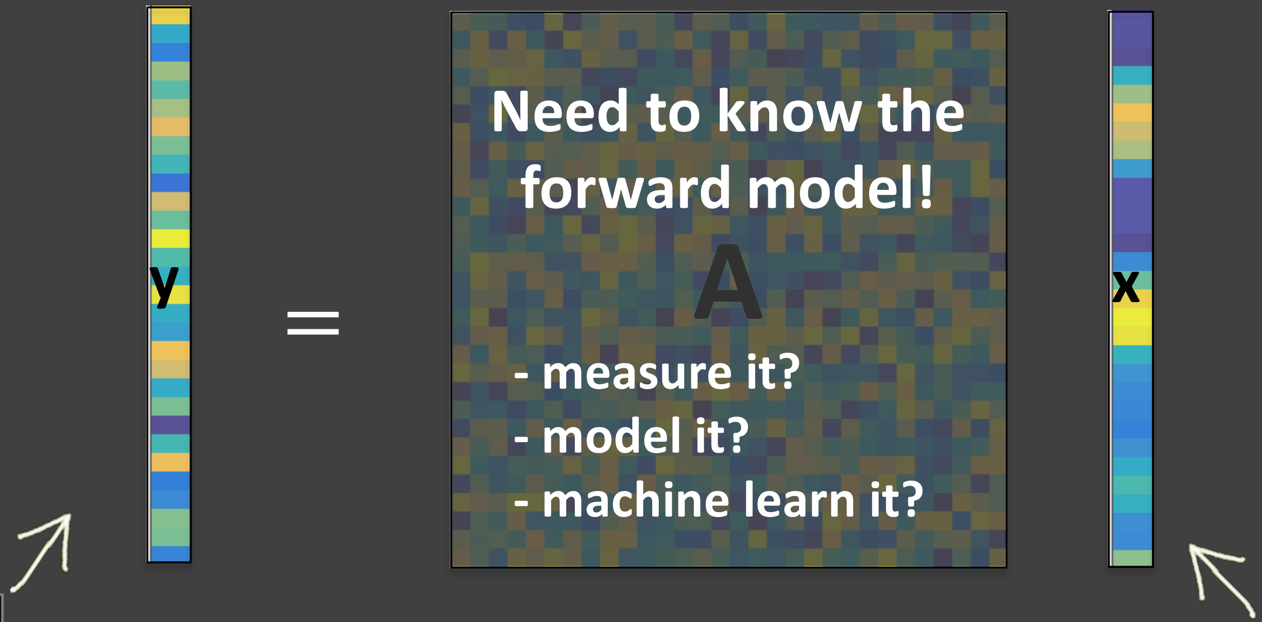


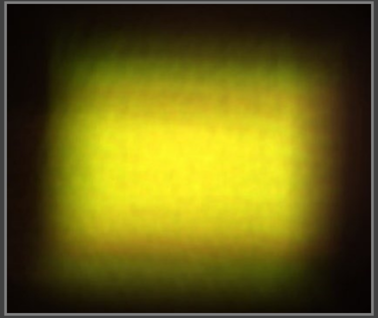
Grace Kuo
Nick Antipa

Traditional cameras take direct measurements



Computational cameras can multiplex

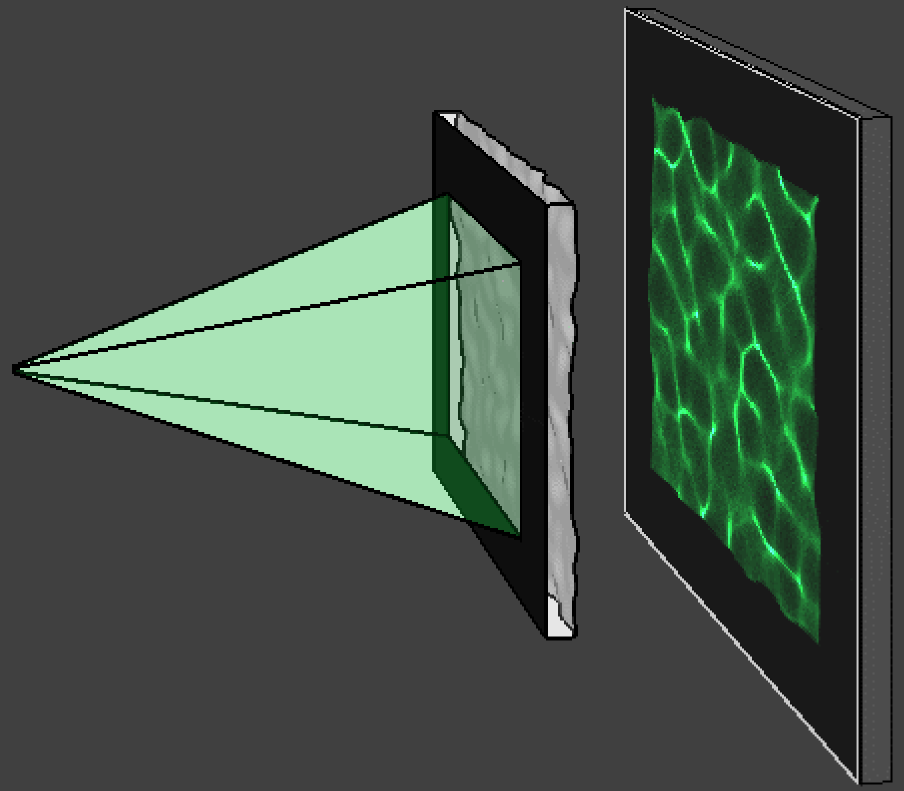




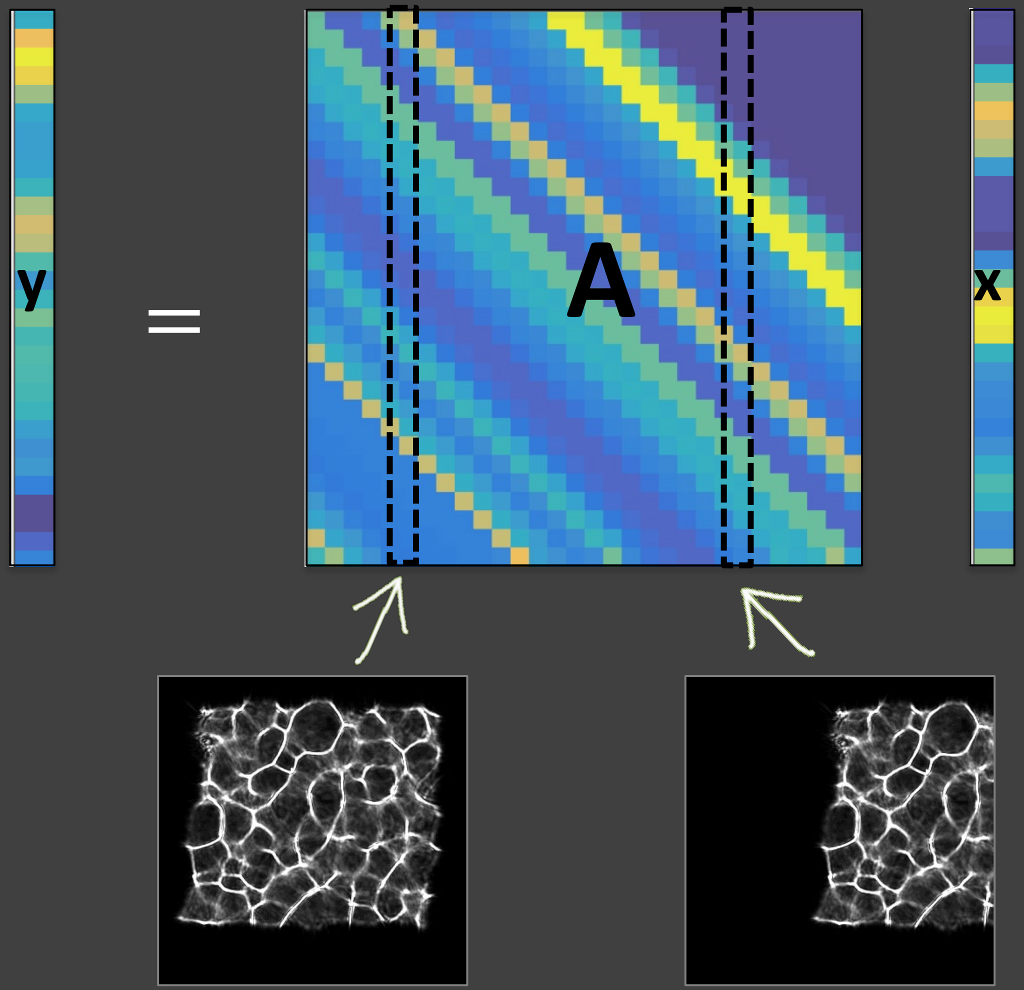
measurement

object

Point spread function shifts with position



DiffuserCam forward model is a convolution



Point Spread Functions
for different image pixels

raw sensor data

recovered scene

*solver is ADMM with TV reg in Halide

Grace Kuo
Nick Antipa

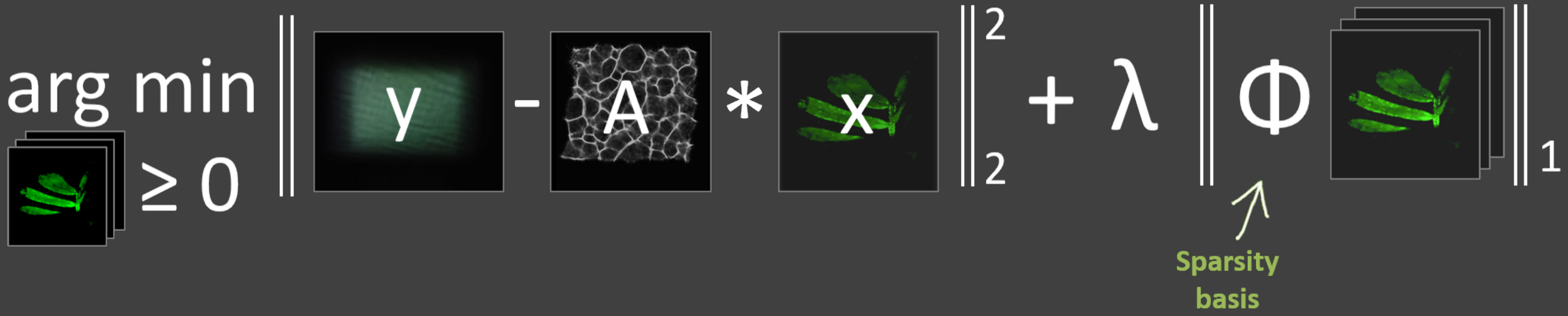
raw sensor data

recovered scene

*solver is ADMM with TV reg in Halide

Grace Kuo
Nick Antipa

Image reconstruction is nonlinear optimization

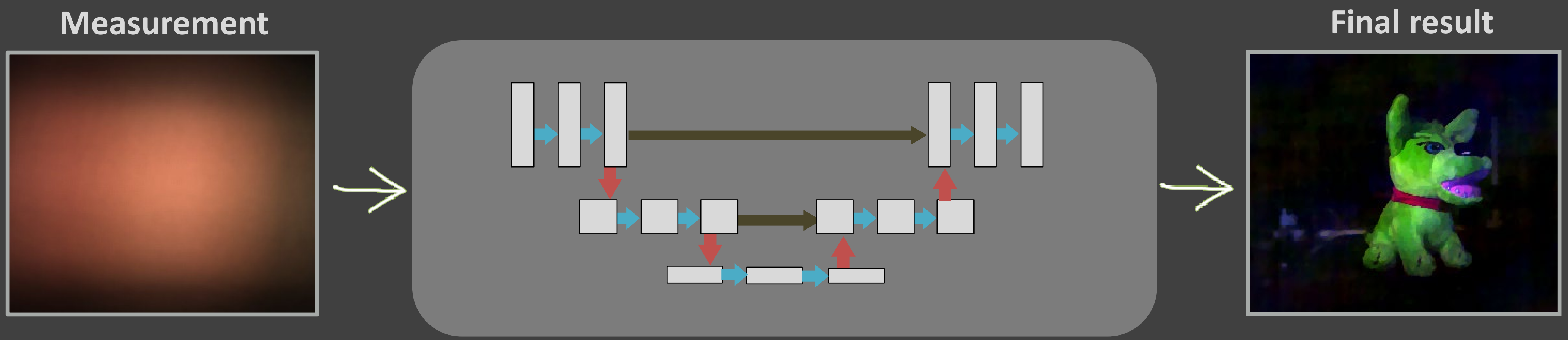


*solved with ADMM in Halide

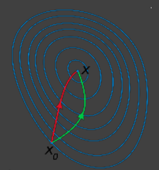
S. Boyd, et al. *Foundations and Trends in Machine Learning* (2011)
J. Ragan-Kelley, et al. *AMC SIGPLAN* (2013)

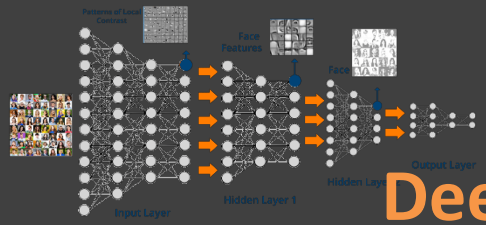
Physics-based image reconstruction

Deep learning based reconstruction



Inverse Problem Philosophies





Physics-based ⟷ **Deep Learning**

gradient descent
(FISTA, ADMM)

CNNs, Unet, Resnet, etc.

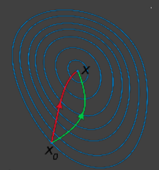
- Interpretable
- Robust

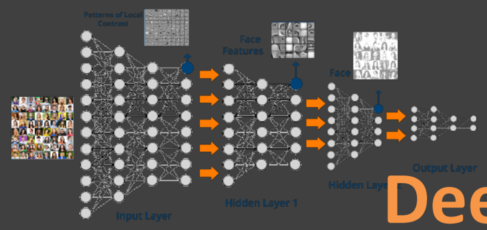
- Slow
- Model mismatch causes artifacts

- Fast recon

- Large training dataset
- Not interpretable
- No guarantees, not robust

Inverse Problem Philosophies

Physics-based 

 Deep Learning

Physics-based learning

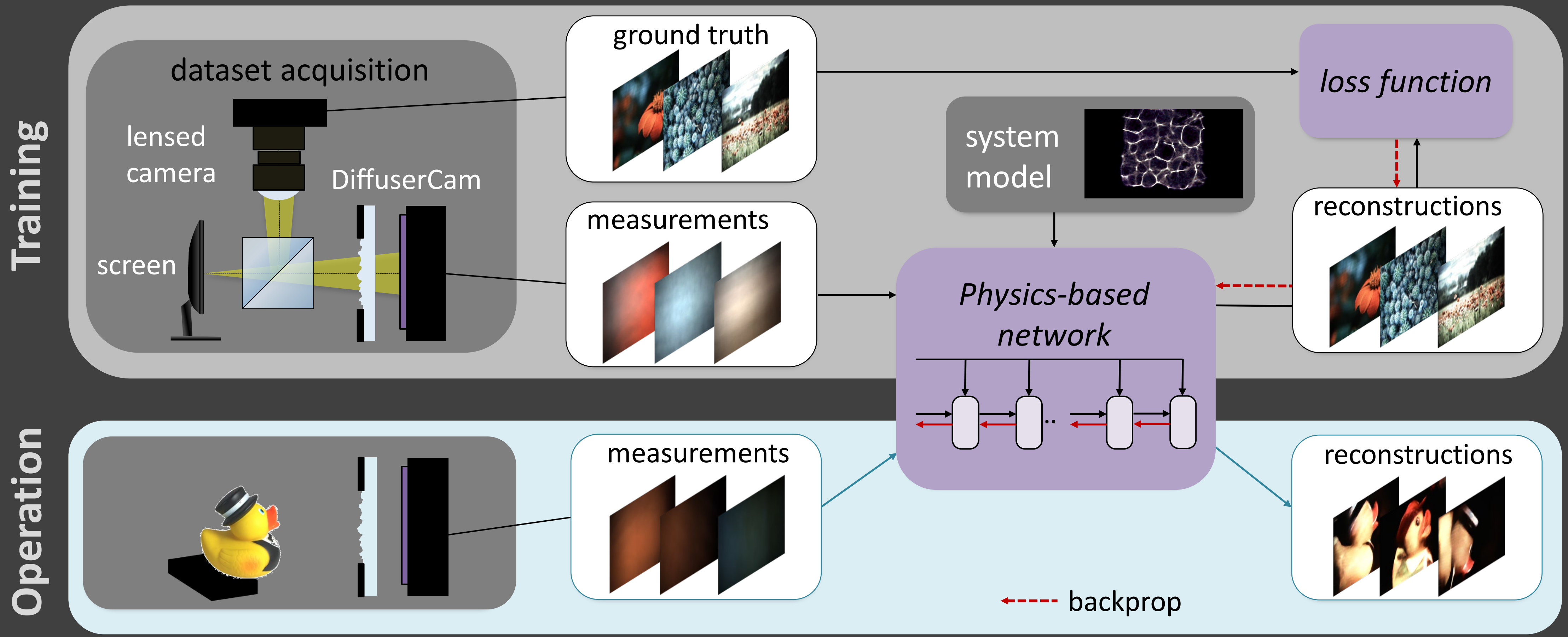
- Efficient parametrization
- Uses known physics
- Learns unknowns

Michael Kellman
Emrah Bostan
Kristina Monakhova

E. Bostan, U. Kamilov, L. Waller, *IEEE Signal Processing Letters* (2018).
M. Kellman, E. Bostan, N. Repina, L. Waller, IEEE Trans. of Comp. Imaging (2019).

Pipeline

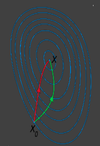


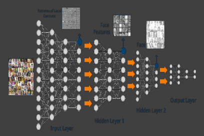
Kristina Monakhova

K. Monakhova, J. Yurtsever, G. Kuo, N. Antipa, K. Yanny, L. Waller, *Optics Express* (2019).

Physics-based learning improves speed + quality

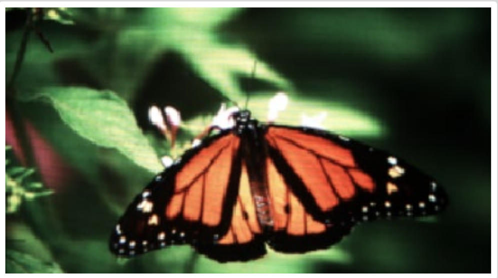
Physics-based



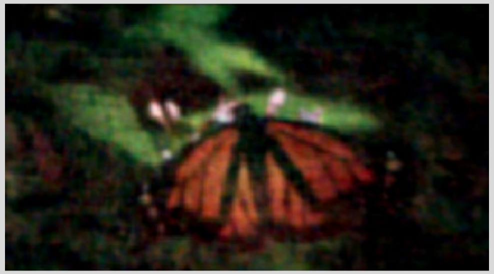


Deep Learning

ground truth



1.5s



75ms

Ours

10ms

Kristina Monakhova

K. Monakhova, J. Yurtsever, G. Kuo, N. Antipa, K. Yanny, L. Waller, *Optics Express* (2019).

raw sensor data

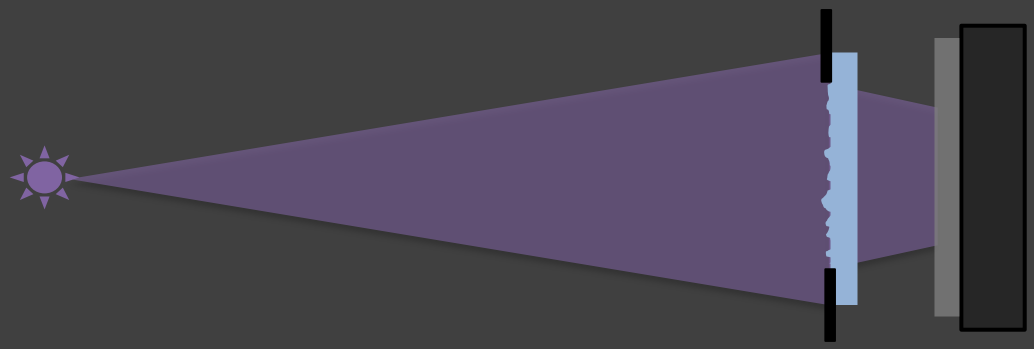
recovered scene

Grace Kuo
Nick Antipa

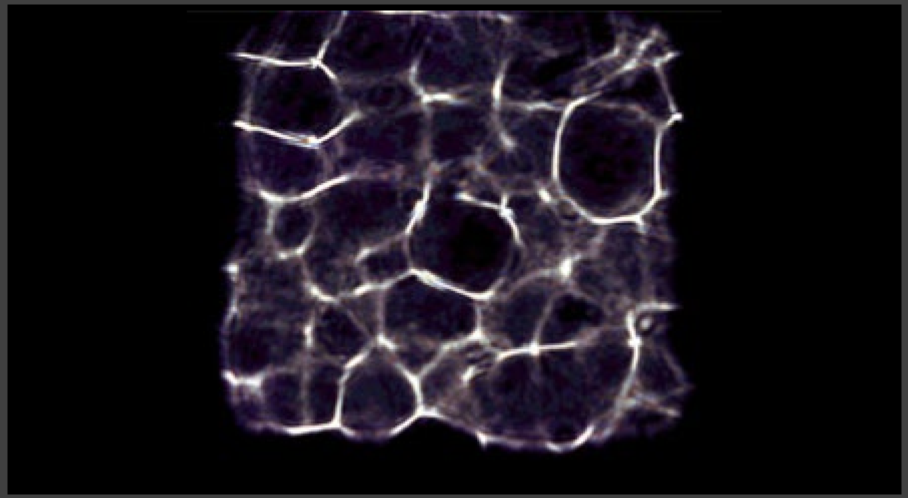
*solver is ADMM with TV reg in Halide

Cute! But what’s it good for?

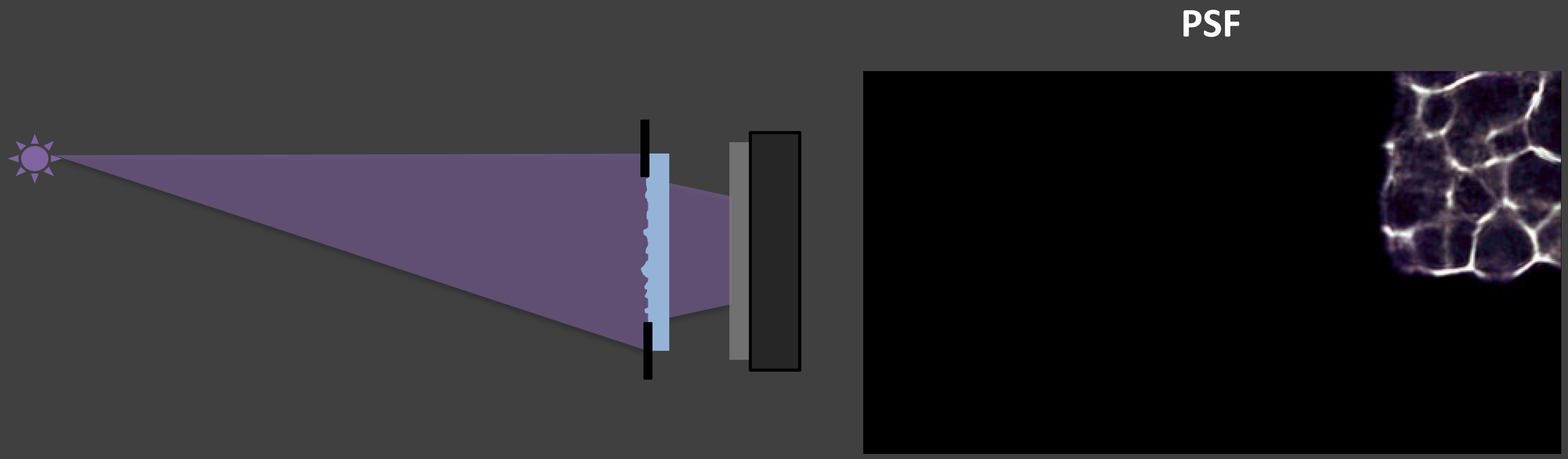
Multiplexed measurements are tolerant to erasures



PSF

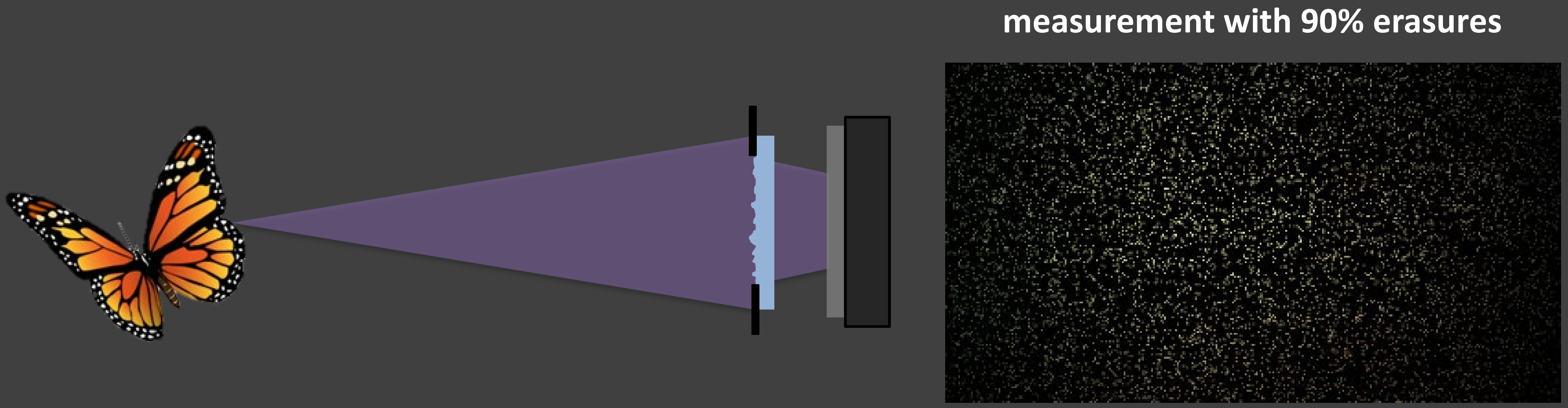


Multiplexed measurements are tolerant to erasures

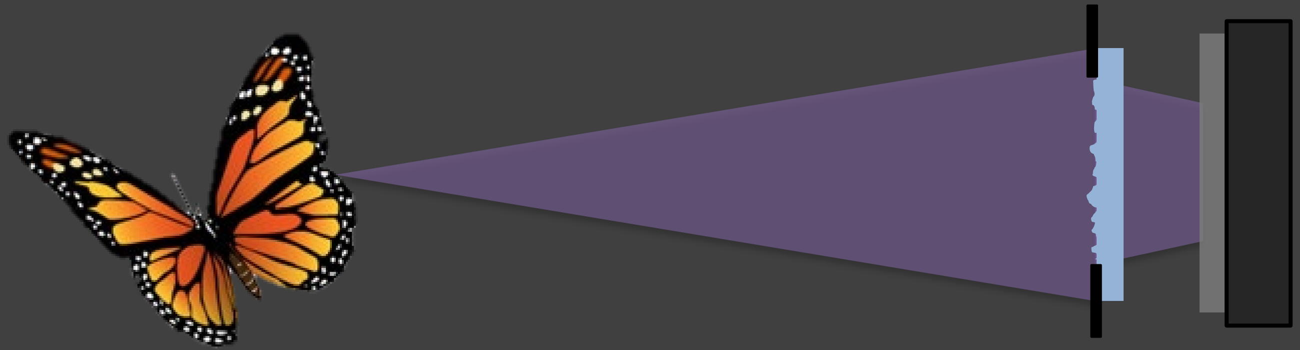


Extended Field of View

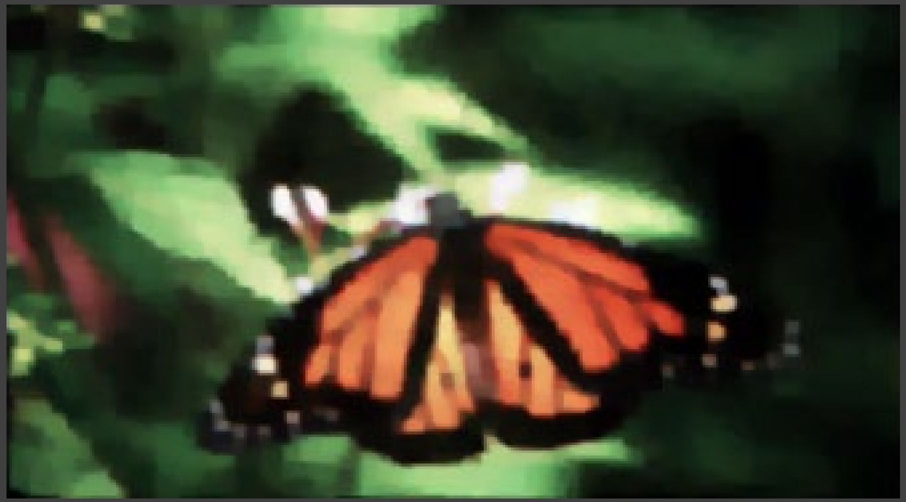
Multiplexed measurements are tolerant to erasures



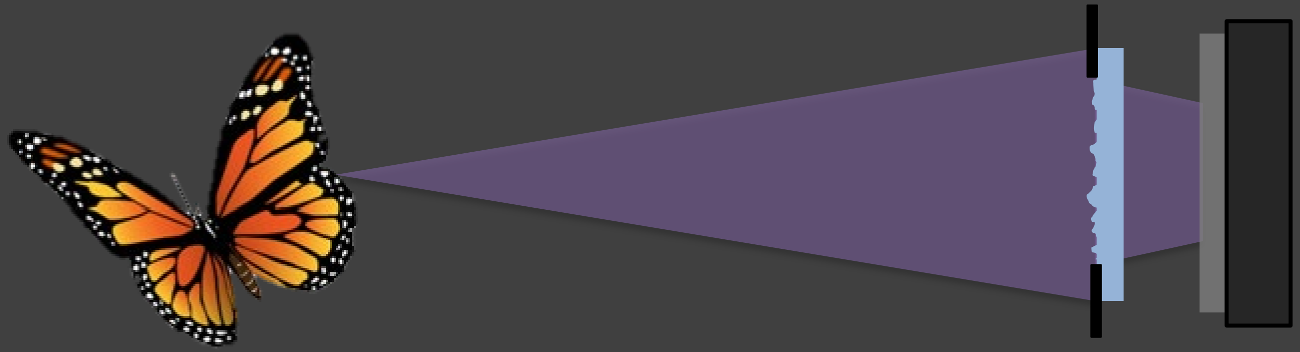
Multiplexed measurements are tolerant to erasures



recovered image with 90% erasures

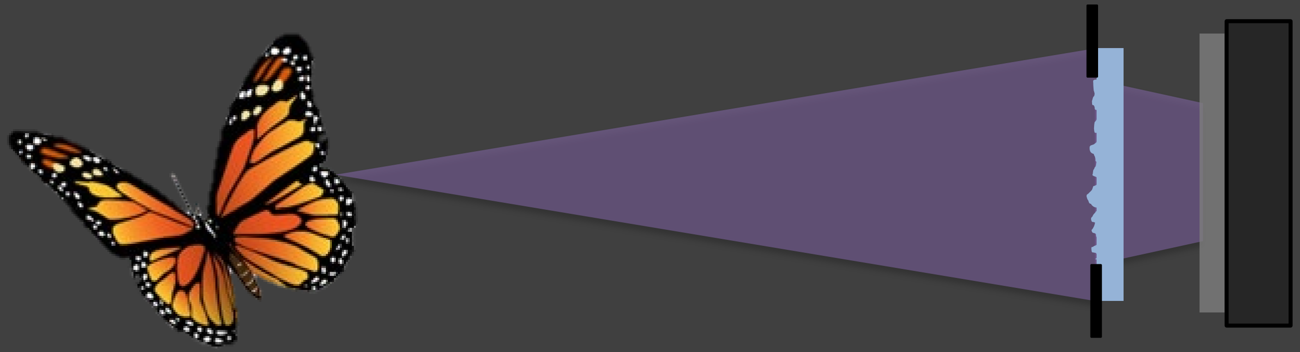


Multiplexed measurements are tolerant to erasures



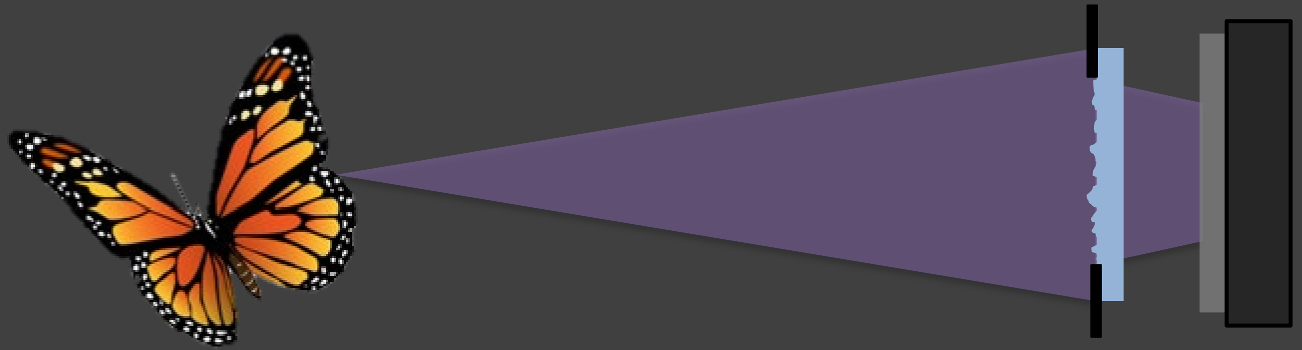
measurement

Multiplexed measurements are tolerant to erasures



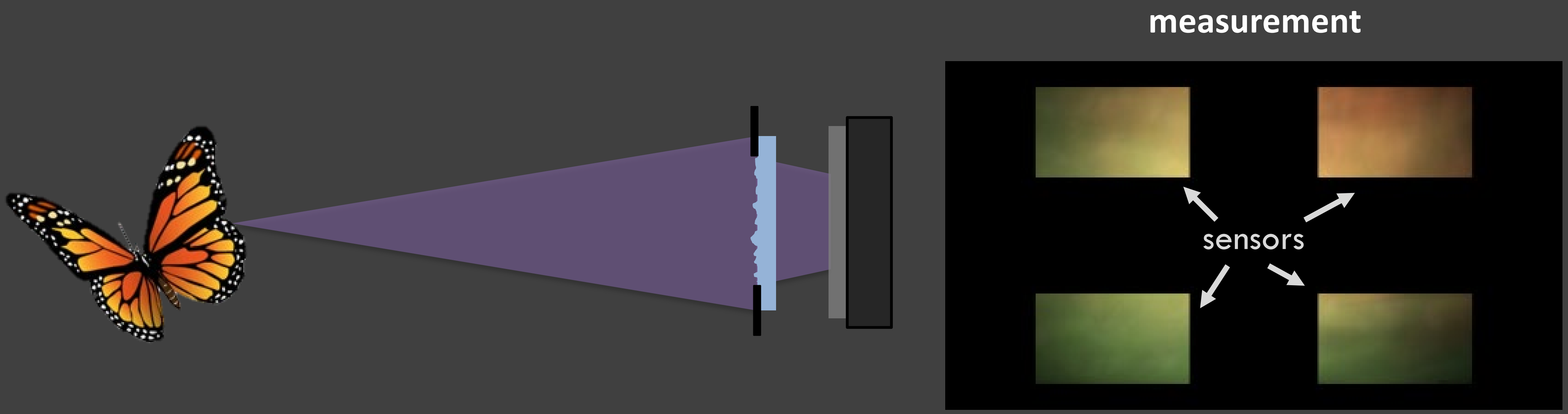
measurement

Multiplexed measurements are tolerant to erasures



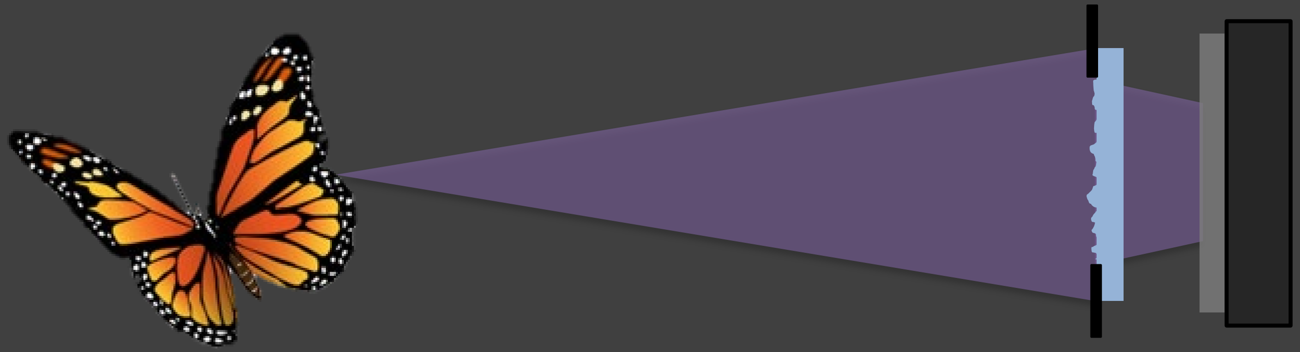
recovered image

Multiplexed measurements are tolerant to erasures

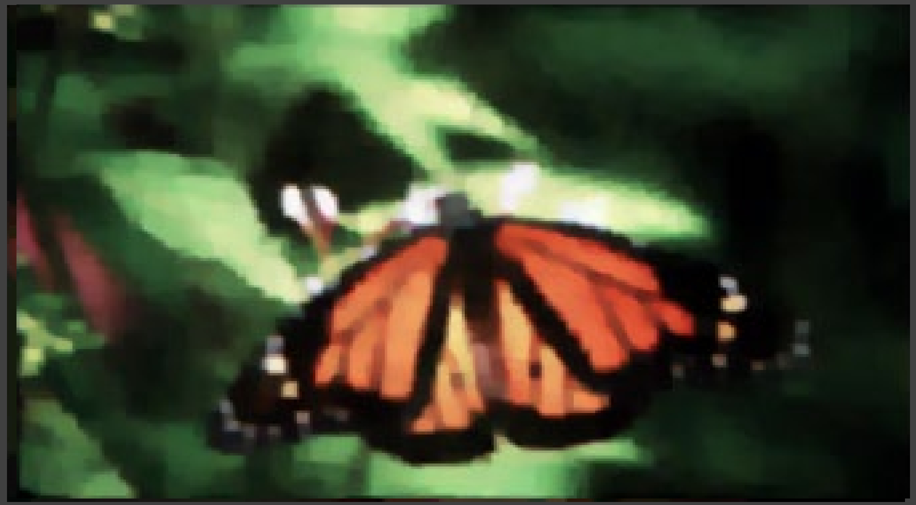


sensors cover only 8% of total area!

Multiplexed measurements are tolerant to erasures



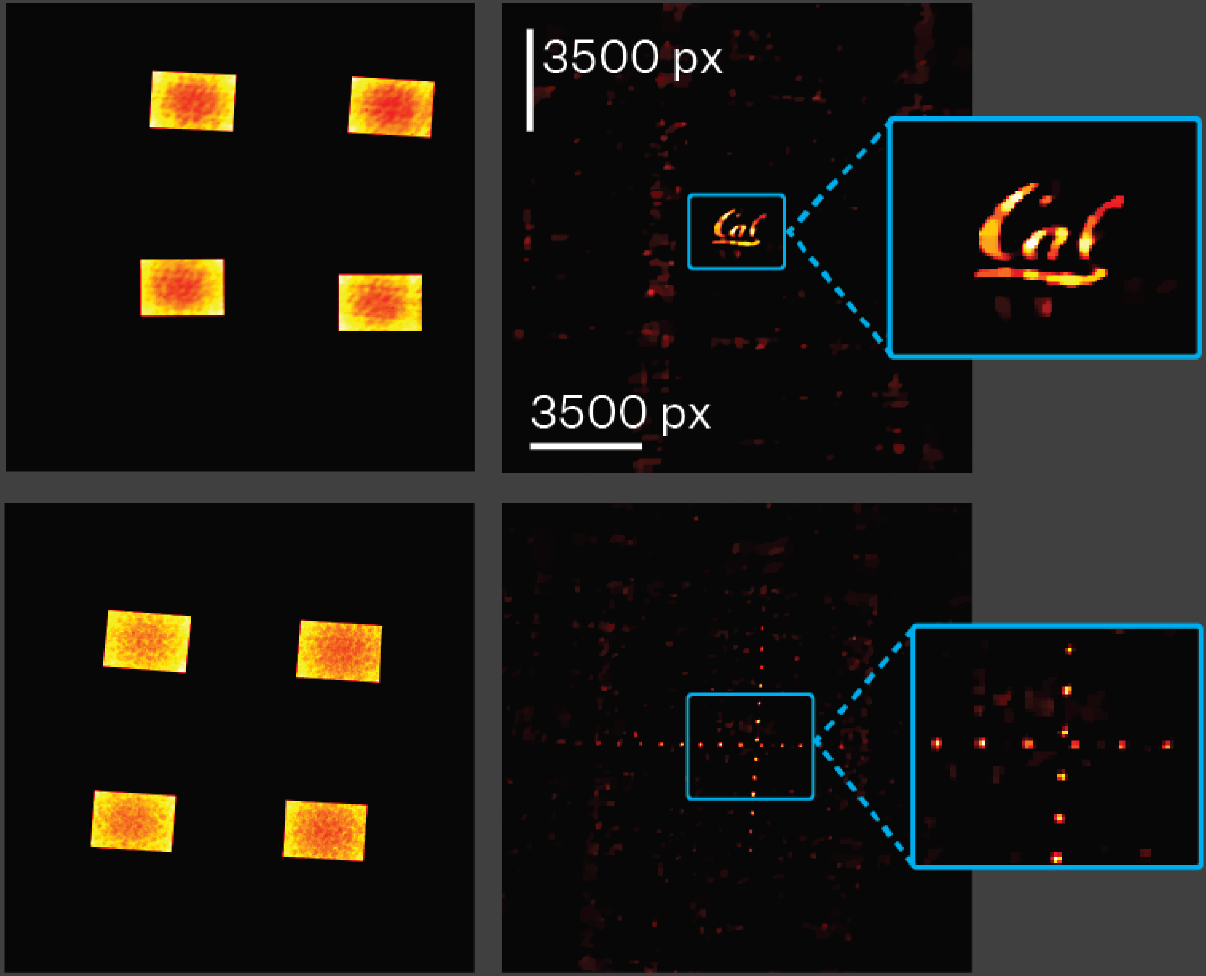
recovered image



sensors cover only 8% of total area!

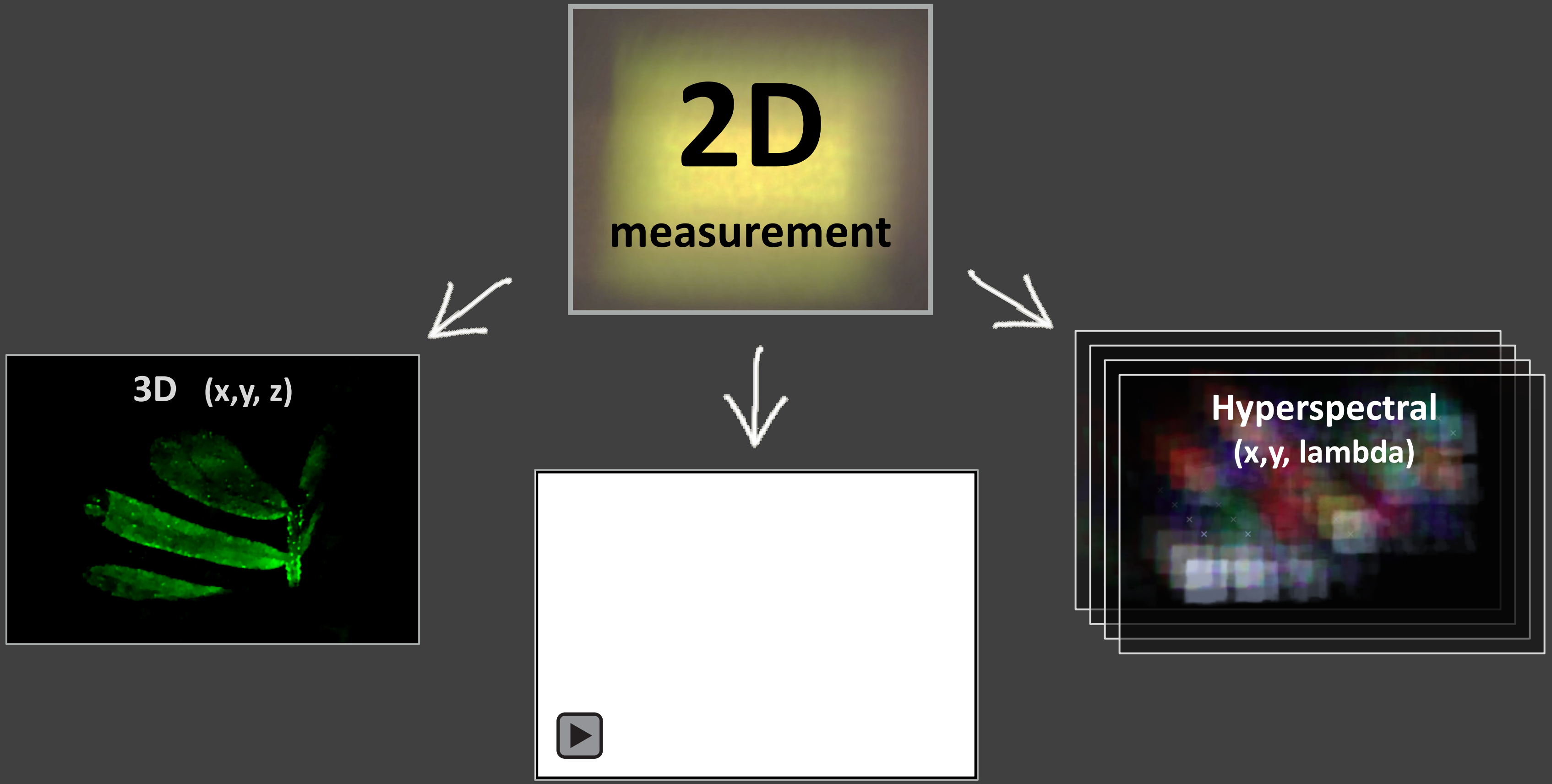
BIG DiffuserCam with tiled sensors

Measurement | **Reconstruction**



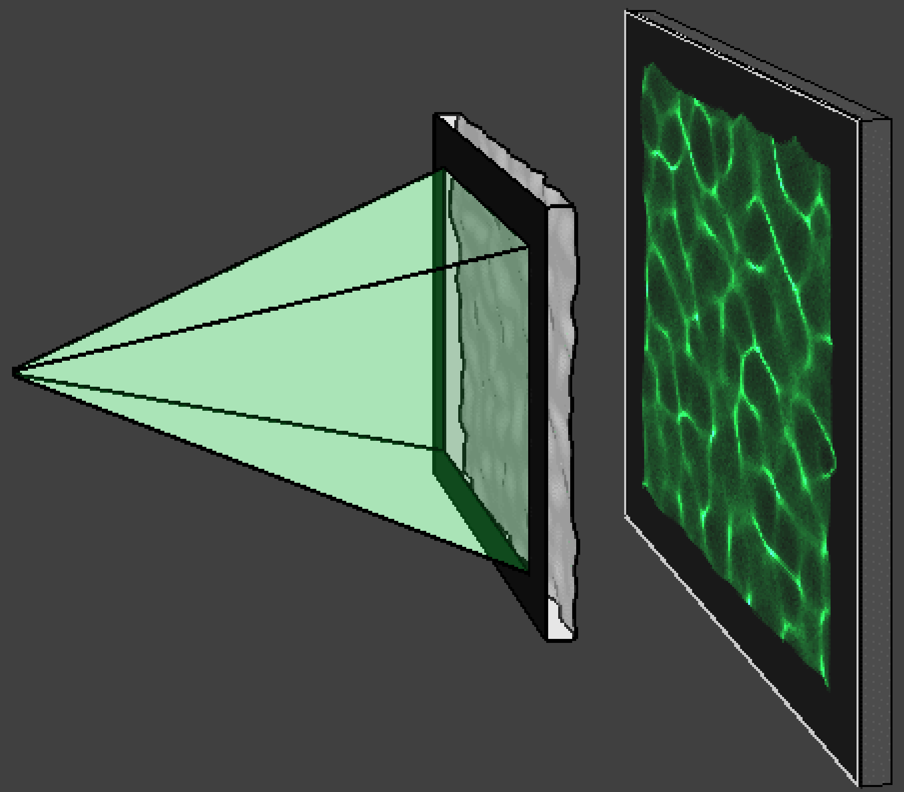
Large-aperture imaging with flat-ish optics?


Nico Deshler
Ellin Zhao

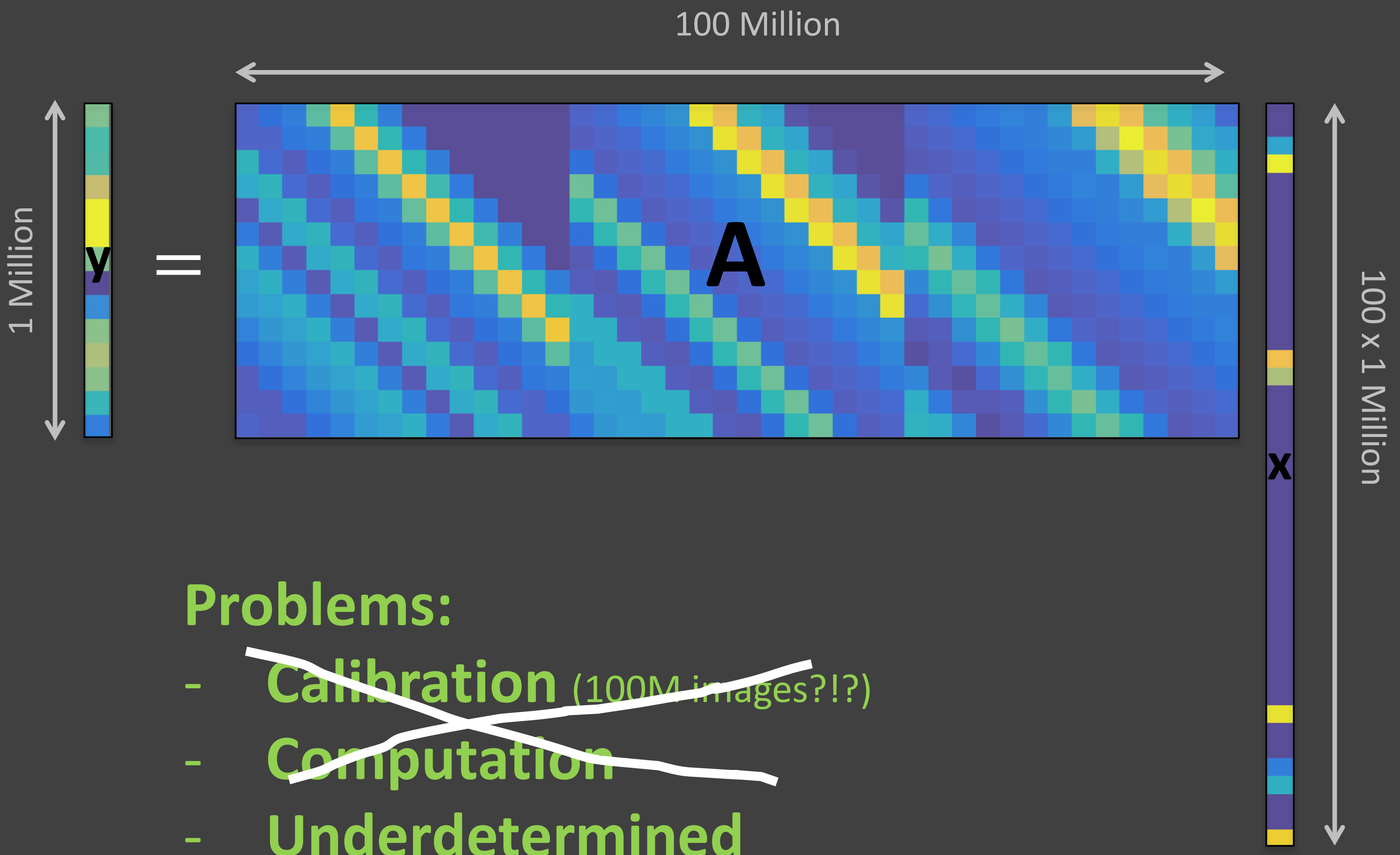

2D
measurement
3D (x,y, z)
Hyperspectral
(x,y, lambda)

2D →

Point spread function scales with depth

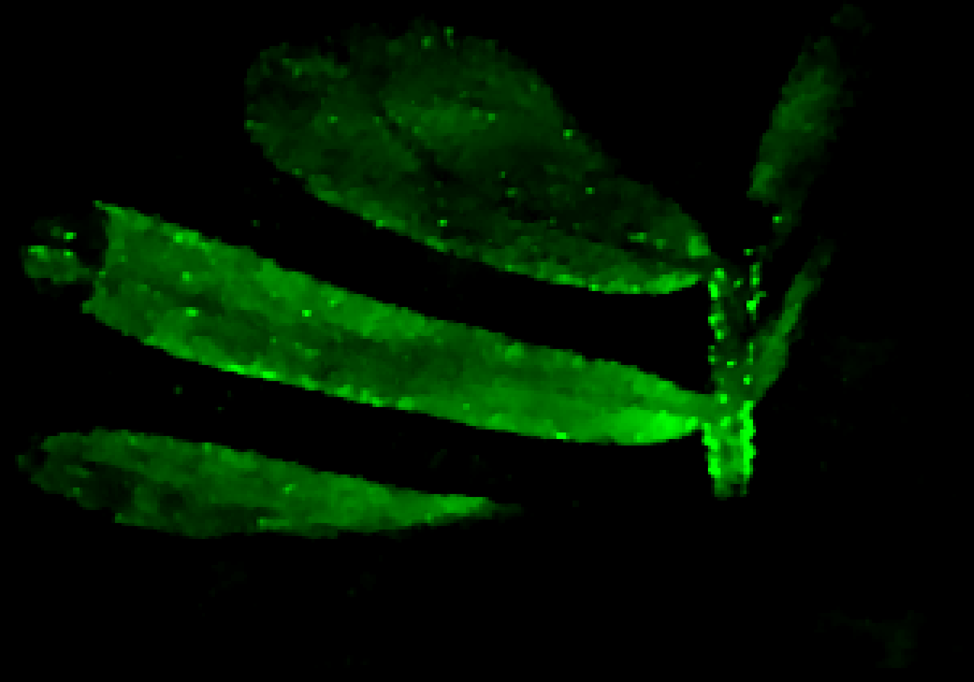


Single-shot 3D is difficult



Problems:

- ~~**Calibration** (100M images?!?)~~
- ~~**Computation**~~
- **Underdetermined**

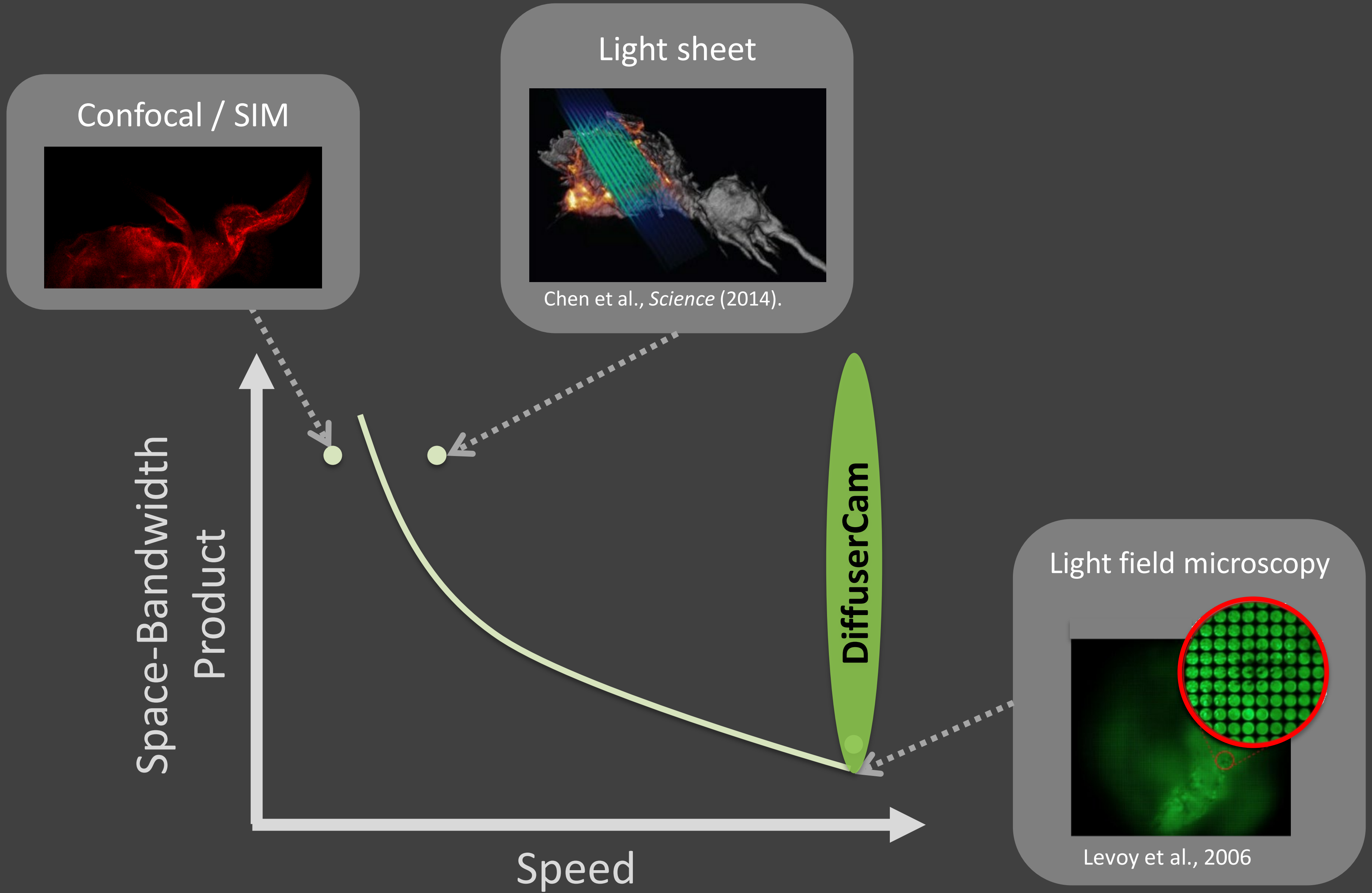


N. Antipa, G. Kuo, R. Heckel, E. Bostan, B. Mildenhall, R. Ng, L. Waller, *Optica* 5(1) (2017).

Scanning Microscopy **vs.** **Compressed Sensing**

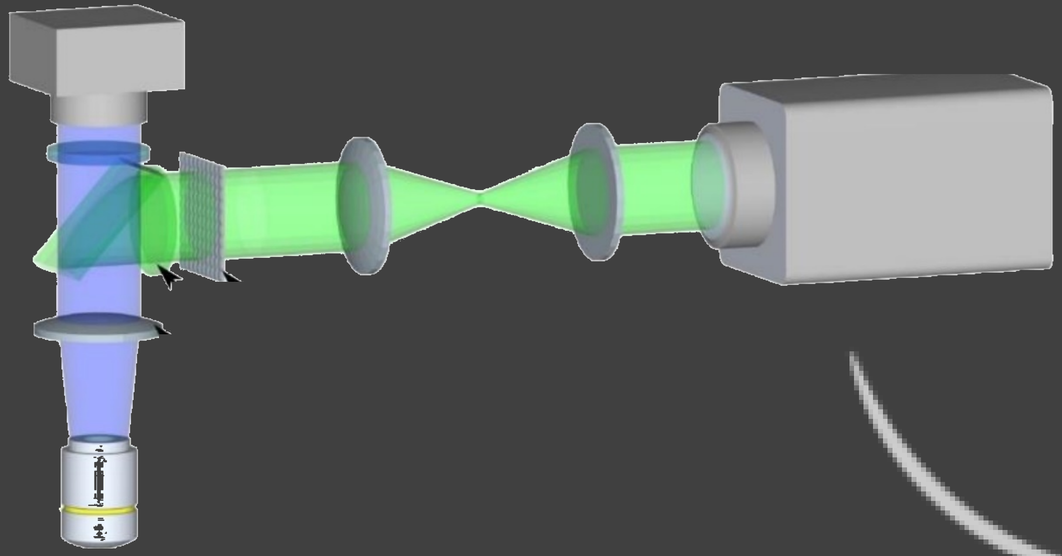
↓ speed scales with # voxels in image

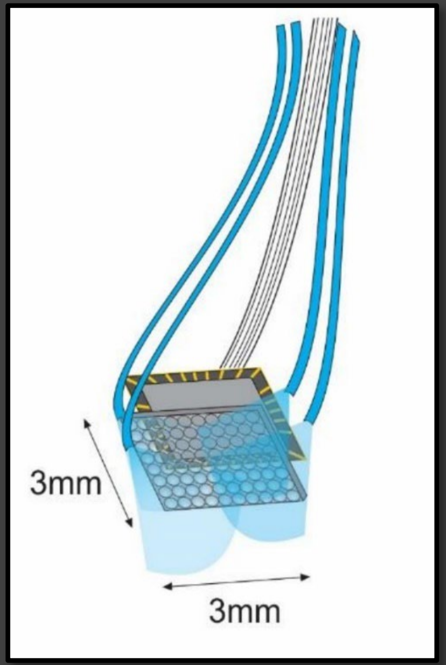
↓ speed scales with *sparsity* of sample



Confocal / SIM
Light sheet
Chen et al., *Science* (2014).
DiffuserCam
Light field microscopy
Levoy et al., 2006
Space-Bandwidth Product
Speed

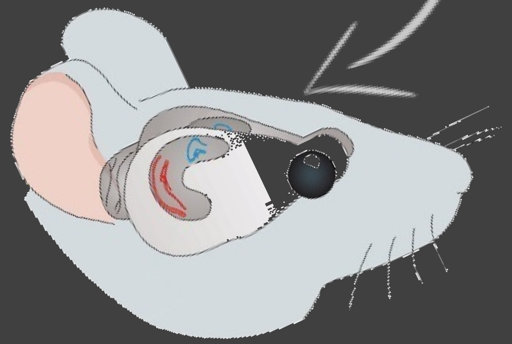
Towards lensless 3D microscopy



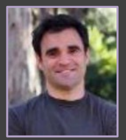


Lensless imager:

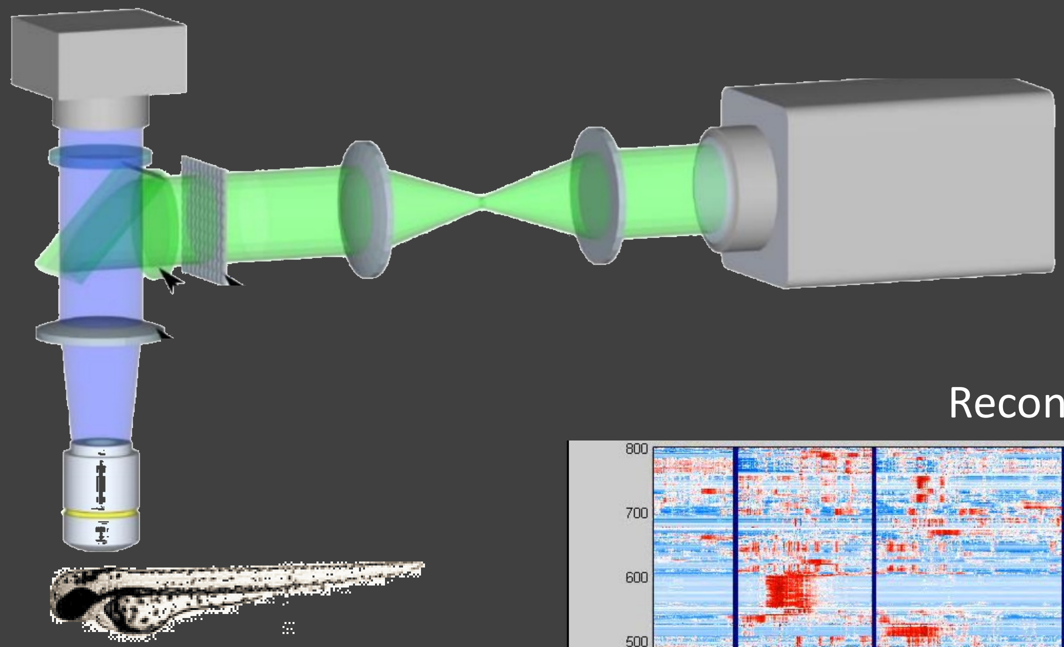
- small
- inexpensive
- enables tiling



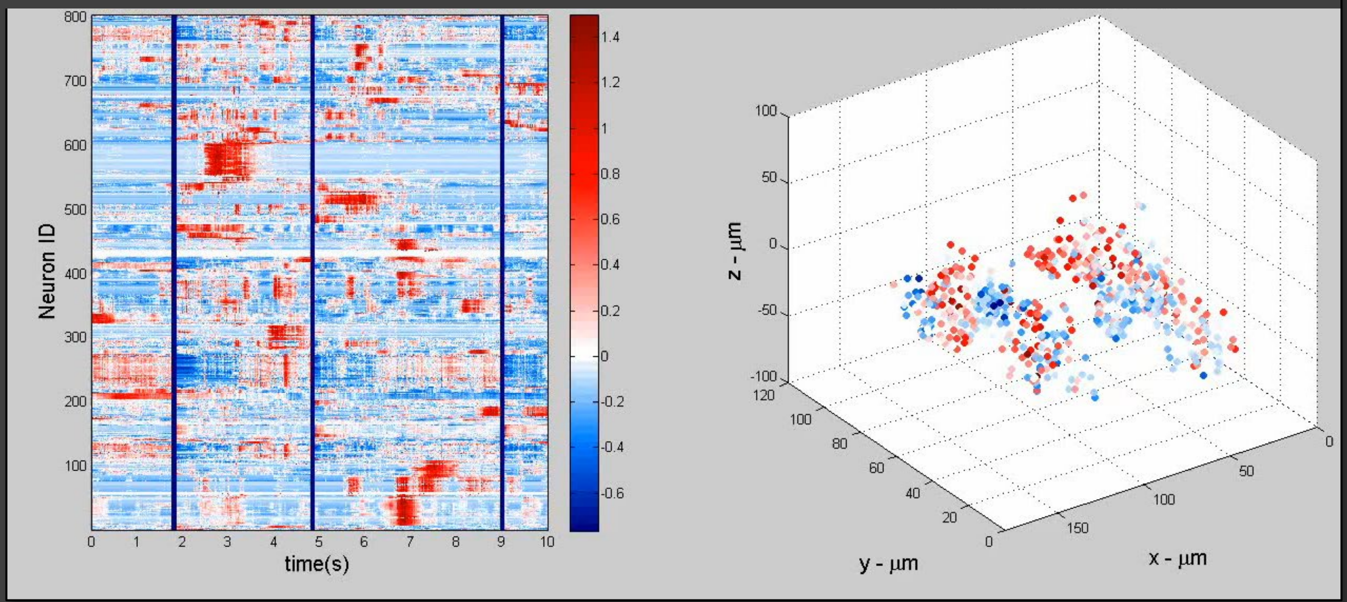
with Adesnik Lab



3D neural activity tracking



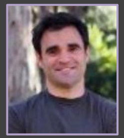
Reconstructed neural activity



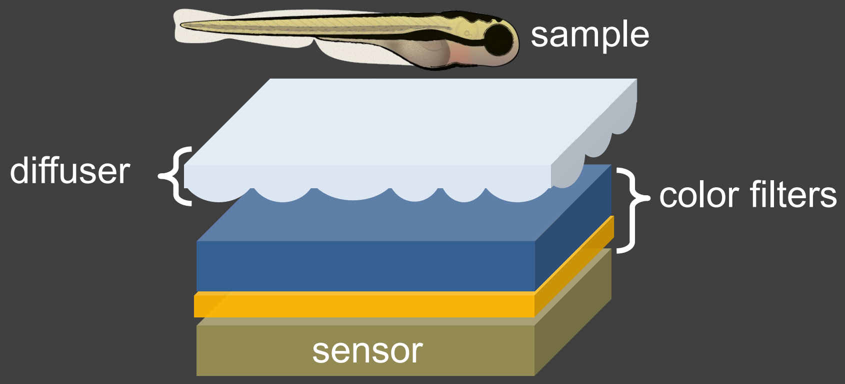
Nico Pegard

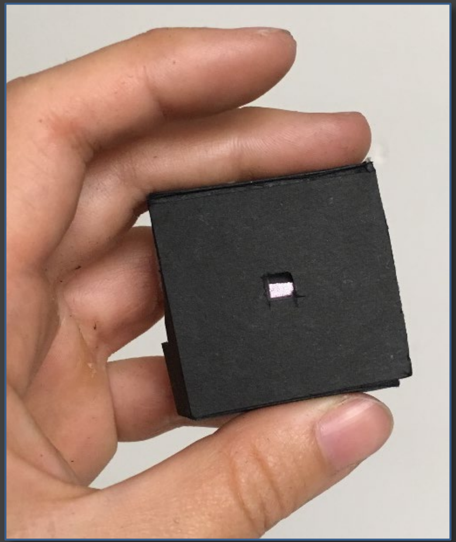
N. Pegard et al, *Optica* 2016

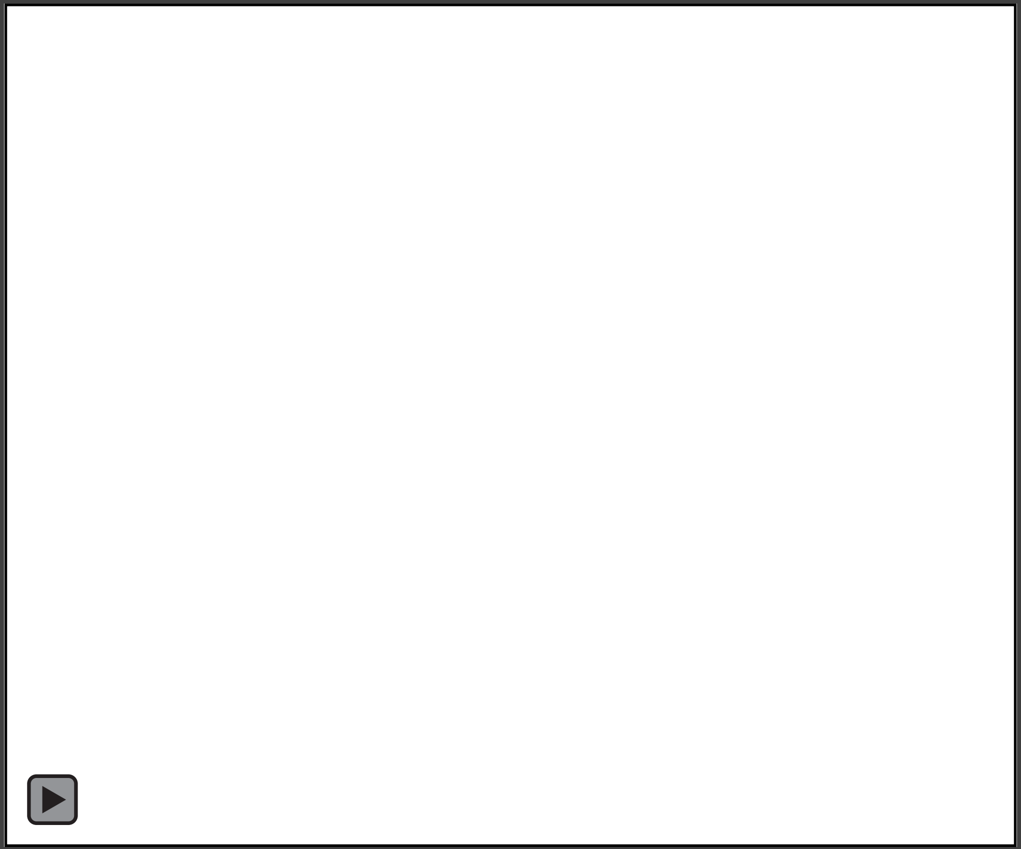
with Adesnik Lab



Neural activity tracking with flat DiffuserScope





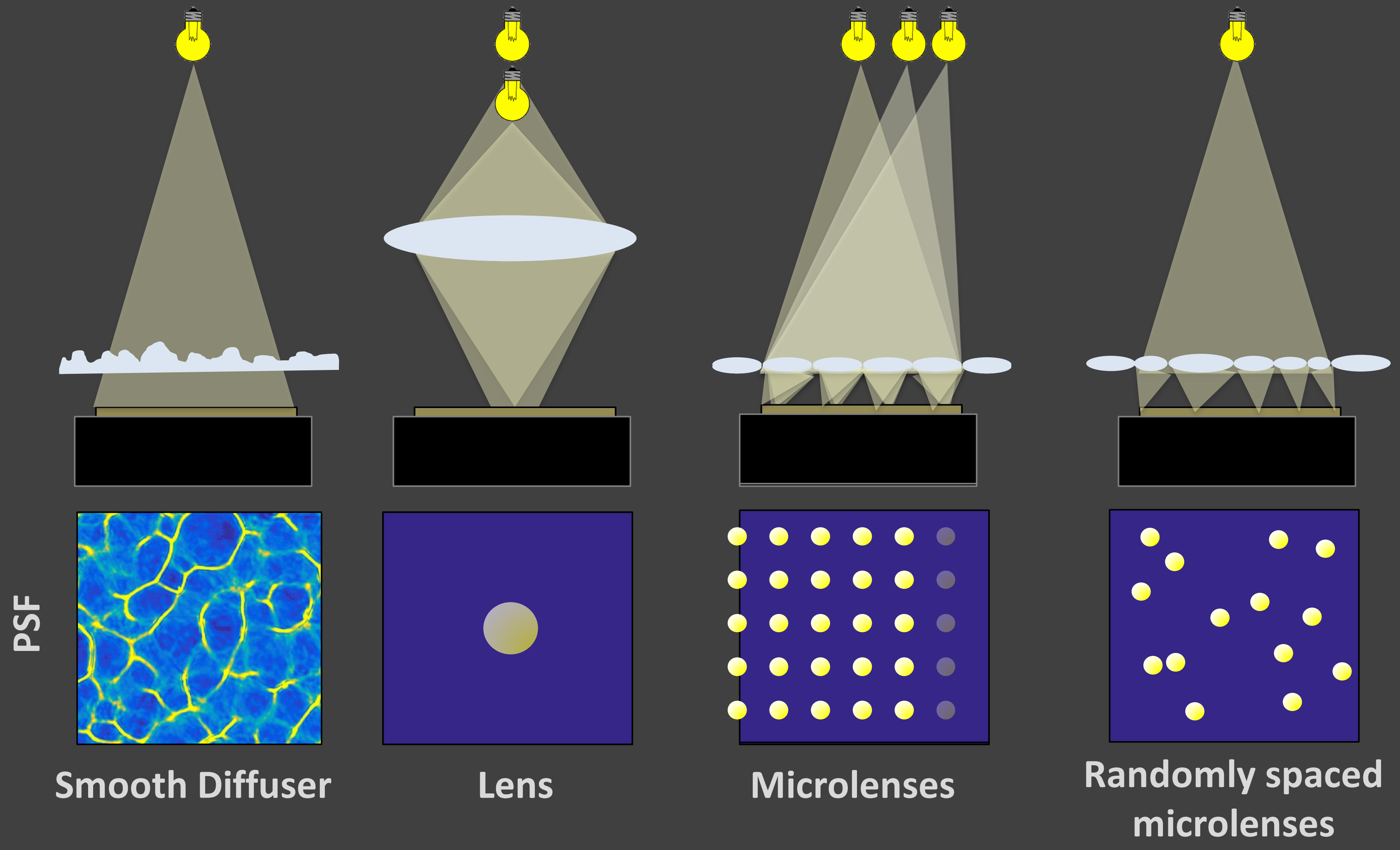


Grace Kuo

G. Kuo, F. Liu, I. Grossrubatscher, R. Ng, L. Waller, *Optics Express* (2020).

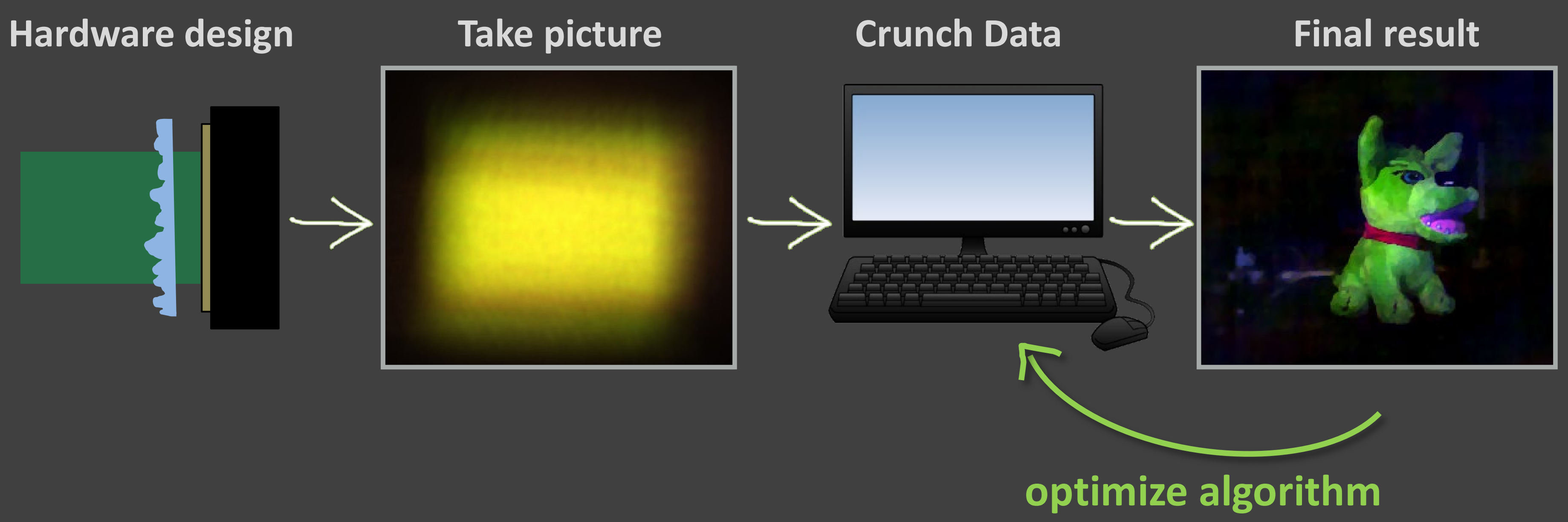
Hmm… is random scattering the best encoder?

Secret #3: off-the-shelf diffusers aren't ideal



Computational imaging pipeline

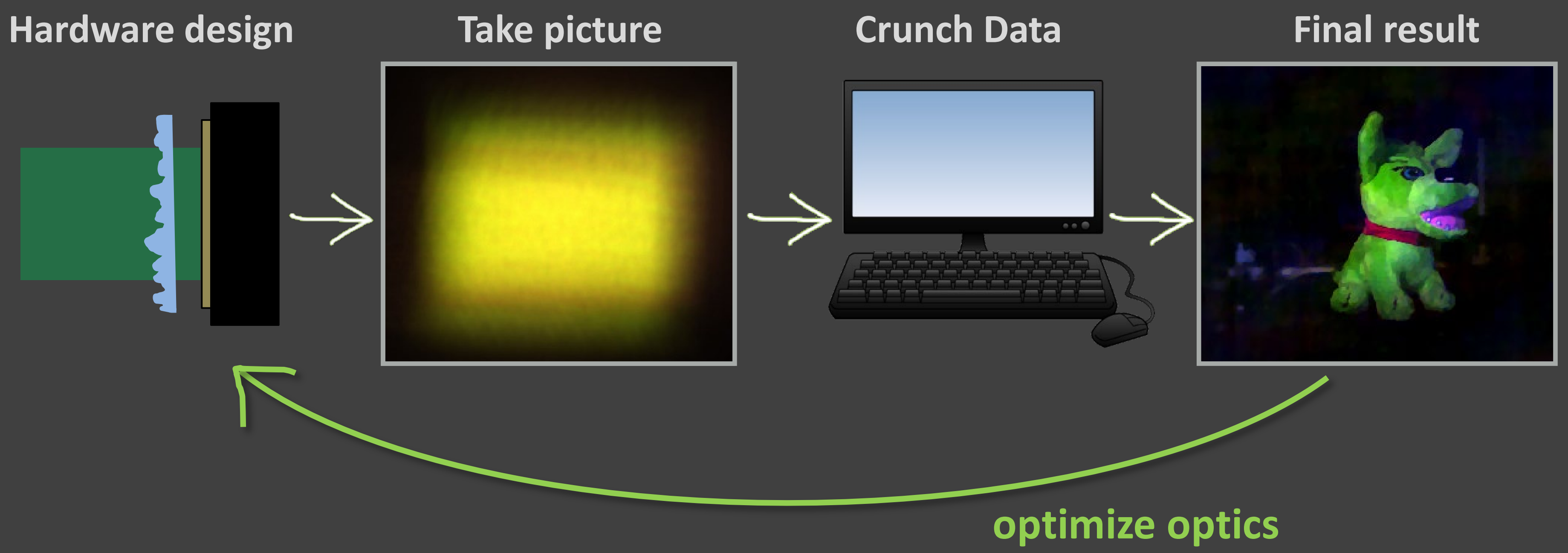
What is the best reconstruction algorithm?



Gregor & LeCun 2010, Yang et al. 2016, Zhang et al. 2017, Diamond et al. 2018
Kamilov et al. *IEEE Sig. Proc. Lett.* 24:12 (2018)
E. Bostan, R. Heckel, M. Chen, M. Kellman, L. Waller, *Optica* 7(6), 559-562 (2020)
K. Monakhova, J. Yurtsever, G. Kuo, N. Antipa, K. Yanny, L. Waller, *Opt. Express* (2019)
E. Bostan, U. Kamilov, L. Waller, *IEEE Sig. Proc. Lett.* 25(7), 989–993 (2018)

Computational imaging pipeline

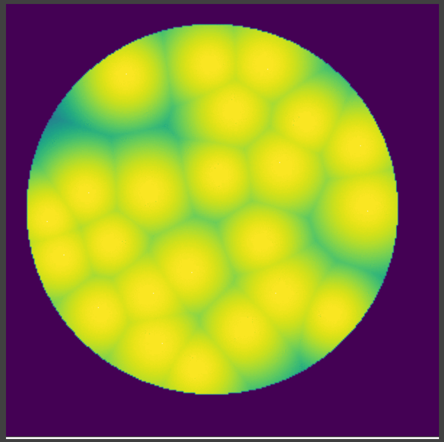
What are the best measurements to take?



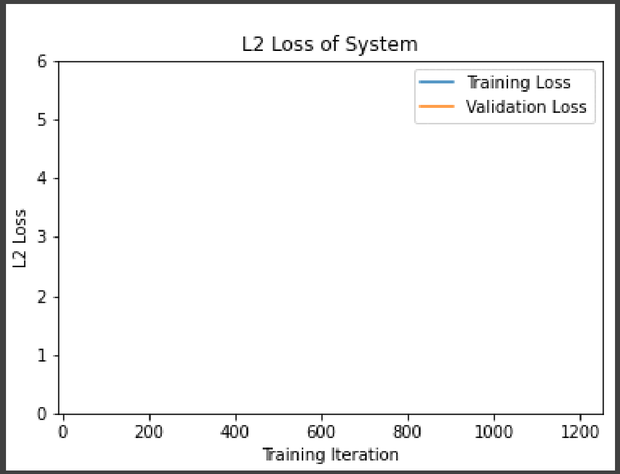
Extended depth-of-field imaging: V. Sitzmann, et al., *ACM Trans. Graphics* 37:4 (2018).
Optical computing [Chang et al. 2018]
Microscopy [Horstmeyer 2017, Hershko et al. 2019, Kellman et al. 2019]
Monocular depth estimation [Wu et al. 2019, Chang et al. 2019]
Single-shot high dynamic range imaging [Metzler et al. 2020, Sun et al. 2020]
Wide-FoV and full spectrum imaging with a single optical element [Peng et al. 2019, Dun et al. 2020]
Holographic displays [Peng et al. 2020]

Learning an optimized diffuser shape

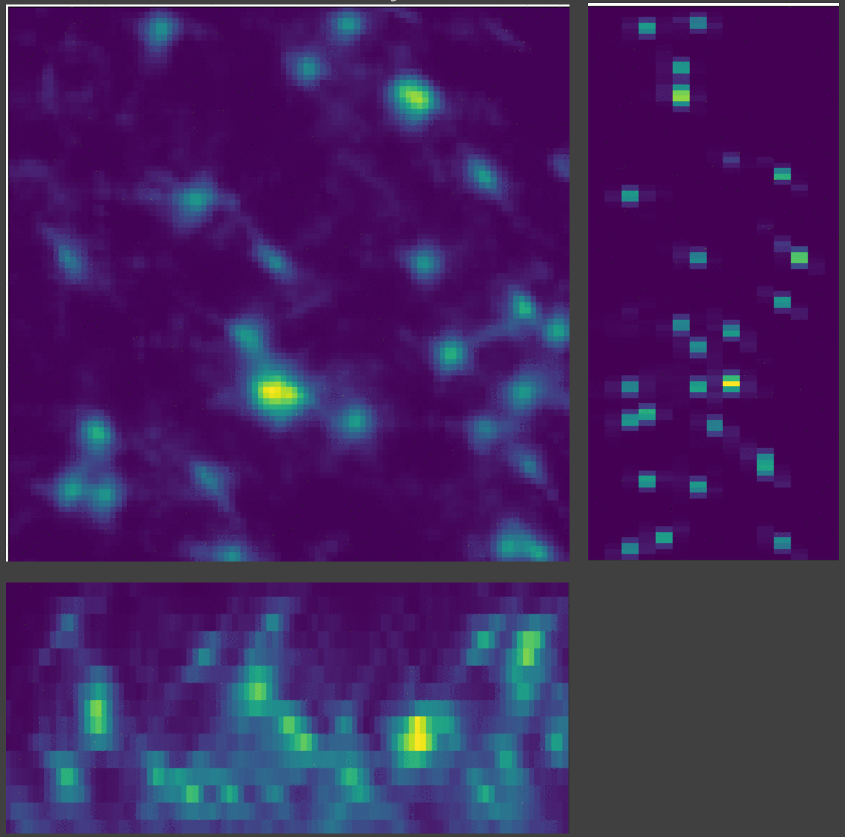
Diffuser Surface



- 40 Unrolls
- 23 Lenslets
- 5 Training Examples
- ADAM Optimization



XY Reconstruction Projection

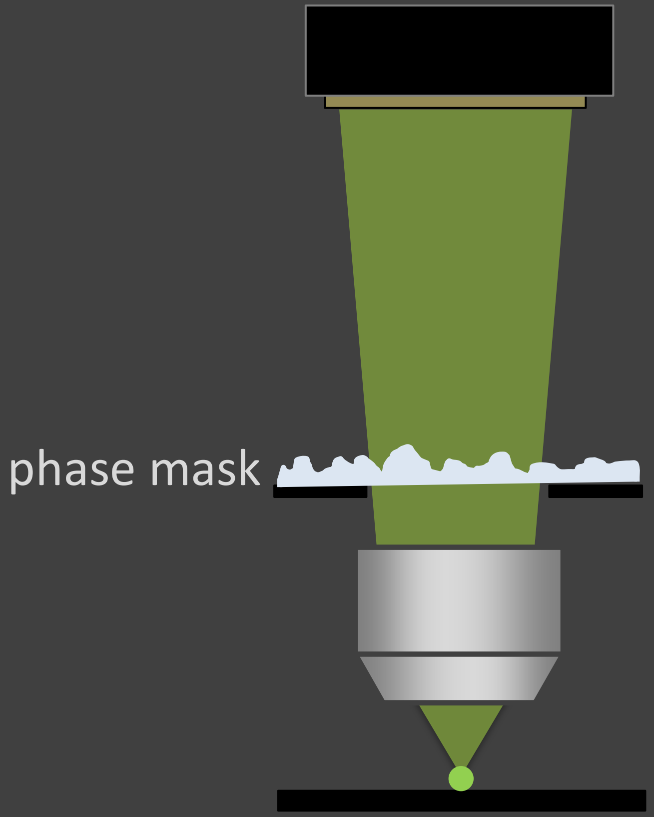


YZ Reconstruction Projection

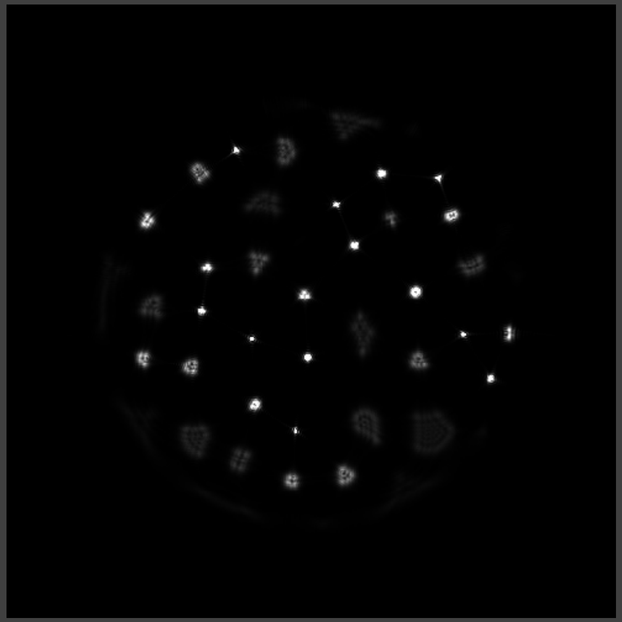
XZ Reconstruction Projection

Eric Markley

Fourier DiffuserScope

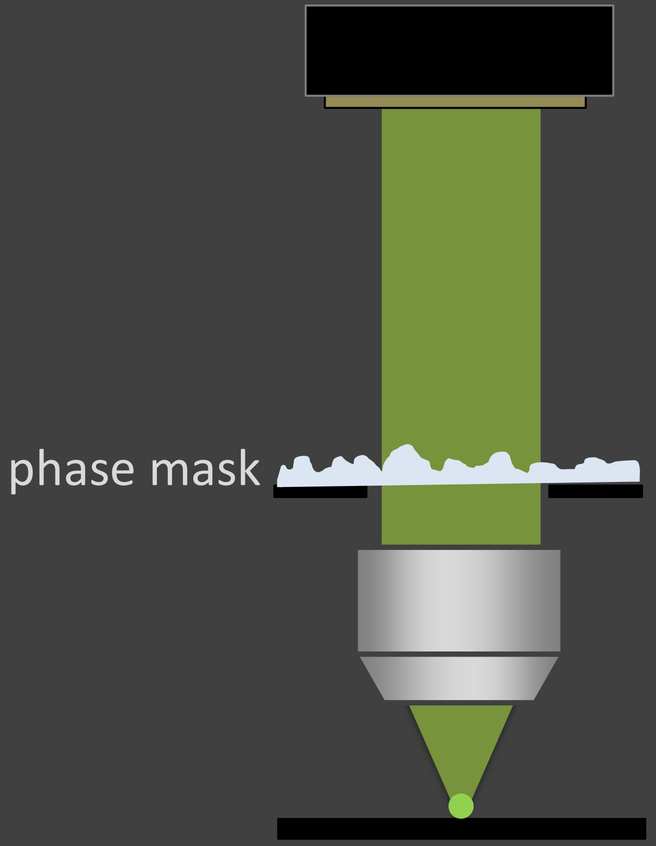


Point Spread Function (PSF)

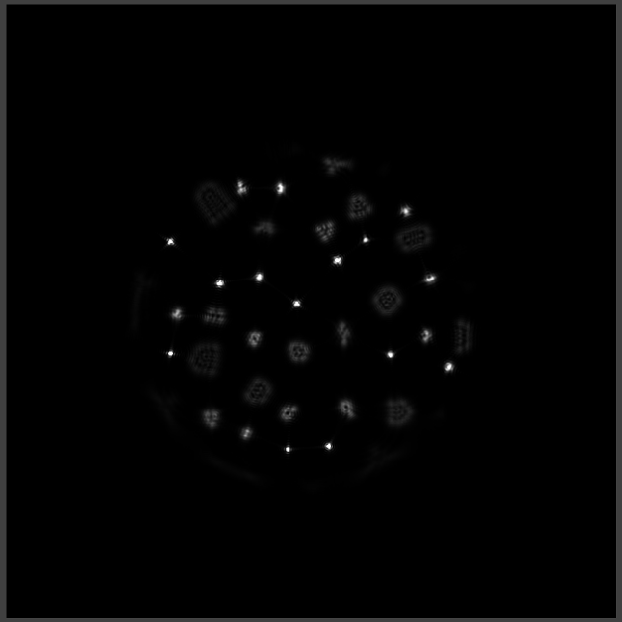


Linda Liu

Fourier DiffuserScope

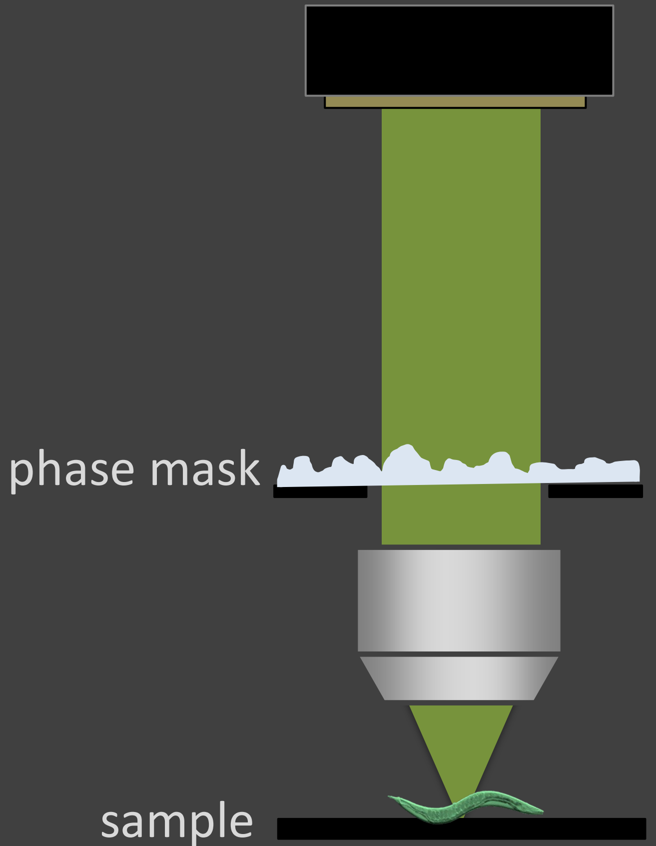


Point Spread Function (PSF)

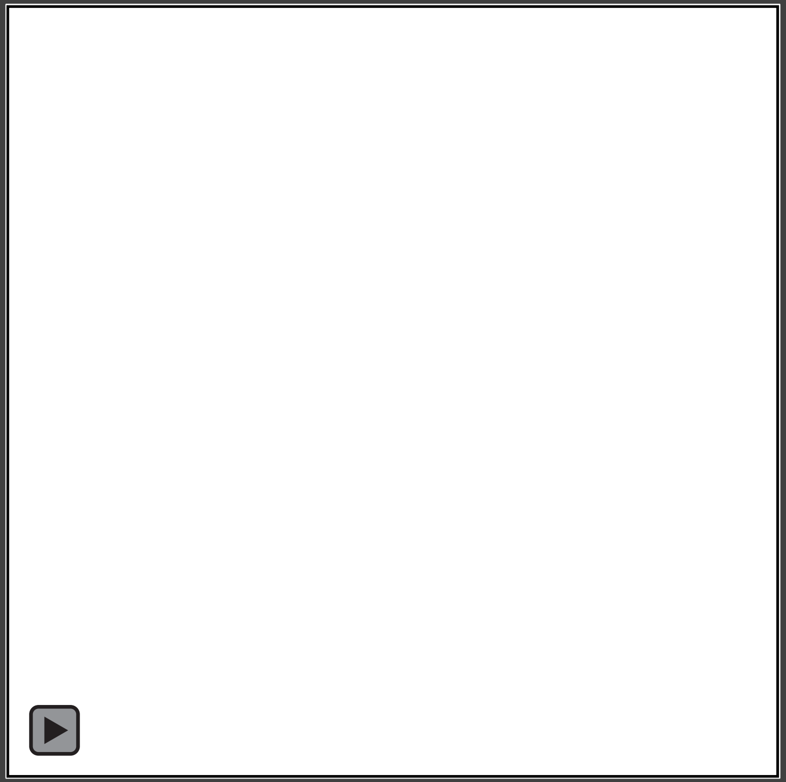


Linda Liu

Fourier DiffuserScope

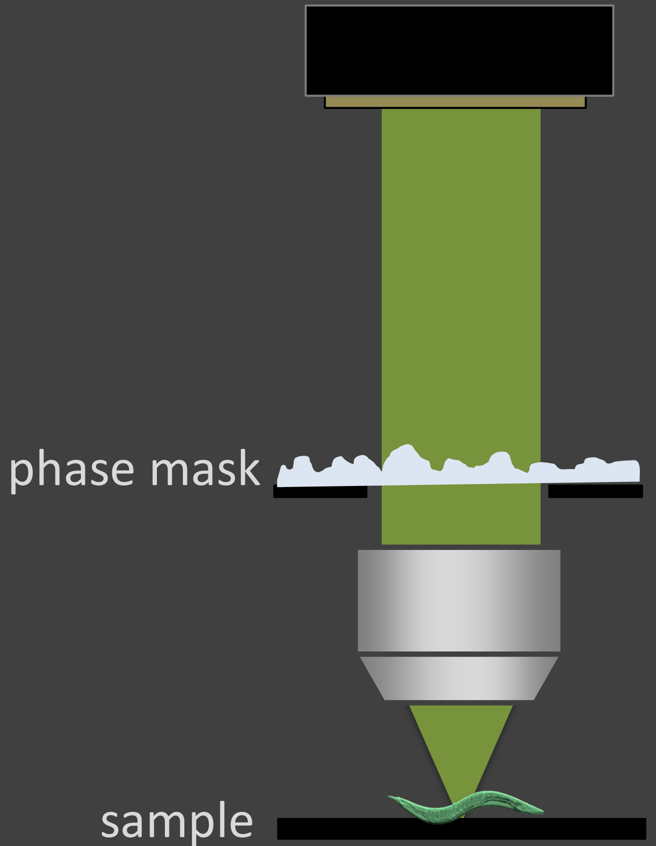


reconstructed 3D video



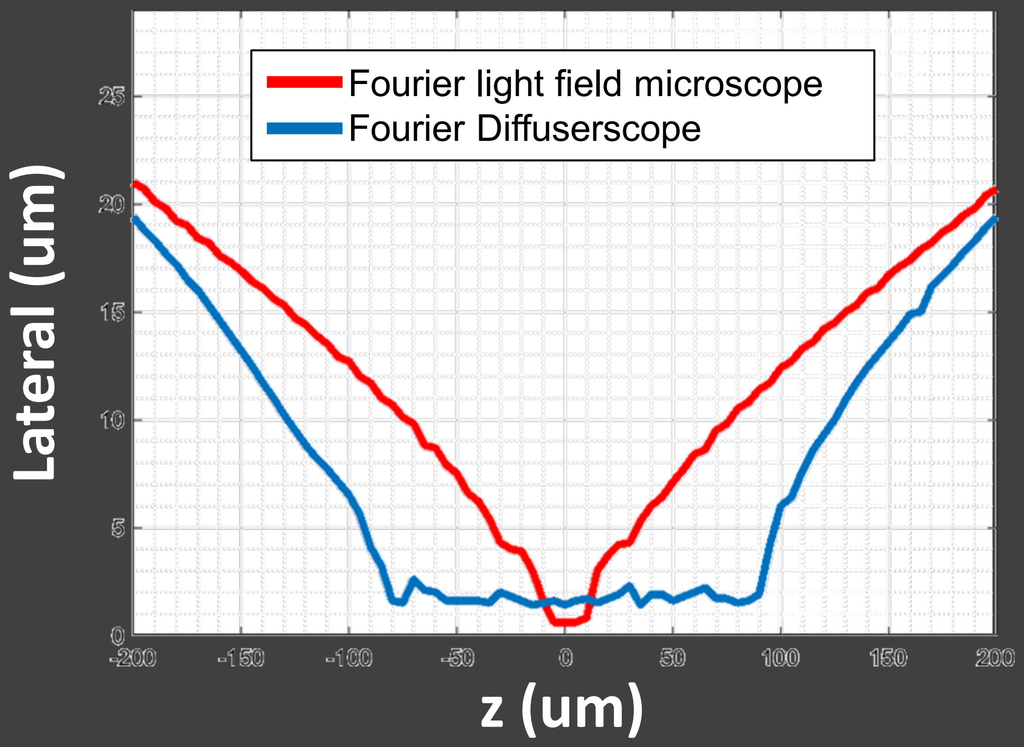
Linda Liu

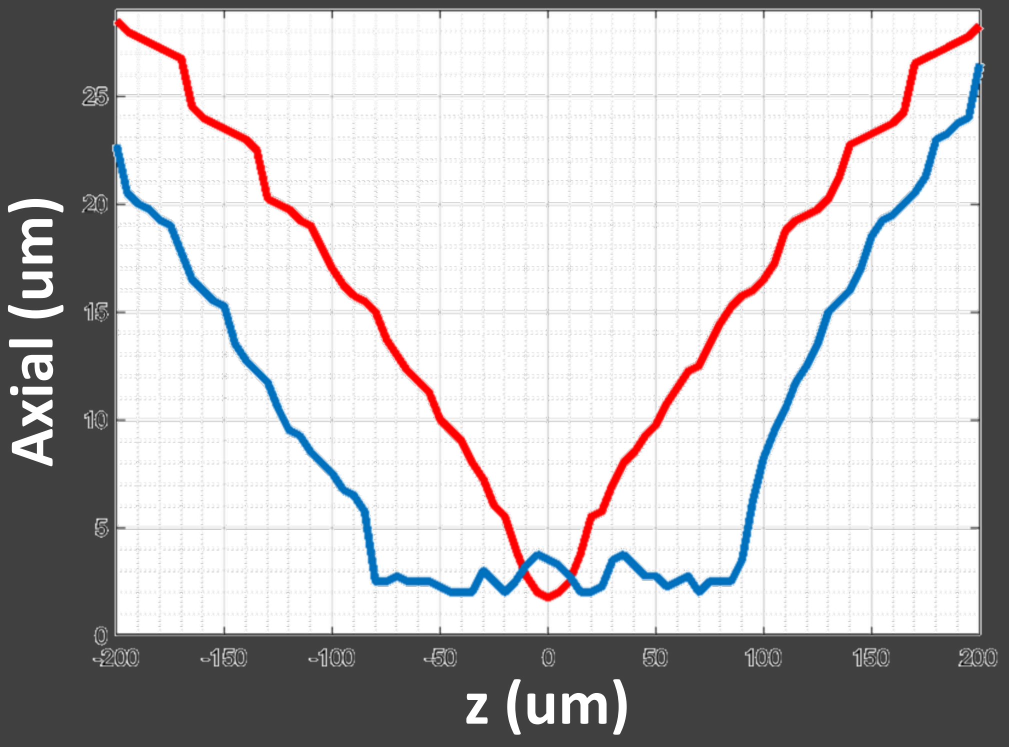
Fourier DiffuserScope



Linda Liu

Resolution is more uniform





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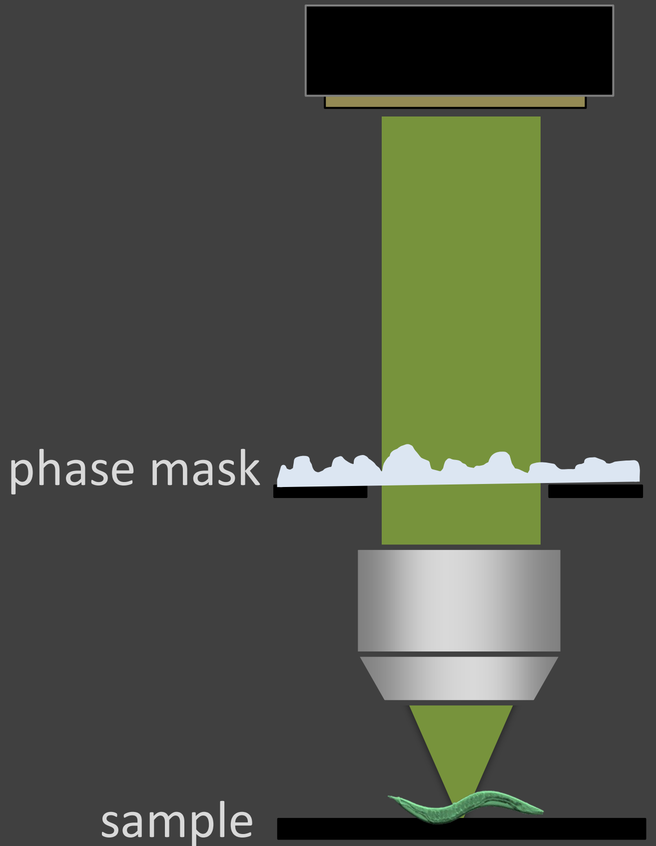
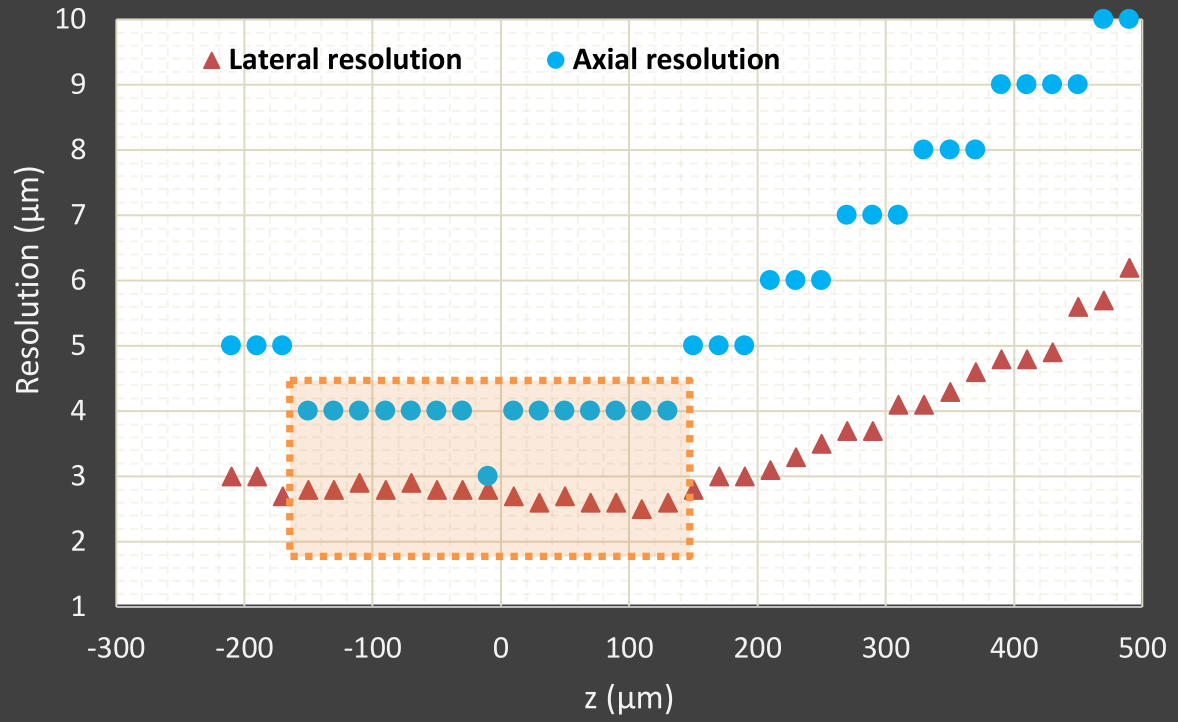
Fourier DiffuserScope





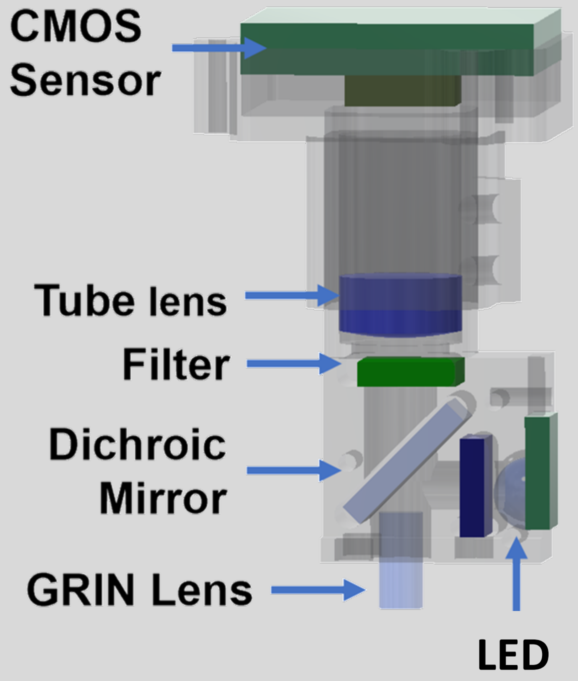
Large volume: 1000×1000×280 µm^3

High-resolution: <3 µm lateral, 4 µm axial

Linda Liu

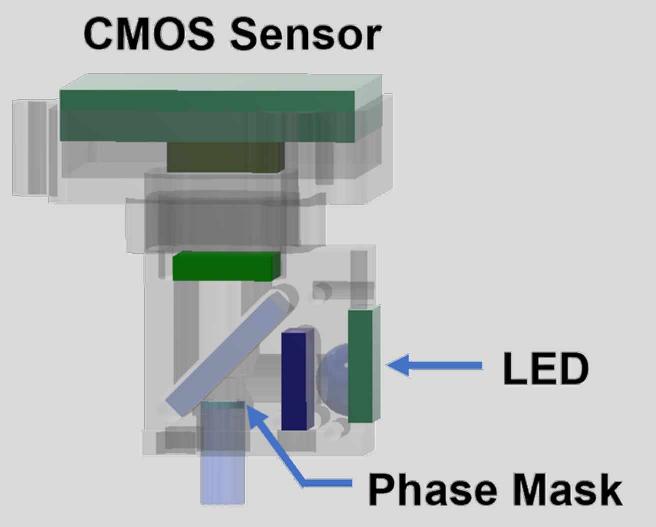
Open-source miniature 3D microscope version

Miniscope



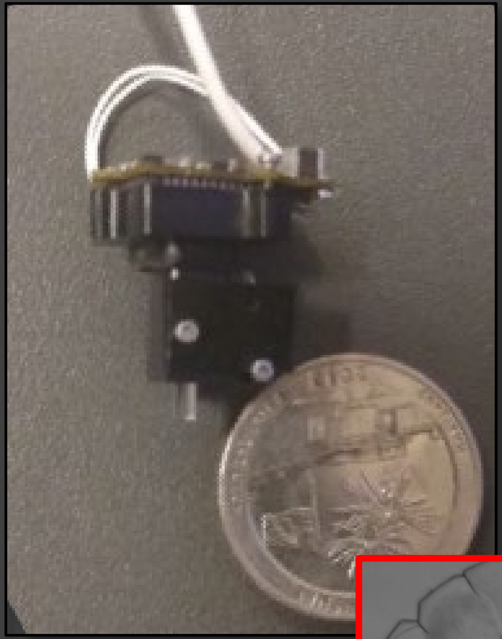
K. K. Ghosh, et al, *Nature Methods* 8, 871 (2011).

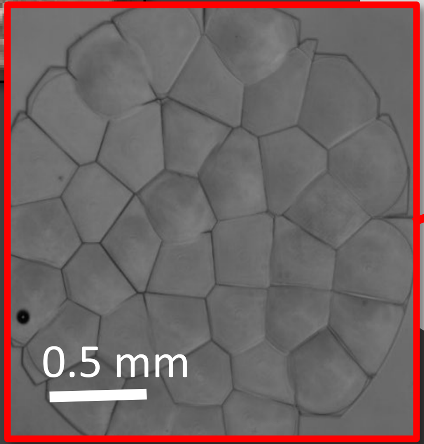
Miniscope3D



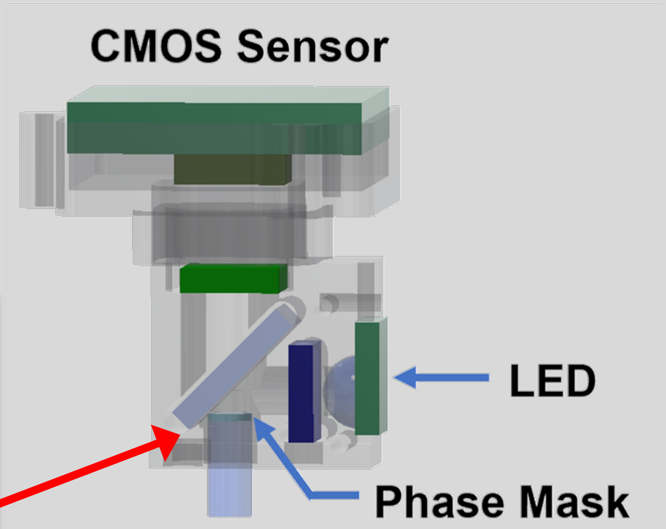
Kyrollos Yanny
Nick Antipa

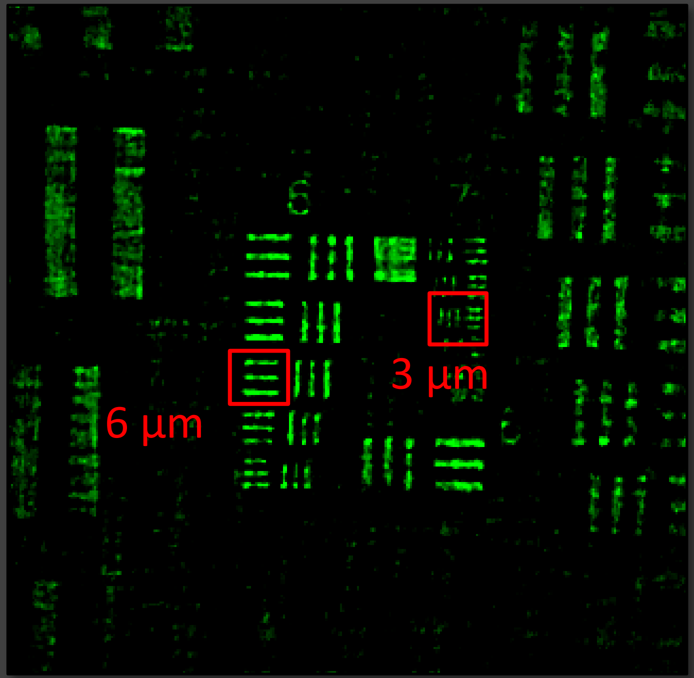
Open-source miniature 3D microscope version





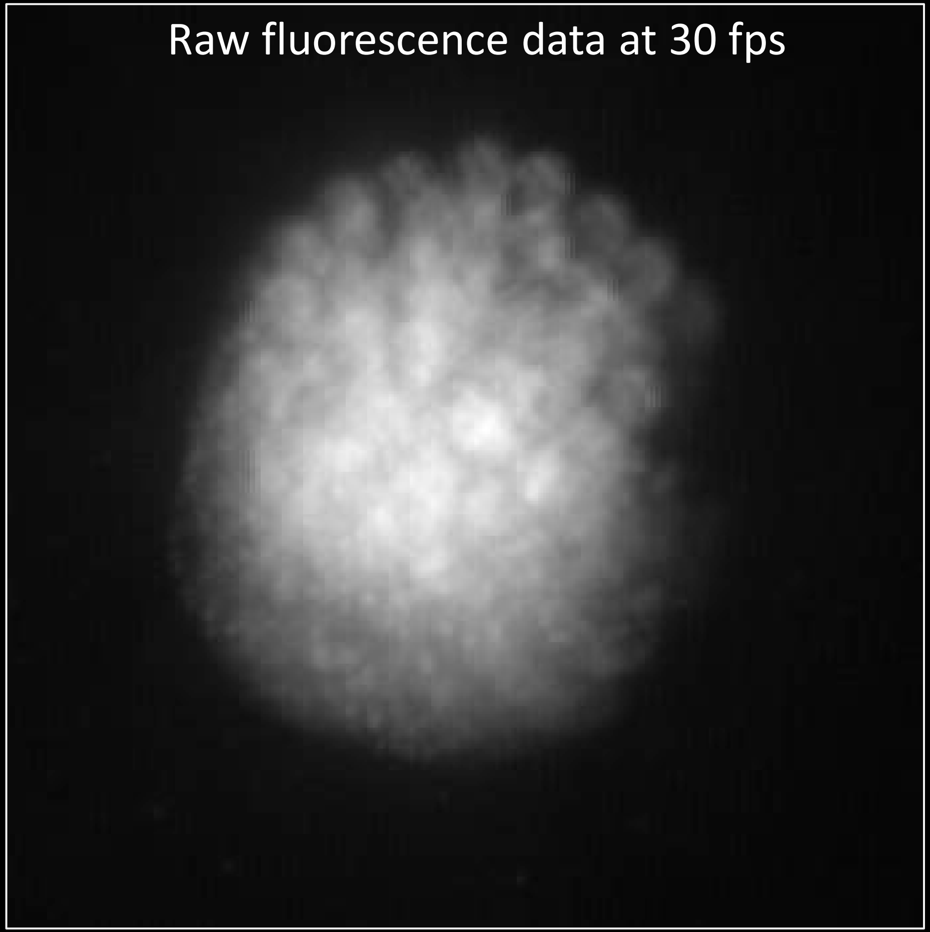
Miniscope3D

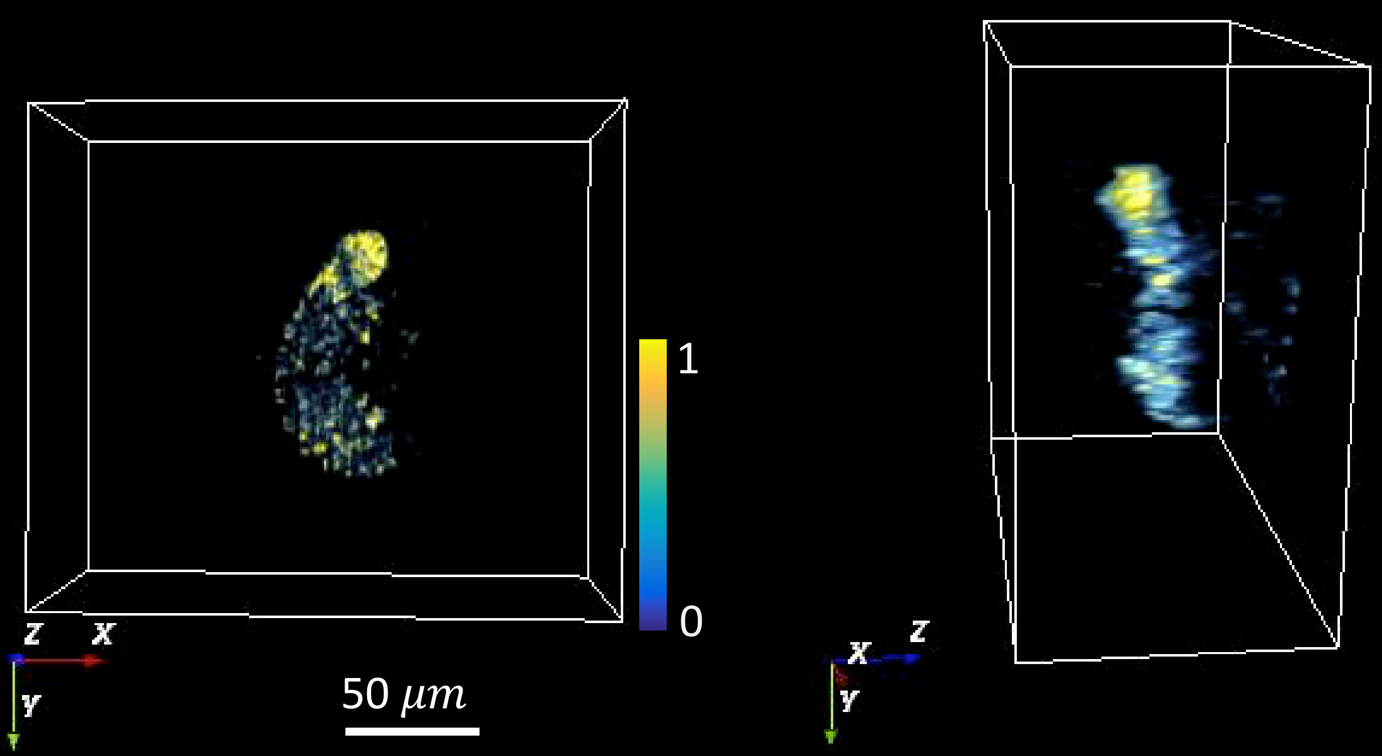




Kyrollos Yanny
Nick Antipa

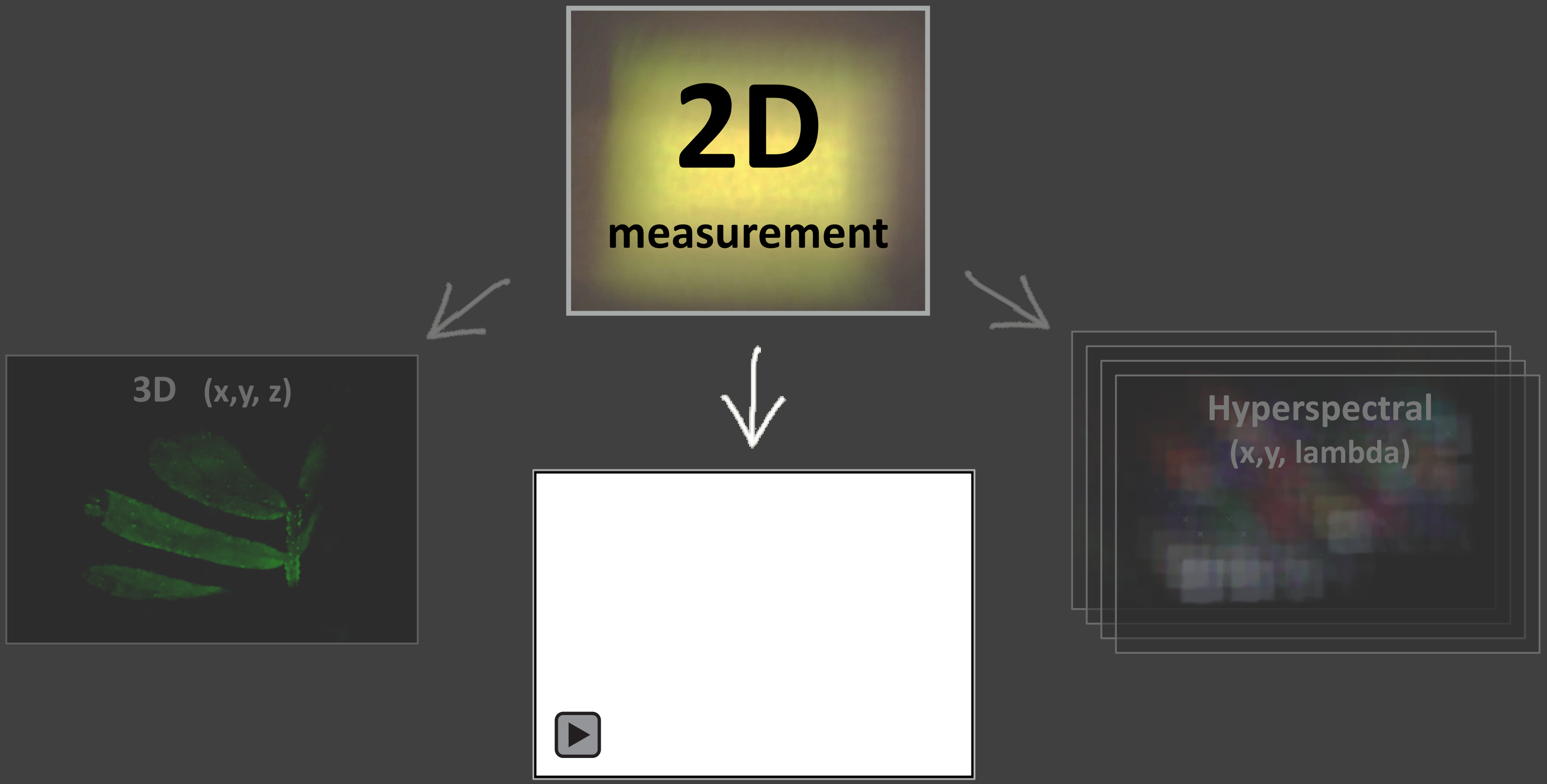
K. Yanny, … **L. Waller**, *Light: Science & Applications* 9:171 (2020).



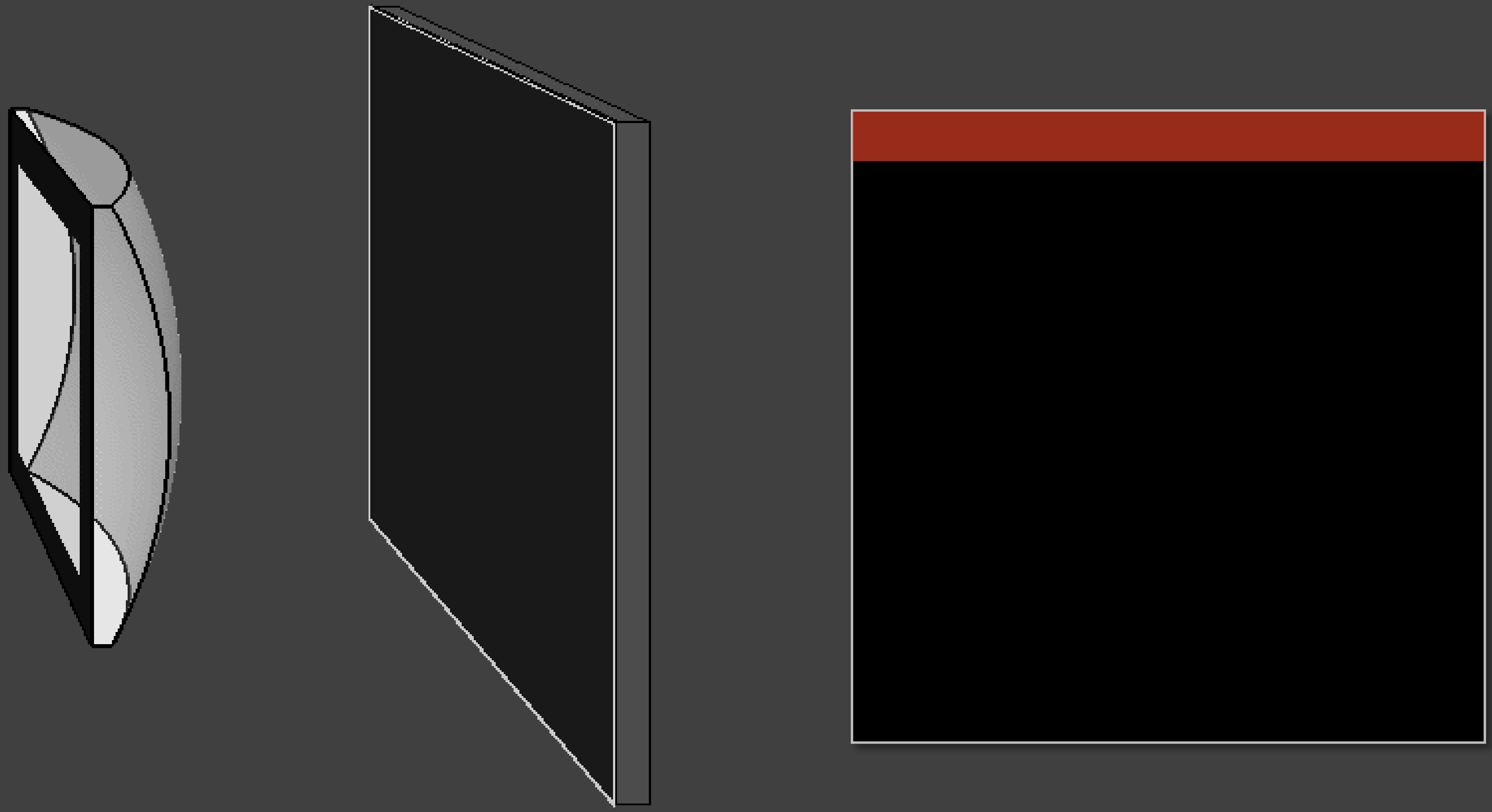


Kyrollos Yanny
Nick Antipa

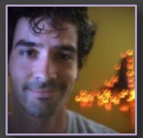
K. Yanny, … **L. Waller**, *Light: Science & Applications* 9:171 (2020).


2D
measurement
3D (x,y, z)
Hyperspectral
(x,y, lambda)

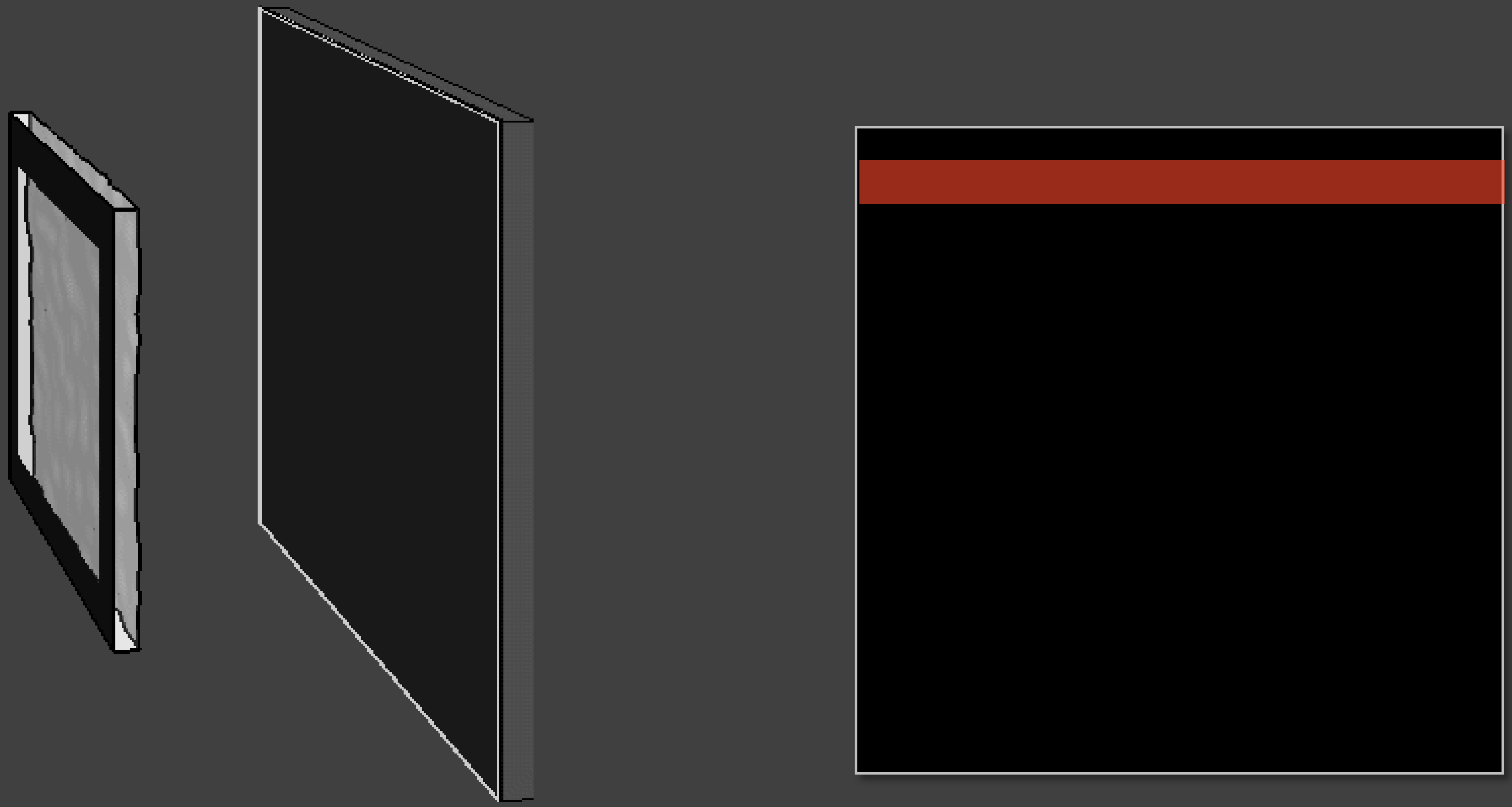
Multiplexing enables temporal encoding with rolling shutter



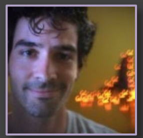
Patrick Oare
Nick Antipa



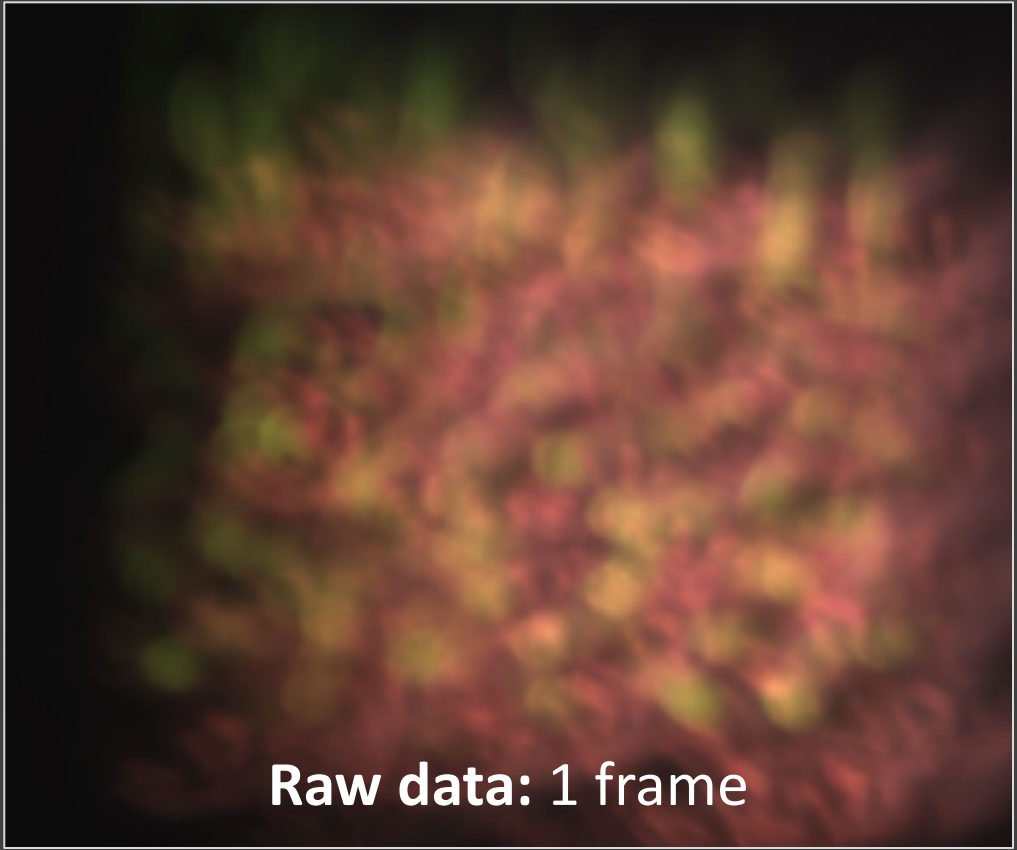
Multiplexing enables temporal encoding with rolling shutter



Patrick Oare
Nick Antipa

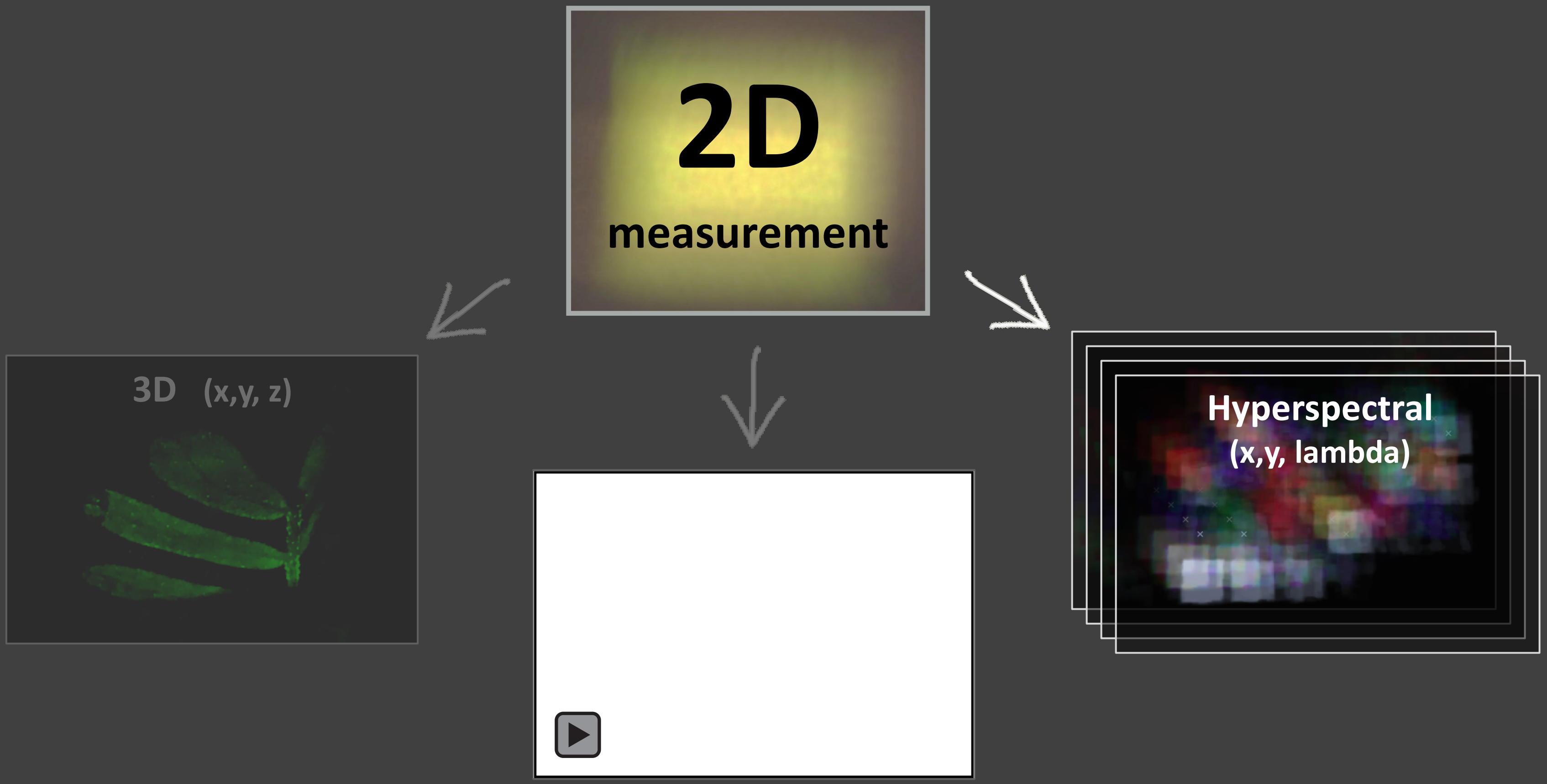


Video from stills with rolling shutter

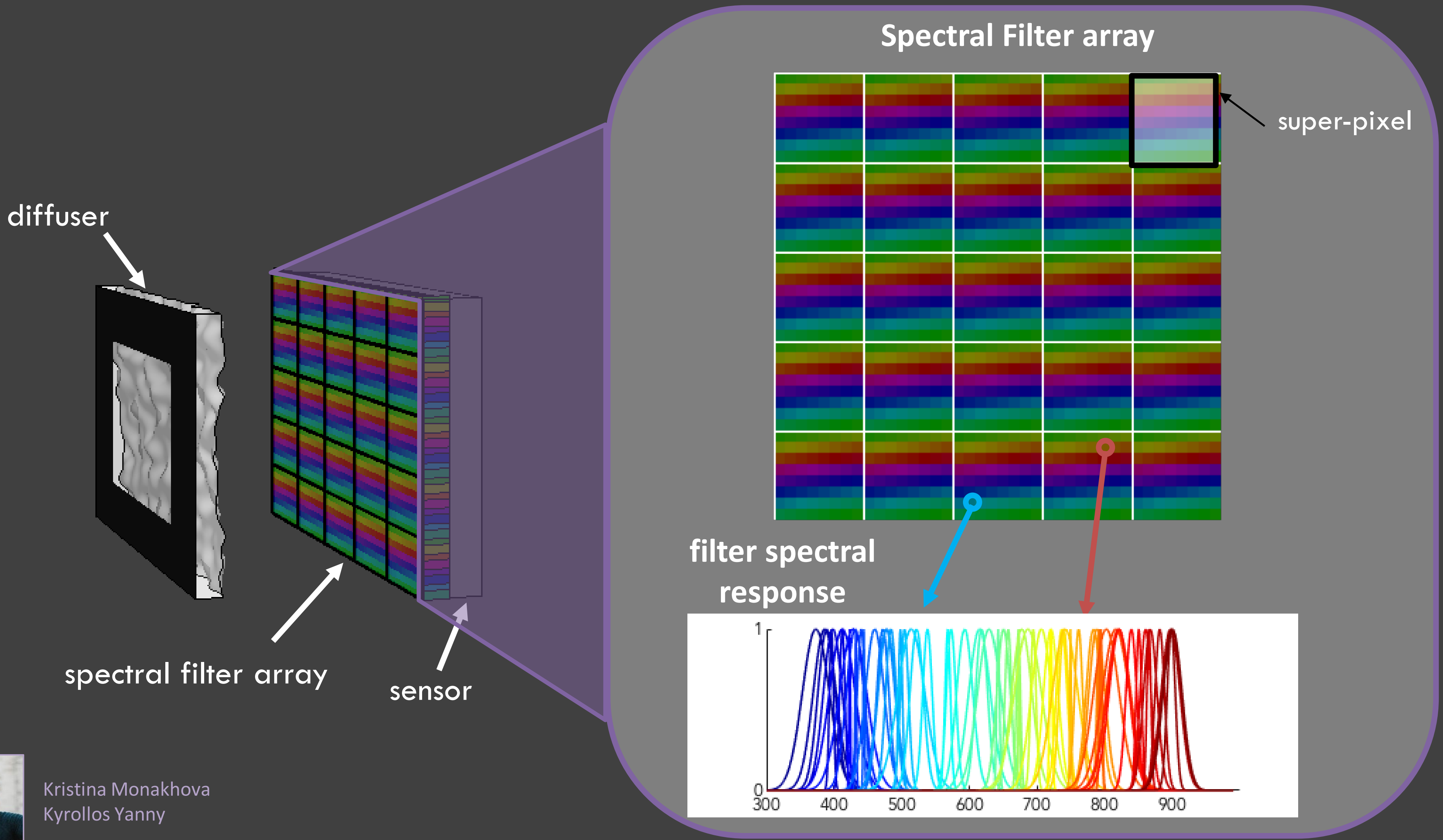


Patrick Oare
Nick Antipa

P. Oare, N. Antipa, E. Bostan, L. Waller *ICCP* 2019

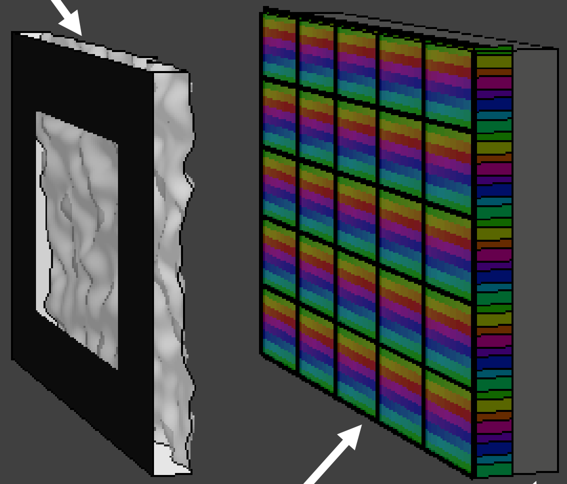

2D
measurement
3D (x,y, z)
Hyperspectral
(x,y, lambda)

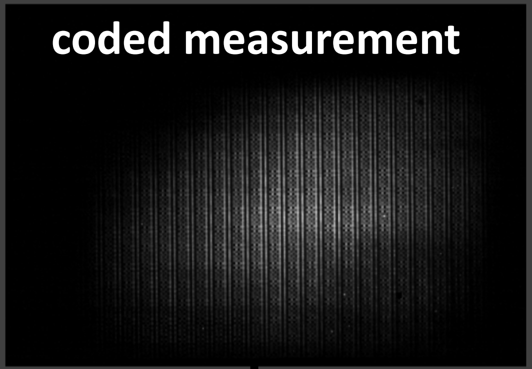
Lensless hyperspectral imaging with color filter array




Kristina Monakhova
Kyrollos Yanny

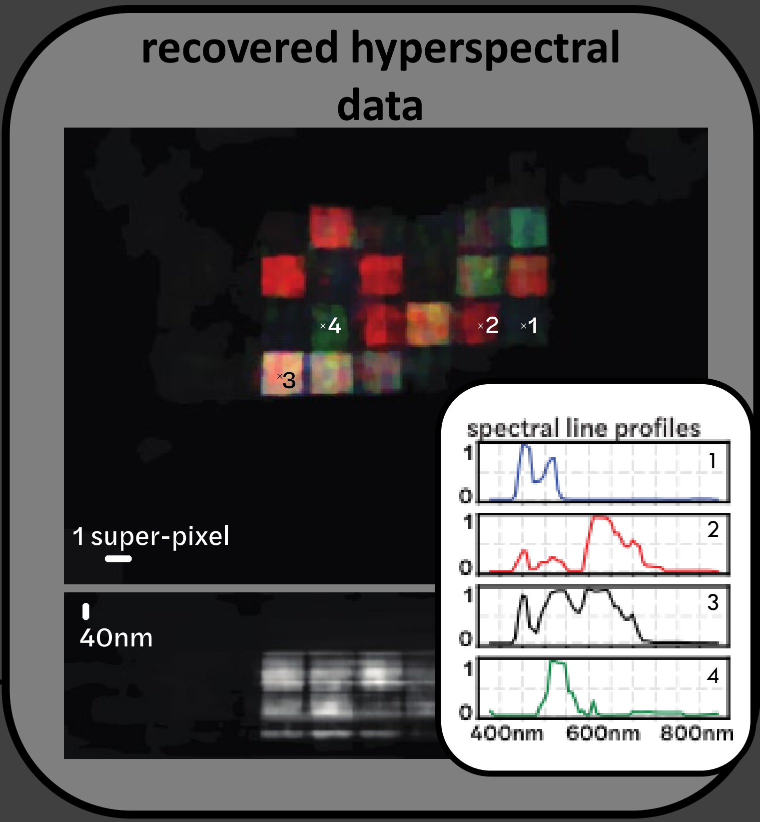
Lensless hyperspectral imaging with color filter array





reconstruction algorithm

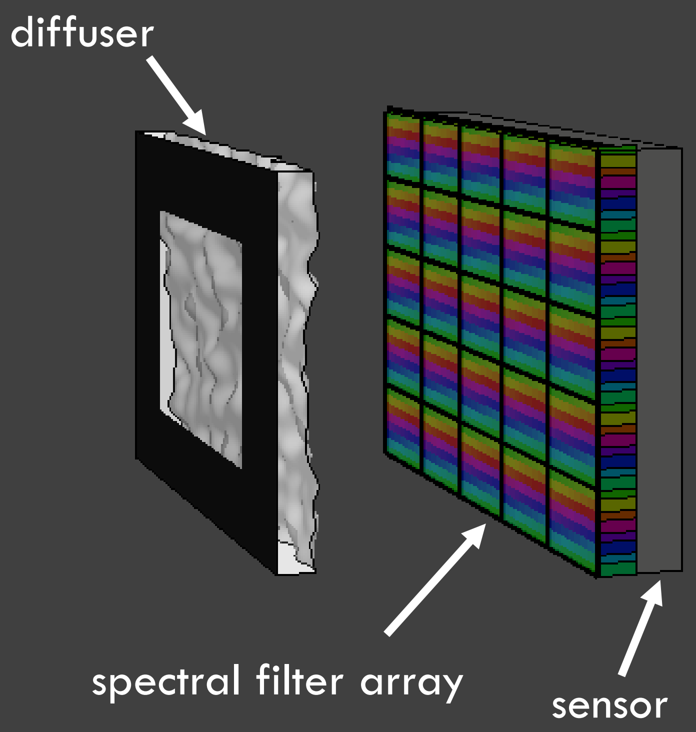
$$\arg\min_{\mathbf{v}\geq 0} \frac{1}{2}\|\mathbf{b} - \mathbf{A}\mathbf{x}\|_2^2 + \tau D(\mathbf{x})$$



Kristina Monakhova
Kyrollos Yanny

K. Monakhova*, K. Yanny*, N. Aggarwal, L. Waller, *Optica* 7(10) 2020

Lensless hyperspectral imaging with color filter array



» **Cheap**: sensor + $5 filter array + diffuser
» **Compact**: 1cm in addition to sensor
» **Flexible**: choose any spectral filters (user-defined sampling and bandwidths)


Kristina Monakhova
Kyrollos Yanny

K. Monakhova*, K. Yanny*, N. Aggarwal, L. Waller, *Optica* 7(10) 2020

Raw measurement

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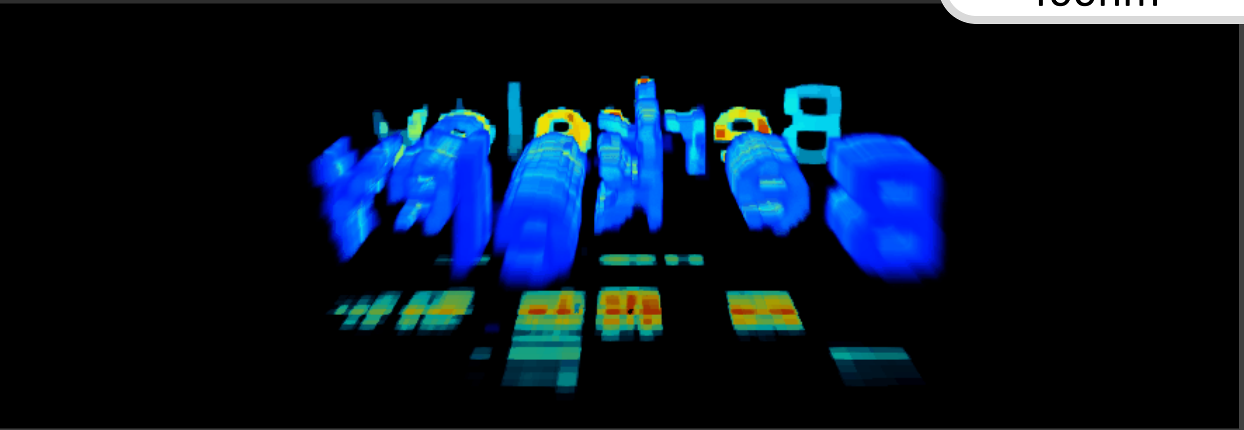
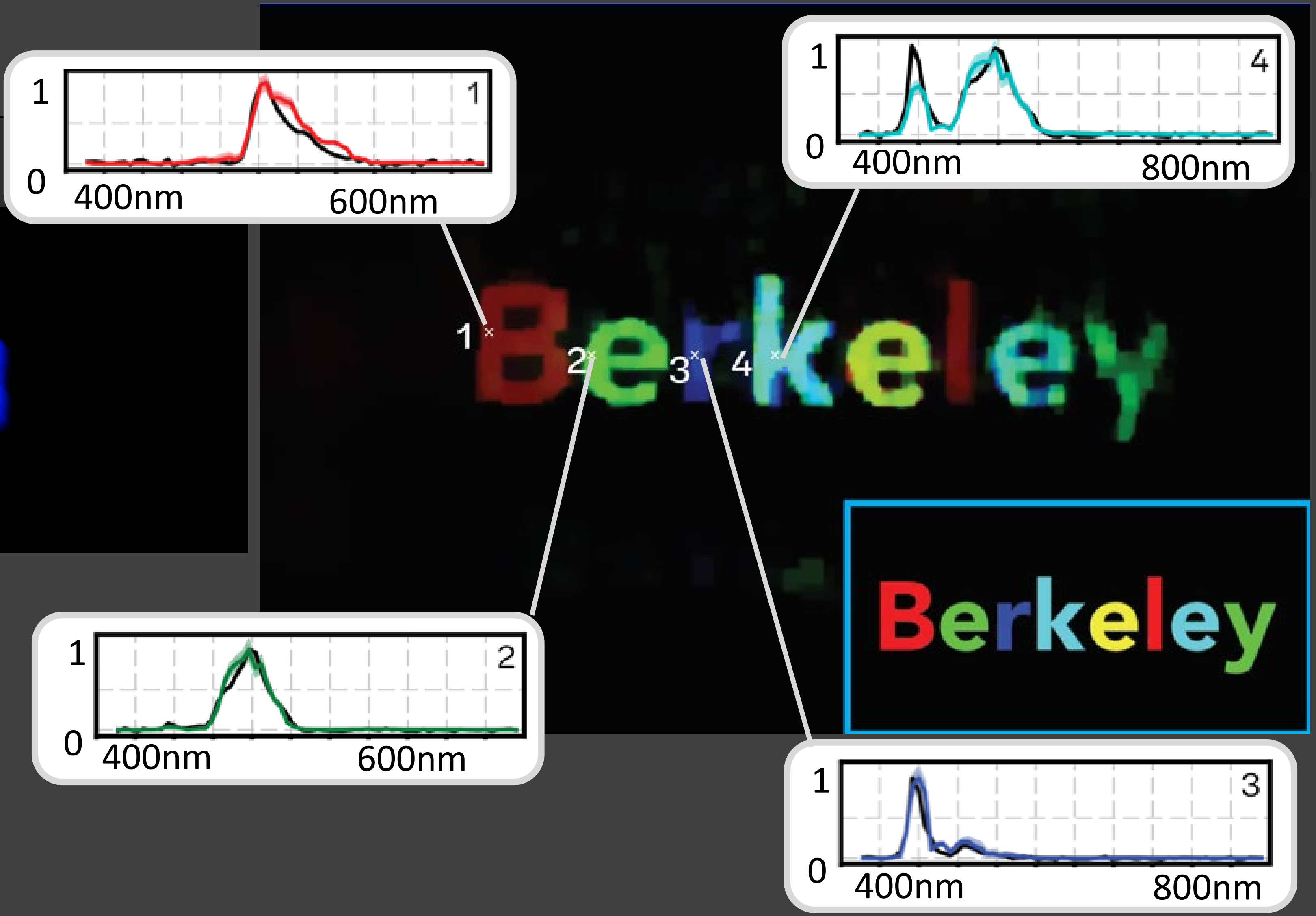
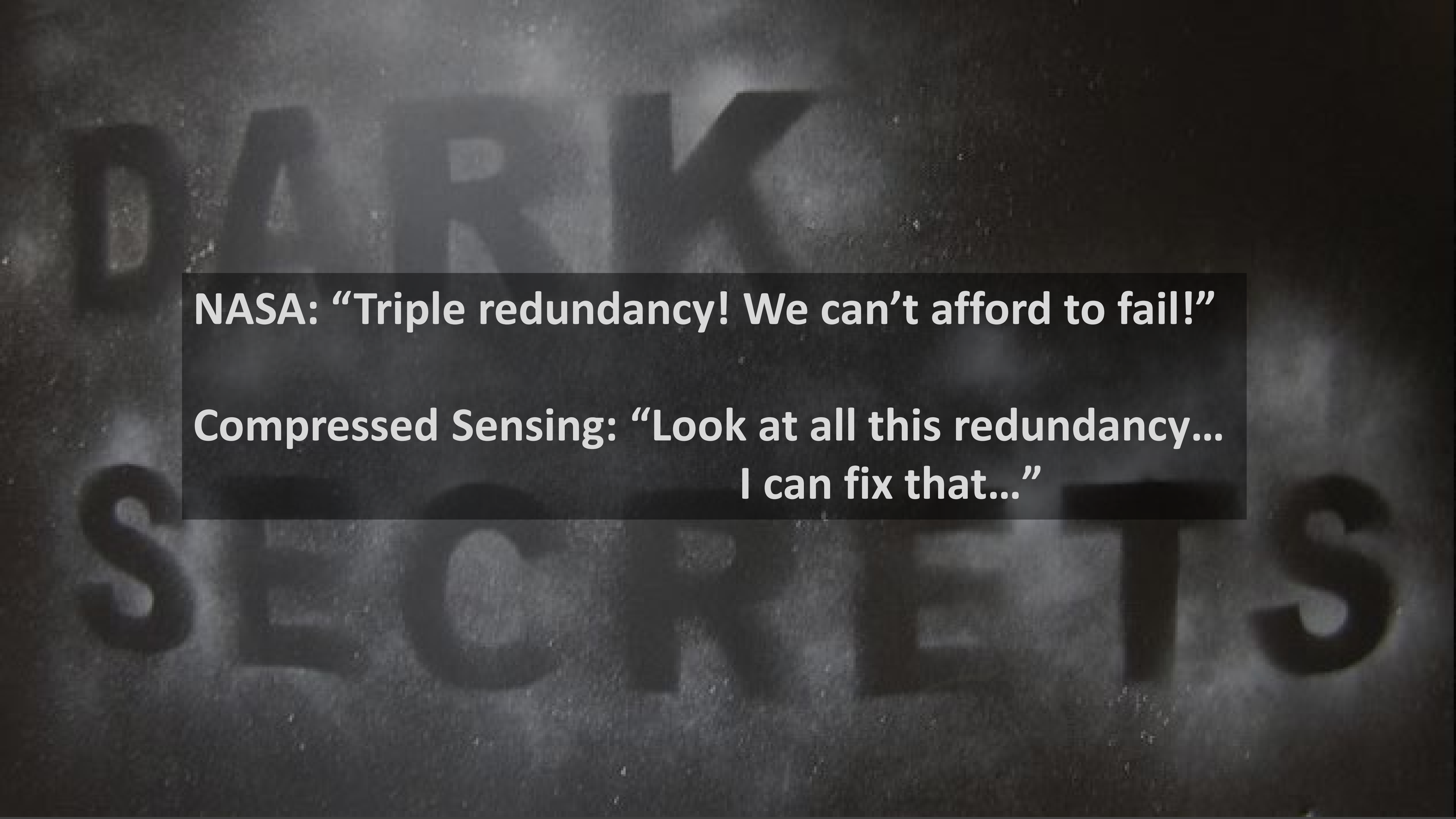
hyperspectral reconstruction





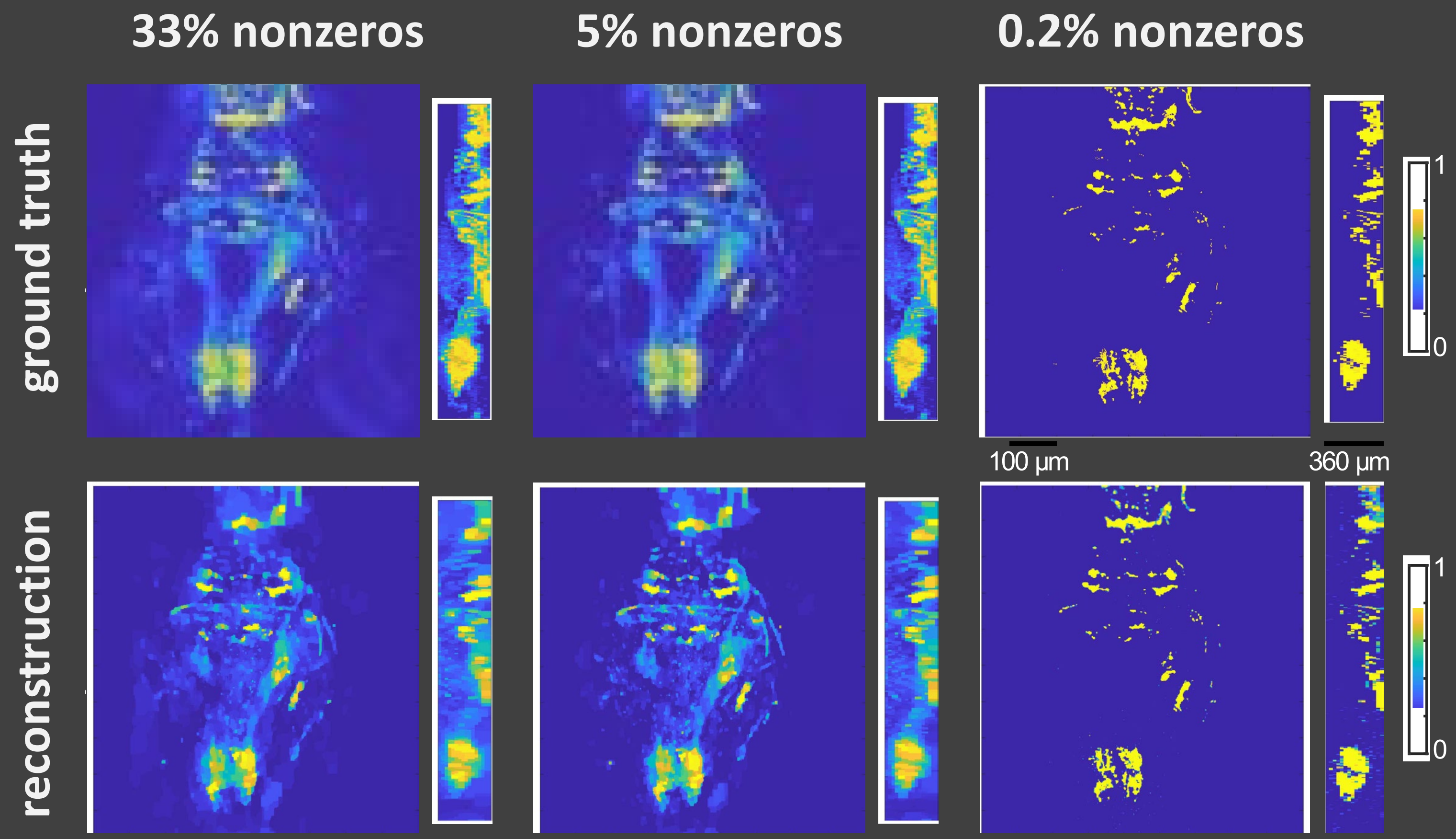
K. **Monakhova***, K. Yanny*, N. Aggarwal, L. Waller, *Optica* 7(10) 2020

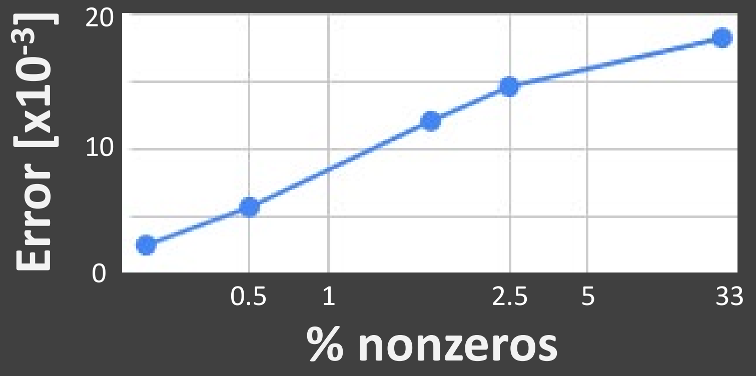


NASA: “Triple redundancy! We can’t afford to fail!”

Compressed Sensing: “Look at all this redundancy…
I can fix that…”

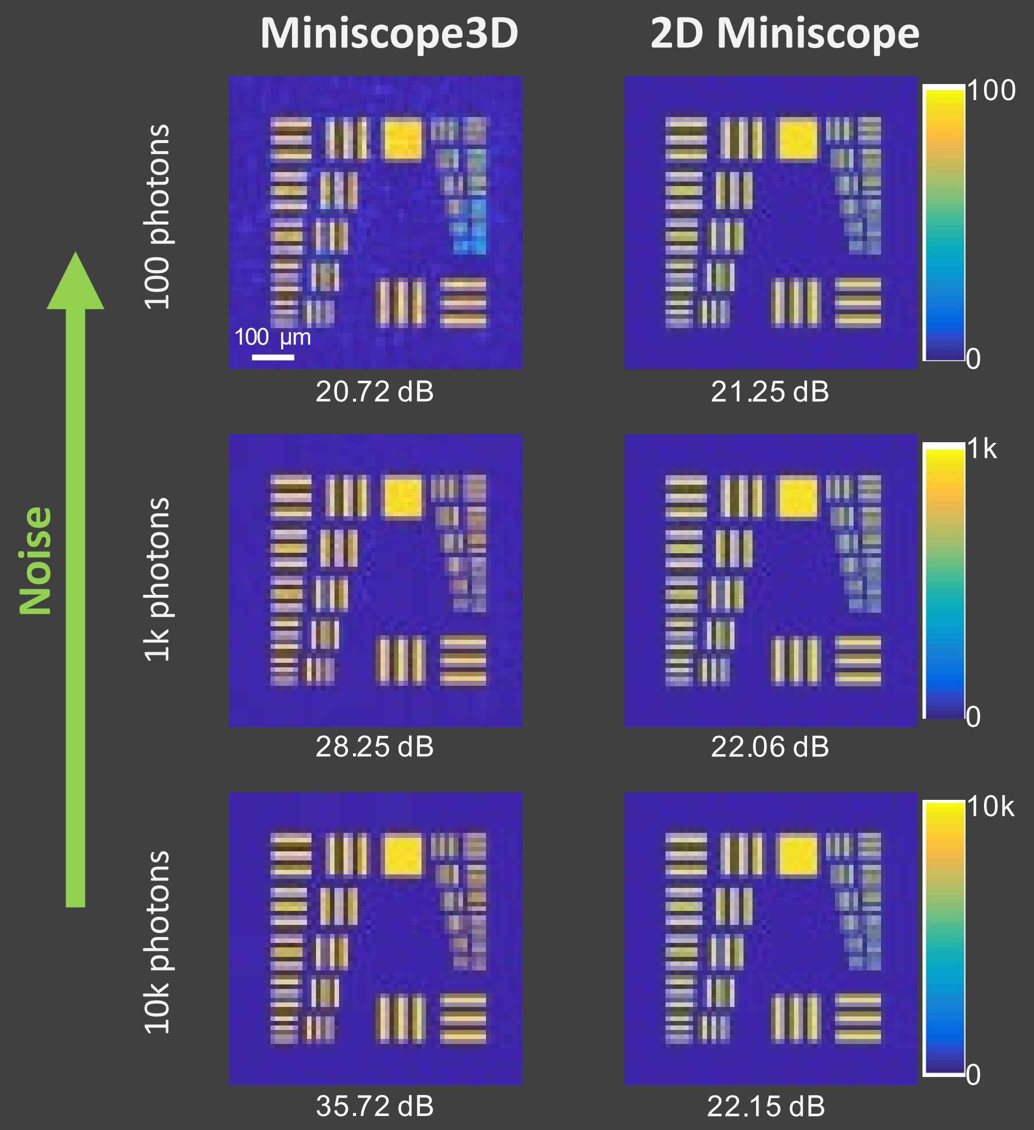
Sparsity is required





Kyrollos Yanny
Nick Antipa


Multiplexing hurts SNR, but not too much



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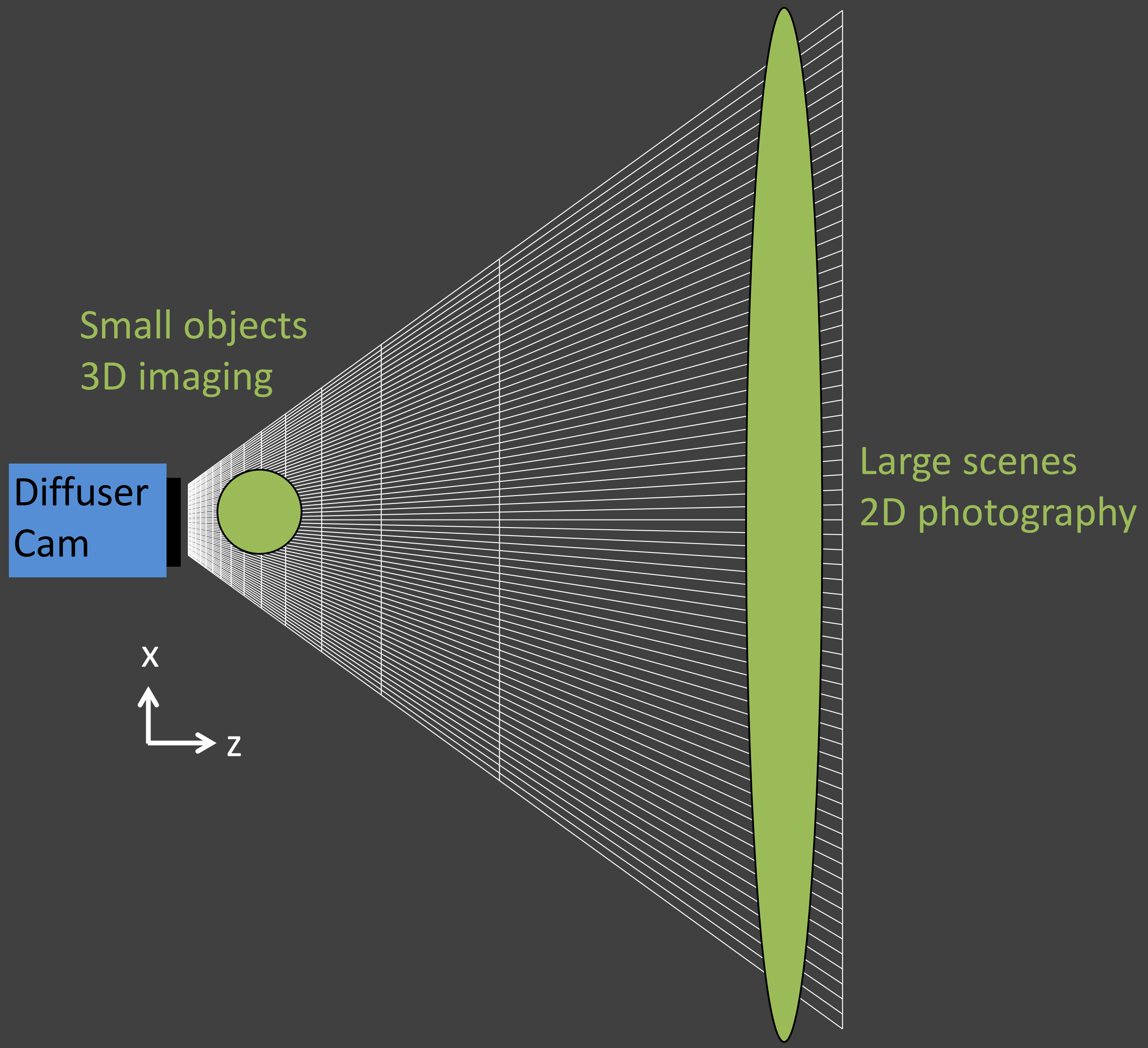
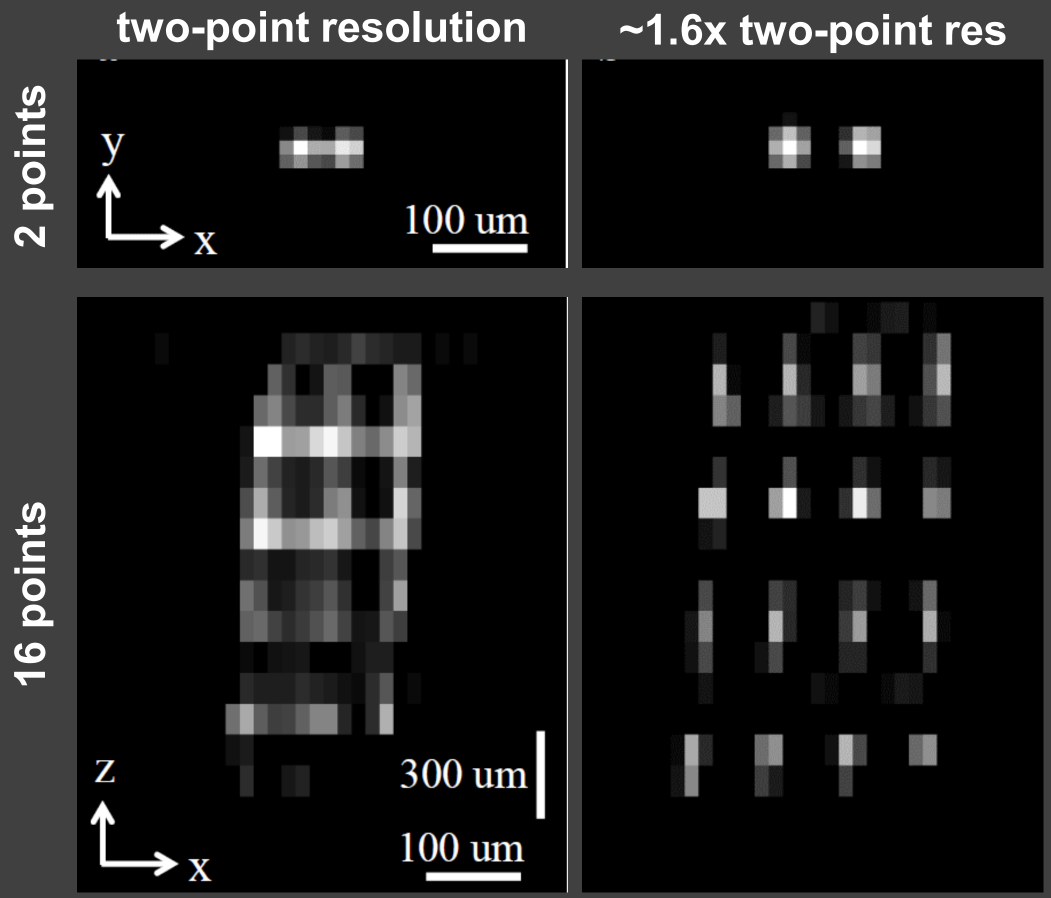
Calculating resolution
is messy!

Secret #2: Resolution is very non-uniform



Challenge: object-dependent resolution

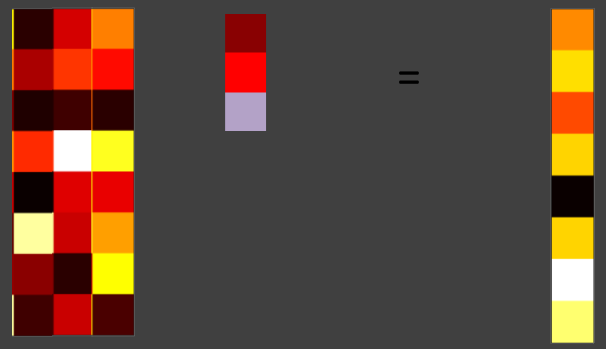


Two-point resolution only predicts *best case* scenario.

Solution?: use condition number of sub-problem

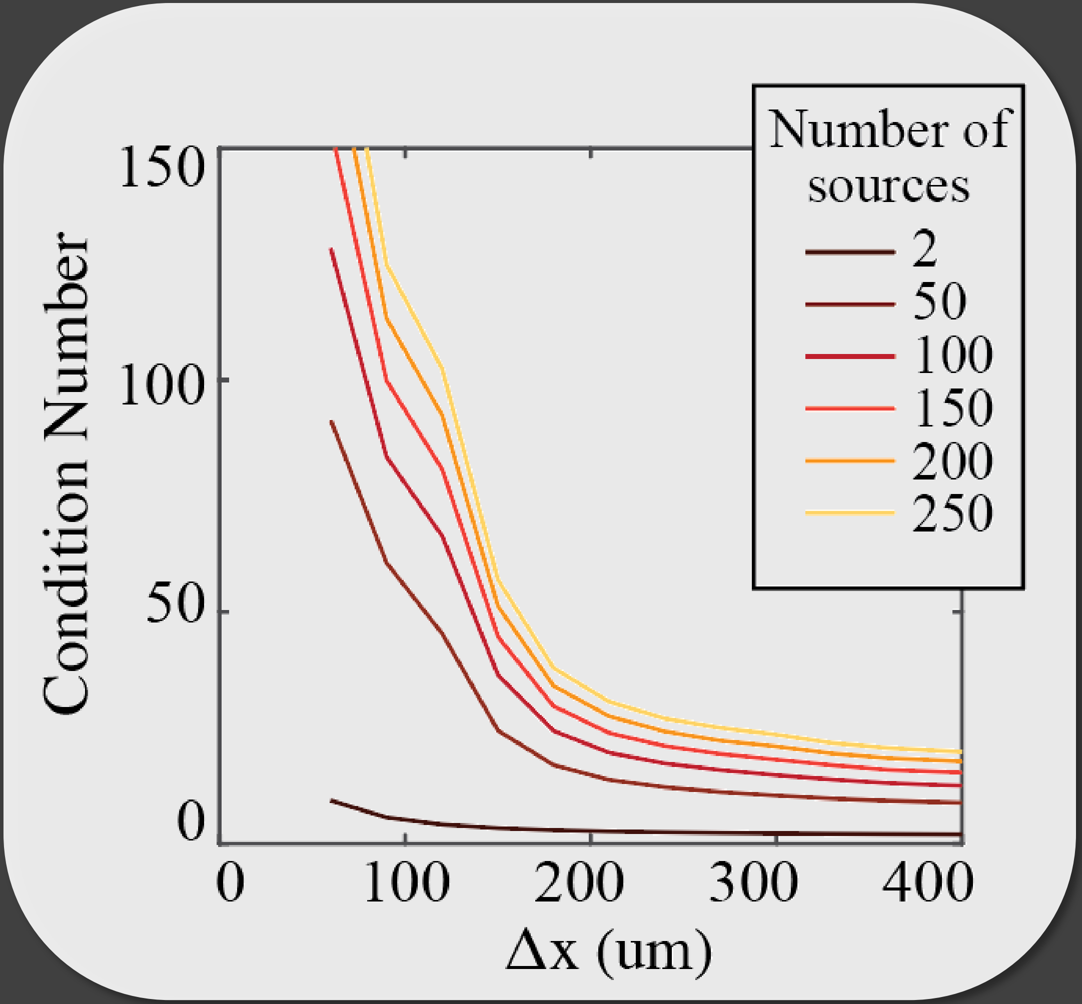
Assume we know where non-zero elements are:

Solution?: use condition number of sub-problem



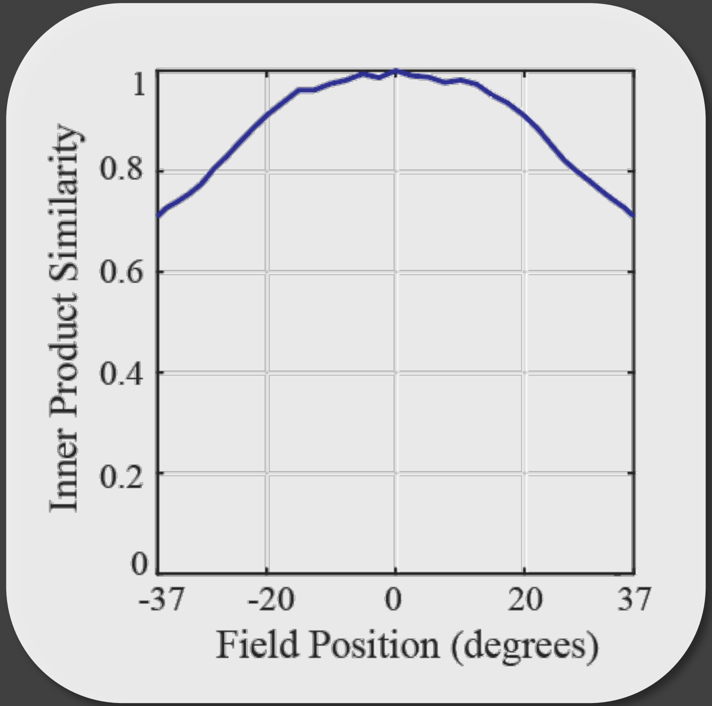
Now it is a small least squares problem

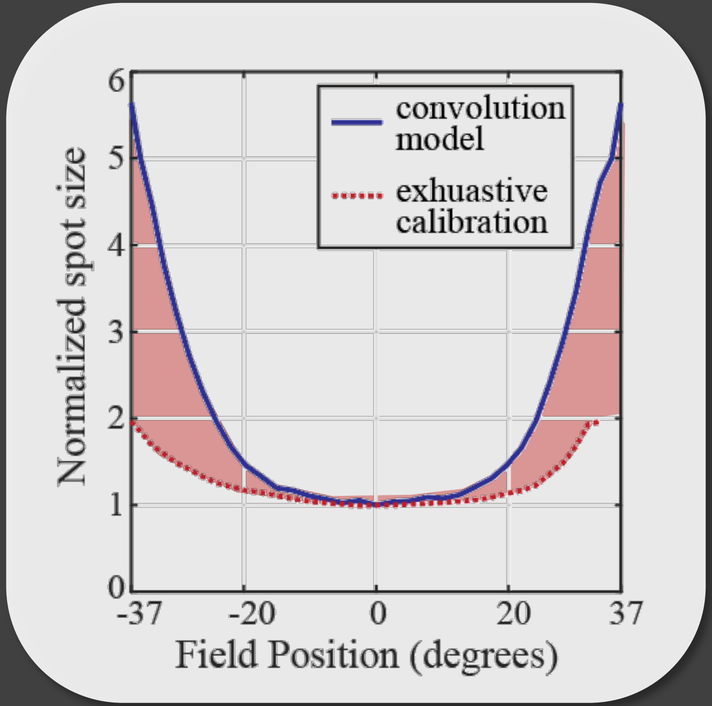
Solution?: use condition number of sub-problem



Local condition number sort of gives worst case scenario

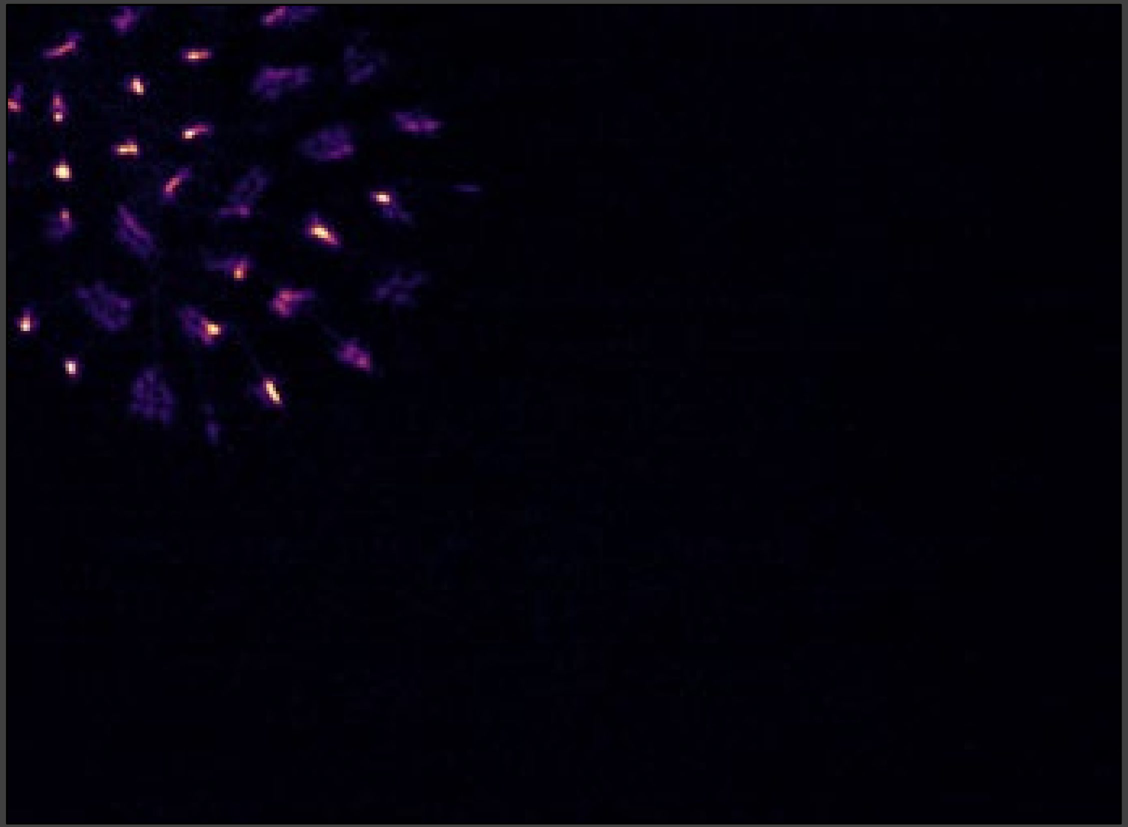
Challenge: model mis-match





Microscope has spatially-varying PSFs

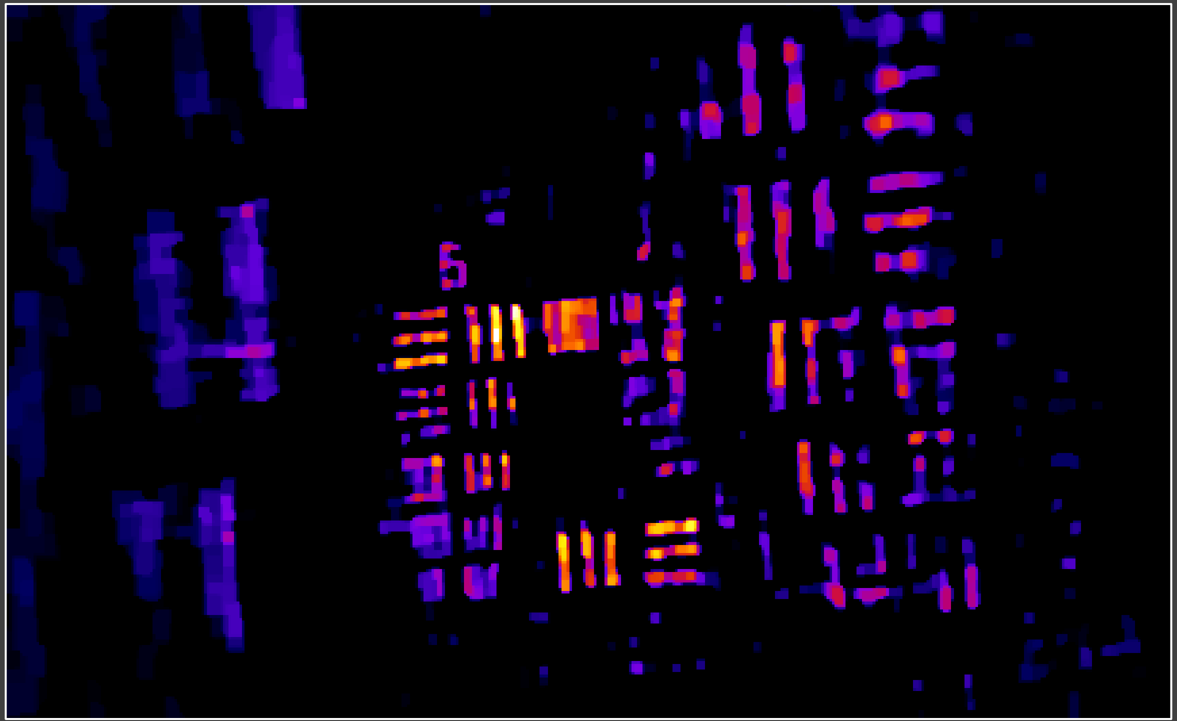
Point source



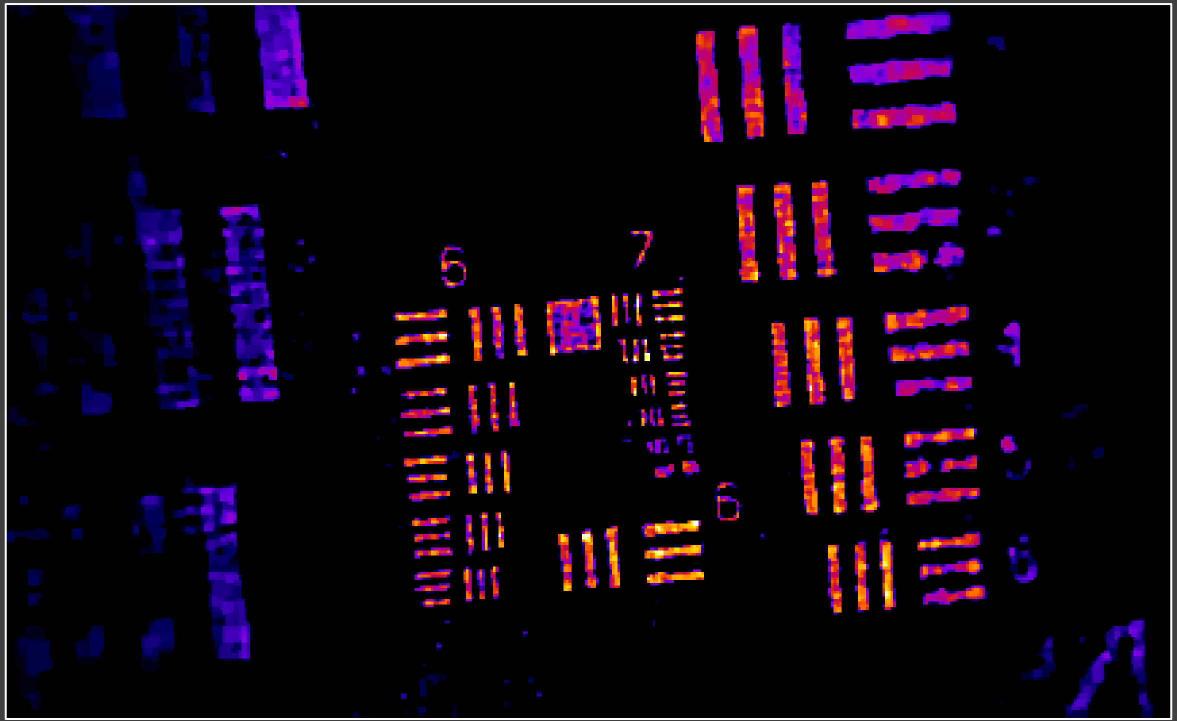
PSF

Solution: Local convolution model

with shift-*invariant* model



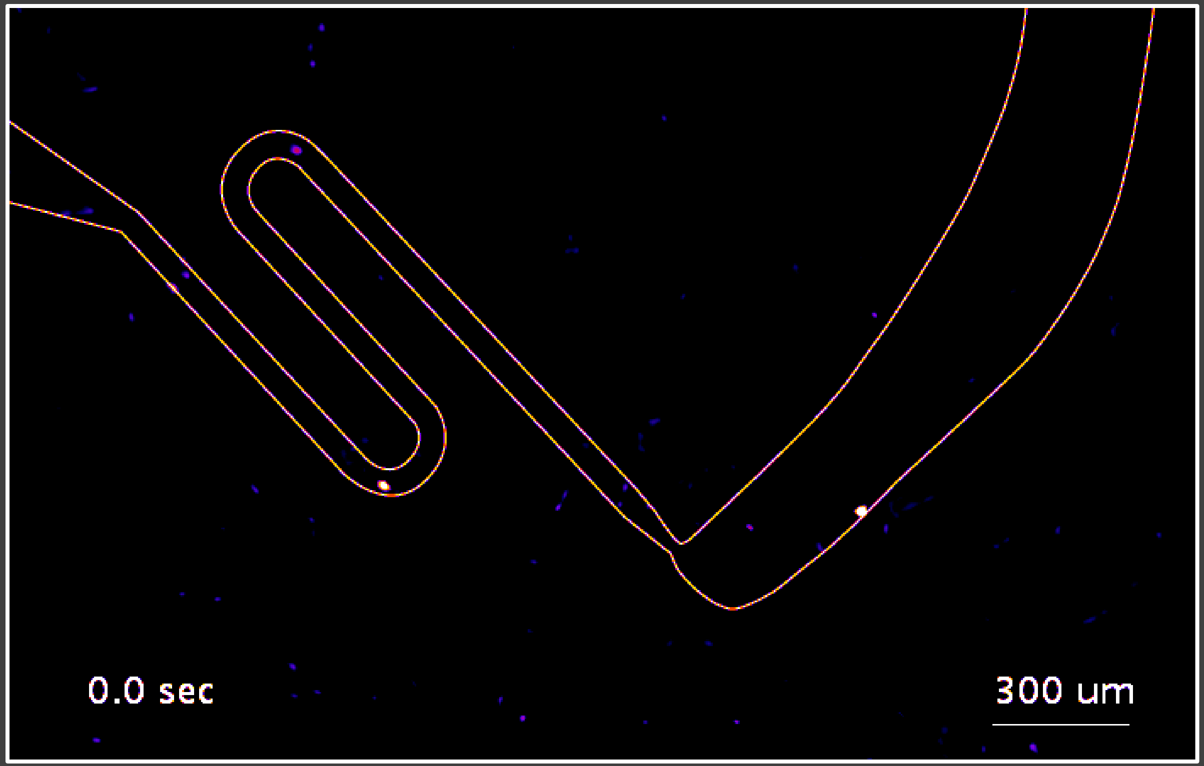
with shift *variant* model



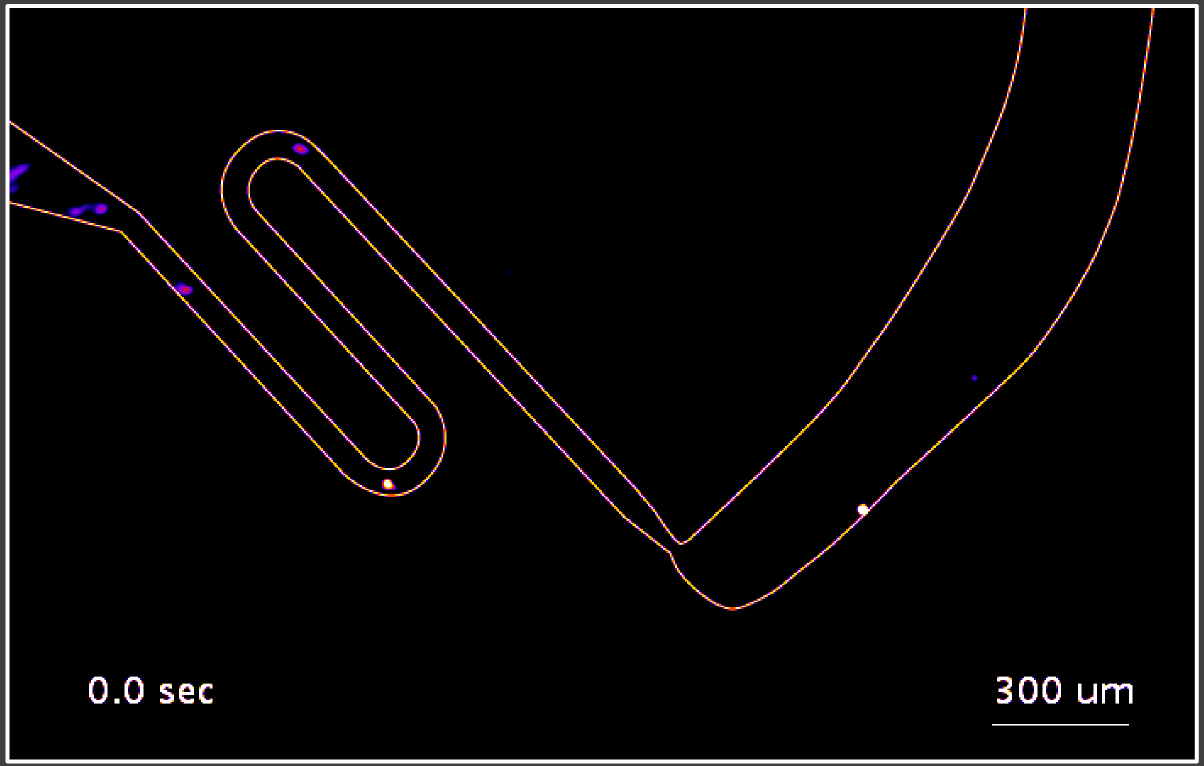
Kyrollos Yanny
Nick Antipa

Solution: Local convolution model

with shift-*<u>in</u>variant* model

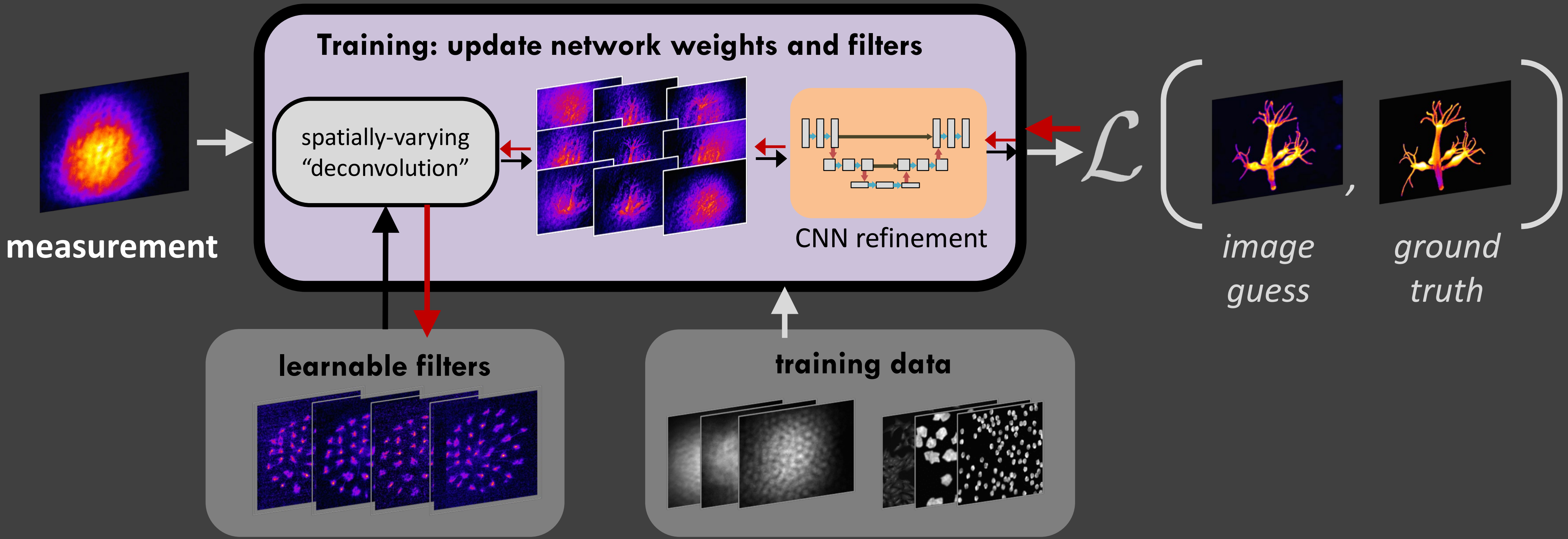


with shift *variant* model

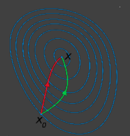


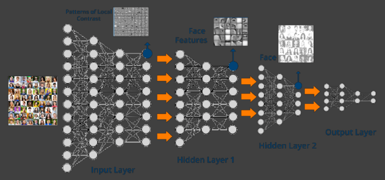
Grace Kuo

Physics-based learning for spatially-varying "deconvolution"

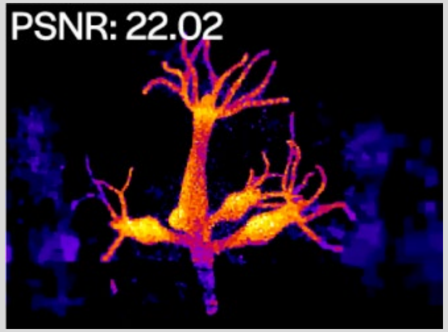


K. Monakhova*, K. Yanny*, R. Shuai, L. Waller, *Optica* 9(1), 2022

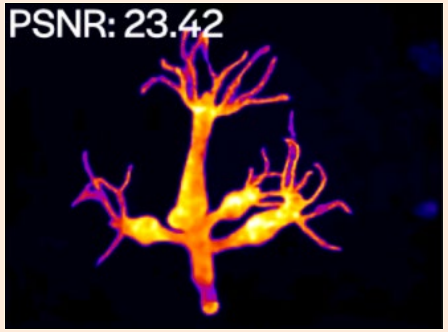
Physics-based 

 Deep Learning

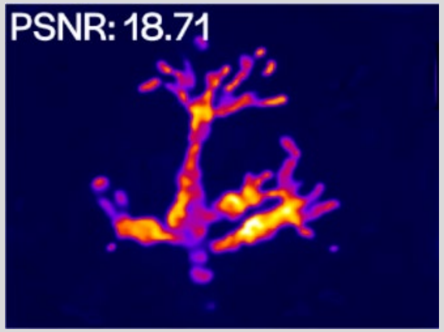
Physics-based learning for spatially-varying "deconvolution"



20s



0.032s



0.021s

> 600X speedup

Kristina Monakhova
Vi Tran

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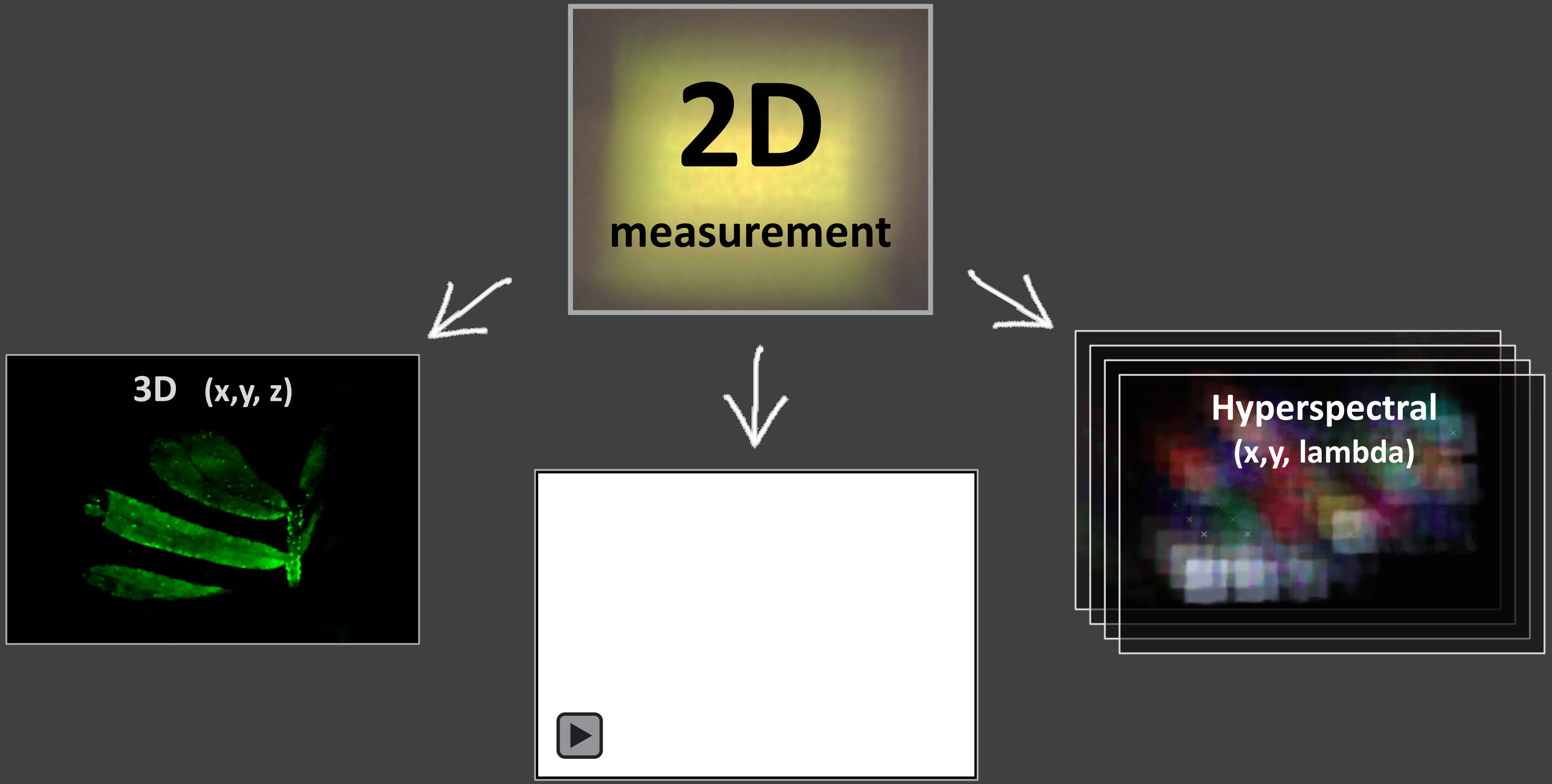
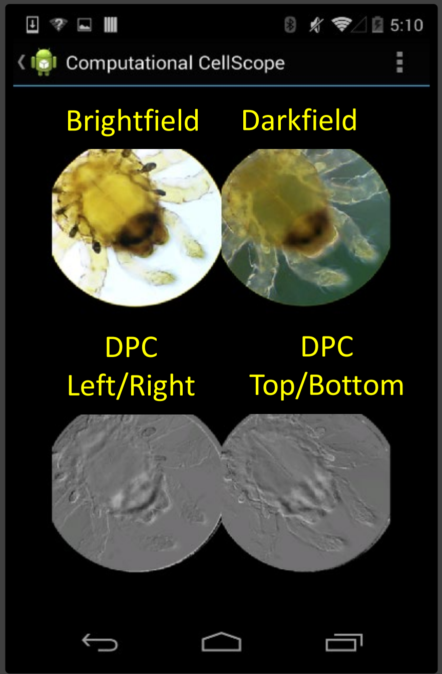
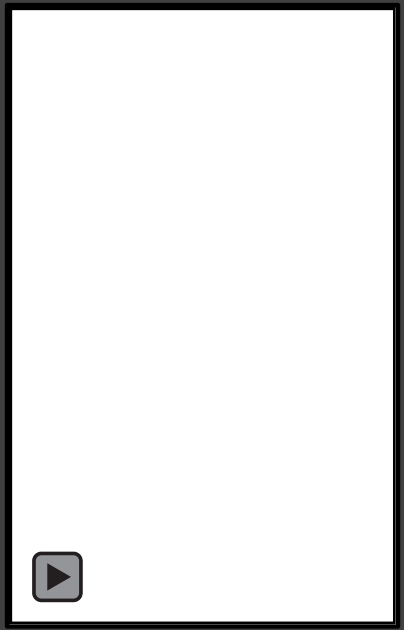

2D
measurement
3D (x,y, z)
Hyperspectral
(x,y, lambda)

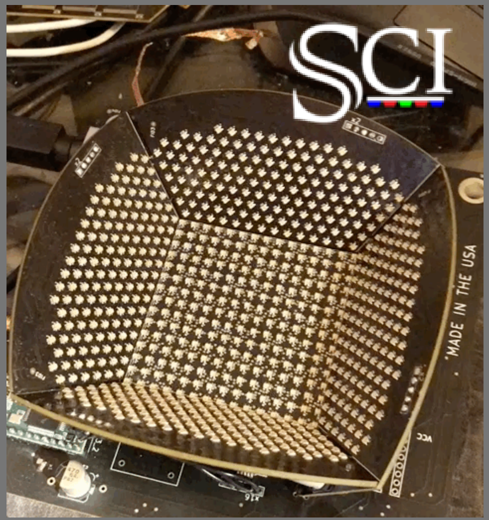
Reproducible = open-source + cheap + simple hardware

Computational CellScope





ScotchTape Cam



Spectral Coded Illumination, Inc.*

*financial interest

www.laurawaller.com/opensource

Pycro Manager

H. Pinkard, N. Stuurman, I. Ivanov, N. Anthony, W. Ouyang, B. Li, B. Yang, M. Tsuchida, B. Chhun, G. Zhang, R. Mei, M. Anderson, D. Shepherd, I. Hunt-Isaak, R. Dunn, W. Jahr, S. Kato, L. Royer, J. Thiagarajah, K. Eliceiri, E. Lundberg, S. Mehta, **L. Waller**, *Nature Methods* 18, 226-228 (2021).

Collaborators:
Hillel Adesnik
Ben Recht
Miki Lustig
Dan Fletcher
Colin Ophus
Mary Scott

Anti-collaborators:

GigaPan: WallerLab_Berkeley
Open-source : www.laurawaller.com
Twitter: @optrickster
Github: Waller_Lab

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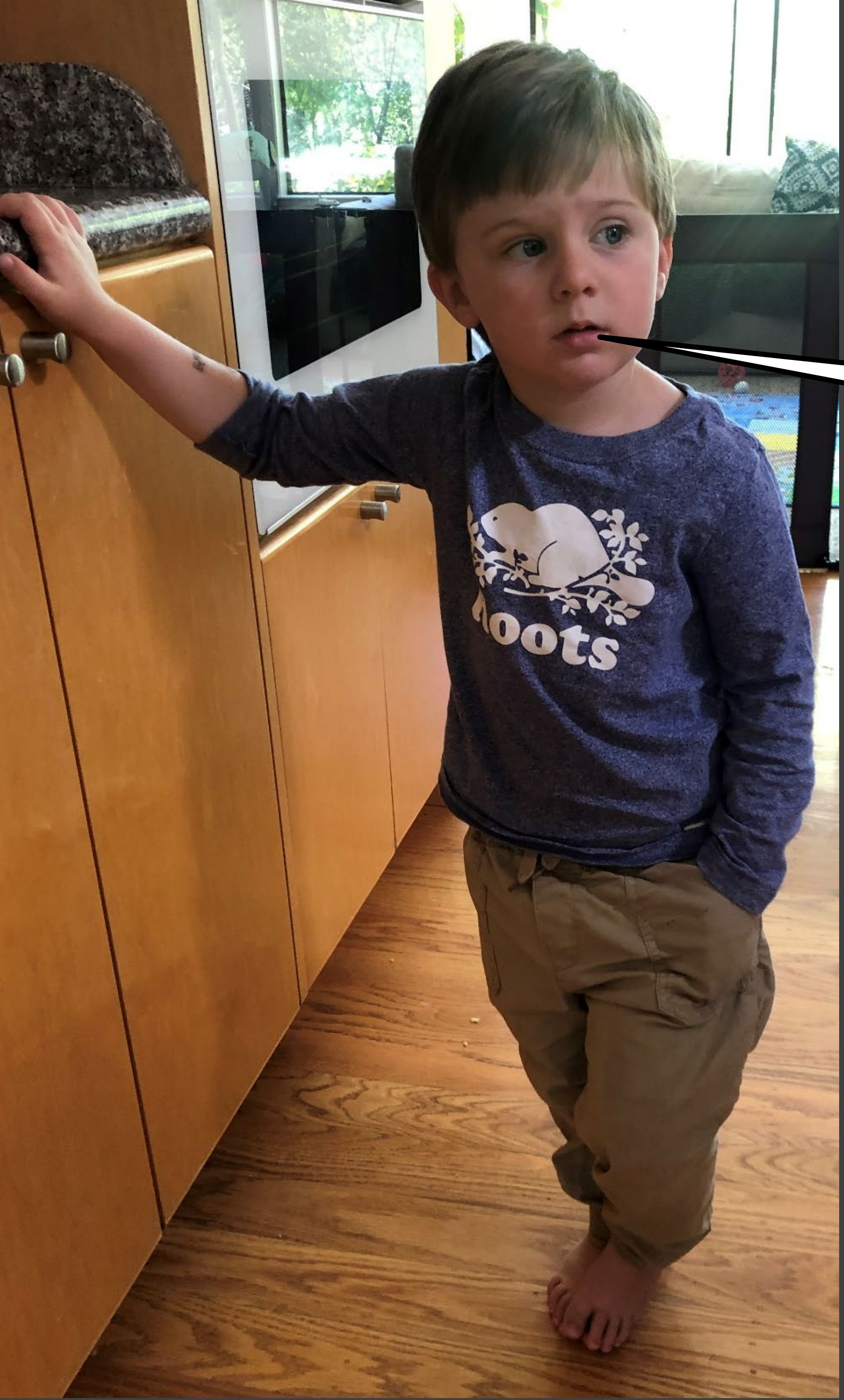
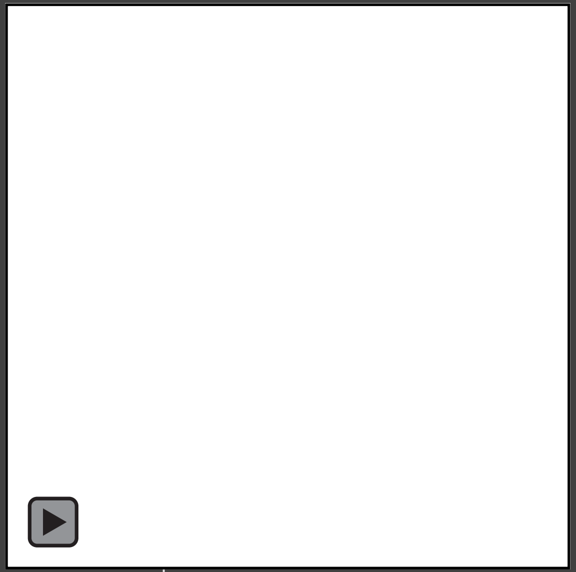


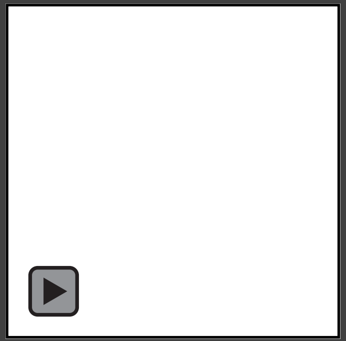
is that ALL it’s good for?

Weak diffusers directly probe system aberrations

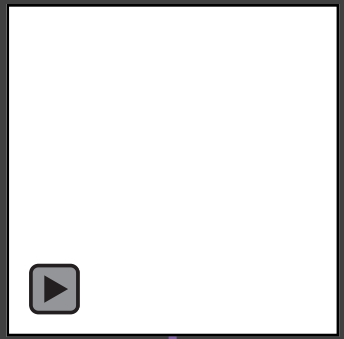


Holographic diffusers, photomask surface roughness, etc.

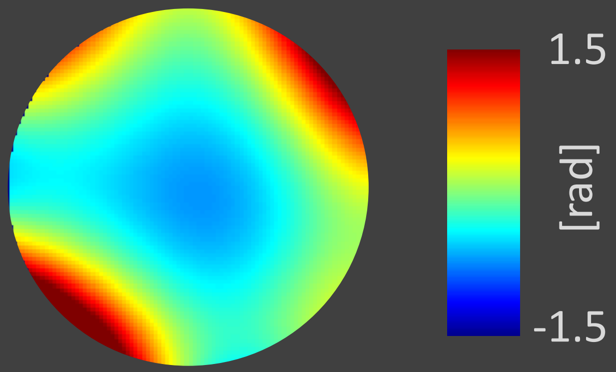
Intensity at sensor plane



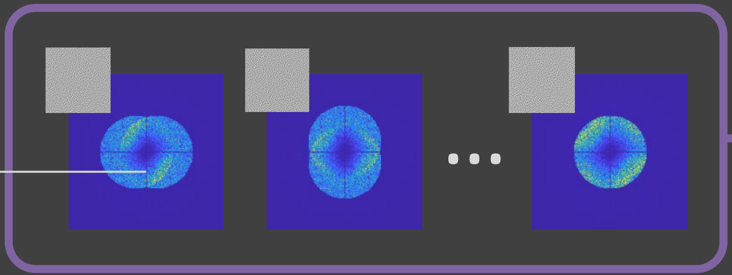
Fourier transform of intensity



Uniquely defined aberration polynomial



Acquired images & their spectra



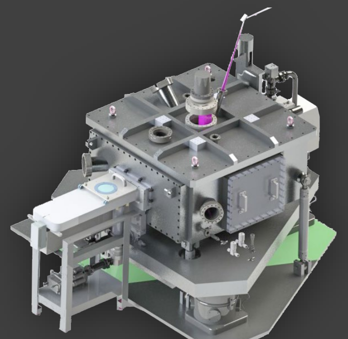
Interference where circles overlap
Acquired patterns should be diverse!

Nonlinear least squares reconstruction algorithm

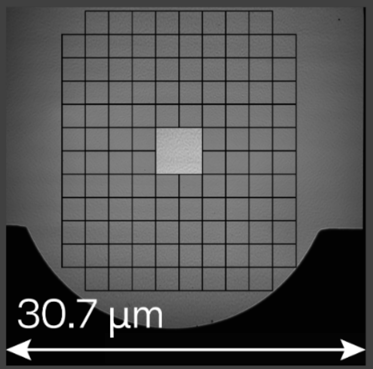
Gautam Gunjala

G. Gunjala, S. Sherwin, A. Shanker, L. Waller, *Optics Express* (2016).

Application: EUV microscope characterization

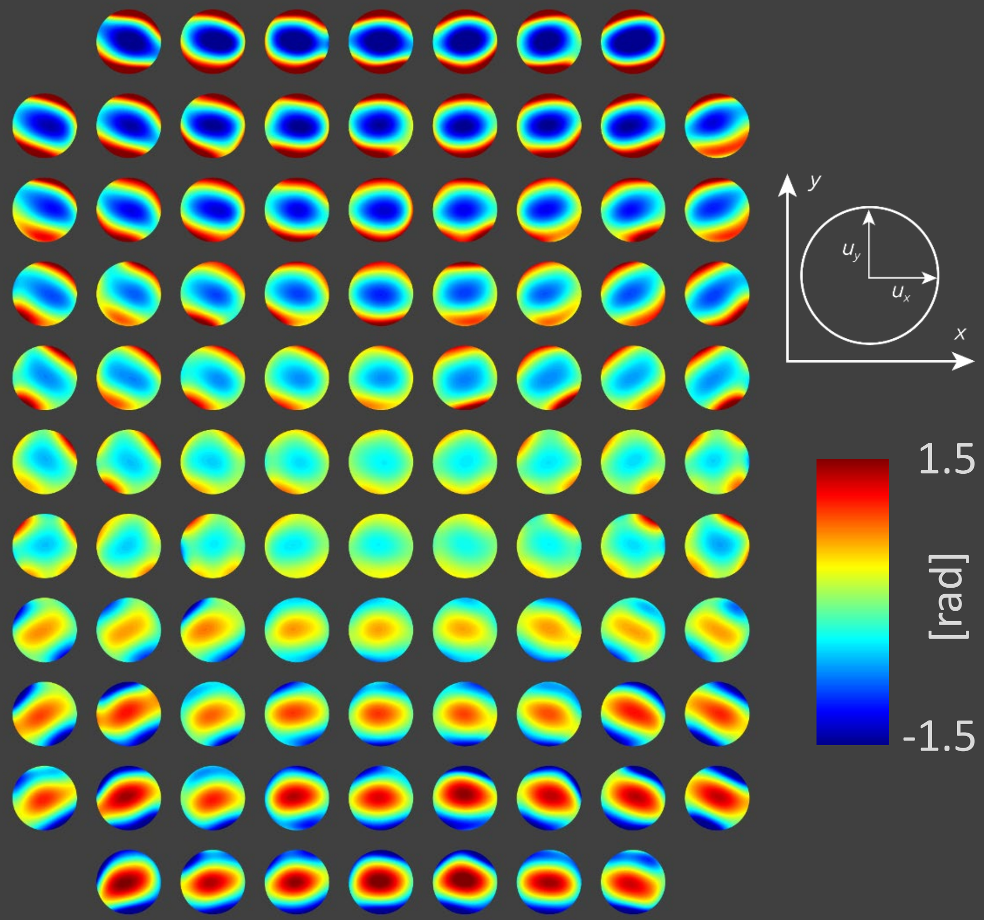


SHARP (LBNL)
λ = 13.5 nm



Imaging FOV

Field-varying aberrations



- Using **10 full-field images of blank photomask surface roughness**, we recover **5th-order** aberration polynomials across the FOV
- Accuracy of technique roughly ***λ* / 182**
- Requires only statistical knowledge of scattering object
- Does not require additional / invasive sensors or hardware
- Does not require fabrication / alignment of test objects

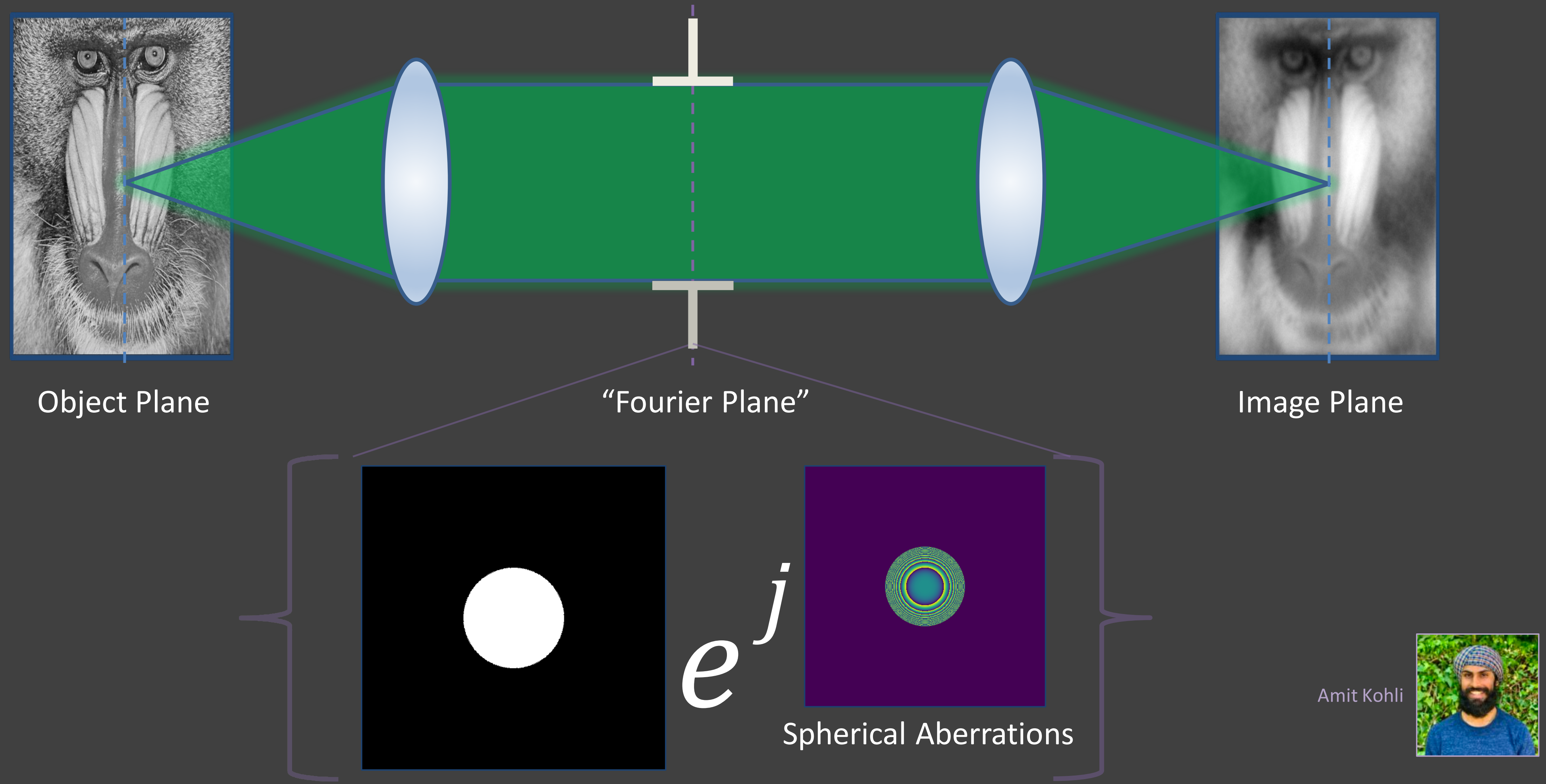
Gautam Gunjala

G. Gunjala, A. Wojdyla, S. Sherwin, [...] L. Waller, *Scientific Reports* (2020).

Aberrations are bad, but maybe we can design "computationally friendly" ones?

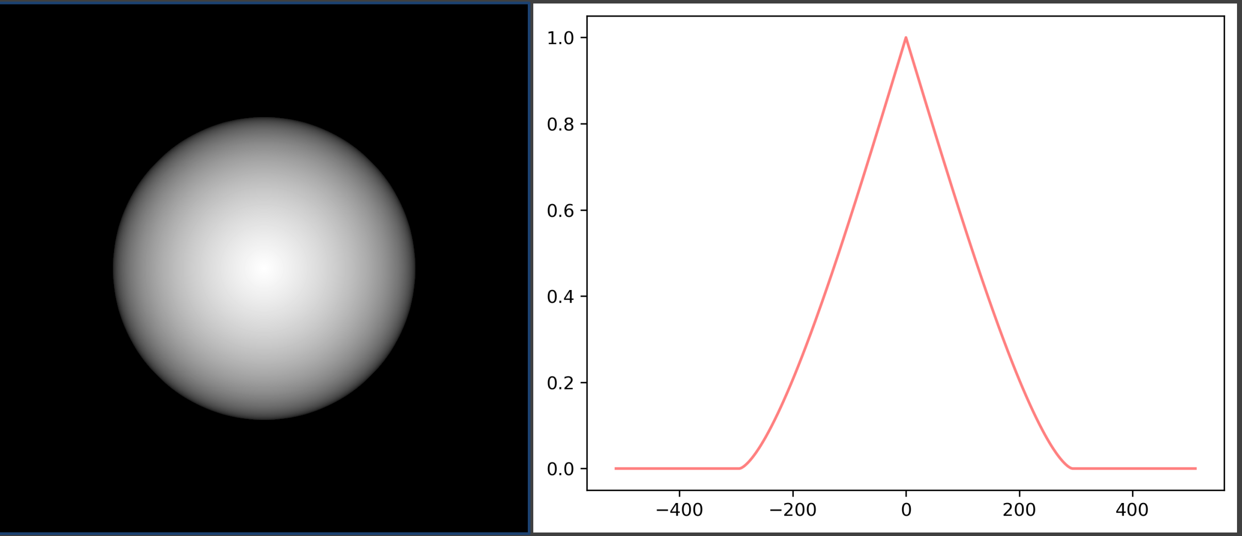
Amit Kohli

Computational aberration correction

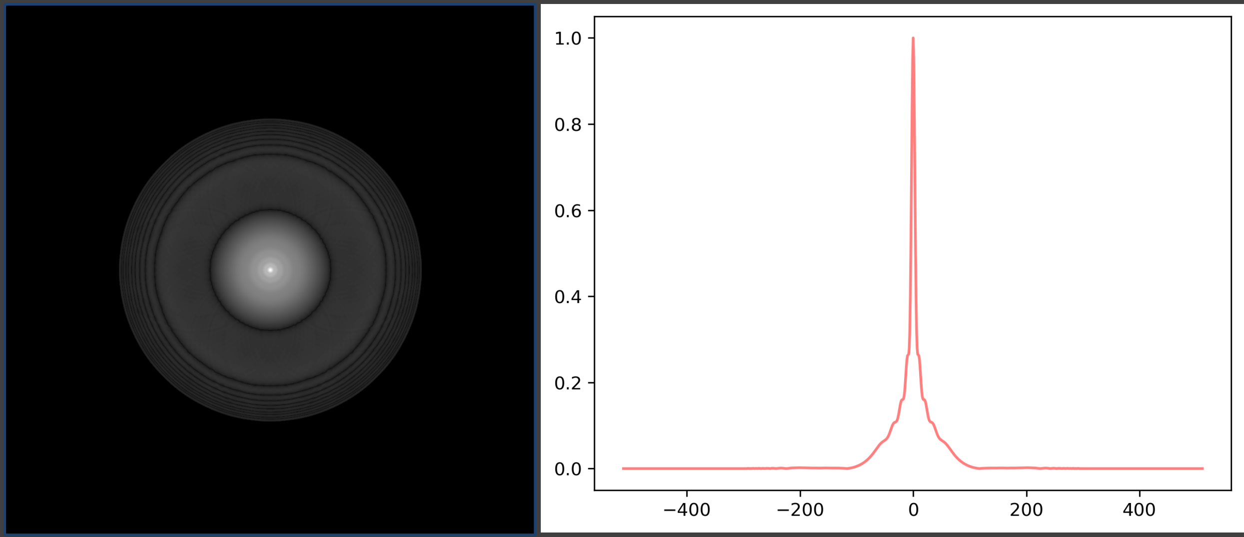


Pupil aberrations can only hurt you

Diffraction Limited MTF



Aberrated MTF

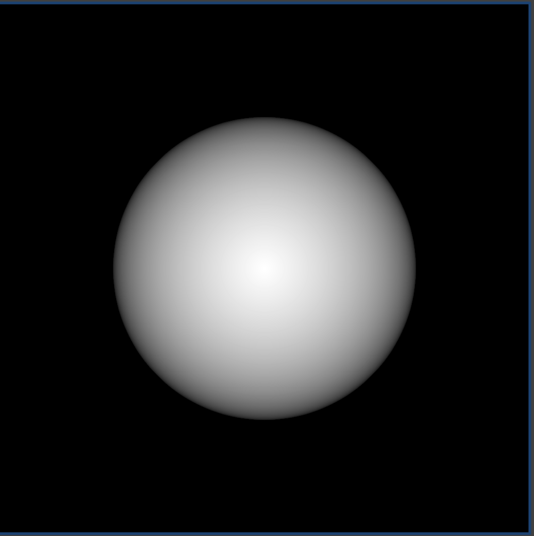


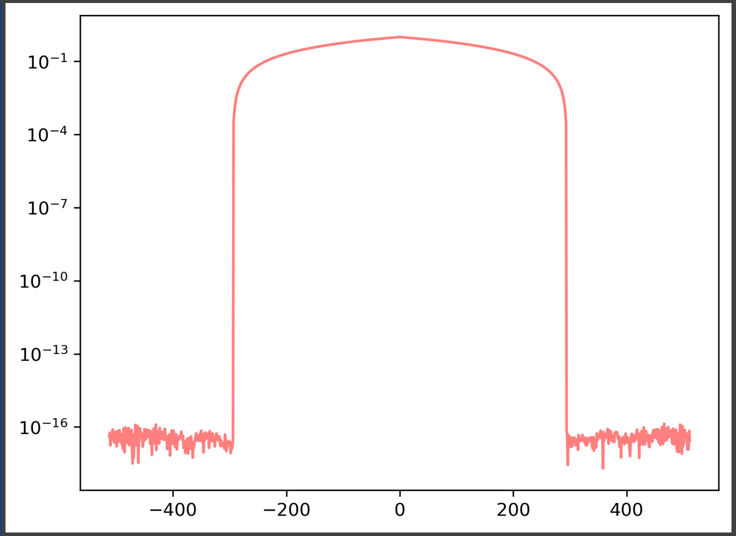
MTF = Modulation Transfer Function = |OTF|

Amit Kohli

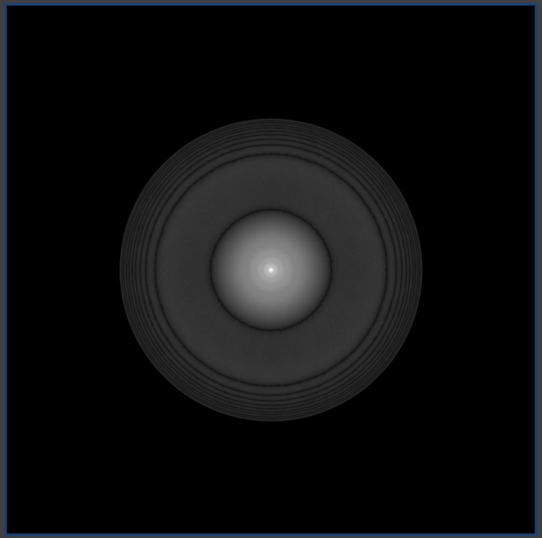
Pupil aberrations can only hurt you

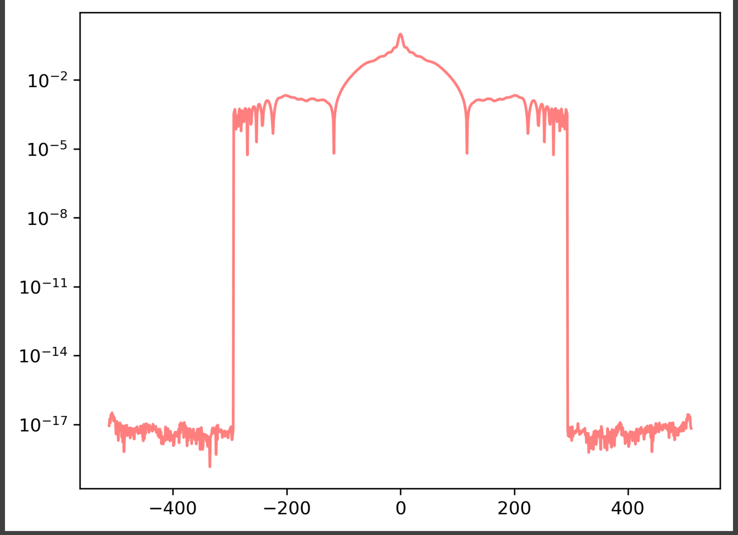
Diffraction Limited MTF





Aberrated MTF





MTF = Modulation Transfer Function = |OTF|

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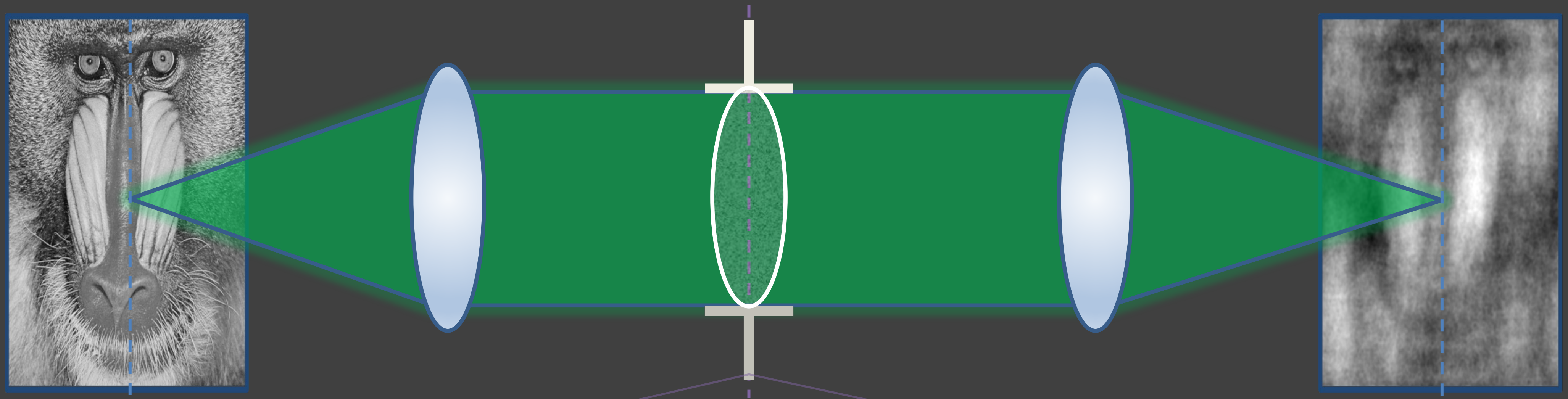
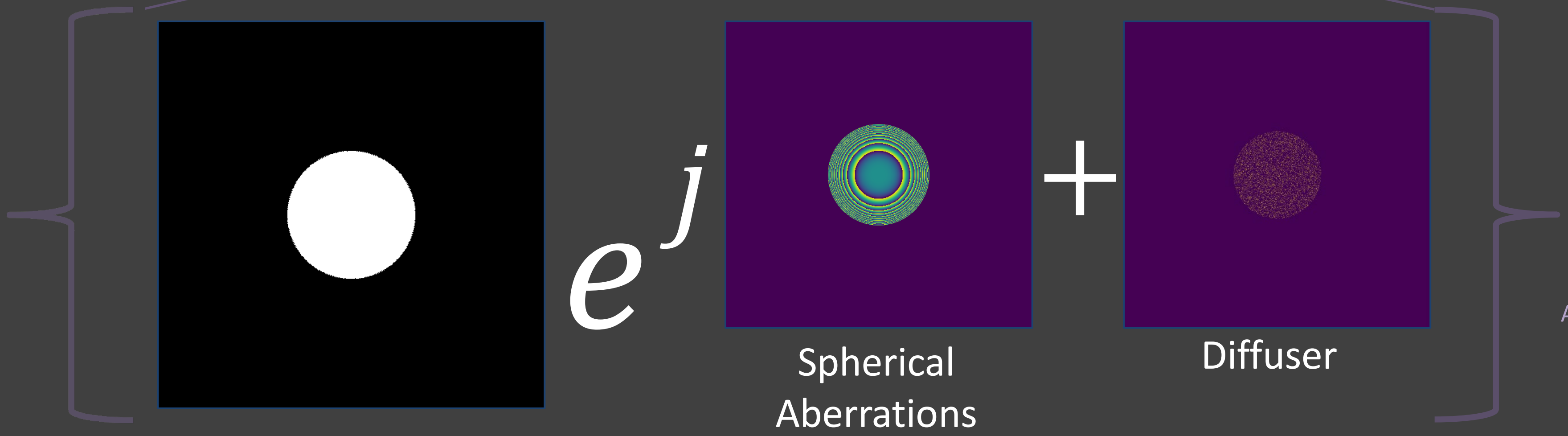
Pupil aberrations + diffuser is worse, no?



Object Plane

"Fourier Plane"

Image Plane



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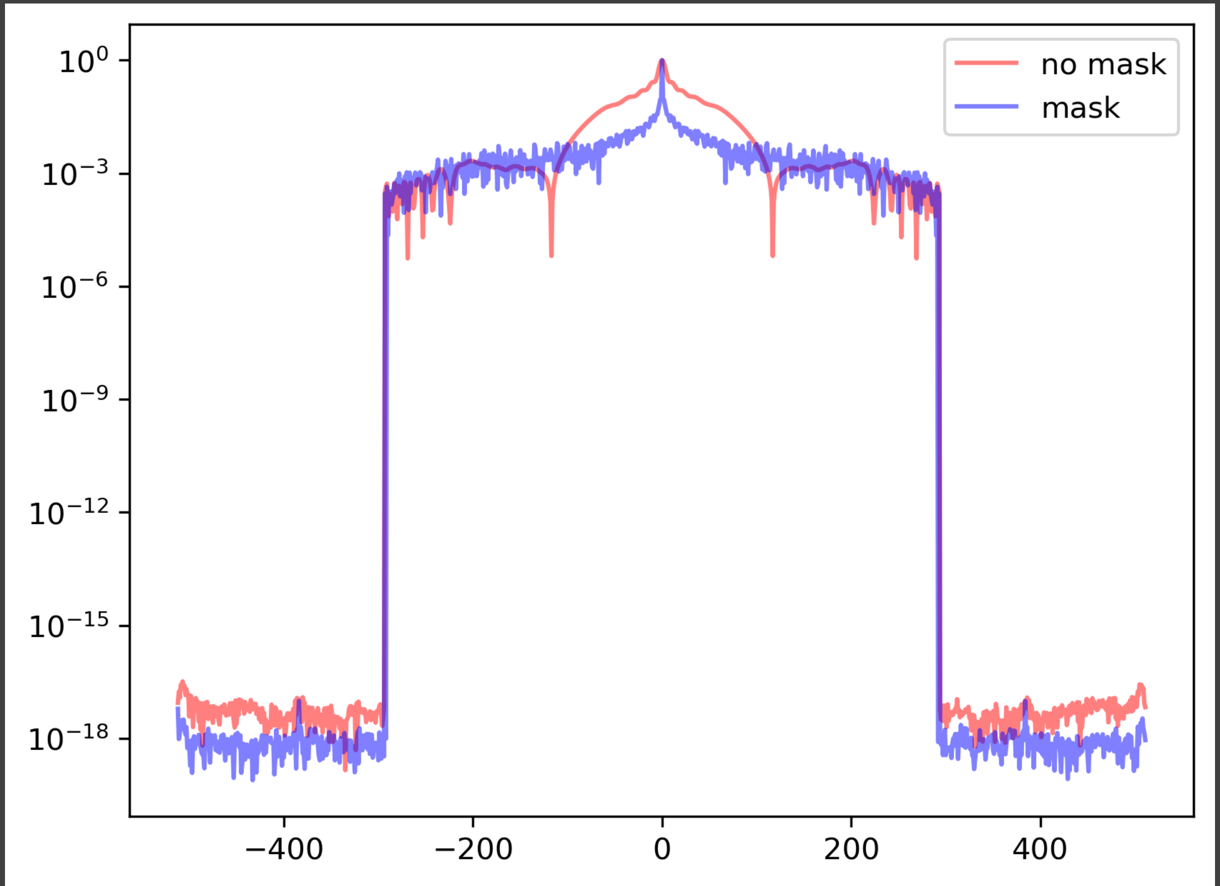
Which MTF is better?



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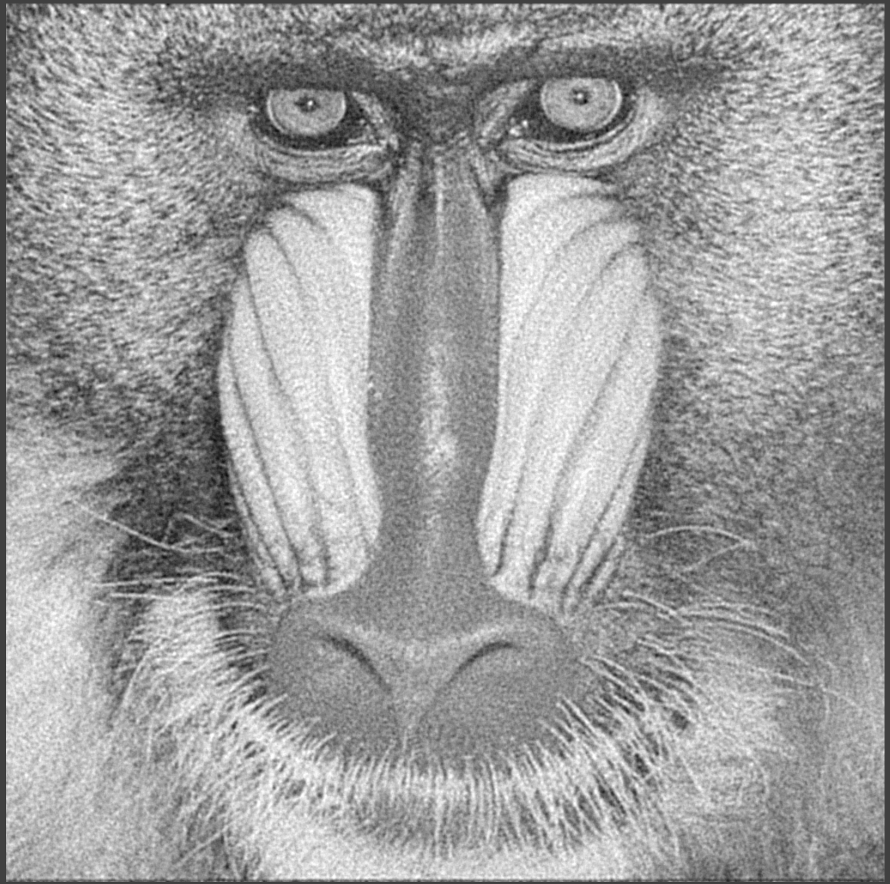
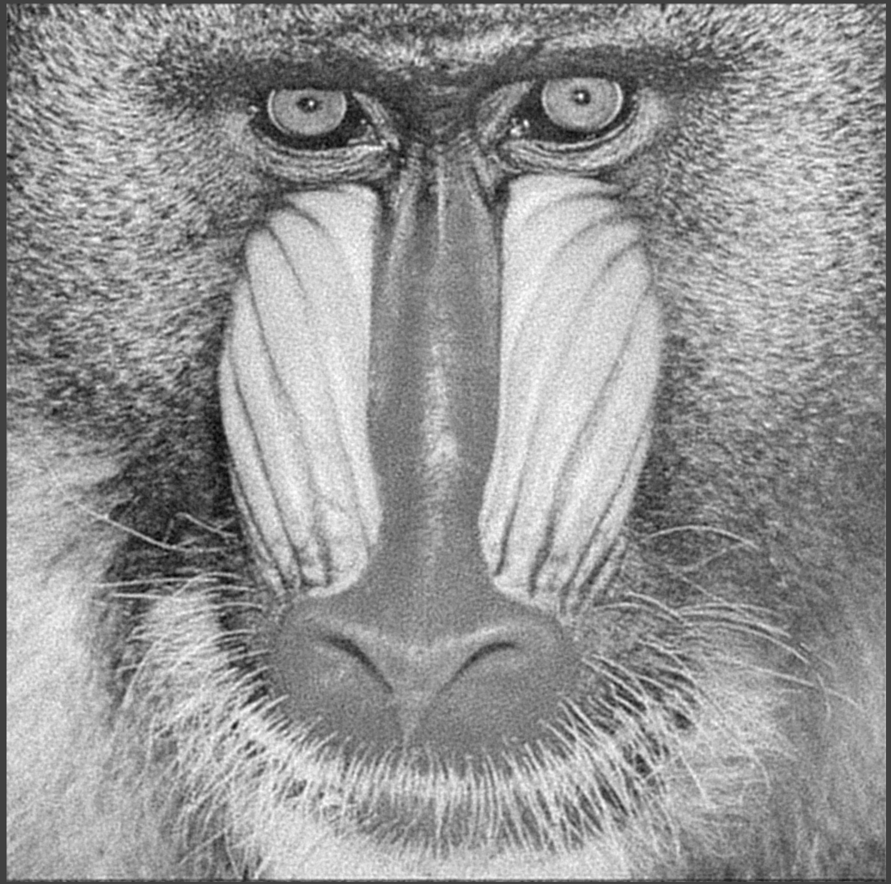
The deconvolution *with diffuser* is better!

No Mask



Mask



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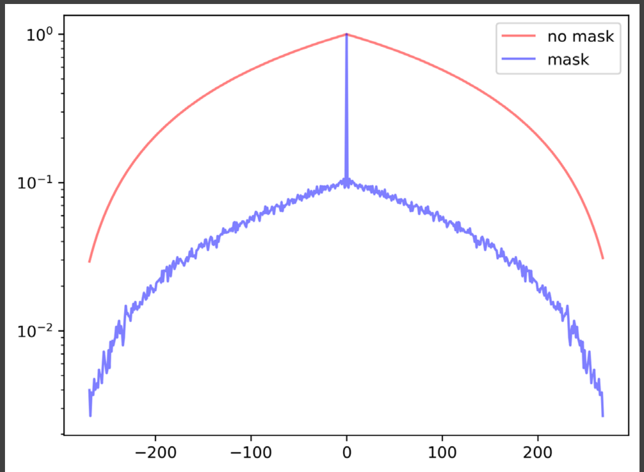
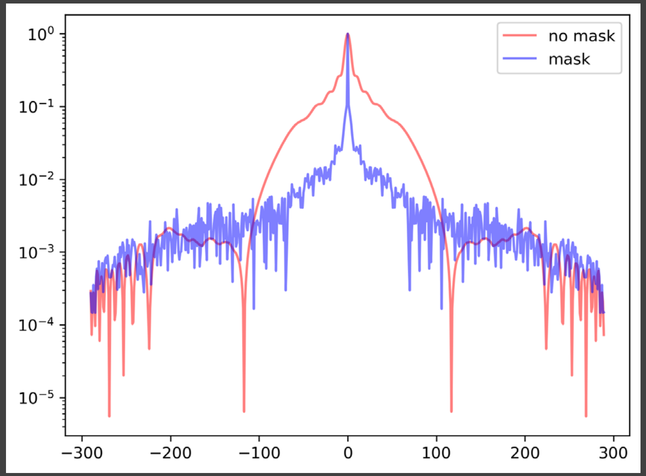
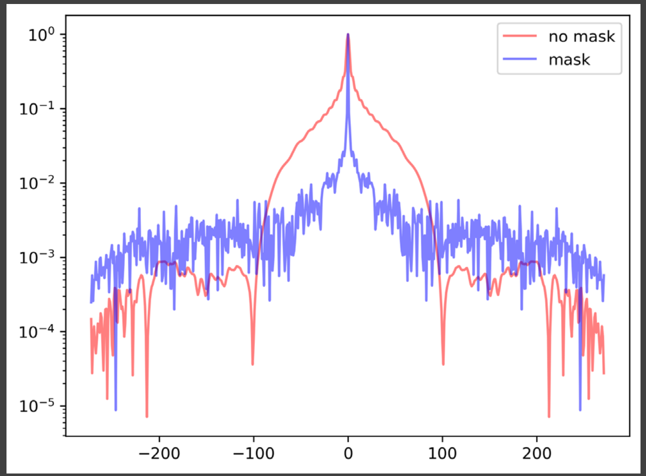
The diffuser system is relatively invariant to aberrations







0
No Aberrations

5
Spherical Seidel Coefficient

10
Very Aberrated

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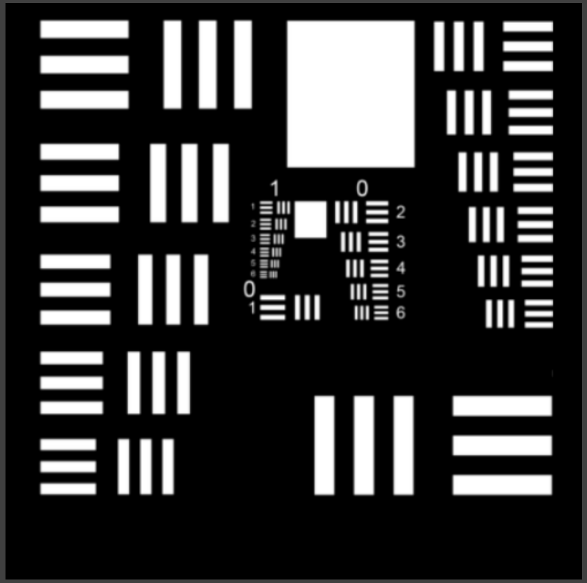
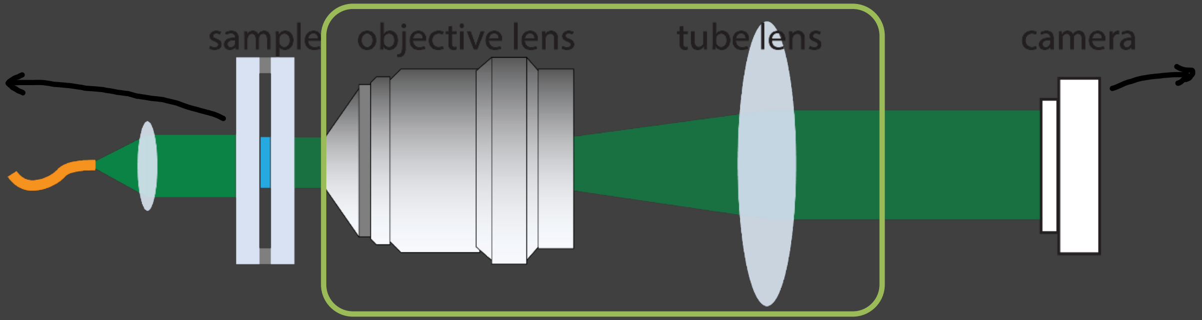
Dynamic Structured Illumination Microscopy with a Neural Space-time Model

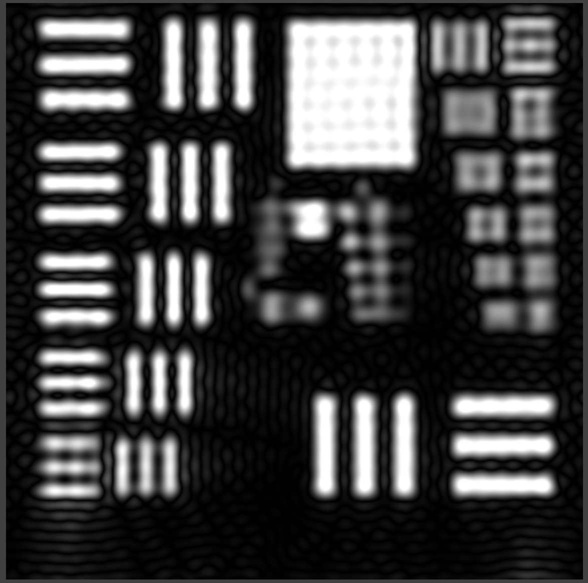
Ruiming Cao

Research update 5/18/2022

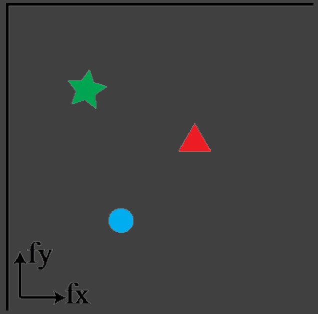
Diffraction-limited system acts as a low-pass filter limiting the spatial resolution



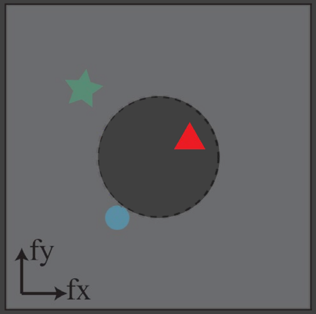




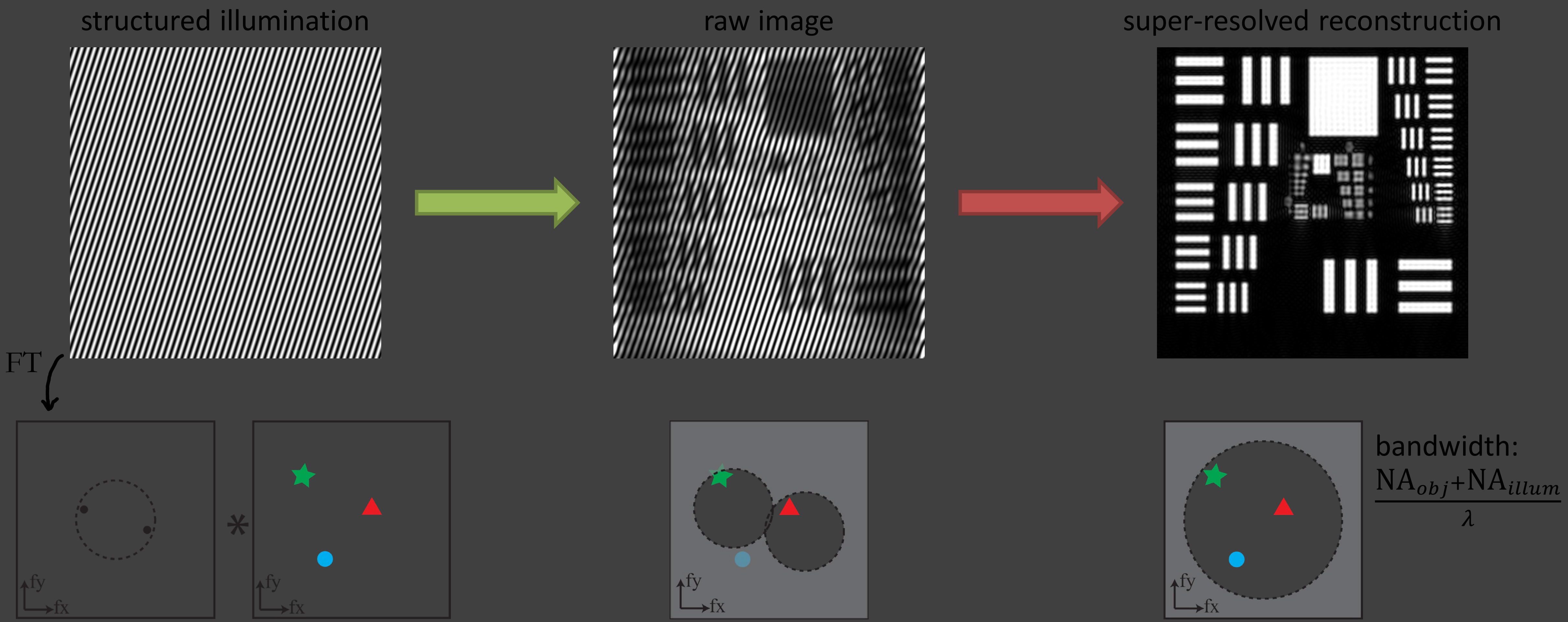
In Fourier space:



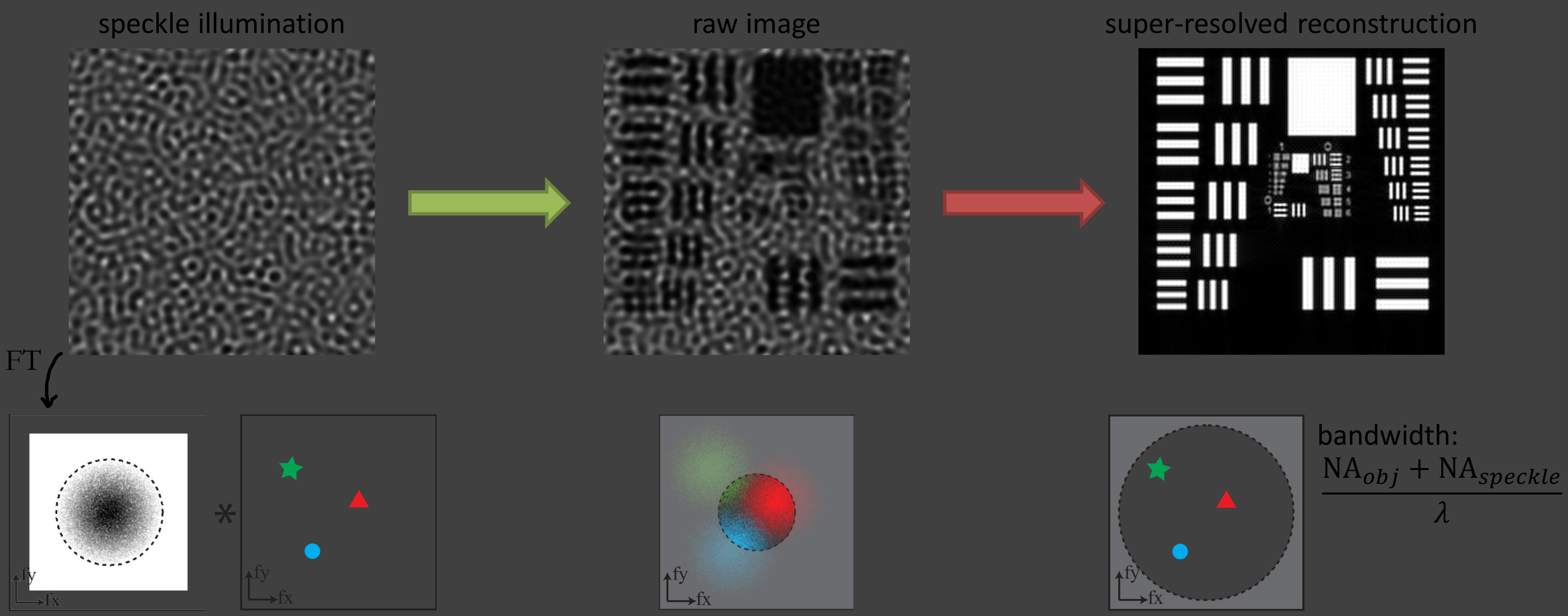
Low-pass filter with bandwidth $\frac{NA_{obj}}{\lambda}$



Sinusoidal structured illumination microscopy (SIM) captures high-frequency from Moiré patterns

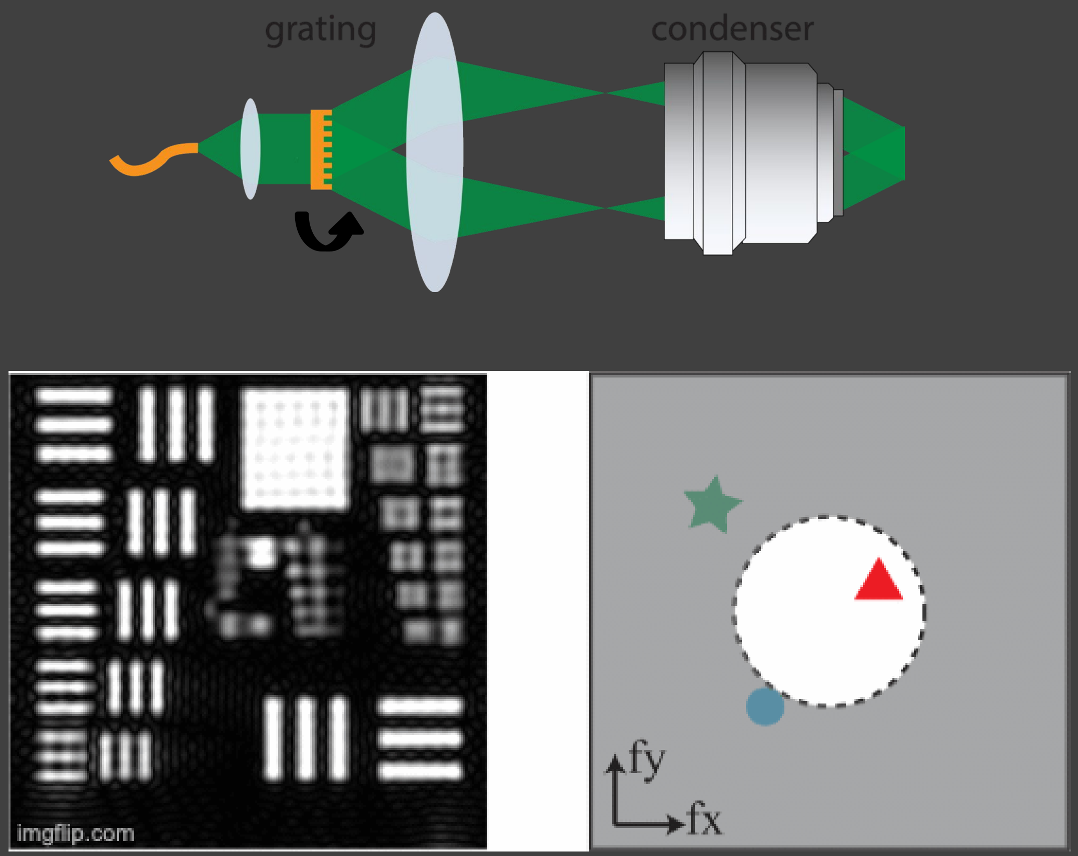


Speckle-structured illumination modulates high-frequency into diffraction limit

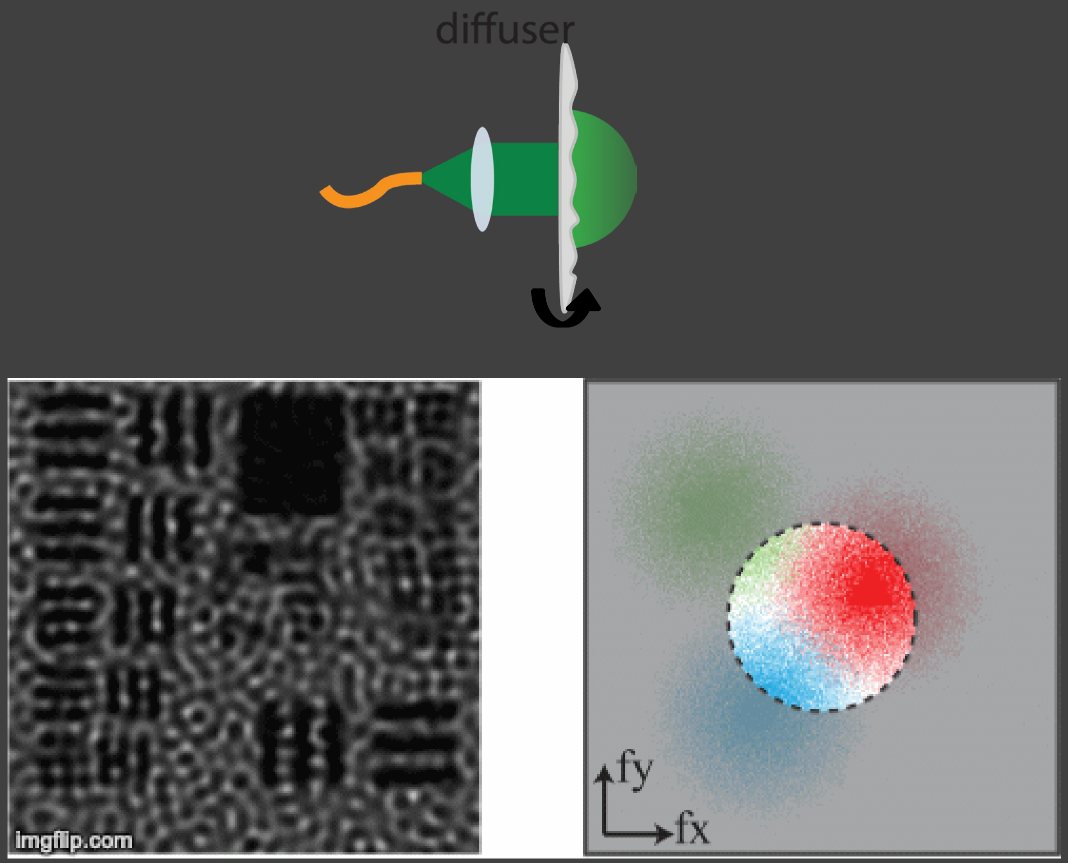


SIM requires multiple raw images for a super-resolved image, trading off temporal resolution

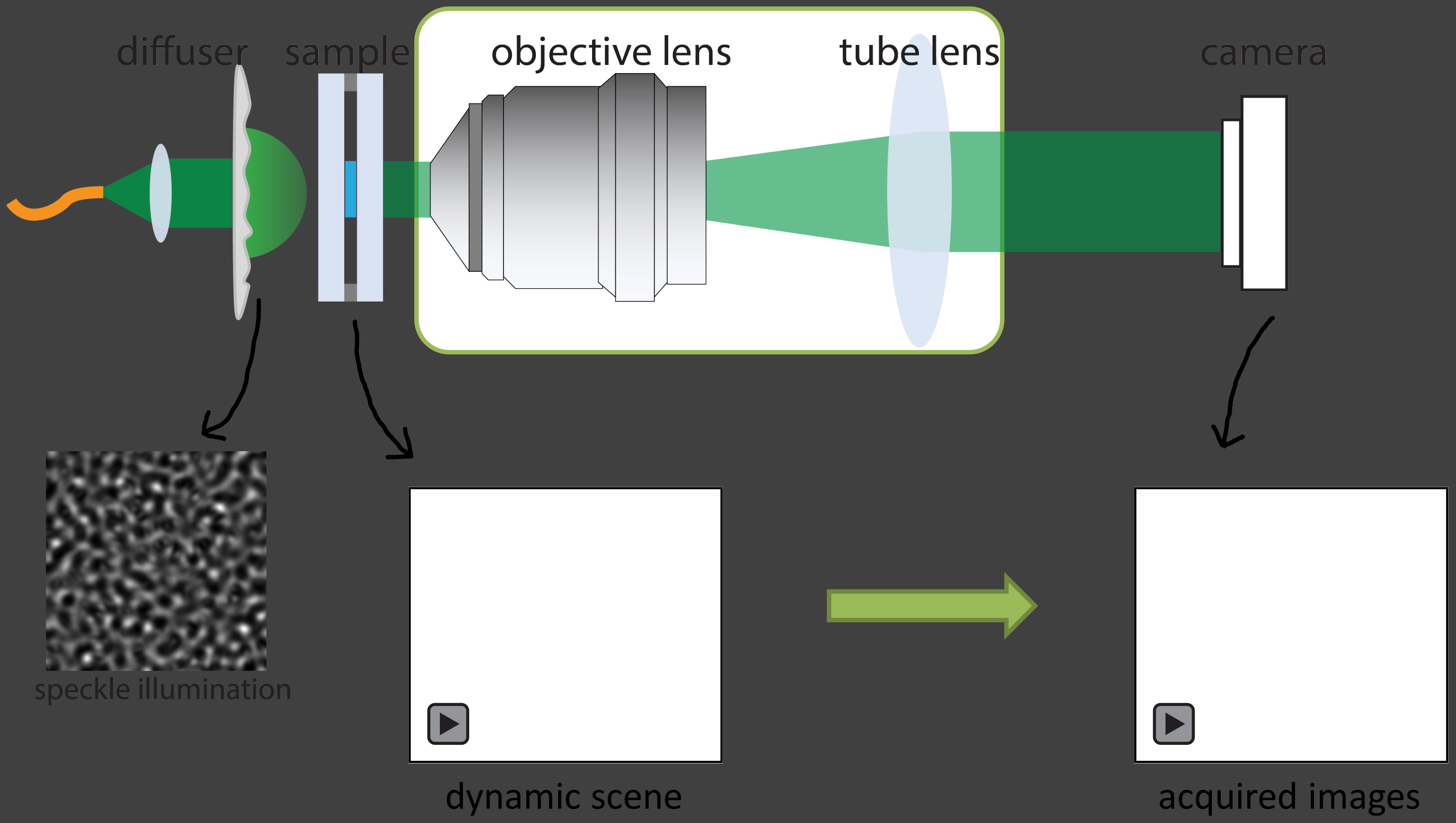
Sinusoidal SIM



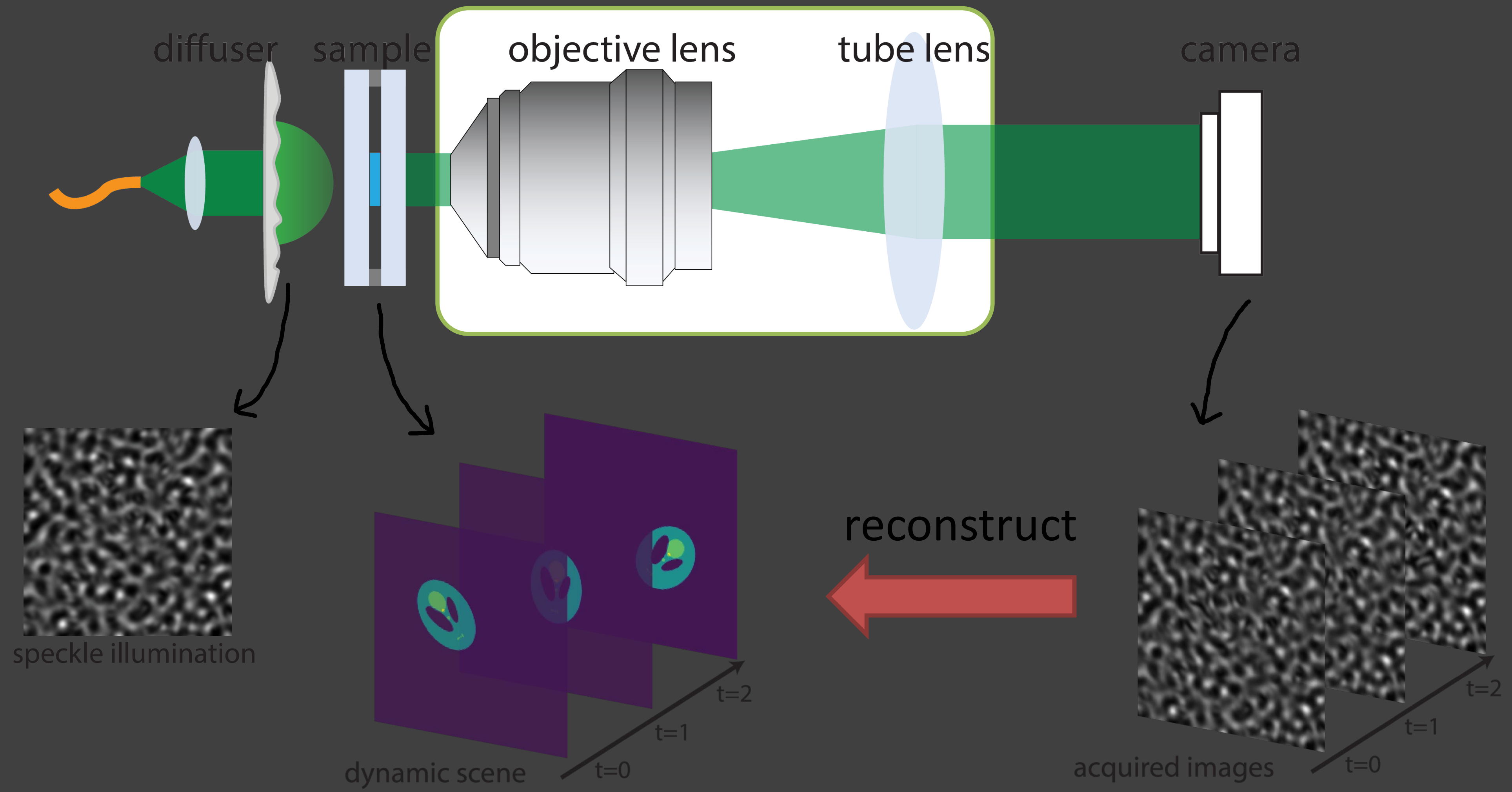
Speckle SIM



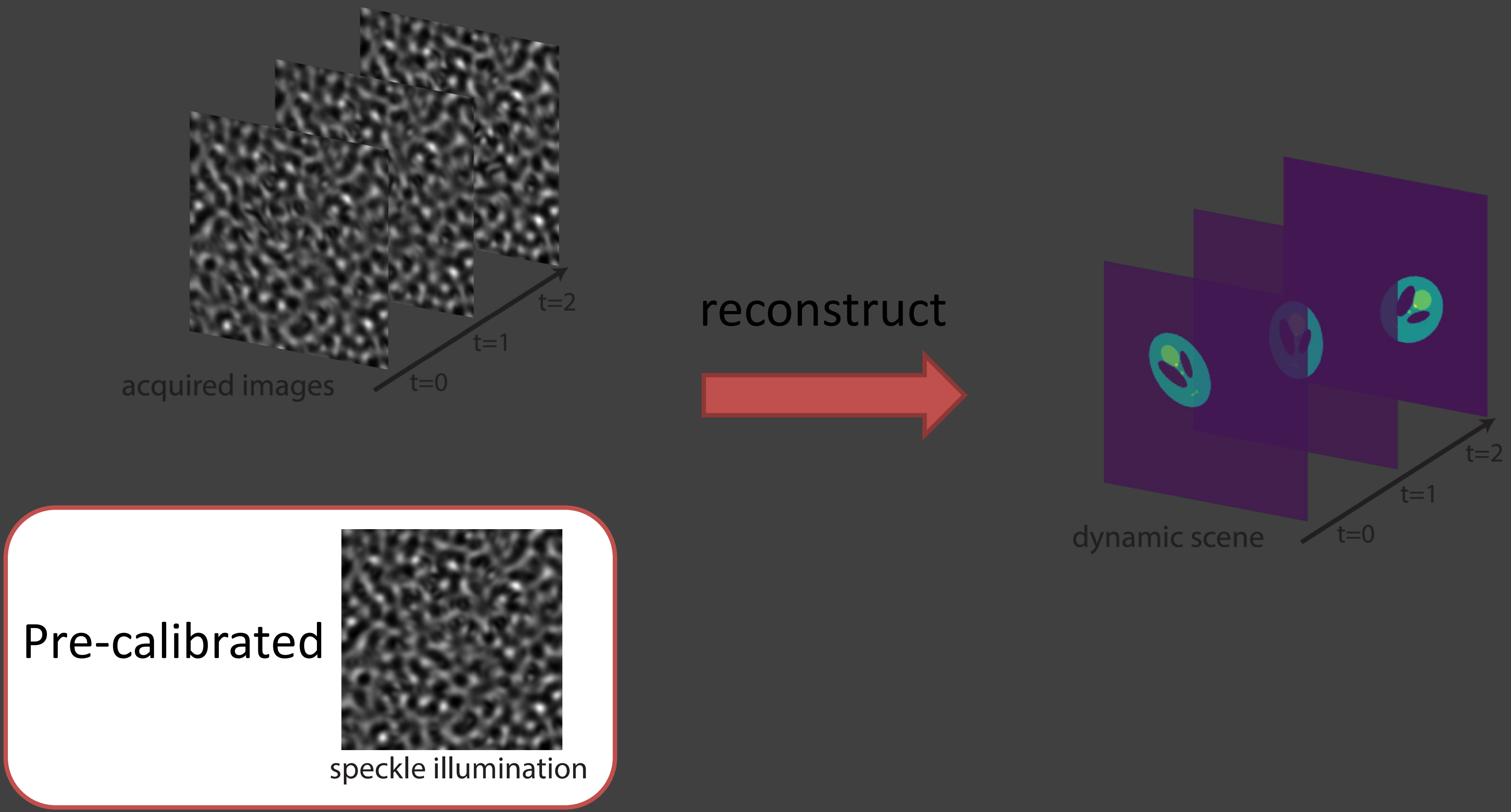
Speckle Flow SIM: Fixed speckle illumination but a dynamic scene to diversify measured information



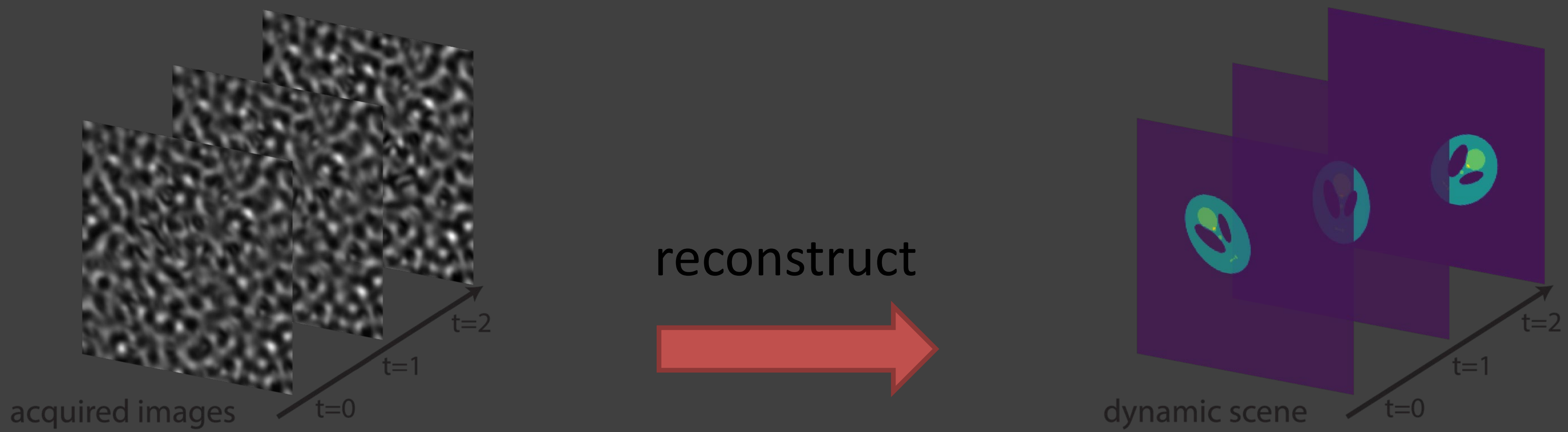
Speckle Flow SIM: super-resolve each frame of a dynamic scene with deformable motion



Fixed speckle-structured illumination can be pre-calibrated, making the reconstruction data-efficient



Reconstructing a sequence of super-resolved frames from the same number of images still requires additional constraint



Each acquired image's bandwidth : $\frac{\mathrm{NA}_{obj}}{\lambda}$

Super-resolution bandwidth: $\frac{\mathrm{NA}_{obj}+\mathrm{NA}_{speckle}}{\lambda} \approx 2 \times \text{acquired bandwidth}$

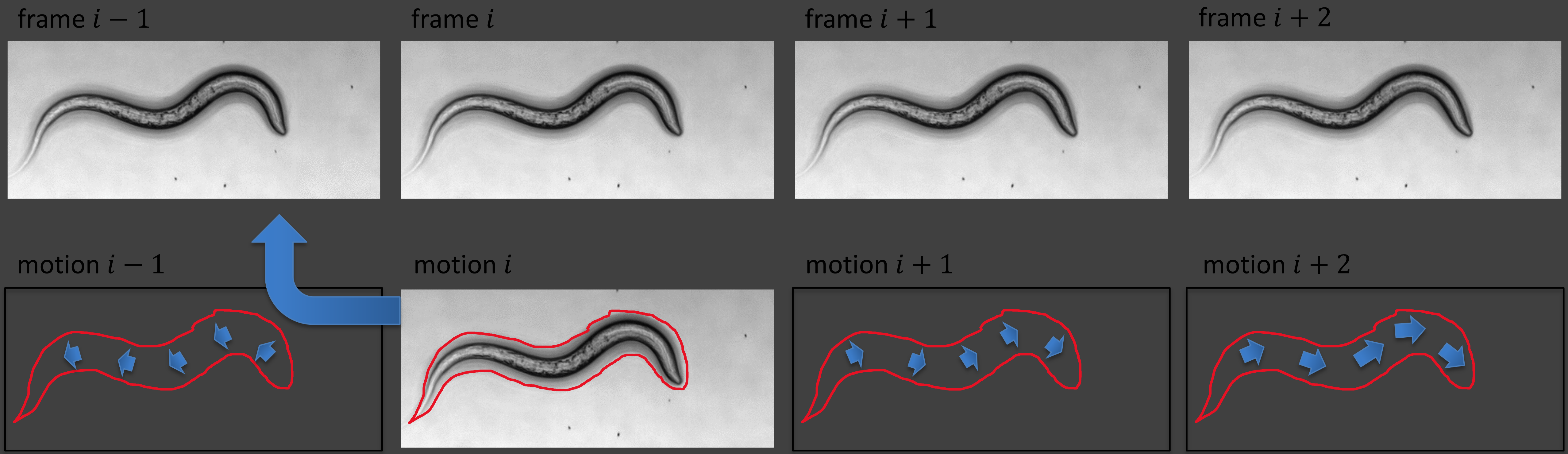
A video often contains temporal redundancy as the motion is smooth

frame 68

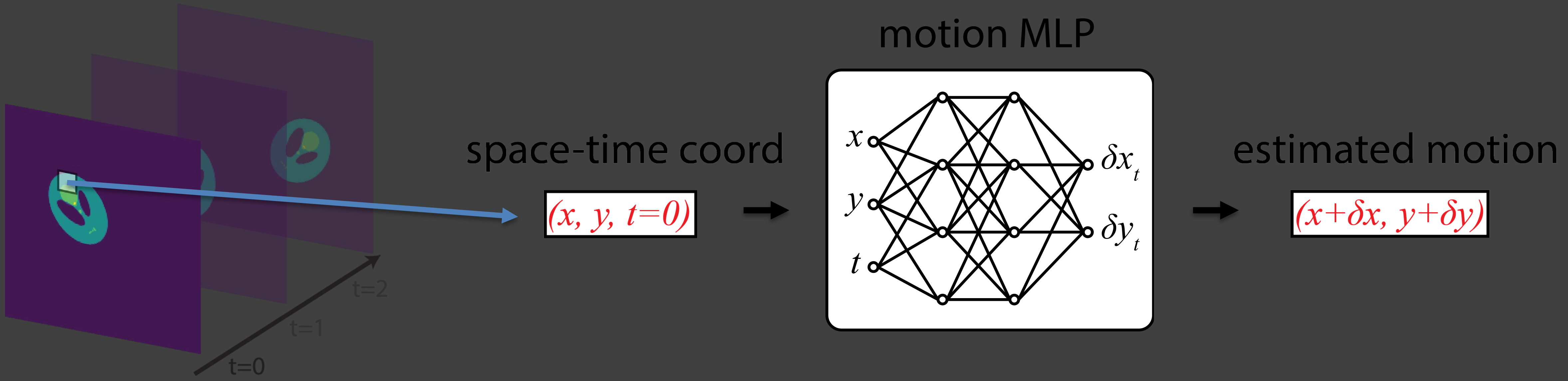
Live C. Elegan

Video by courtesy of Michael Kellman

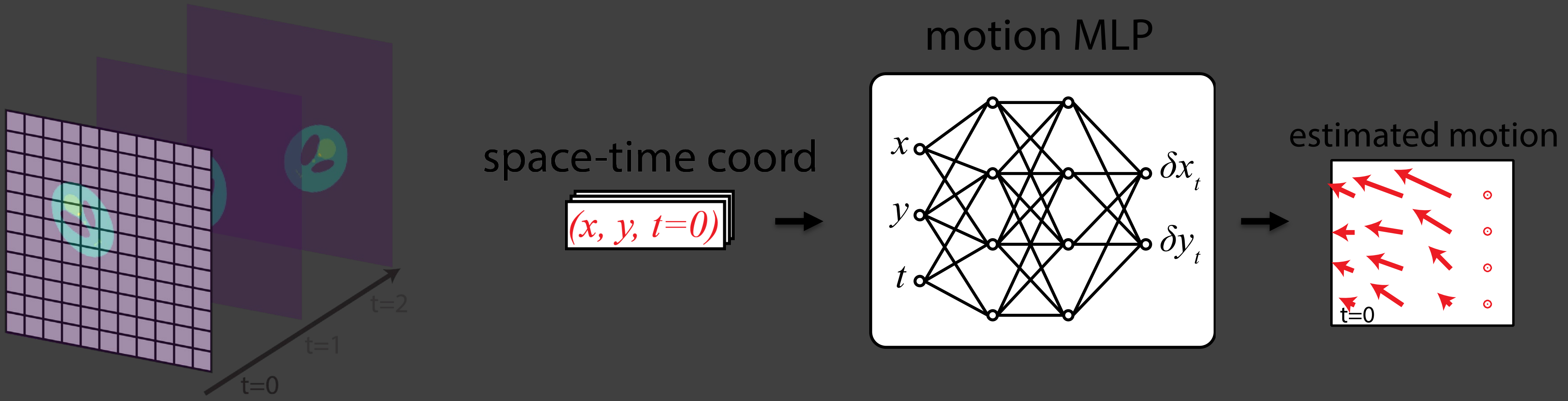
A dynamic scene represented by a single static scene + motion kernel for each timepoint



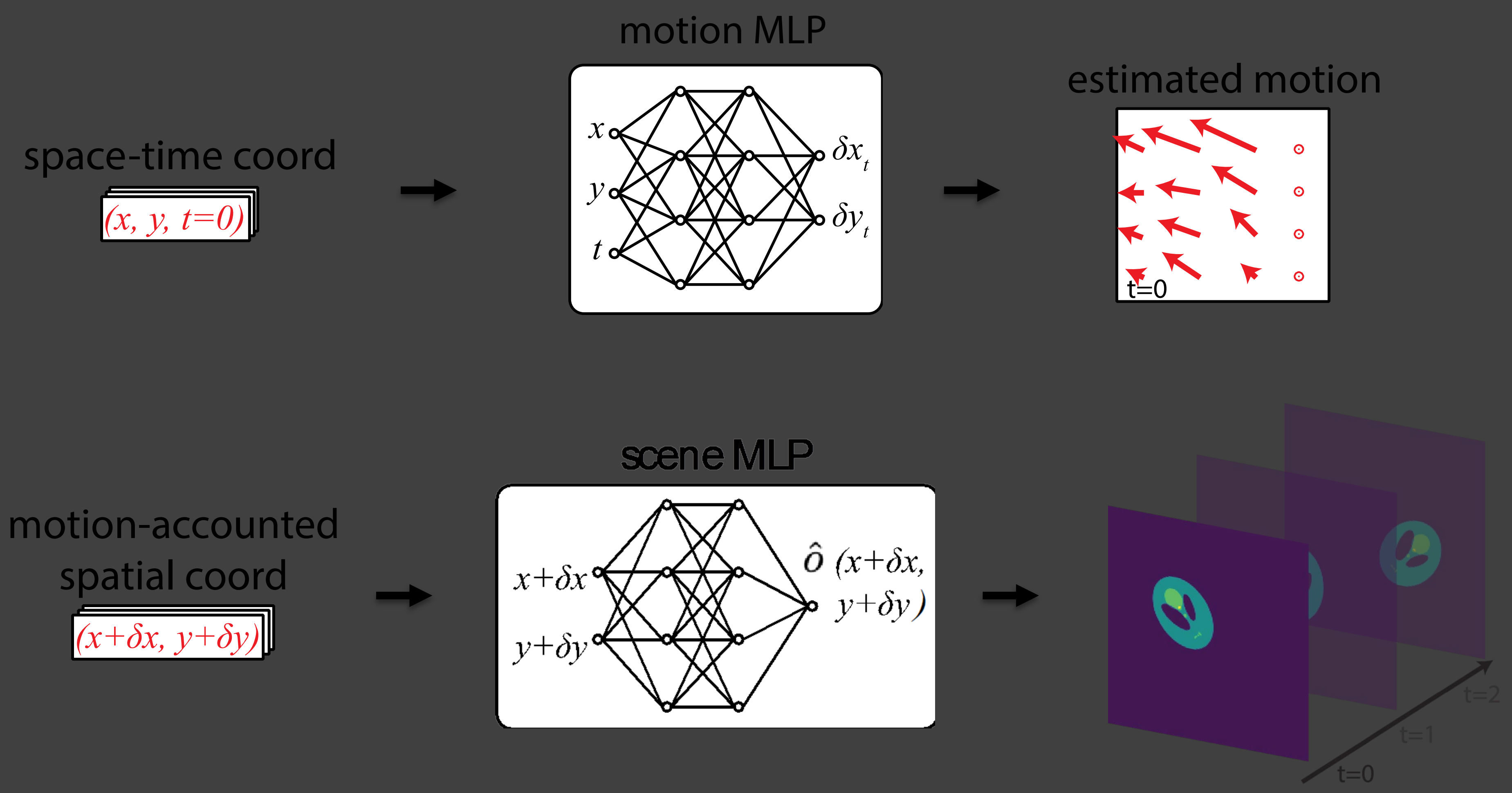
A coordinate-based multi-layer perceptron (MLP) to estimate motion for each space-time coordinate



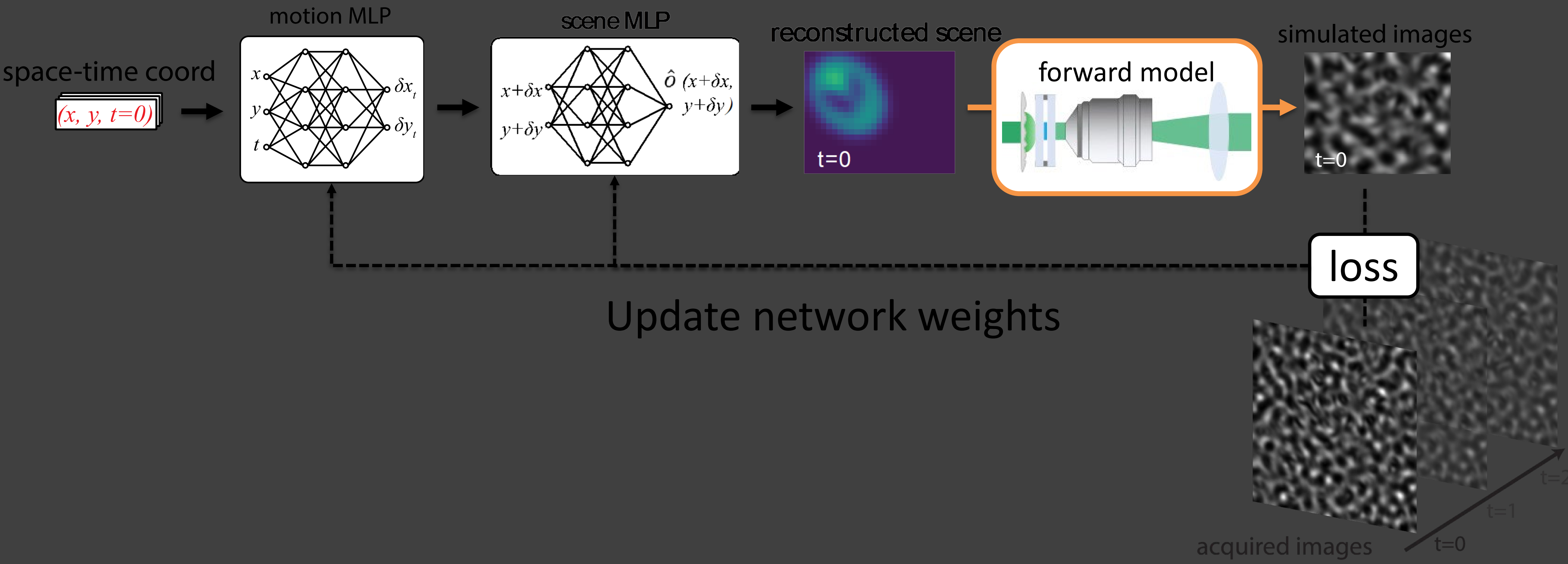
Motion MLP estimates the motion at pixel-level



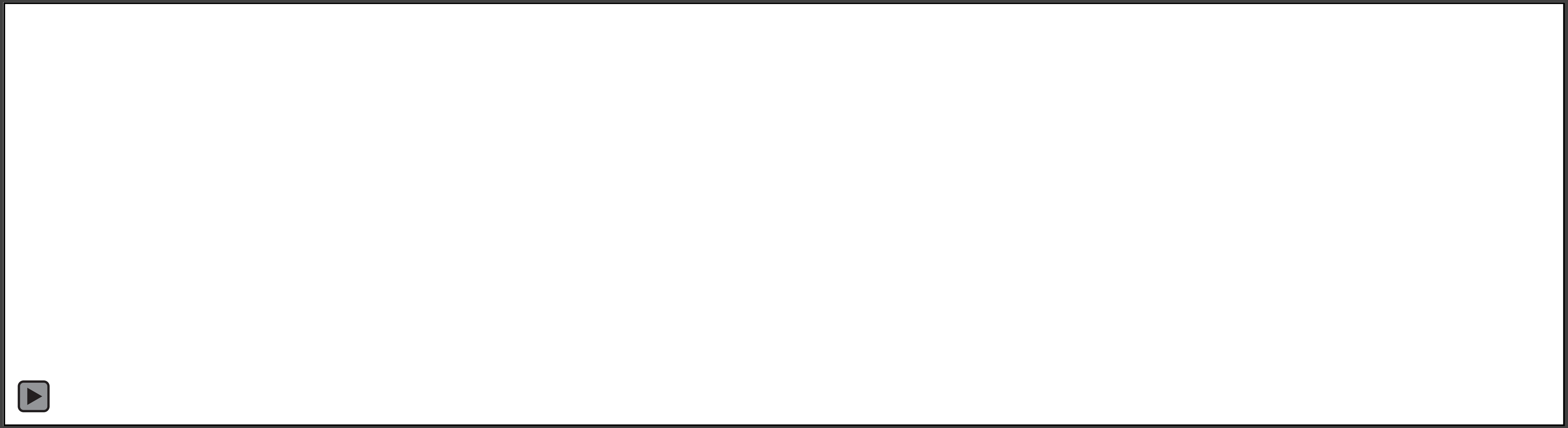
Neural space-time model: a dynamic scene represented by motion MLP and scene MLP



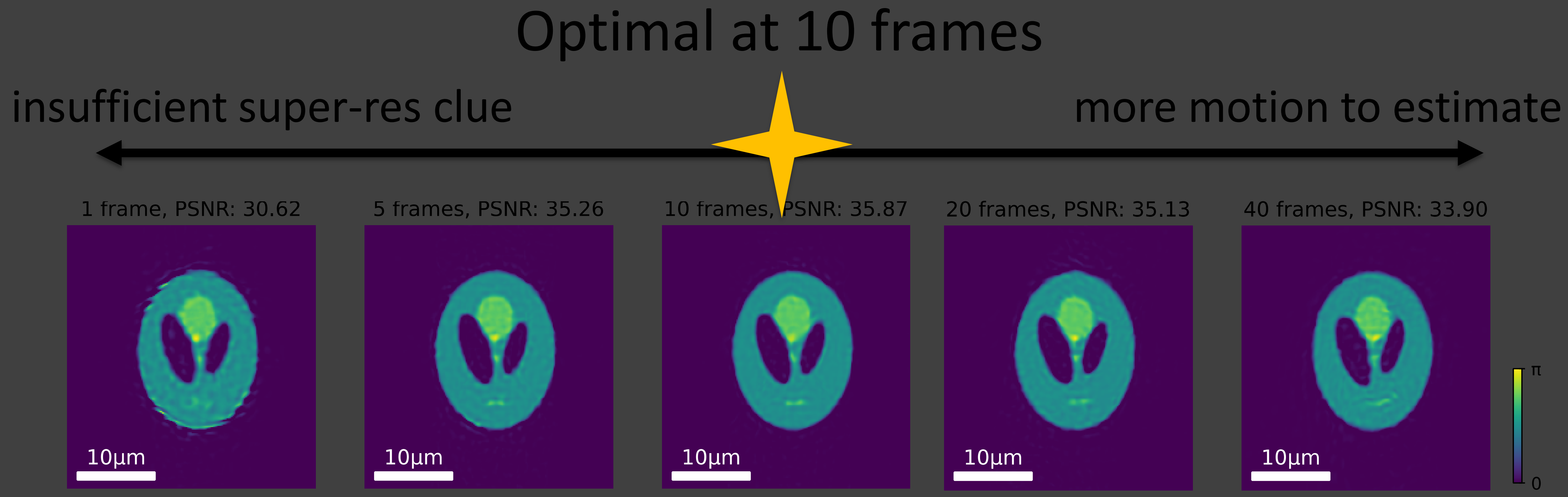
Update model's weights to reconstruct motion dynamics and a super-resolved scene



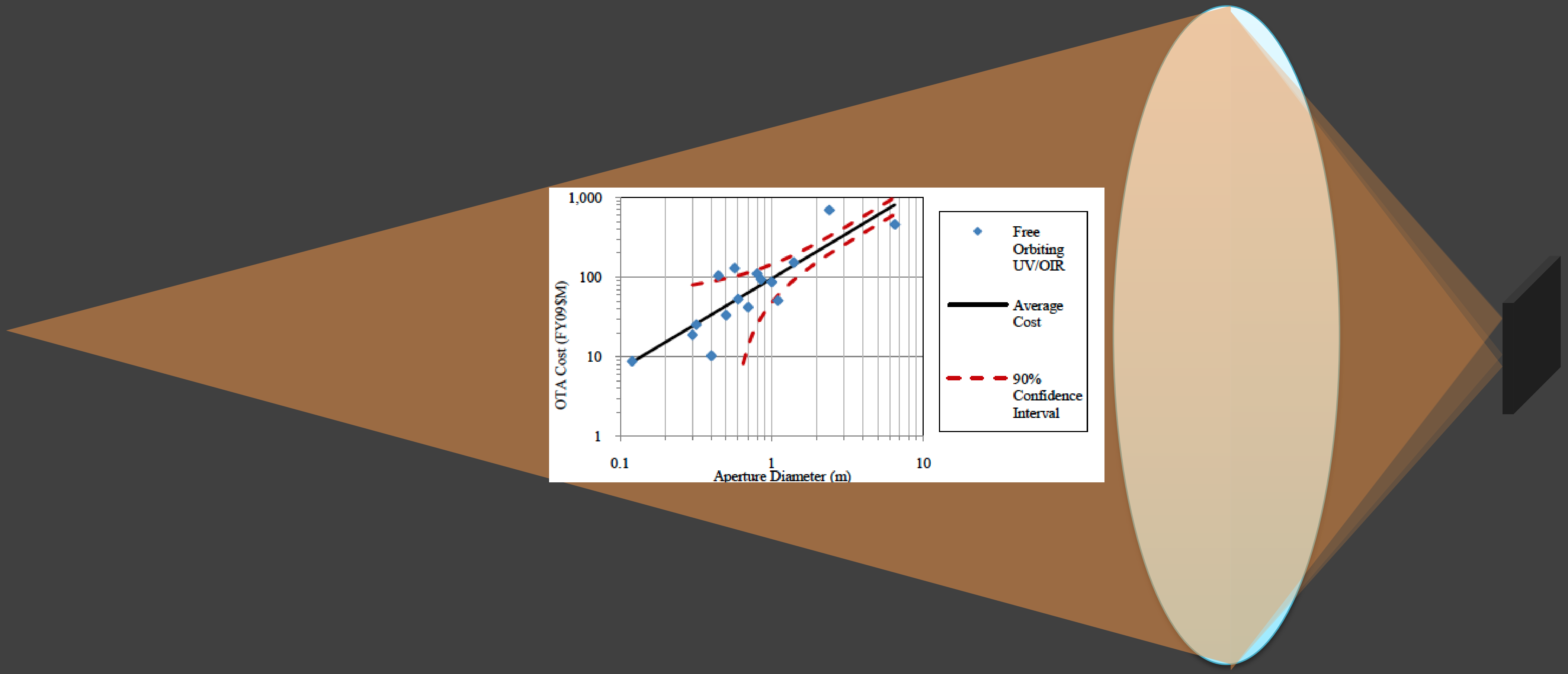
Speckle Flow SIM to recover deformable motion



Number of input frames affects reconstruction



Experimental result of 1.88x super-resolution for a continuously moving sample


1,000
100
10
1
OTA Cost (FY09$M)
0.1
1
10
Aperture Diameter (m)
Free Orbiting UV/OIR
Average Cost
90% Confidence Interval