

```
void box_filter_3x3(const Image &in, Image &blurV) {  
    __m128i one_third = _mm_set1_epi16(21846);  
    #pragma omp parallel for  
    for (int yTile = 0; yTile < in.height(); yTile += 32)  
        __m128i a, b, c, sum, avg;  
        __m128i blurH[(256/8)*(32+2)]; // allocate tile bl  
        for (int xTile = 0; xTile < in.width(); xTile += 2  
            __m128i *blurHPtr = blurH;  
            for (int y = -1; y < 32+1; y++) {
```

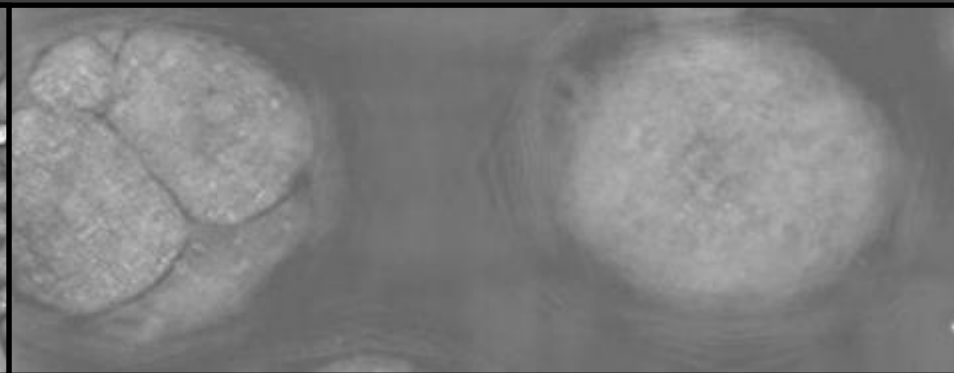
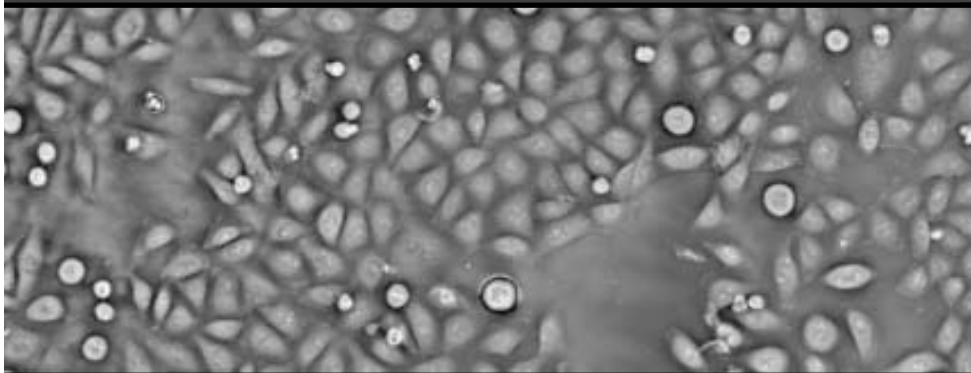
Computational Microscopy for 3D fluorescence imaging

Laura Waller

Ted Van Duzer Associate Professor

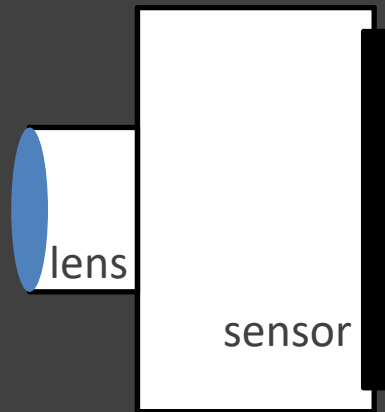
Electrical Engineering and Computer Sciences

UC Berkeley

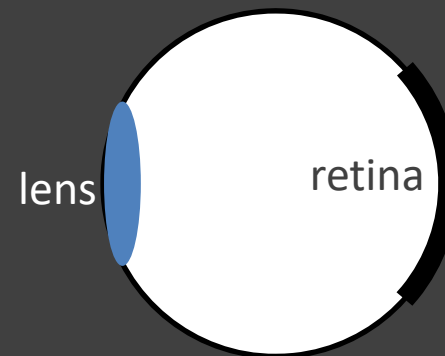


Traditional imaging systems are boring

simplified camera design

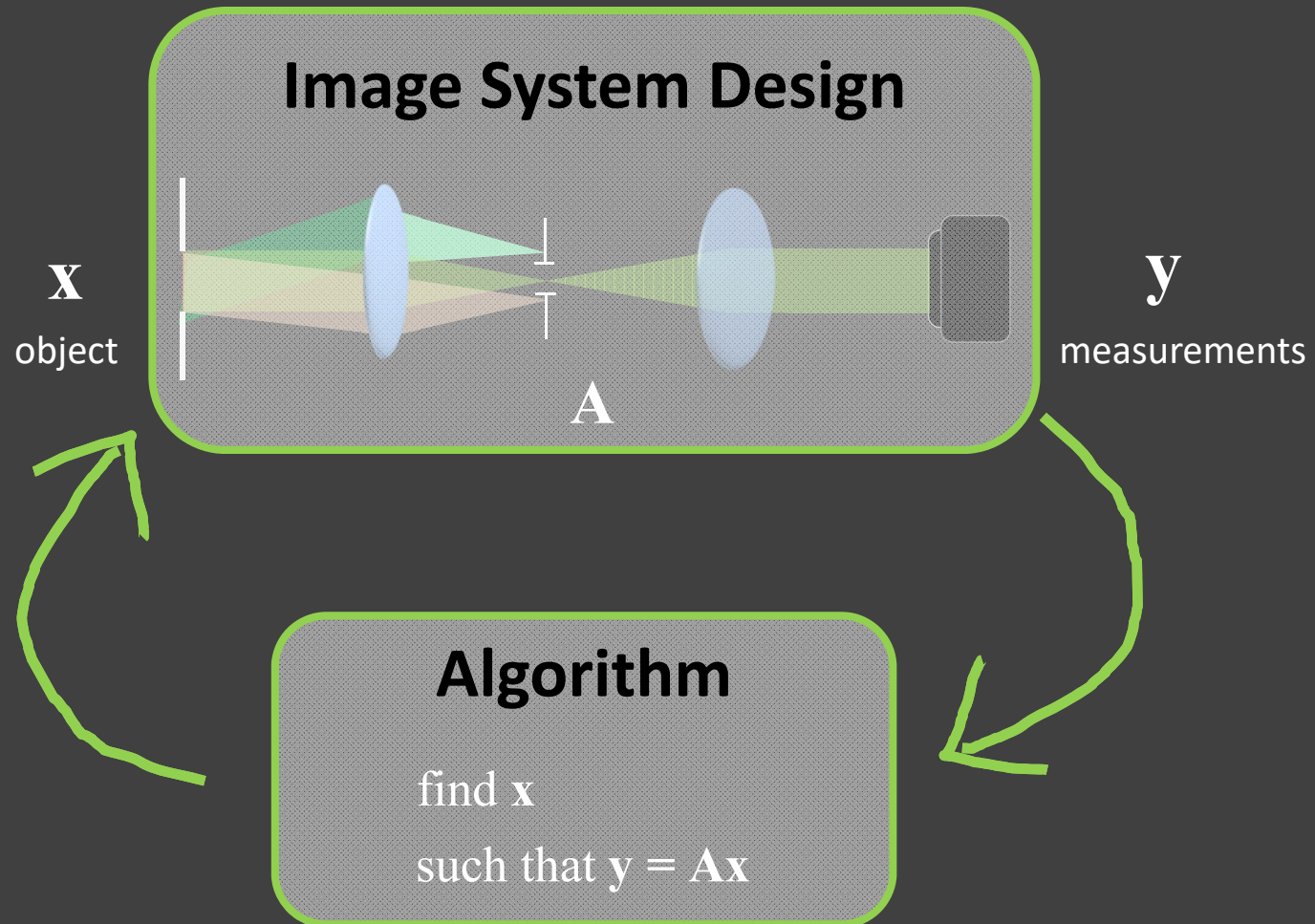


simplified eye



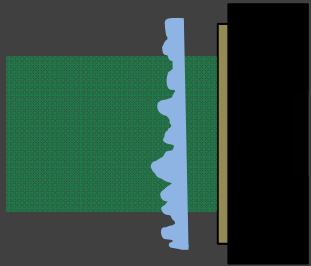
Coincidence? bio-mimetic? lack of creativity?

Joint design of hardware and software

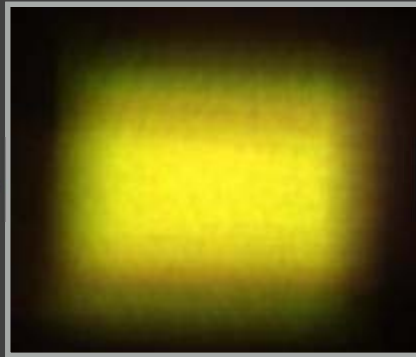


Computational imaging pipeline

Hardware design



Take picture



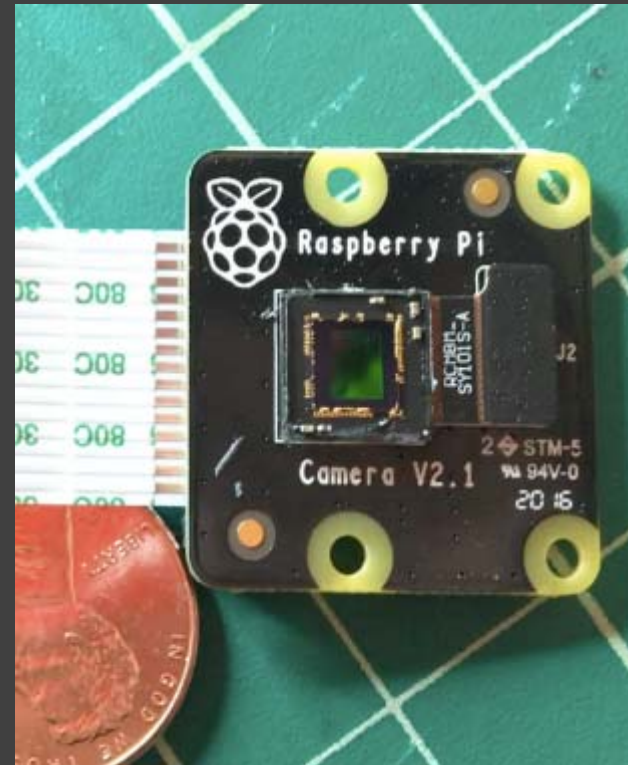
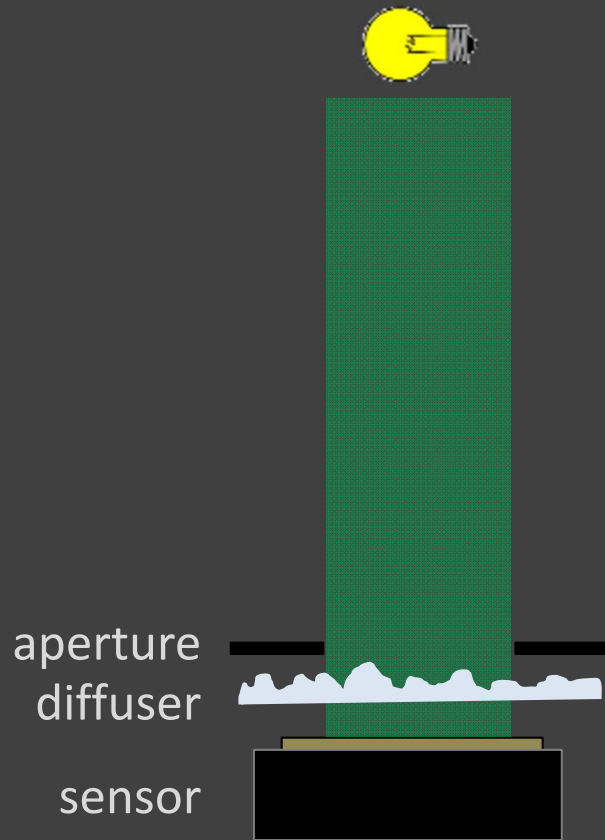
Crunch Data



Final result



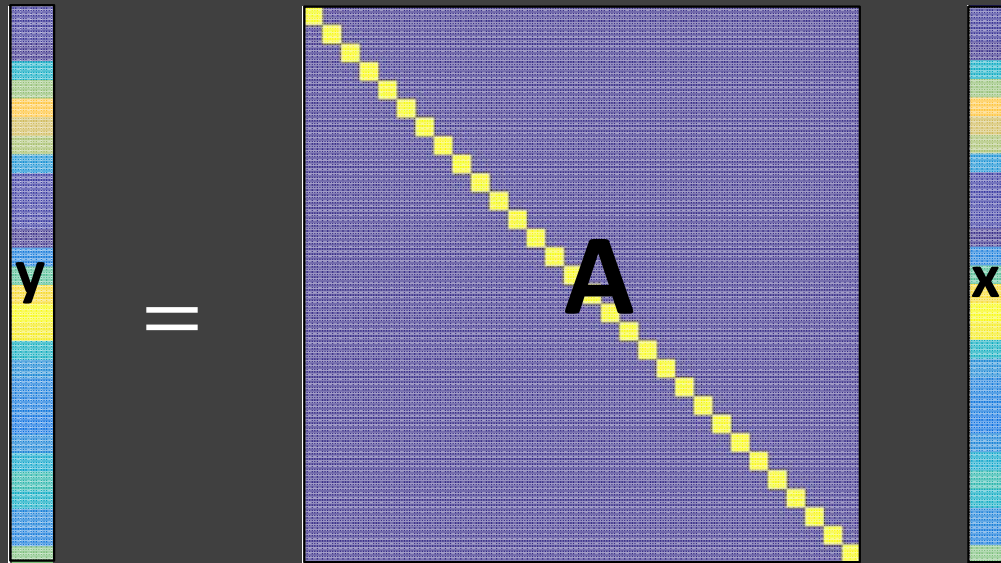
DiffuserCam: tape a diffuser onto a sensor



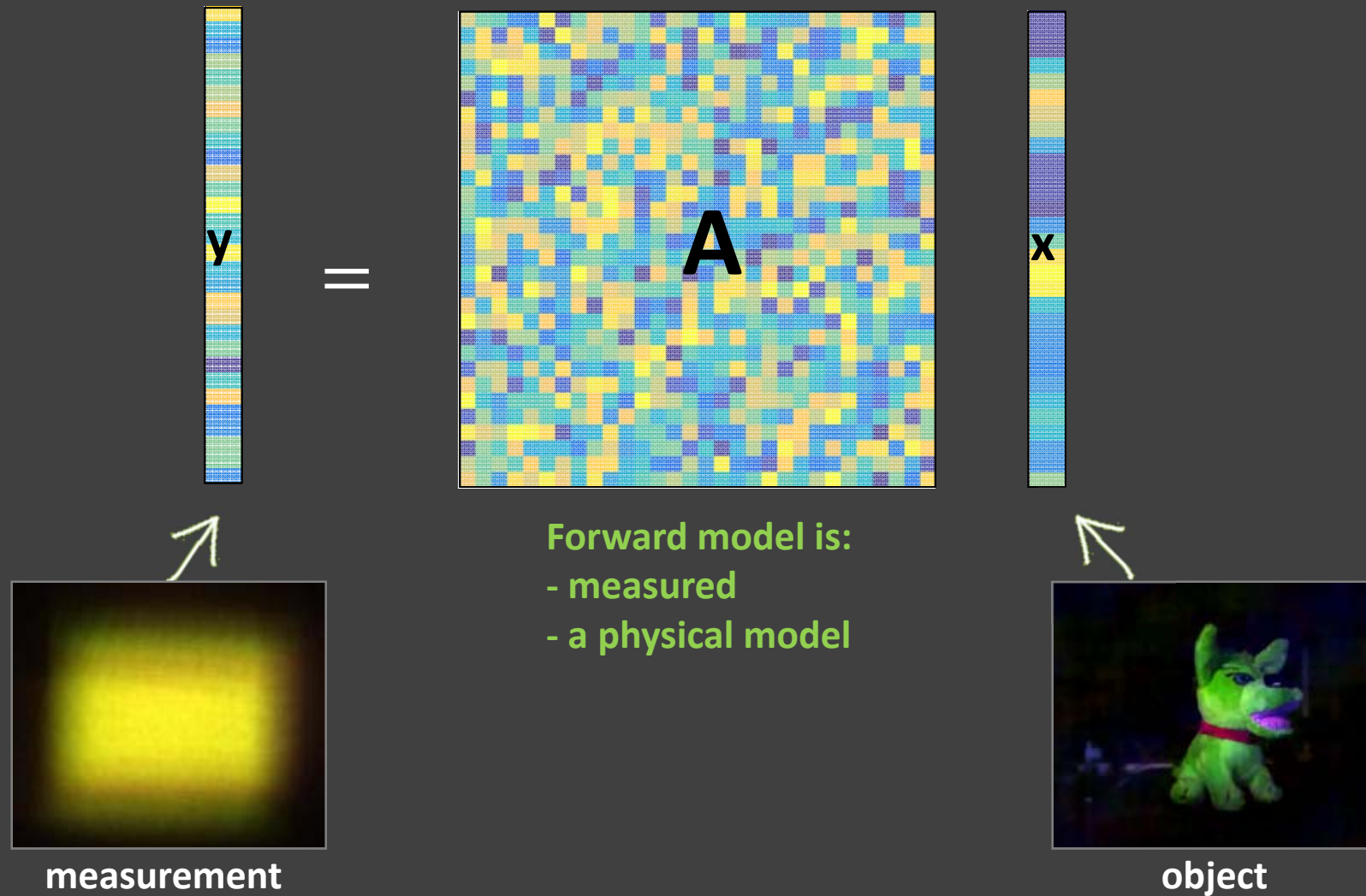
Grace Kuo
Nick Antipa



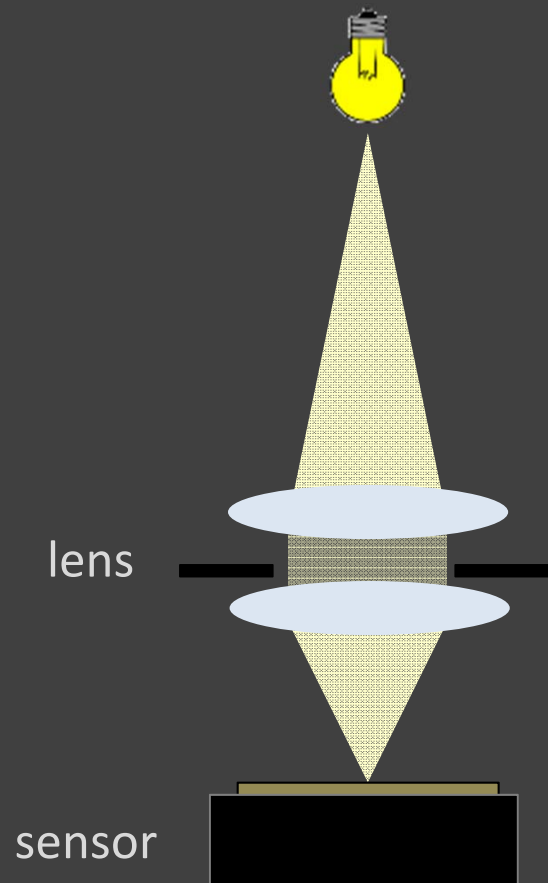
Traditional cameras take direct measurements



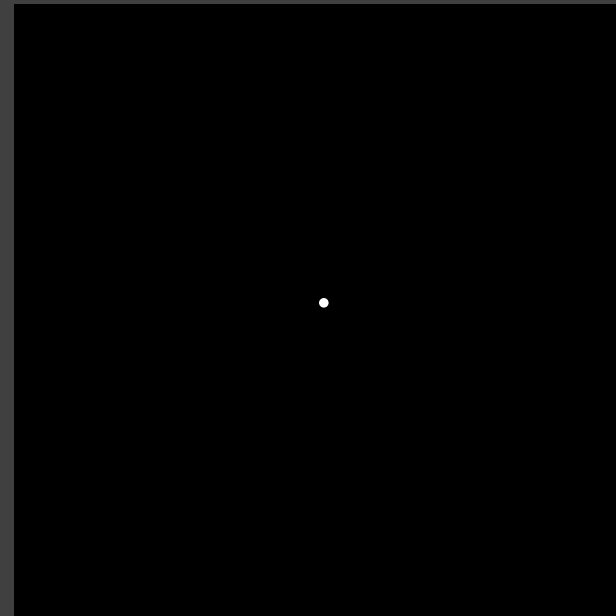
Computational cameras can multiplex



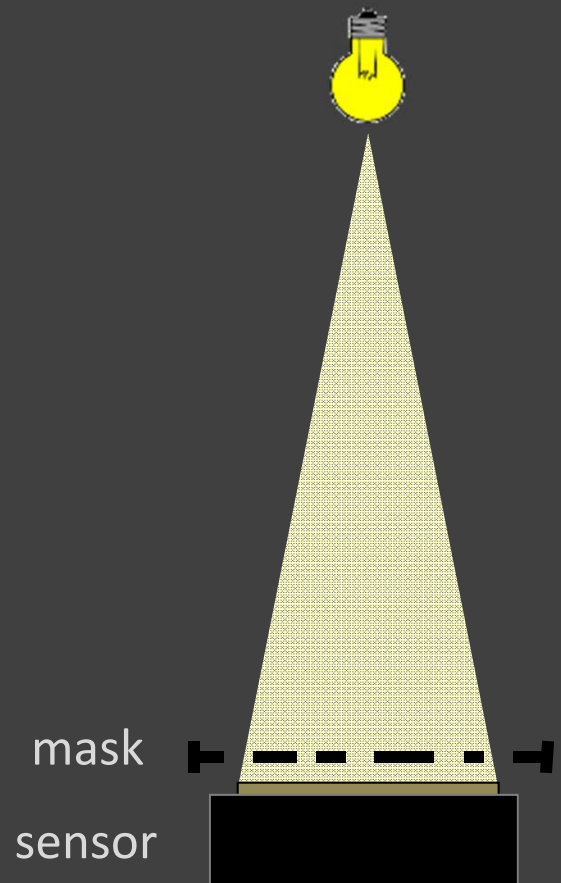
Lenses map points to points



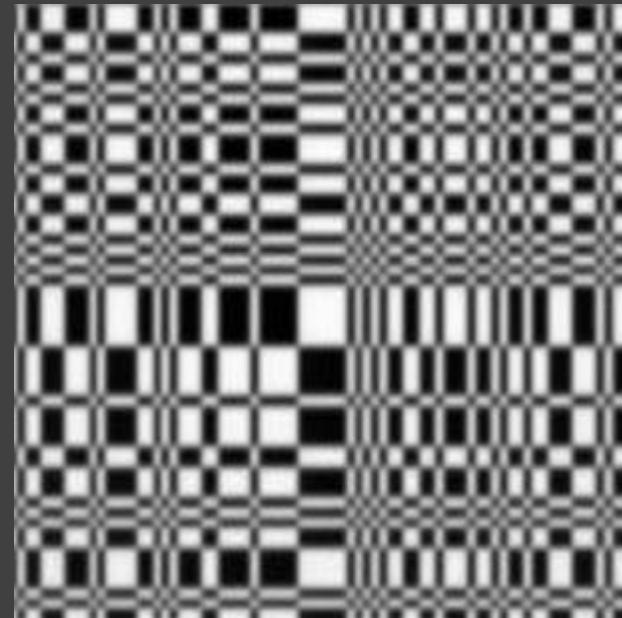
Point Spread Function (PSF)



Mask-based cameras multiplex

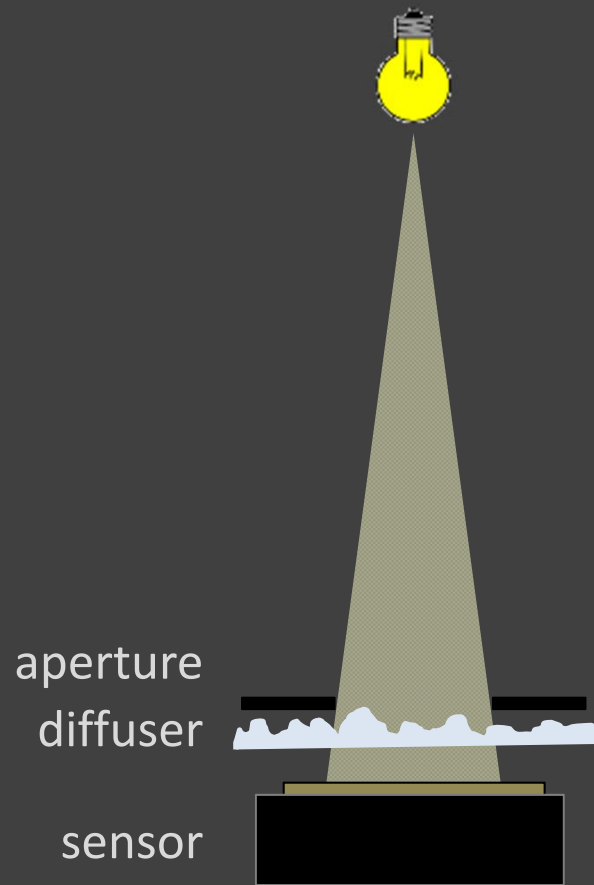


Point Spread Function (PSF)

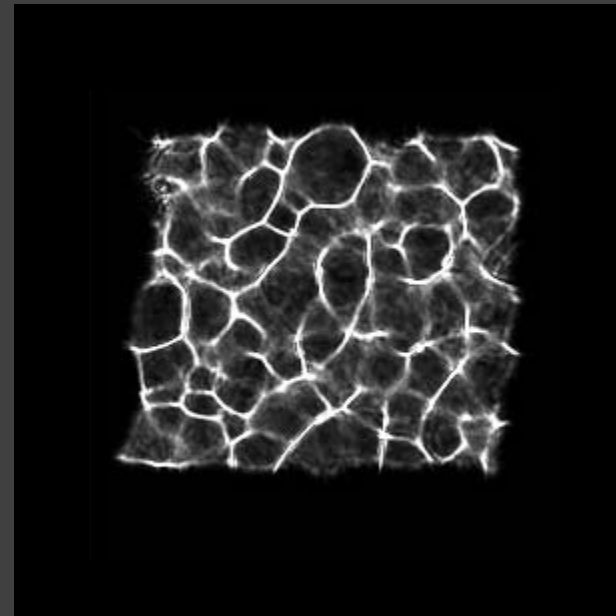


M. S. Asif, et al. *ICCVW* (2015)
J. Tanida, et al. *Applied optics* (2001)
K. Tajima, et al. *ICCP* (2017)
D. G. Stork, et al. *Int. J. Adv. Systems and measurements* (2014)

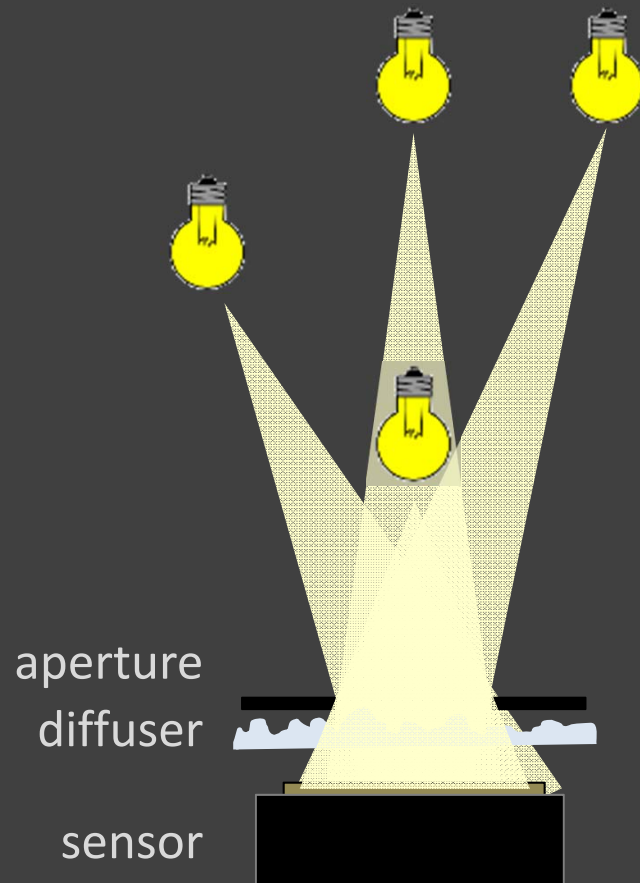
Diffuser indirectly encodes information



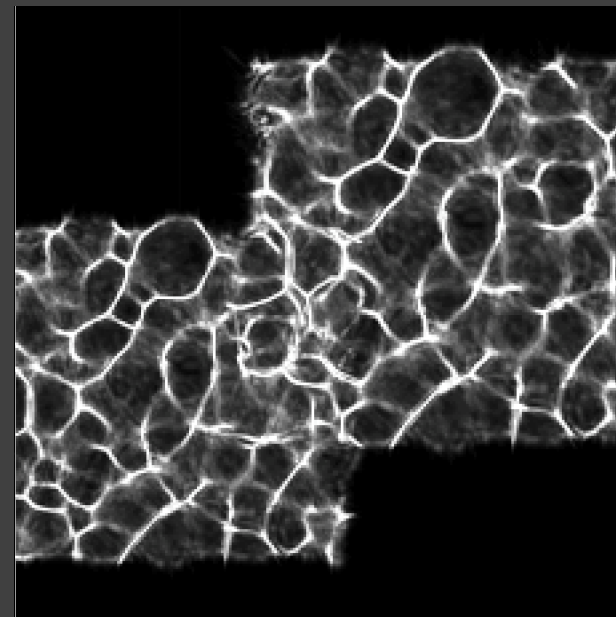
Point Spread Function (PSF)



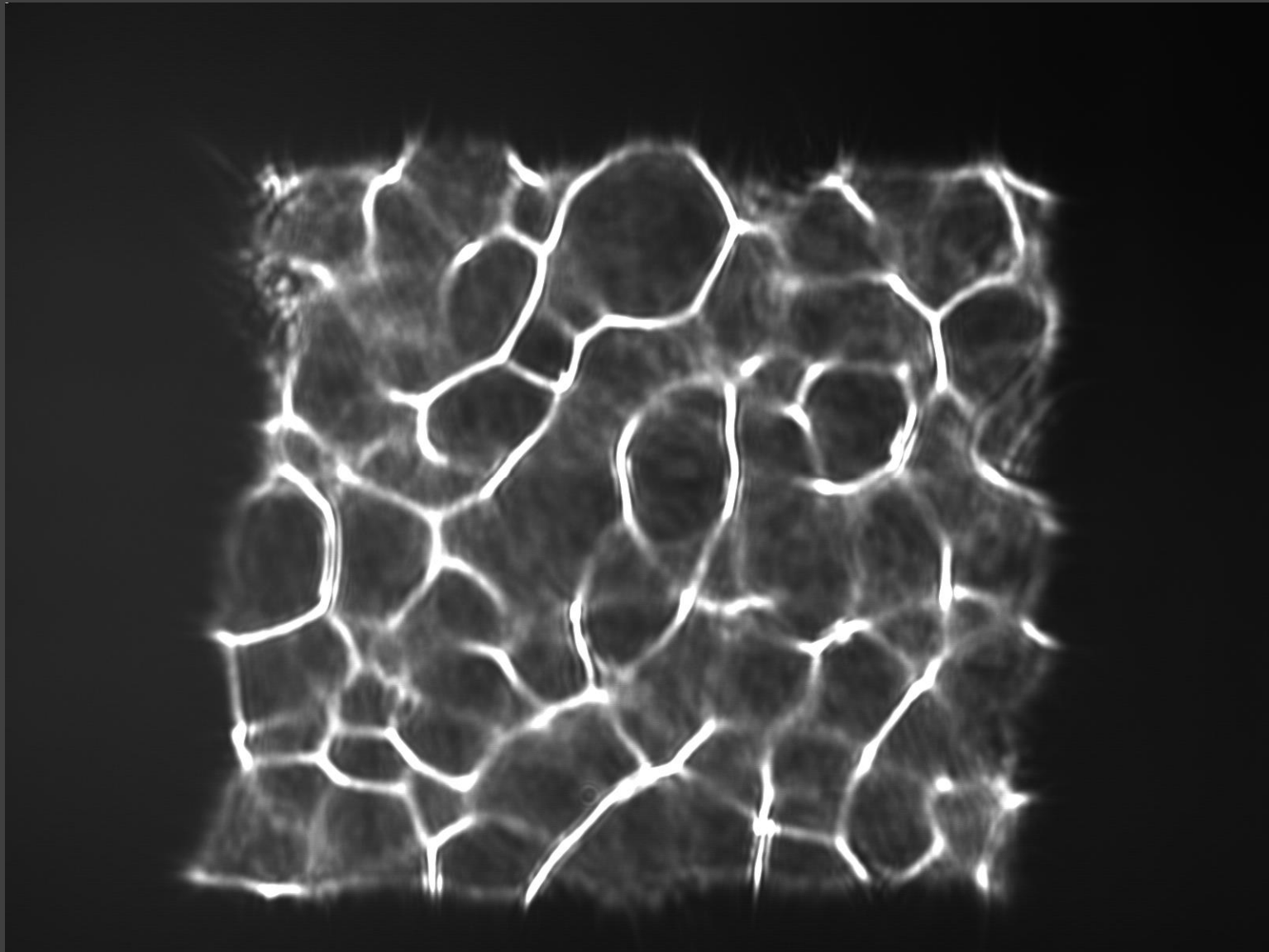
Diffuser indirectly encodes information



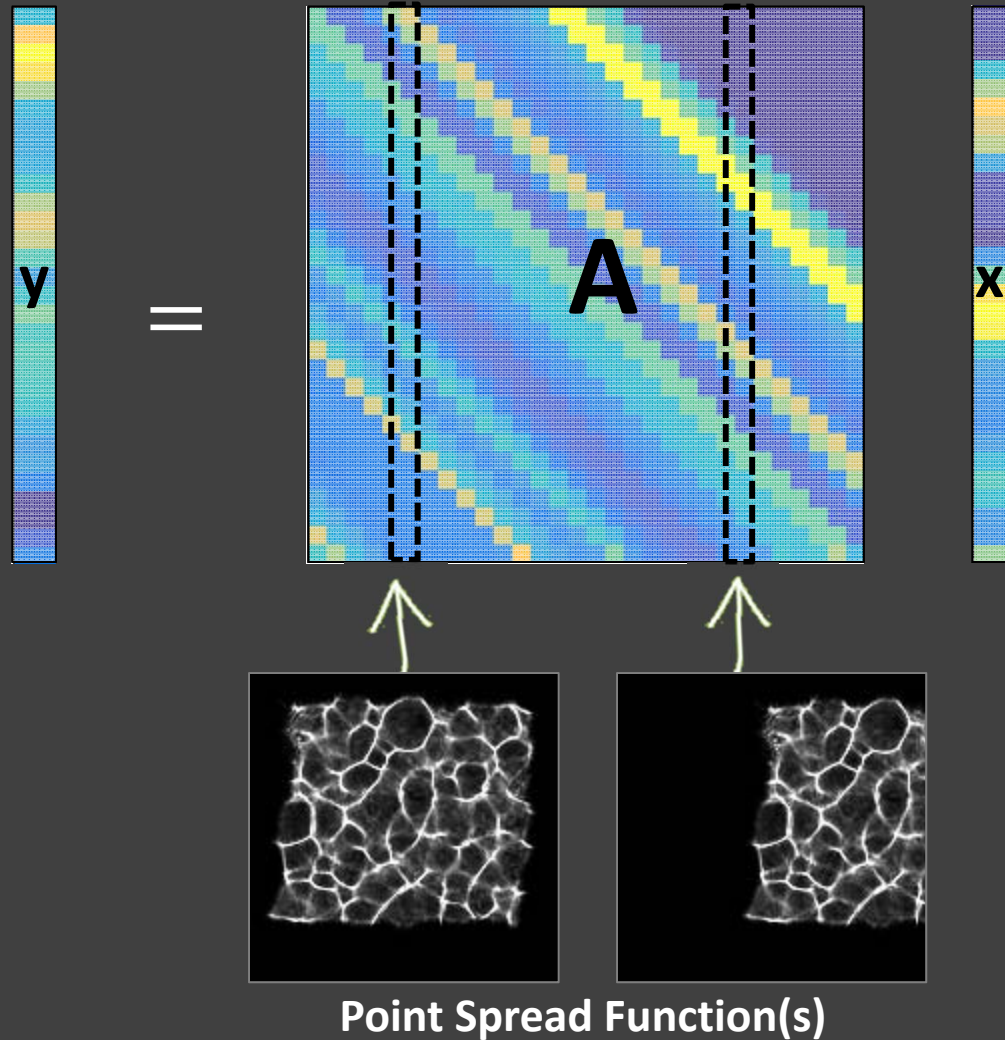
Point Spread Function (PSF)



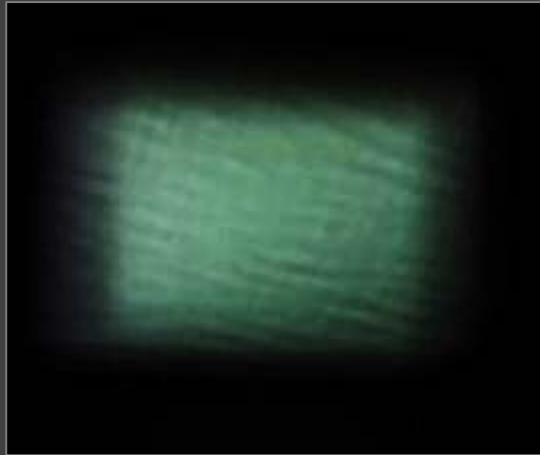
Point spread function shifts with object



DiffuserCam forward model is a convolution

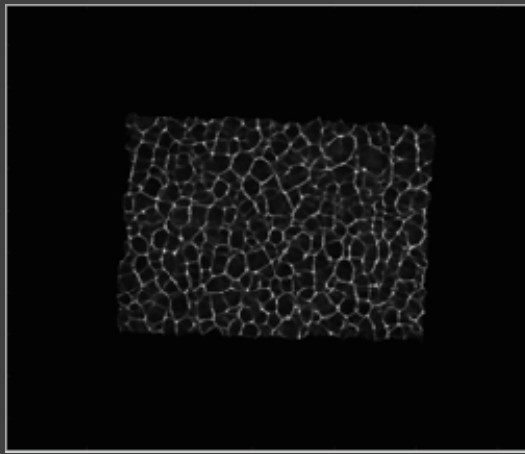


2D Photography Forward Model



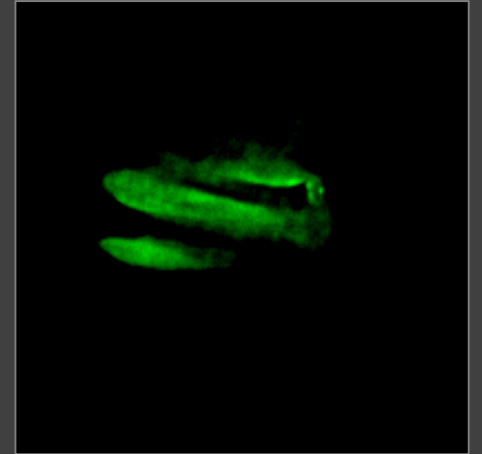
Measurement

=

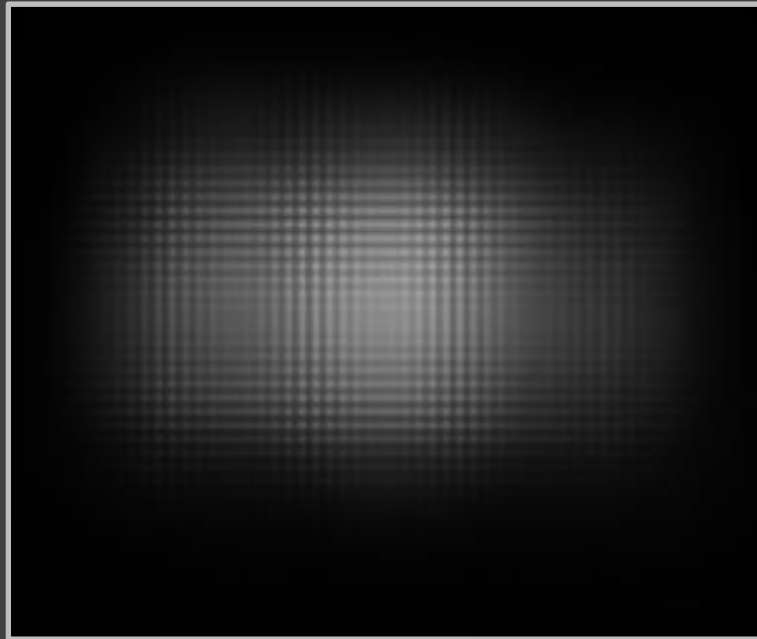


Point Spread Function

*



Object



raw sensor data



recovered scene

*solver is ADMM with TV reg in Halide



raw sensor data



recovered scene

*solver is ADMM with TV reg in Halide



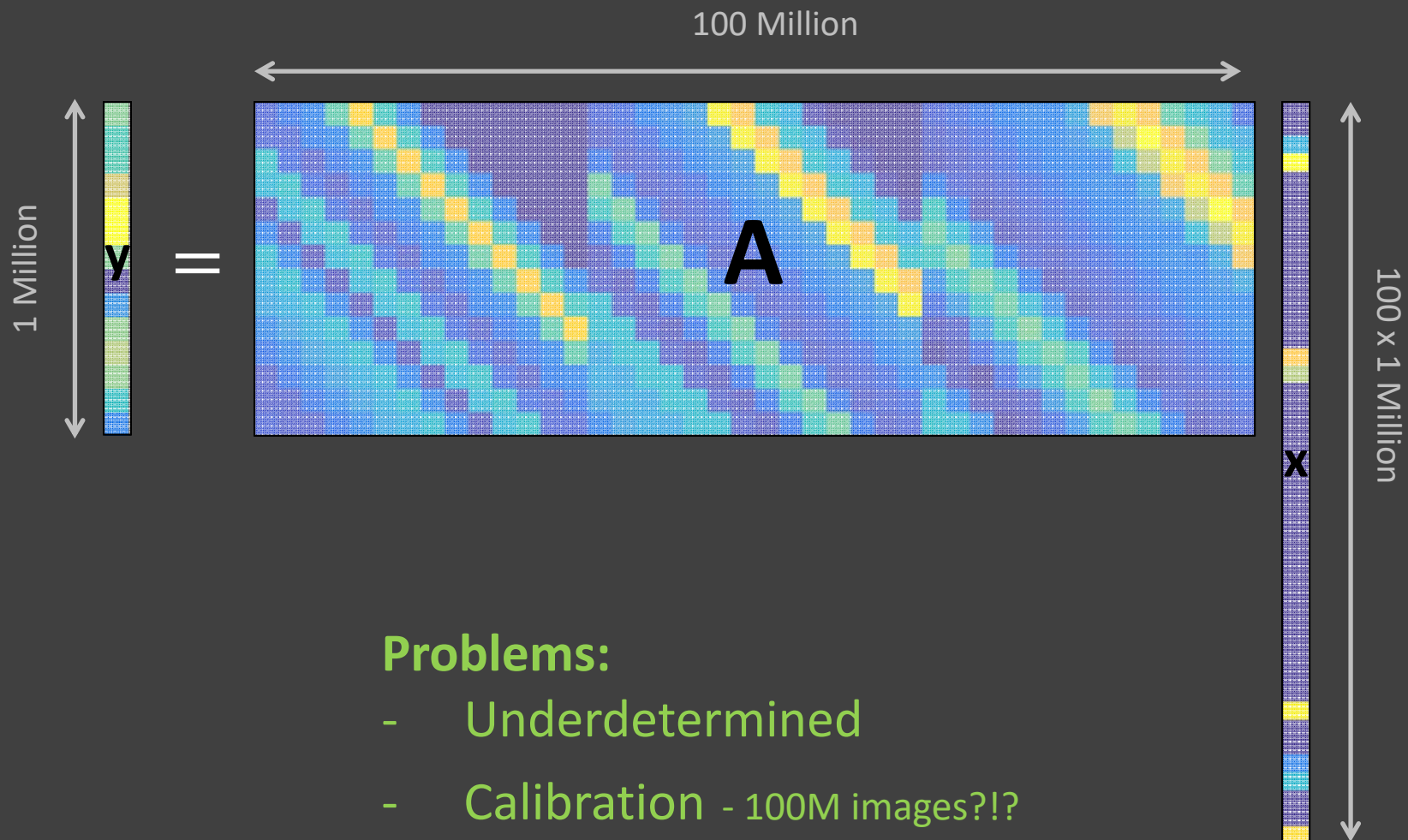
raw sensor data



recovered scene

*solver is ADMM with TV reg in Halide

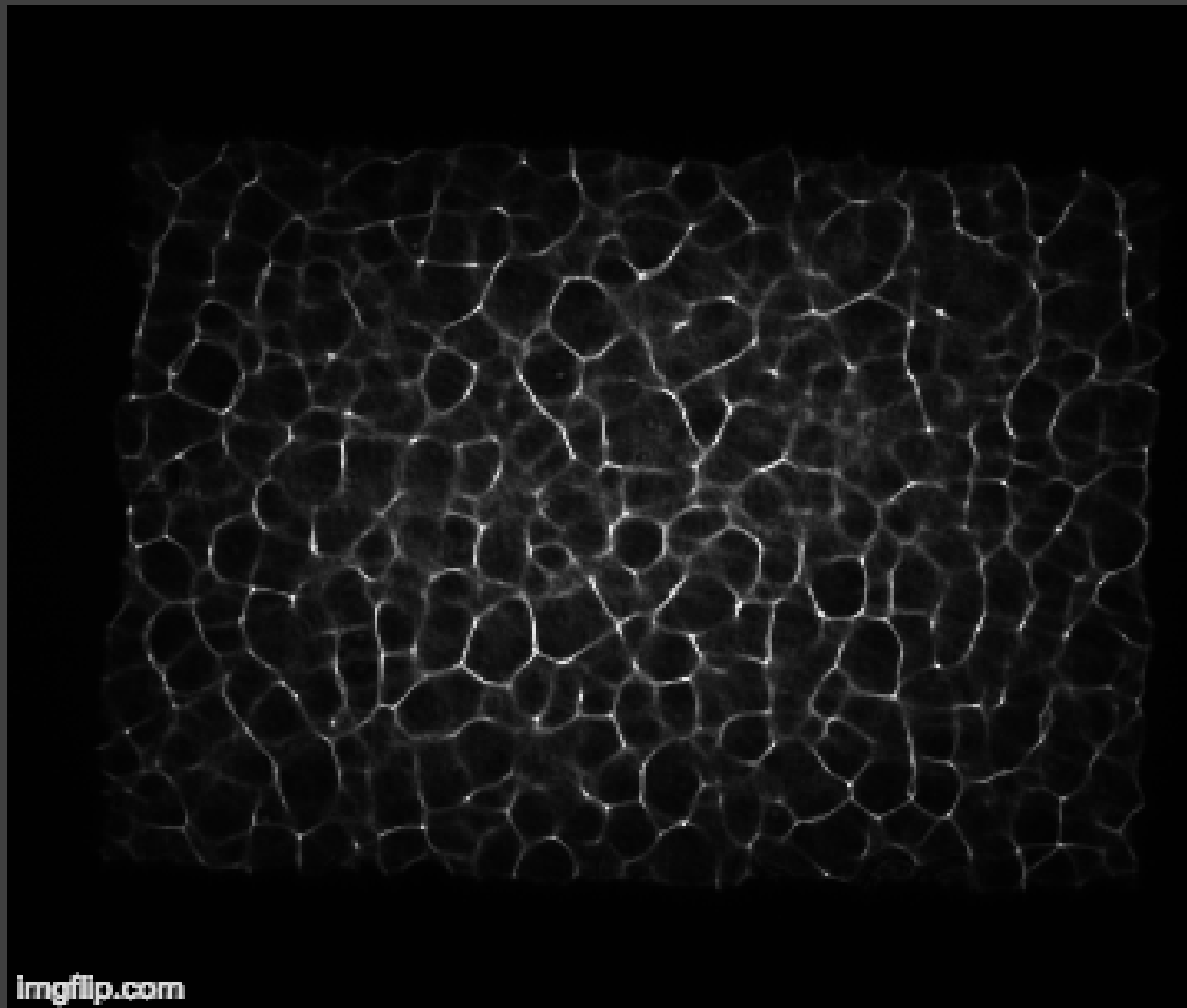
3D is not so easy



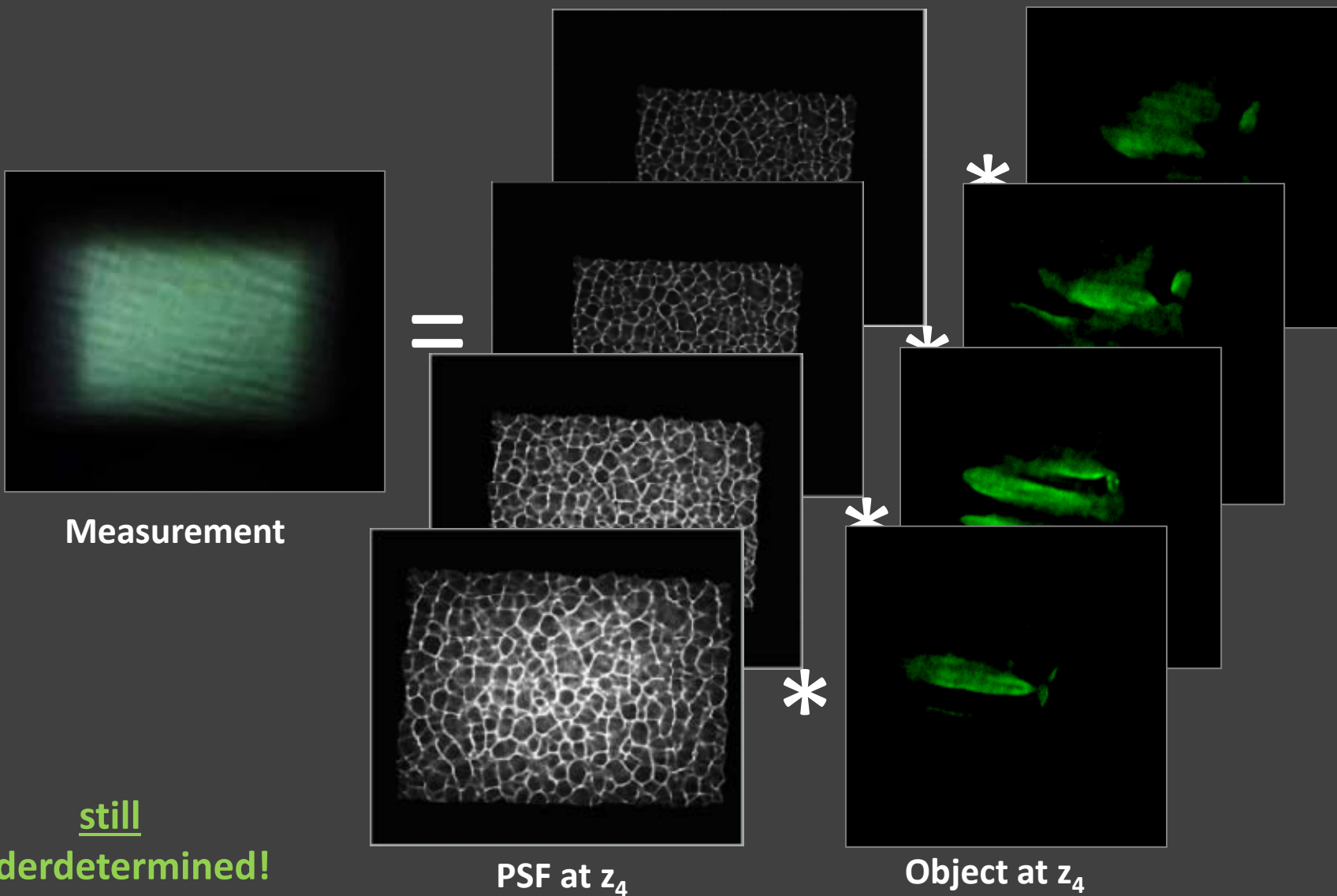
Problems:

- Underdetermined
- Calibration - 100M images?!?

The PSF changes with depth

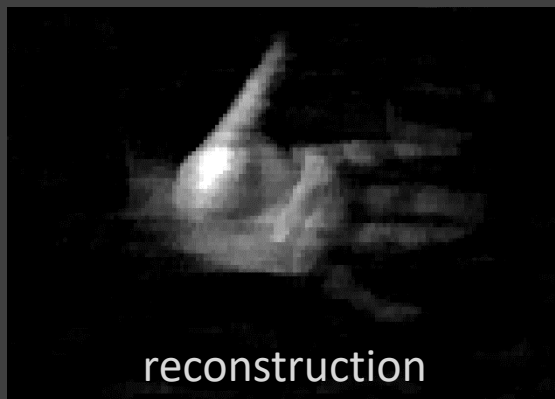
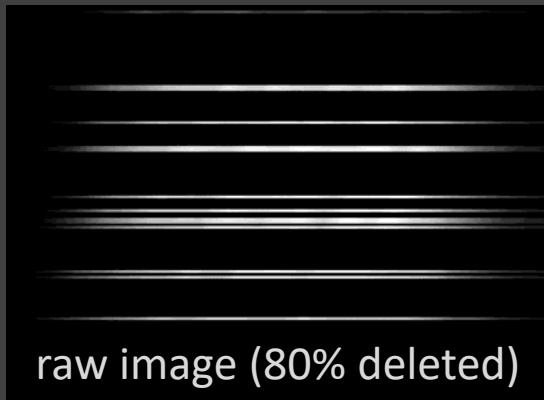


3D Forward Model: Sum of Convolutions



Compressed sensing

solves under-determined problems via sparsity prior



Take less samples with
this one weird trick...



[CLICK HERE to Find Out More!](#)

Sponsored | Compressed Sensing News

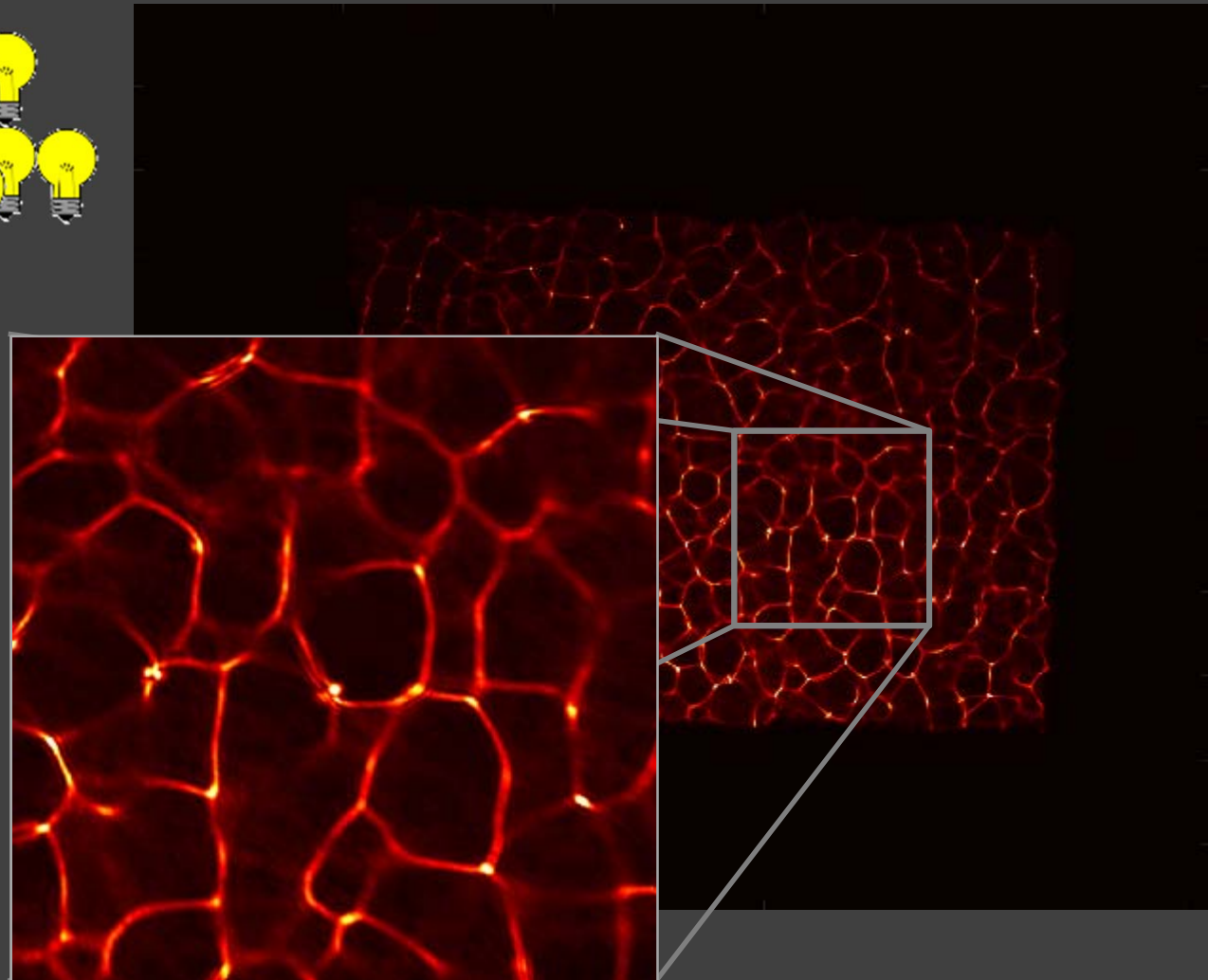
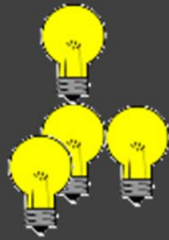
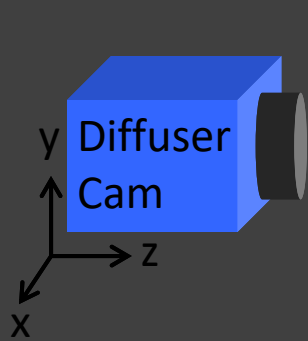
Image Reconstruction with Sparsity Prior

$$\arg \min_{x \geq 0} \left\| \begin{array}{c} \gamma \\ - \\ Ax \end{array} \right\|_2^2 + \lambda \text{TV}^{[1]}(x)$$

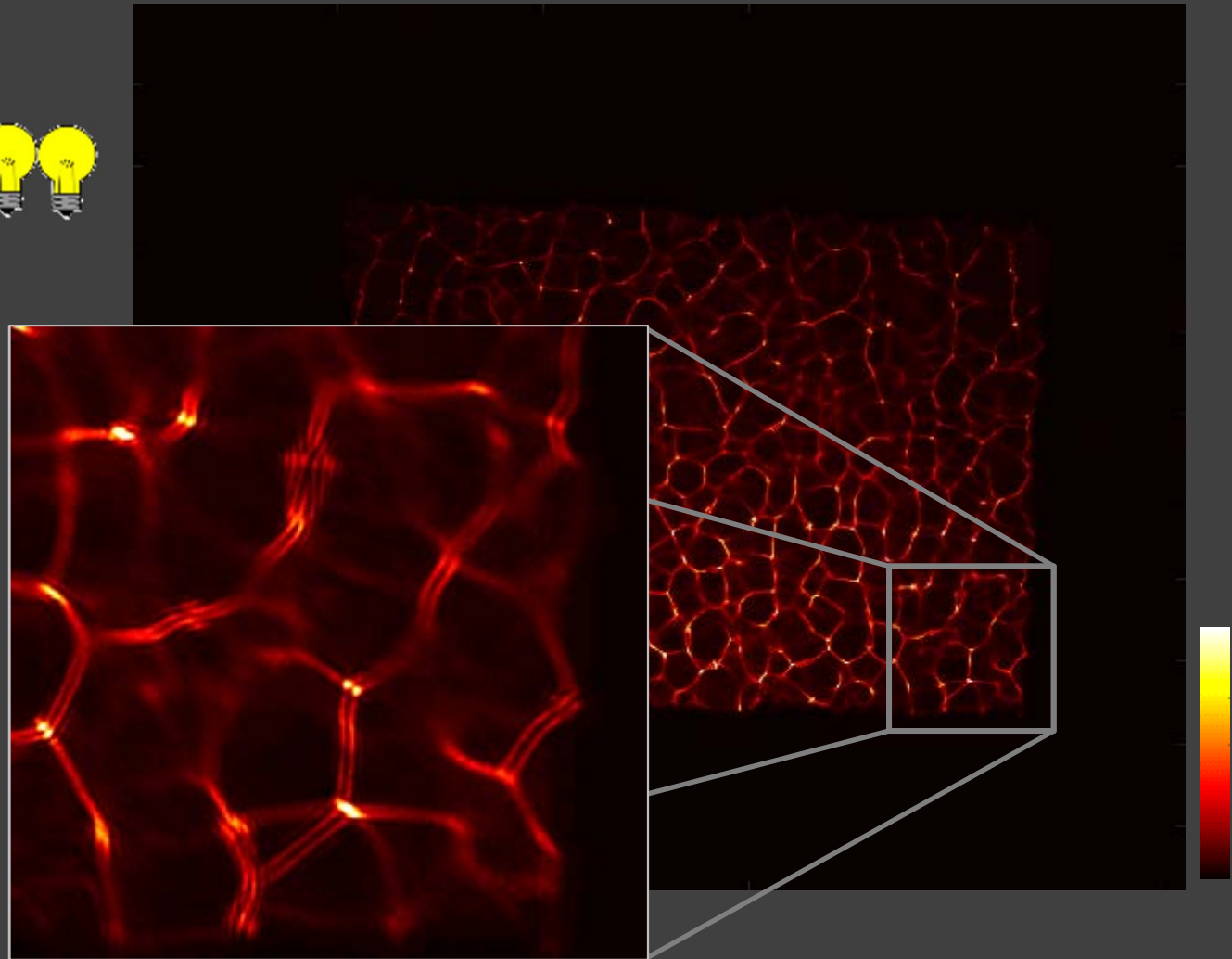
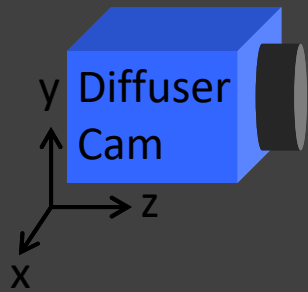
The diagram illustrates the image reconstruction process with a sparsity prior. It shows the following components:

- Observed Data (γ):** A blurry green image of a leaf.
- Measurement Matrix (A):** A grid of white lines representing the measurement process.
- Product (Ax):** A sharp green image of a leaf, representing the reconstructed image.
- Sparsity Basis:** A set of green leaf images, representing the basis for the sparsity prior.
- Regularization Term ($\lambda \text{TV}^{[1]}(x)$):** A term that penalizes the total variation of the reconstructed image, promoting sparsity.

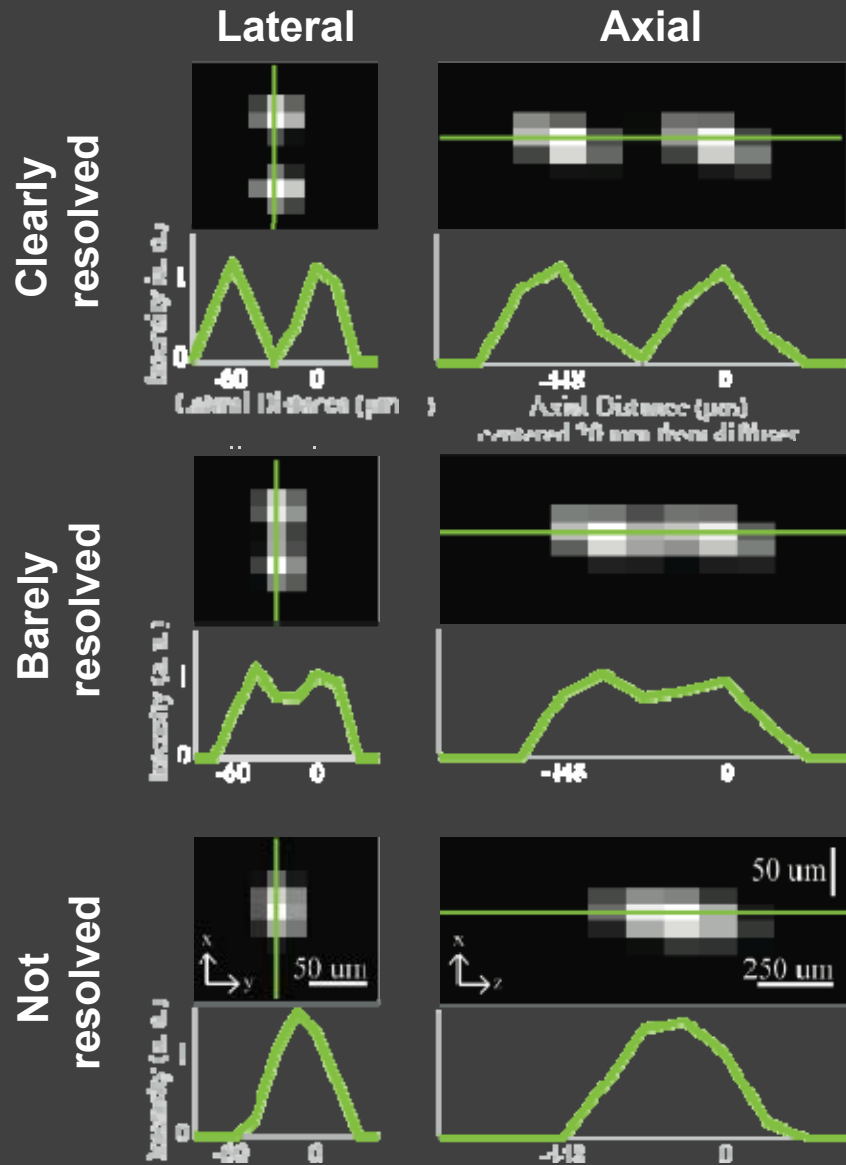
High frequencies define resolution



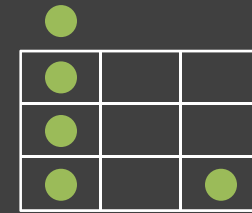
High frequencies define resolution



Experimental resolution sets voxel size

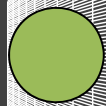


Diffuser
Cam



Experimental resolution sets voxel size

Small objects for
3D reconstruction

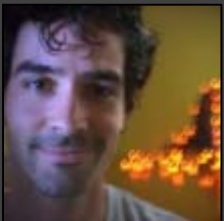
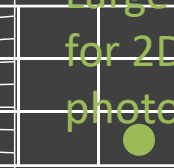


1 cm

Diffuser
Cam



Large scenes
for 2D
photography



Nick Antipa
Lensless Diffuser-Based Photography
Tues. June 27 at 2:30 pm

EDMUND



USAF 1951 1X

$z = 16.14 \text{ mm}$



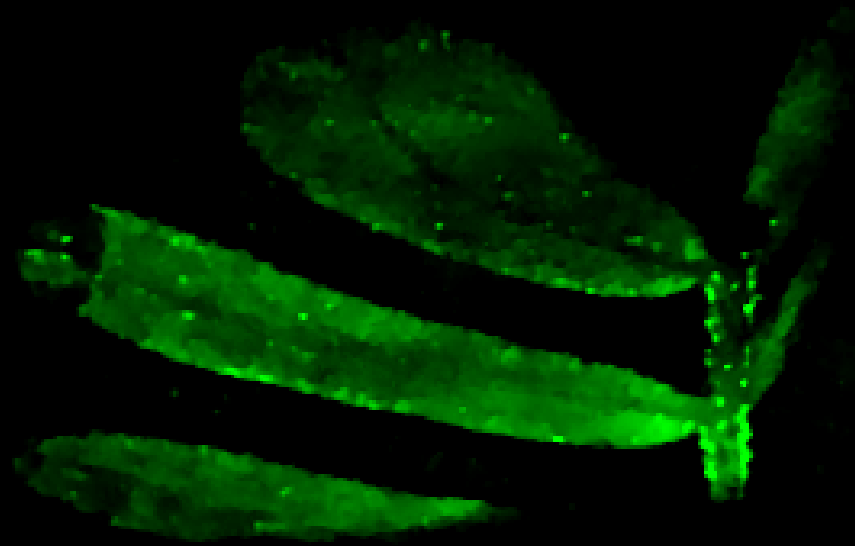
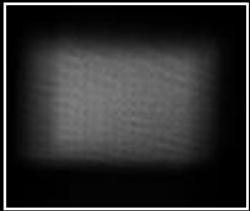
EDMUND



USAF 1951 1X

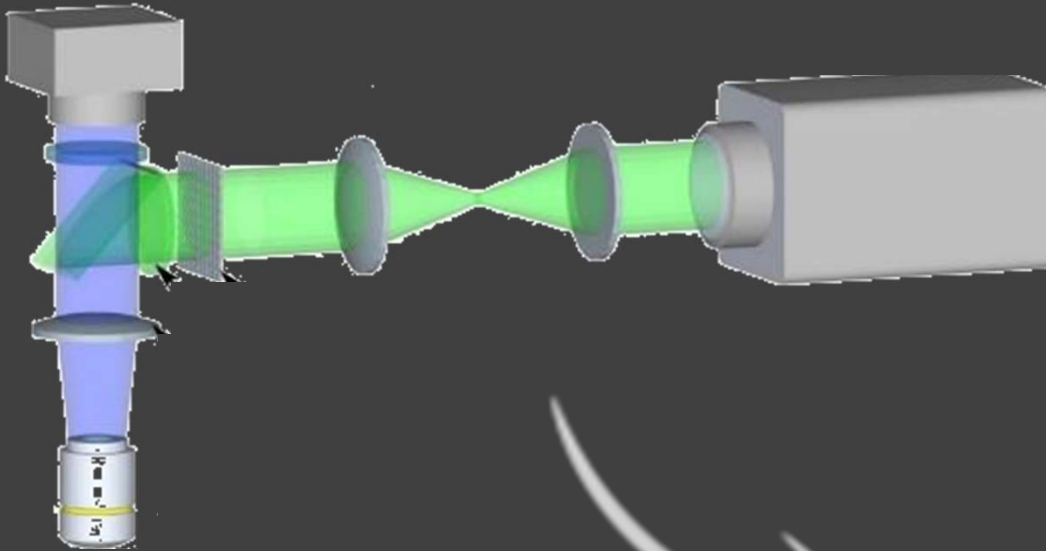


128x more pixels for **FREE!**



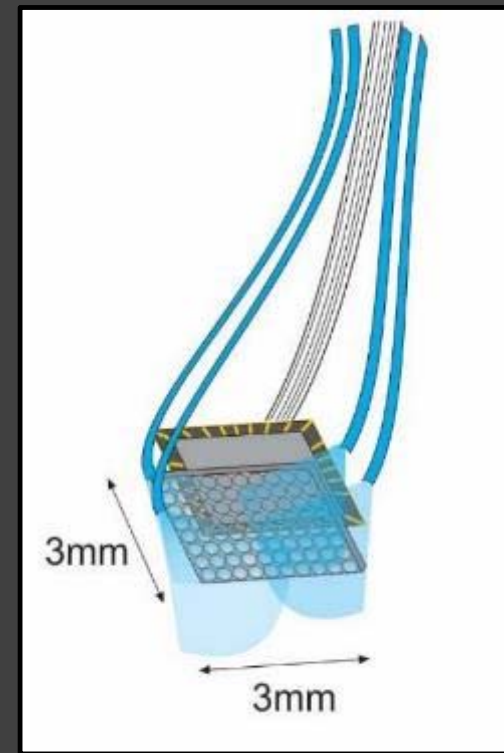
128x more pixels for **FREE!**

Towards lensless 3D microscopy

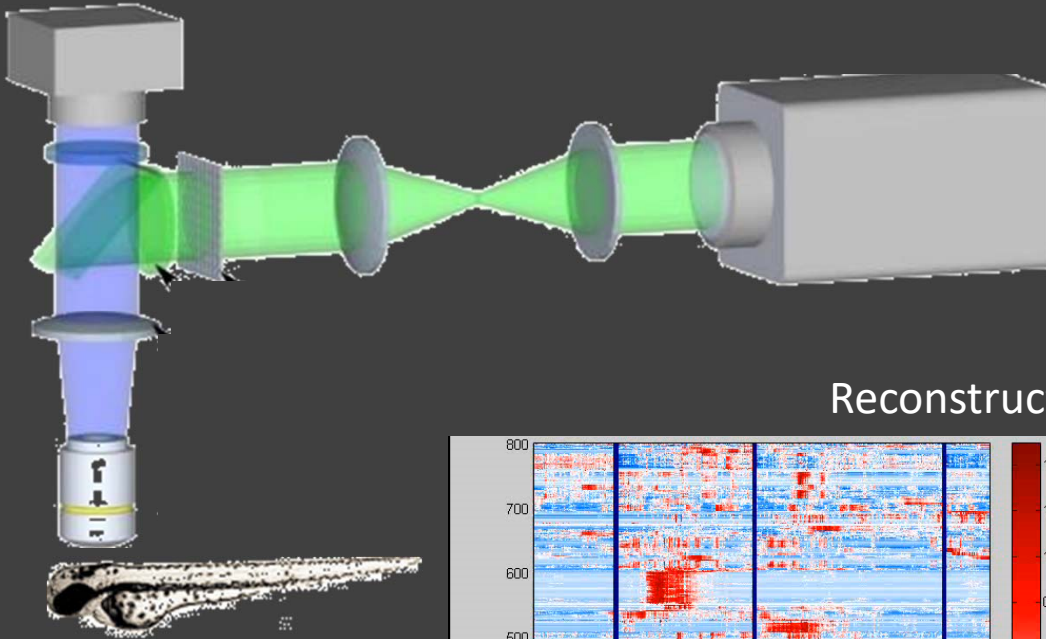


Lensless imager:

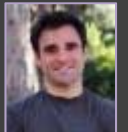
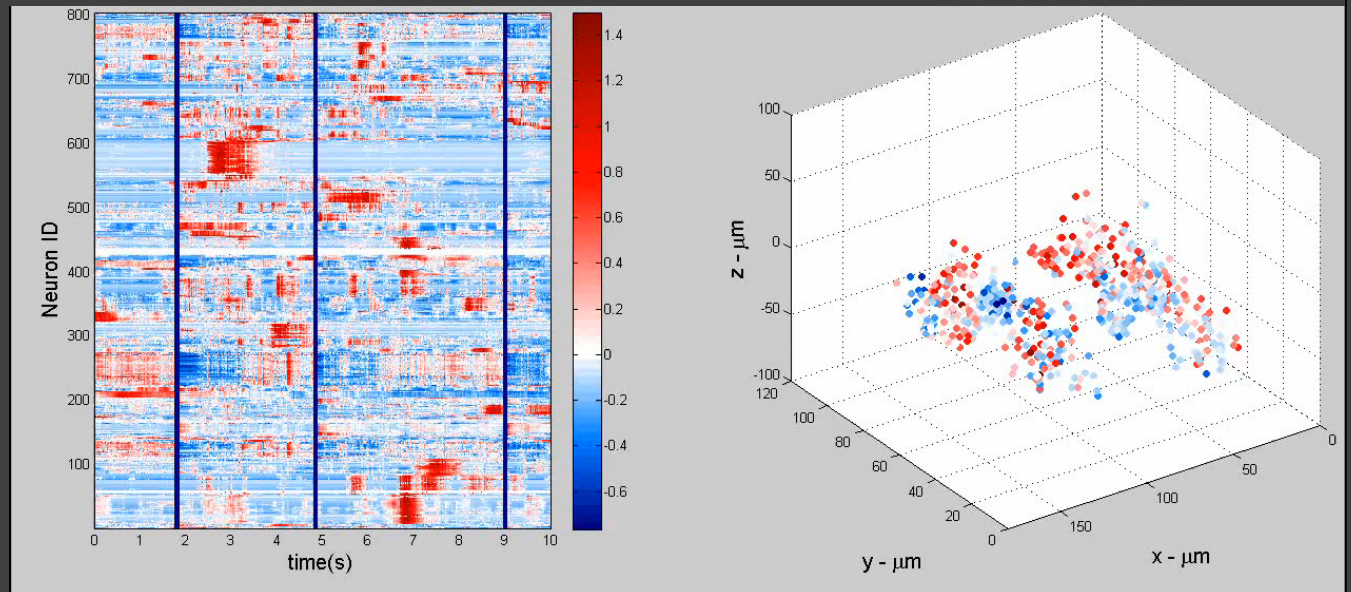
- small
- inexpensive
- enables tiling



3D imaging of brains



Reconstructed neural activity



Scanning

vs.

**Compressed
Sensing**

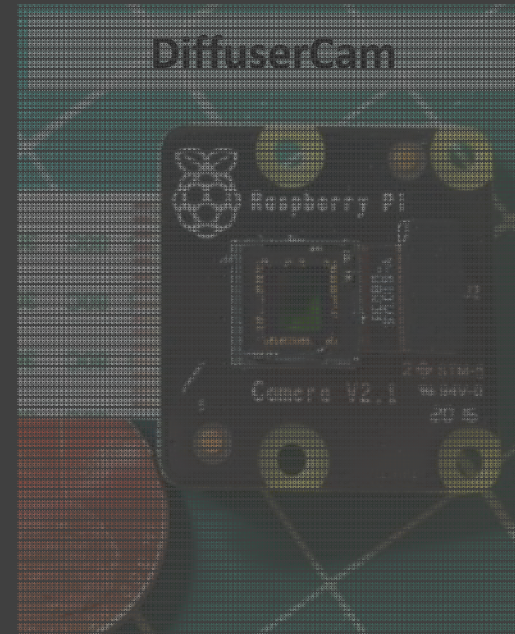
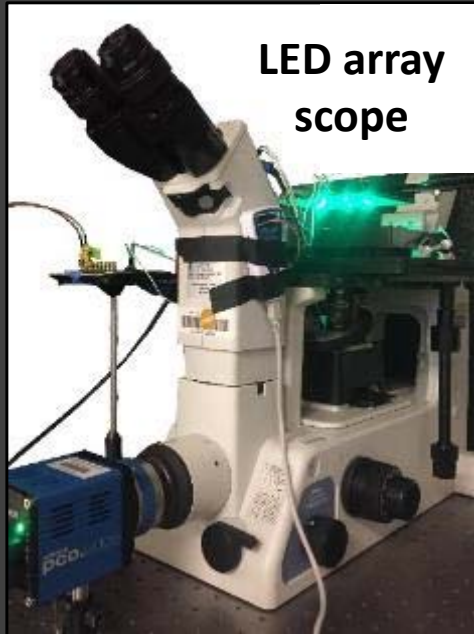


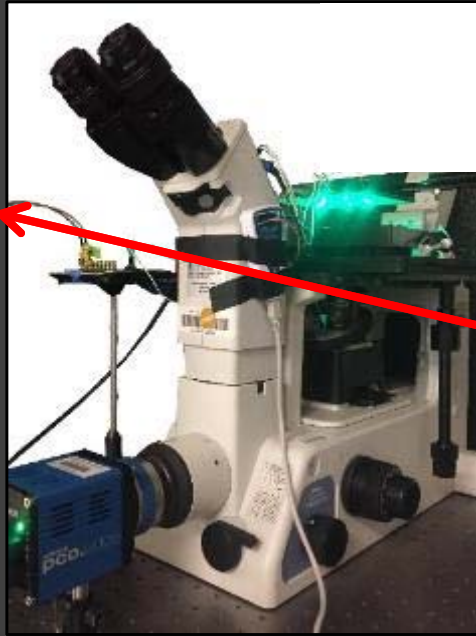
**speed scales with #
voxels in image**



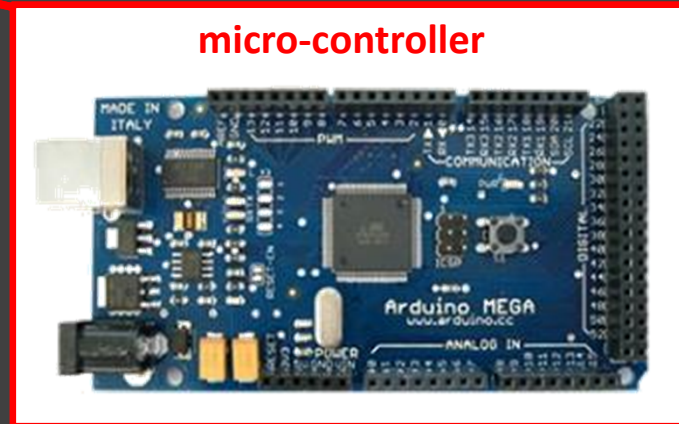
**speed scales with
sparsity of sample**

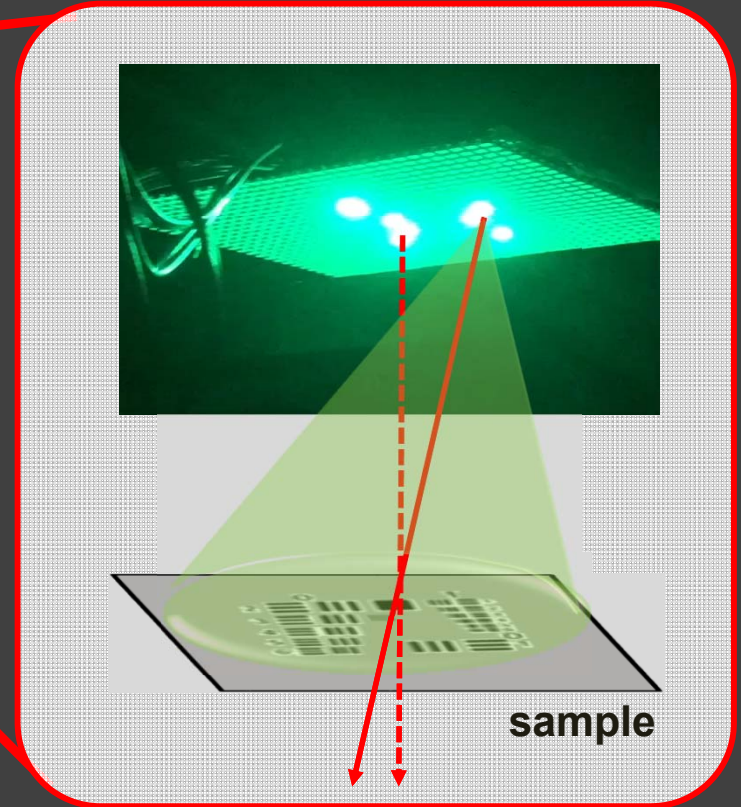
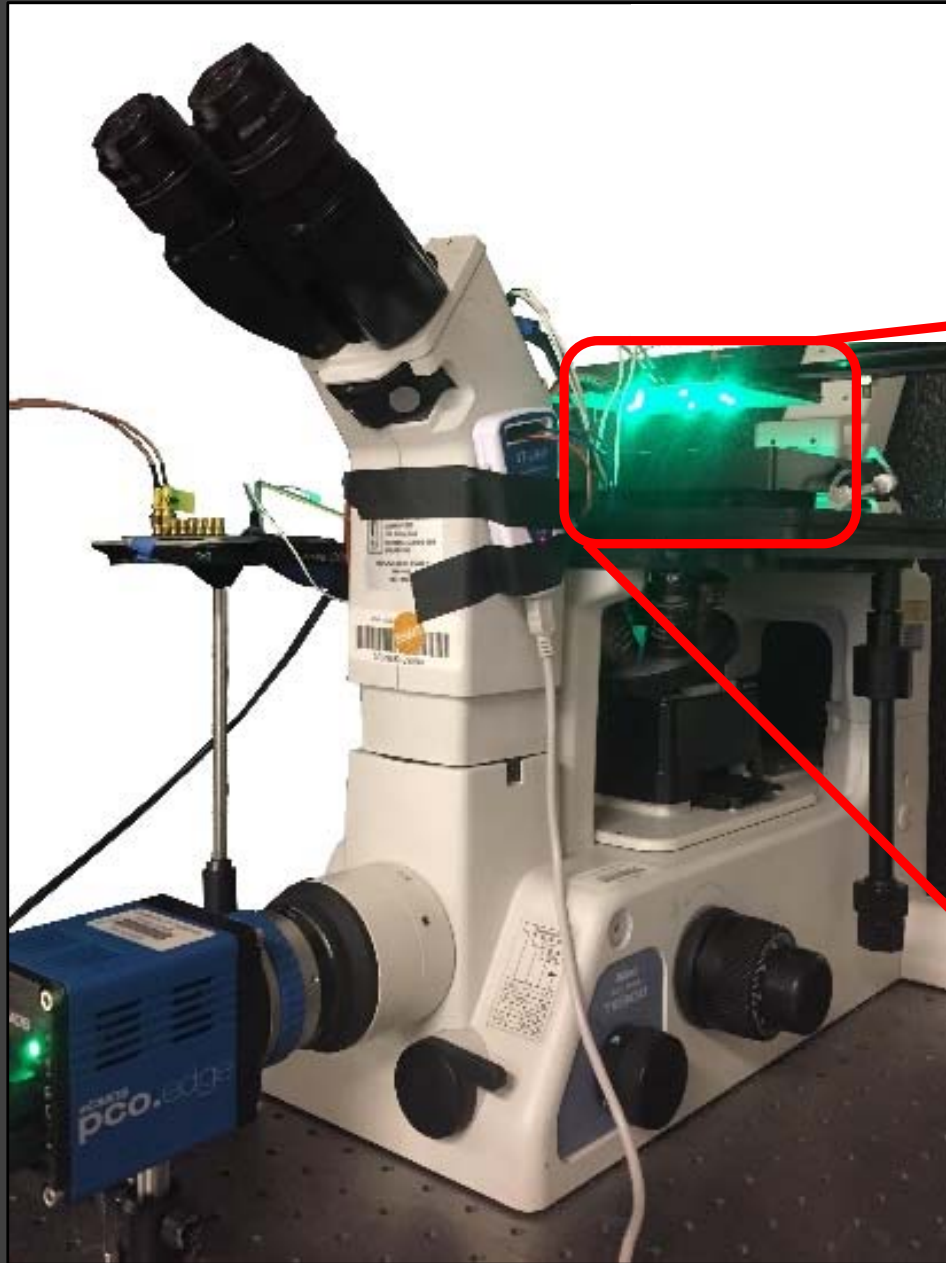
This talk:



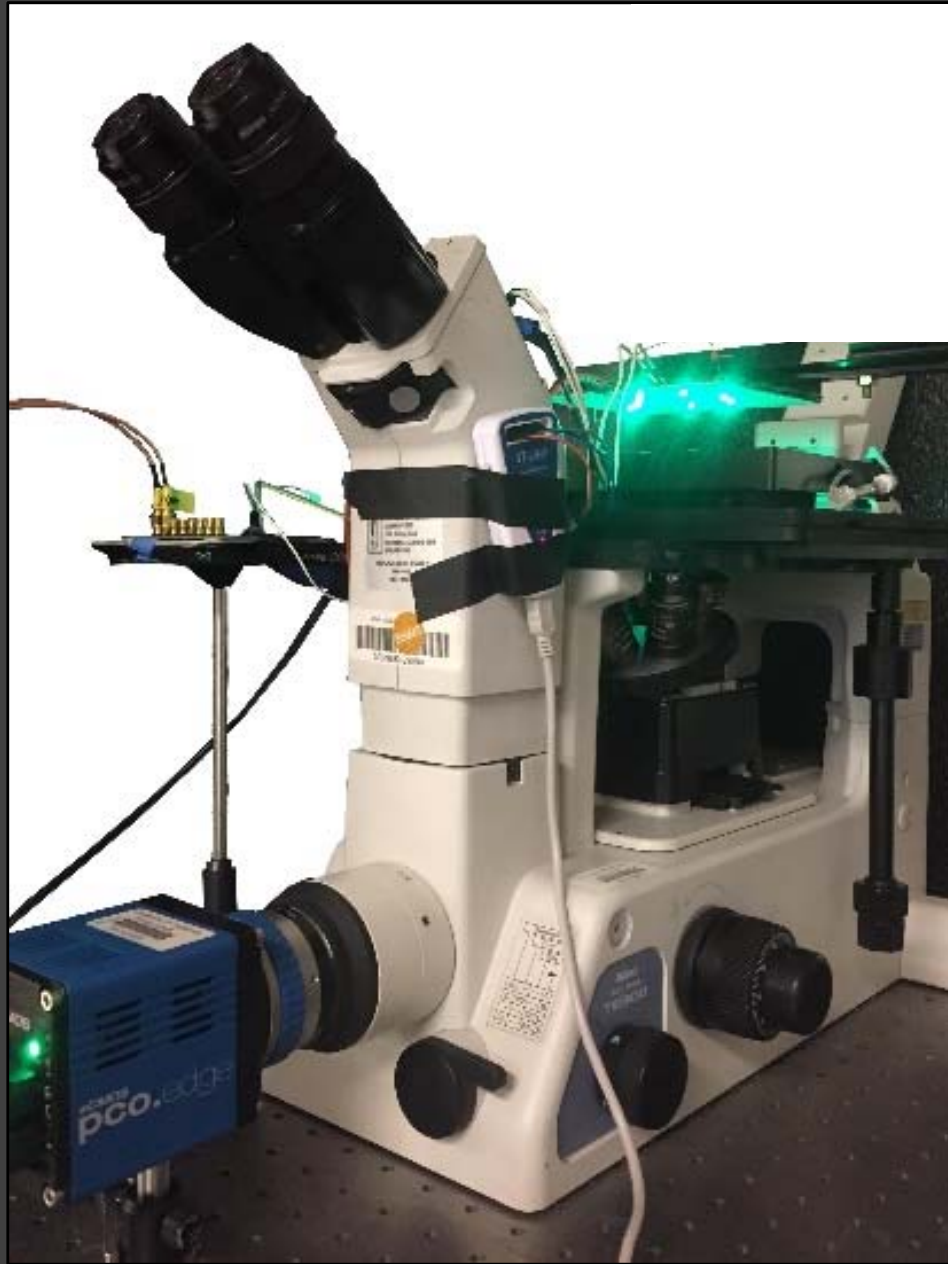


micro-controller

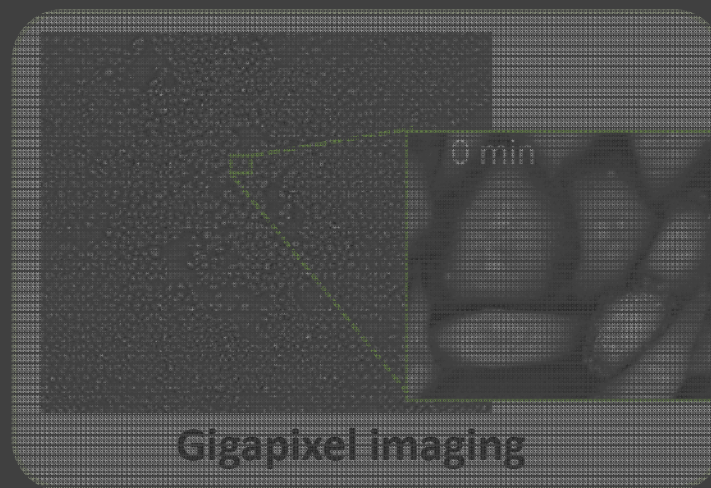
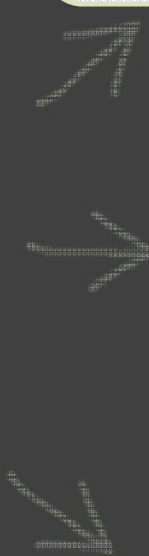




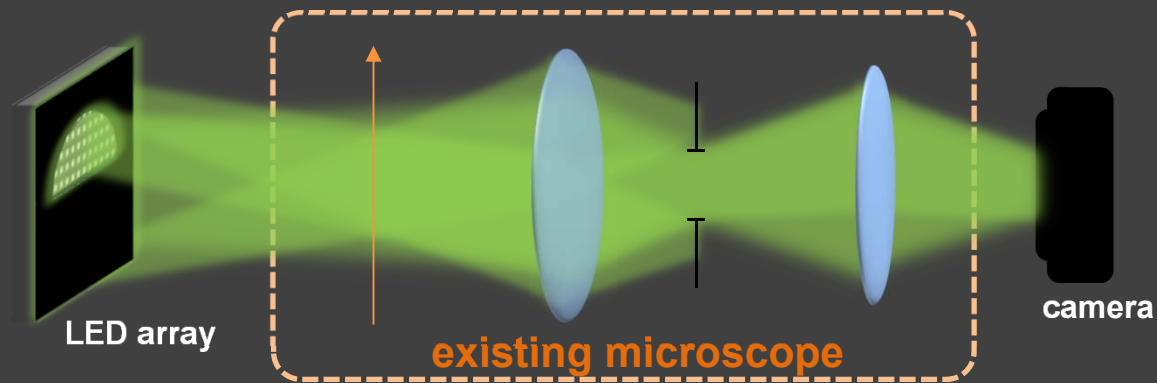
LEDs pattern illumination angles



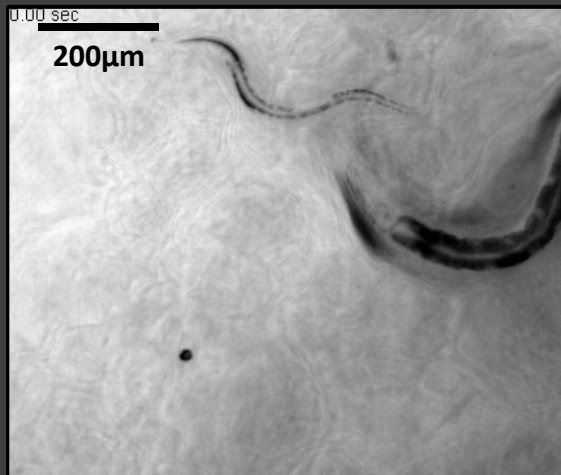
Real-time multi-contrast



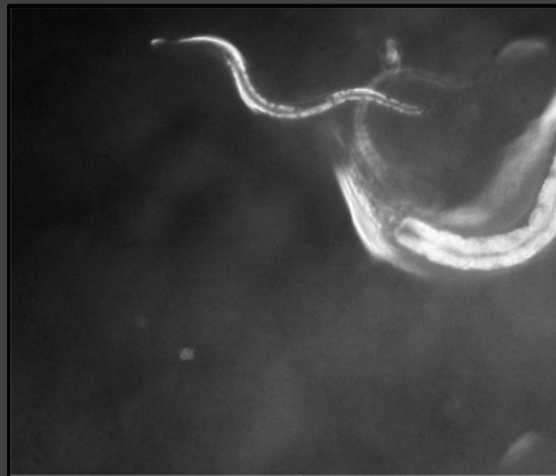
Multi-contrast with an LED array microscope



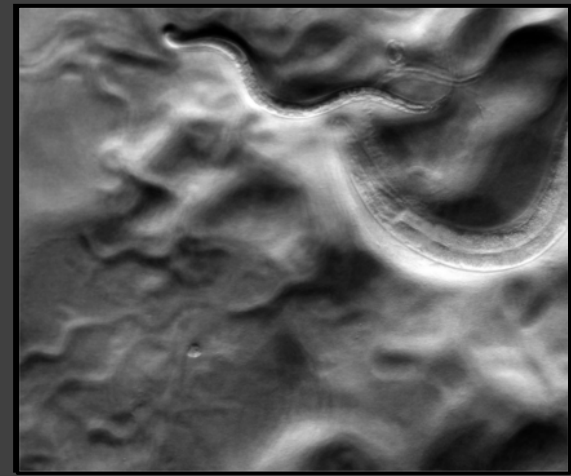
brightfield



darkfield^[1]



phase contrast^[2]

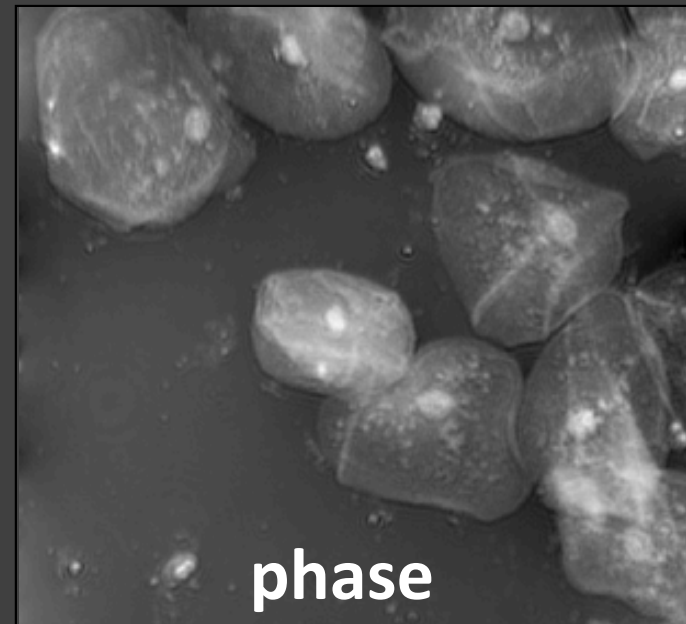
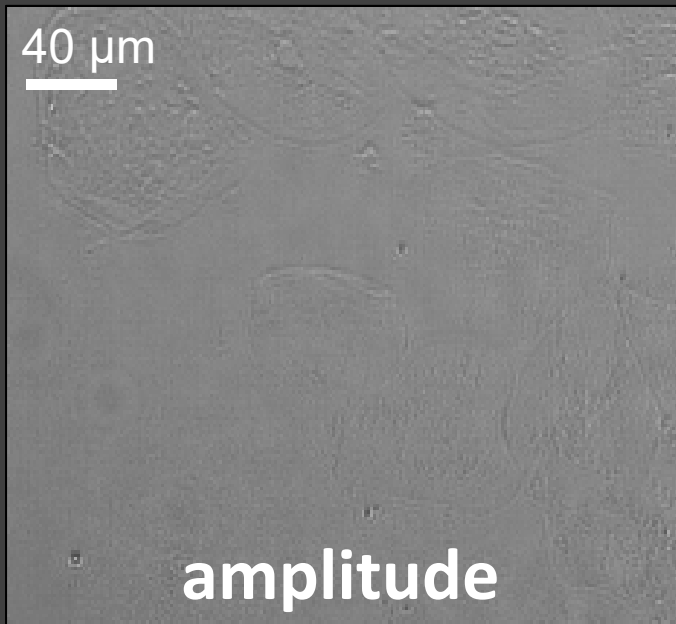


[1] G. Zheng, C. Kolner, C. Yang, *Opt. Lett.* (2011).

[2] L. Tian, J. Wang, L. Waller, *Opt. Lett.* (2014).

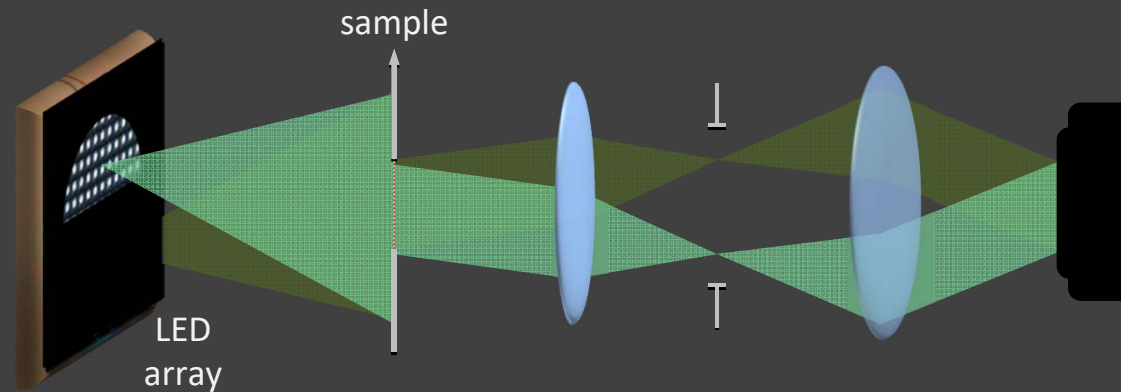
Computational ^{Phase} imaging

phase imaging *must* be computational

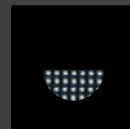


We can only measure intensity $y = |\mathbf{Ax}|^2$

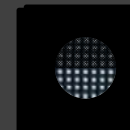
Differential Phase Contrast (DPC)



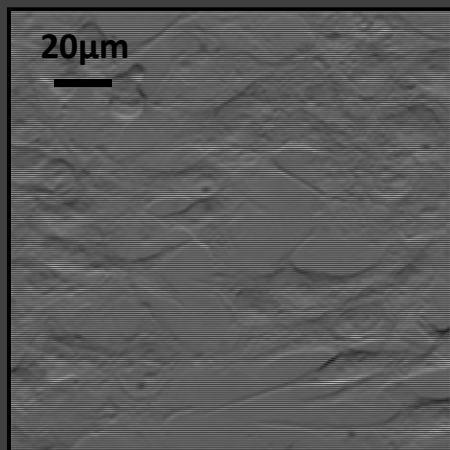
top



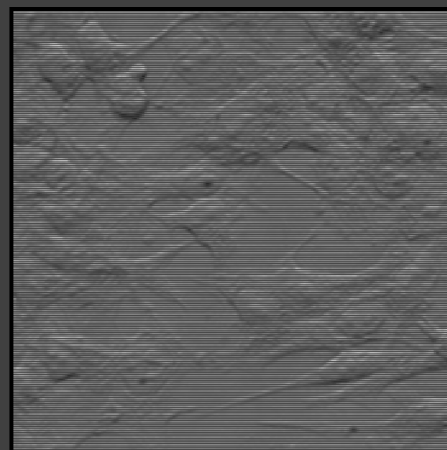
bottom



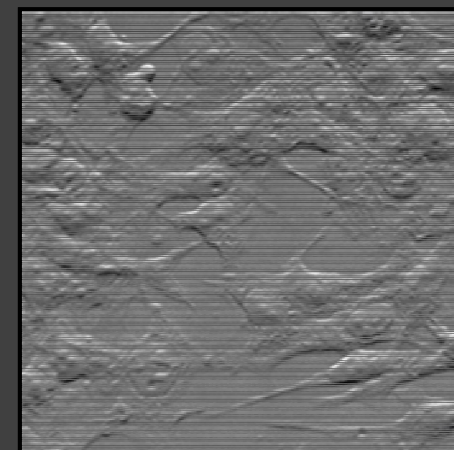
$$\text{DPC} = \frac{\text{top} - \text{bottom}}{\text{top} + \text{bottom}}$$



-



=



Kachar, *Science* 227, 27 (1985).

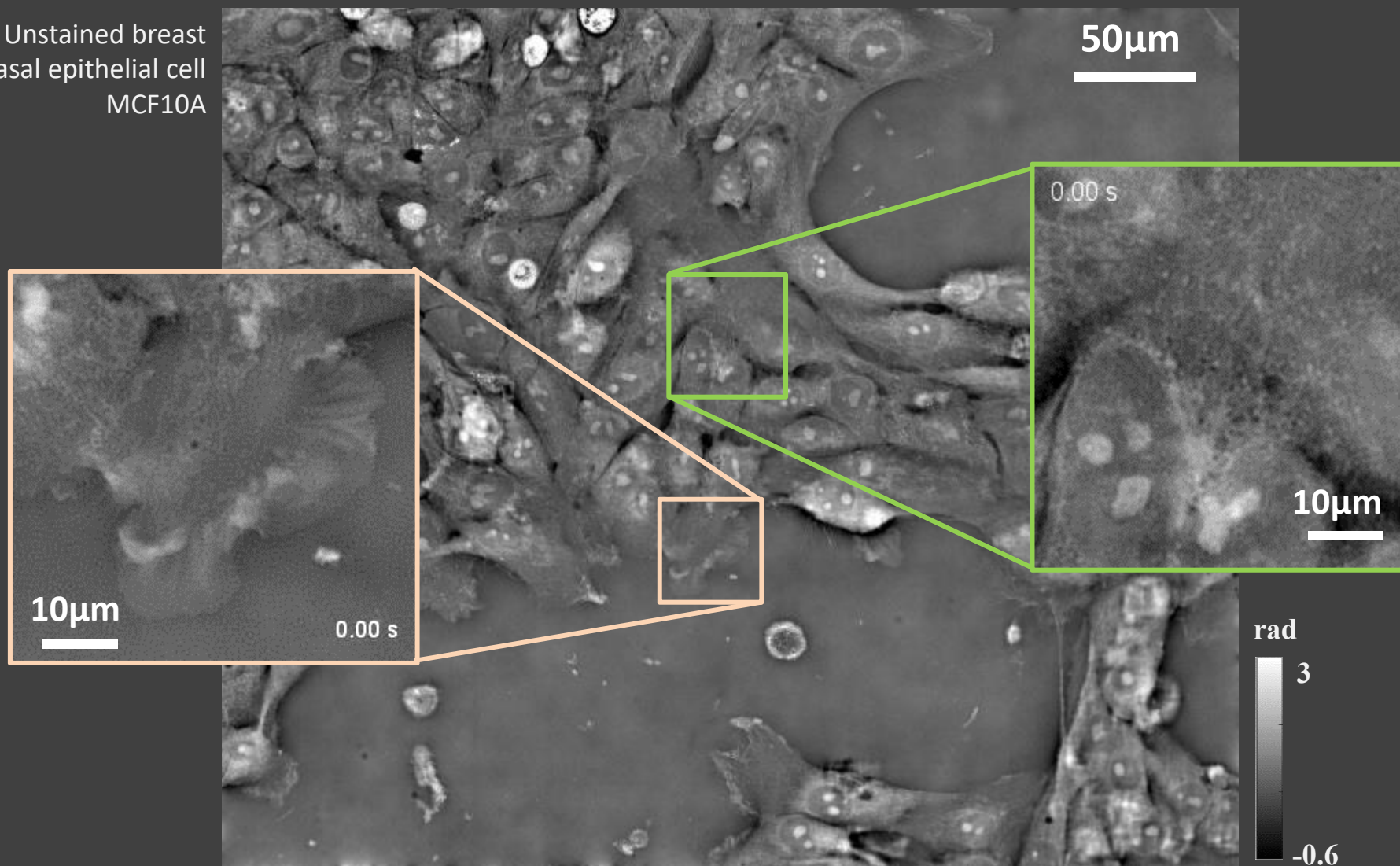
Ford, Chu, Mertz, *Nat. Methods* 9, 1195 (2012).

Mehta, Sheppard, *Opt. Lett.* 34, 1924 (2009).

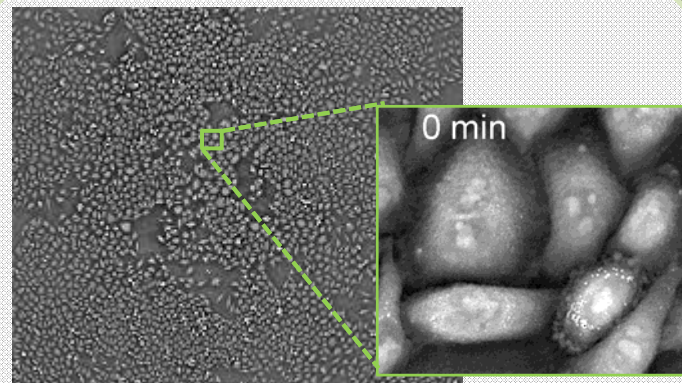
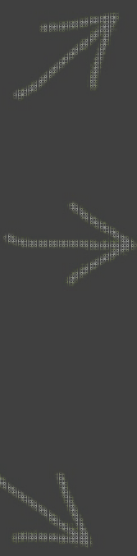
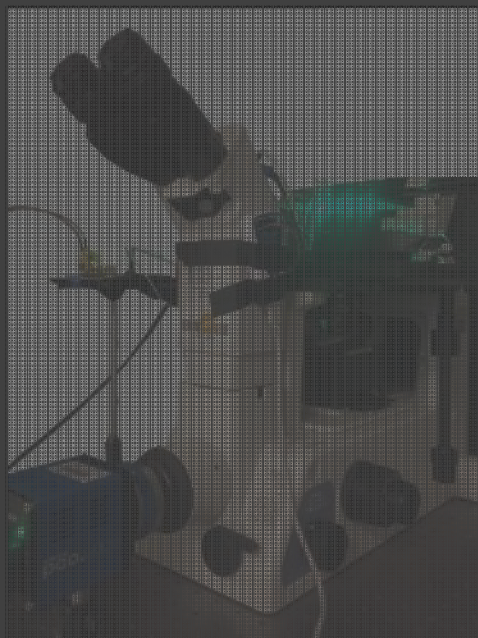
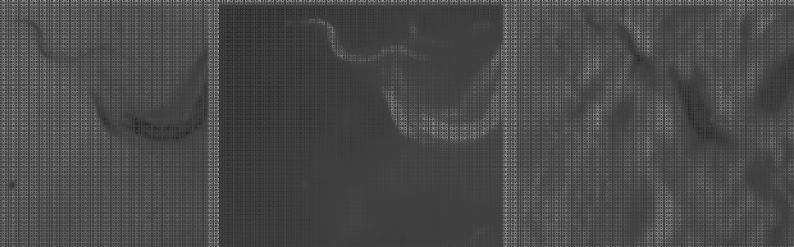
Tian, Waller, *Opt. Express* 23(9), 11394-11403 (2015).

Real-time phase *in vitro*

Unstained breast
basal epithelial cell
MCF10A

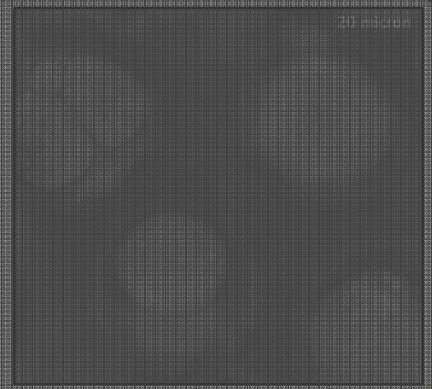


Real-time multi-contrast

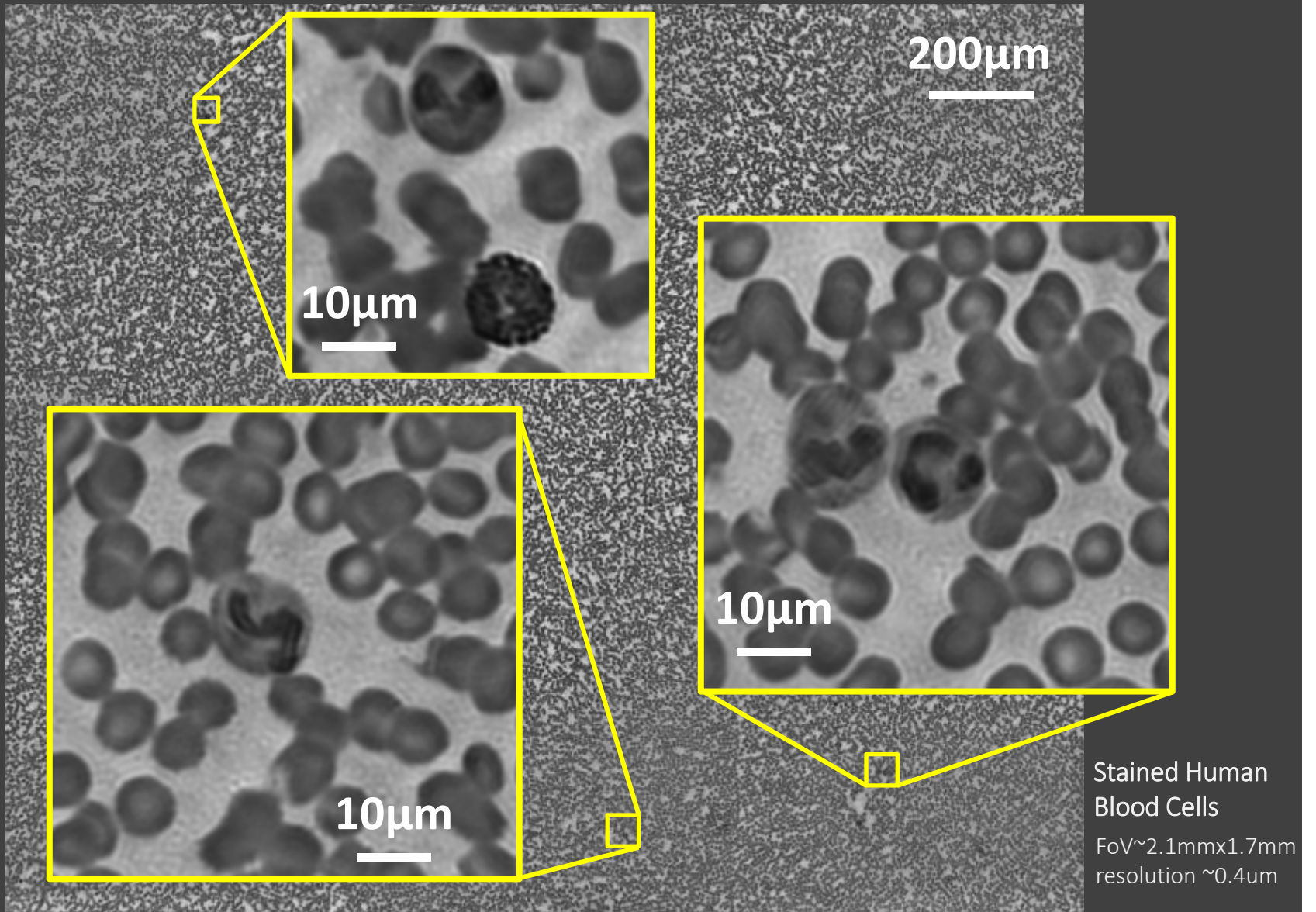


Gigapixel imaging

3D
imaging



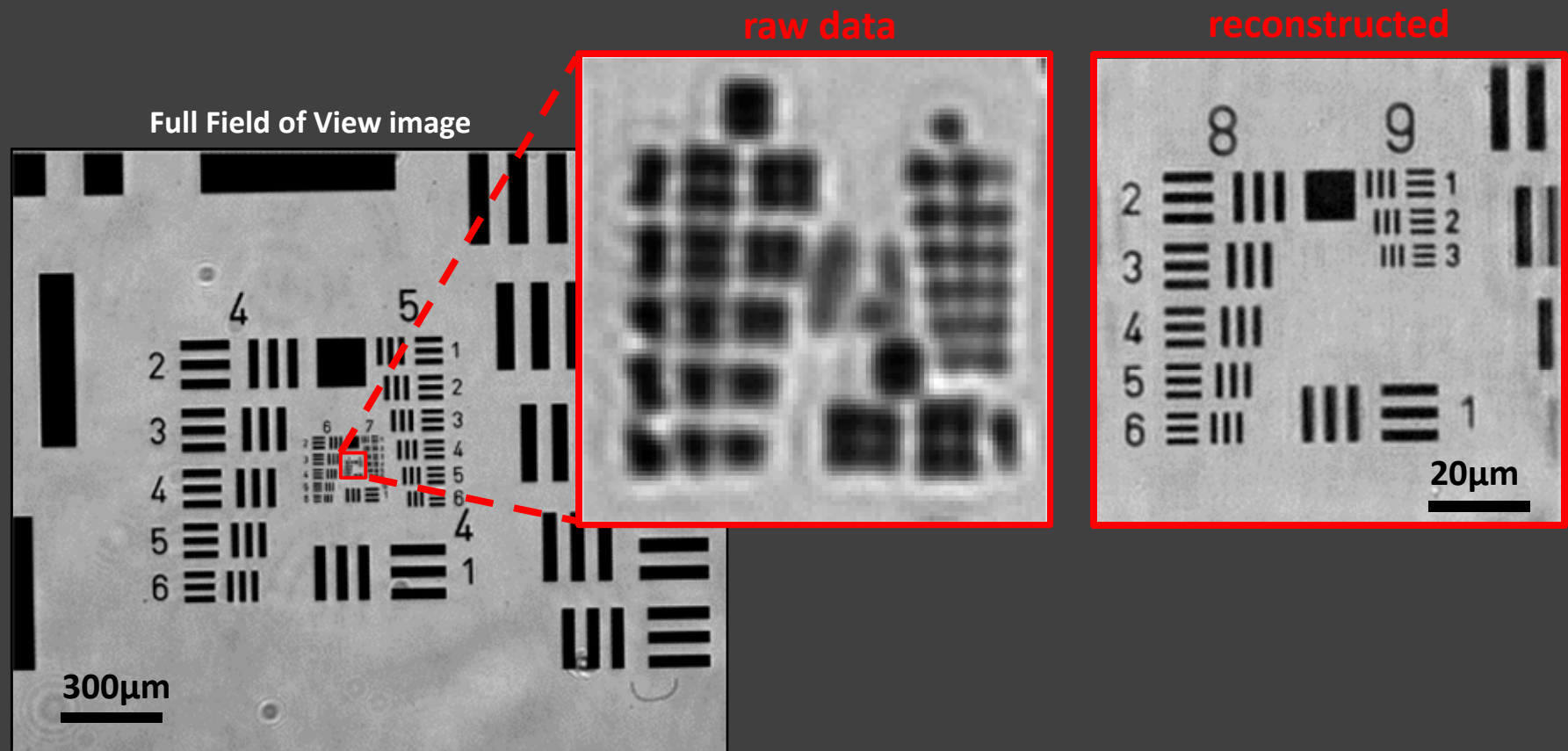
Gigapixel imaging for disease screening



Our version of: G.Zheng, R. Horstmeyer, C. Yang, *Nat. Photon.* (2013).
L.Tian, X.Li, K.Ramchandran, L. Waller, *Biomed. Opt. Express* (2014).

26k x 22k pixels

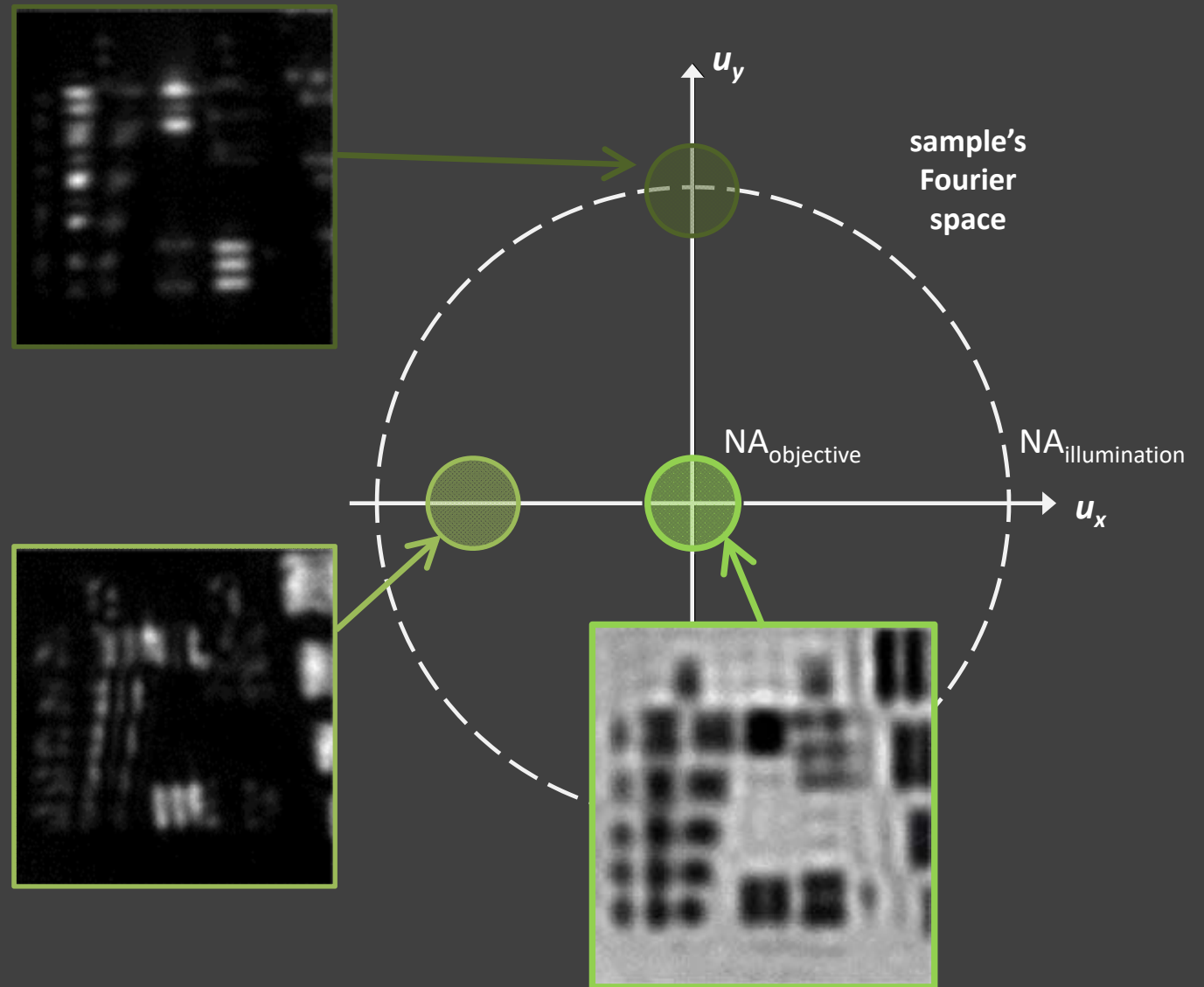
Gigapixel imaging by Fourier Ptychography



G.Zheng, R. Horstmeyer, C. Yang, *Nat. Photon.* (2013).

L.Tian, X.Li, K.Ramchandran, L. Waller, *Biomed. Opt. Express* (2014).

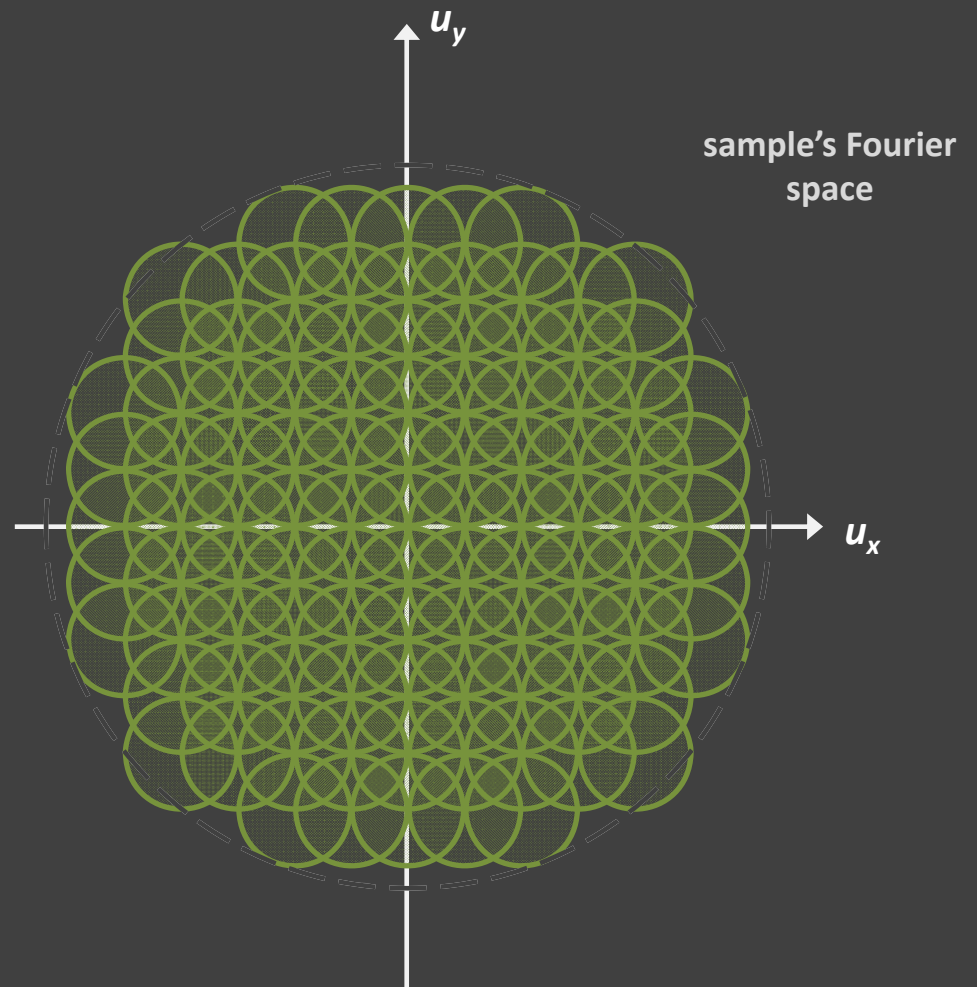
Darkfield images give super-resolution



Our version of ideas in:
G.Zheng, R. Horstmeyer, C. Yang, *Nat. Photon.* (2013).

Darkfield images give super-resolution

But we have *intensity-only* measurements?



Inverse problem uses nonlinear optimization

Forward model:

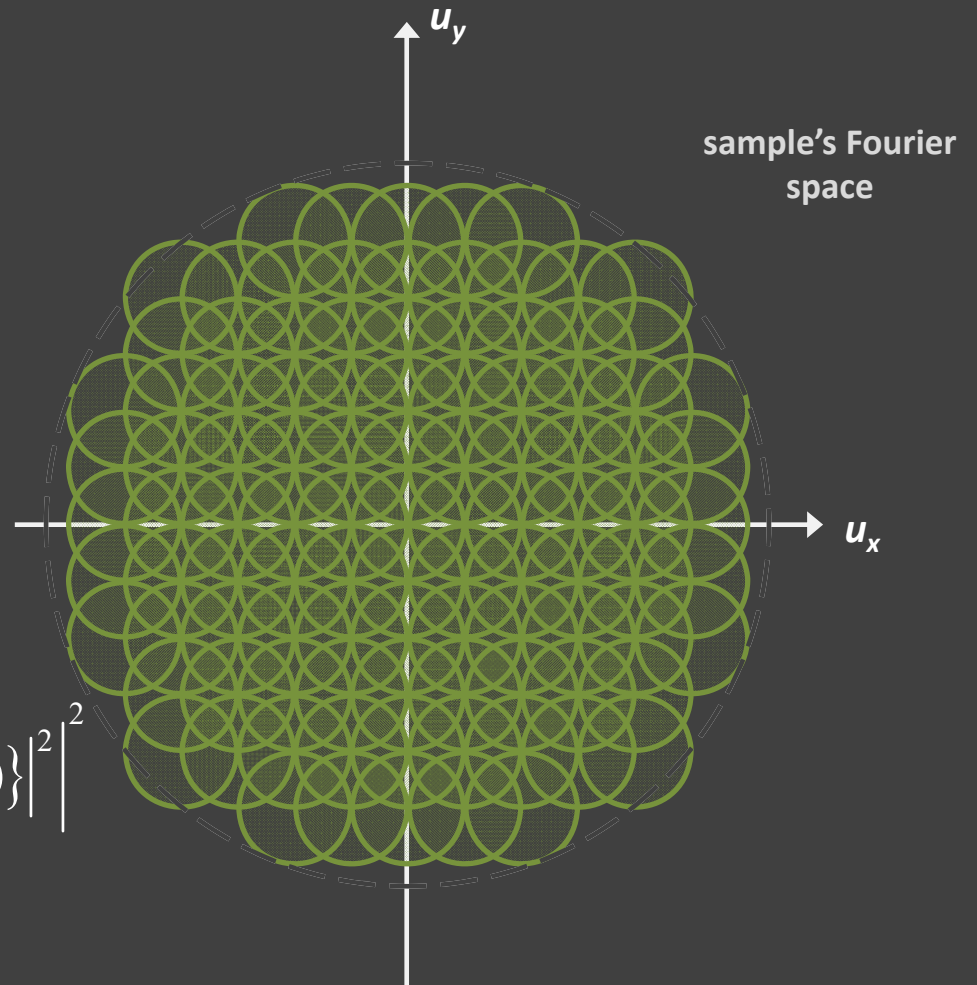
$$\mathbf{y} = |\mathbf{A}\mathbf{x}|^2$$

measurements system matrix object

Inverse problem:

$$\min_{\mathbf{O}(\mathbf{u})} \sum_n \sum_r \left| \mathbf{I}_n(\mathbf{r}) - \left| \mathfrak{F}^{-1} \left\{ \mathbf{O}(\mathbf{u} - \mathbf{u}_n) \cdot \mathbf{P}(\mathbf{u}) \right\} \right|^2 \right|^2$$

Solve for me!

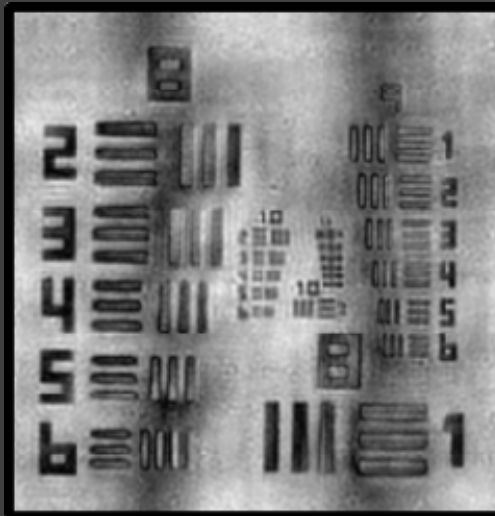


J. Rodenburg, H. Faulkner, *Appl. Phys. Lett.* 85 (2004).
M. Guizar-Sicairos, J. Fienup, *Opt. Express* 16 (2008).
L.Tian, X.Li, K.Ramchandran, L. Waller, *Biomed. Opt. Express* (2014).
S. Alexandrov, T. Hillman, T. Gutzler, D. Sampson, *Phys. Rev. Lett.* 97 (2006).

A. Kirkland, et al., *Ultramicroscopy* 57 (1995).
G.Zheng, R. Horstmeyer, C. Yang, *Nat. Photon.* (2013).
O. Xu, C. Yang, *Opt. Express* (2013).
P. Thibault, et al., *Ultramicroscopy* 109 (2009).
T. Hillman et al., *Opt. Express* (2009).

2nd order optimization is better

1st order
(Gerchberg-Saxton)

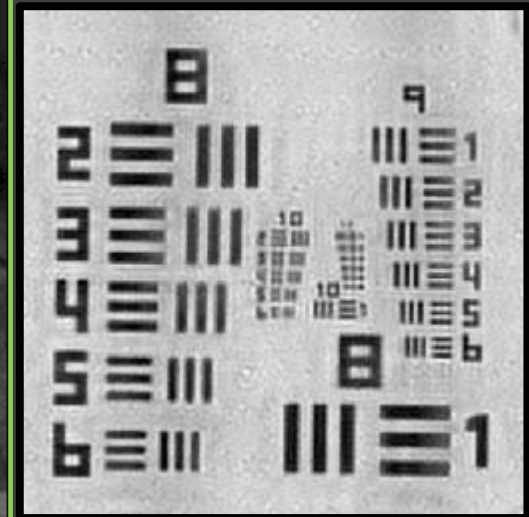


3 seconds

quasi 2nd order



2nd order
(Newton)



100 seconds

Li-Hao Yeh

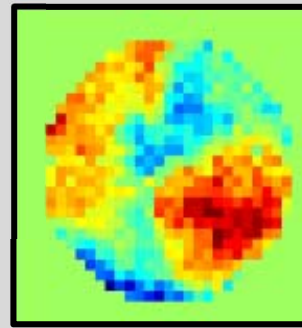


Algorithmic self-calibration

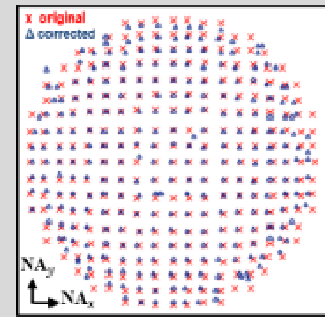
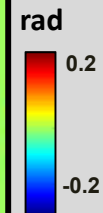
$$y = |Ax|^2$$

measurements system matrix object

Experimental errors:

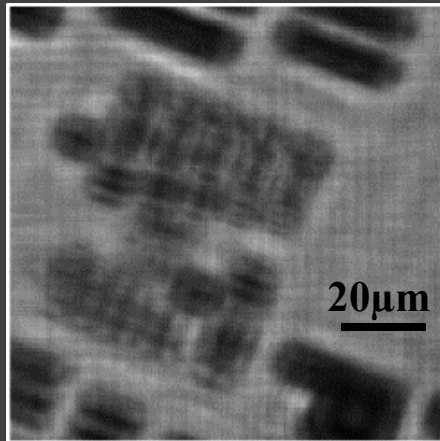


Aberrations

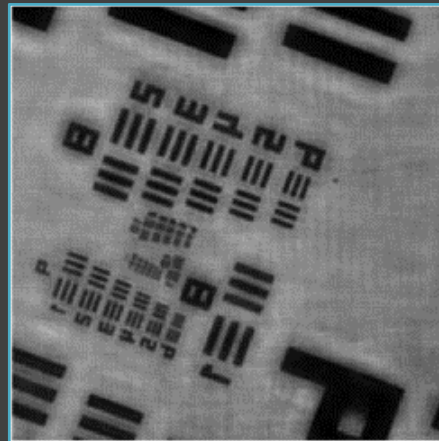


LED positions

not calibrated



calibrated



calibration parameters

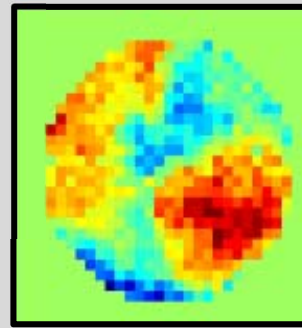
$$A \rightarrow A(\theta)$$

Algorithmic self-calibration

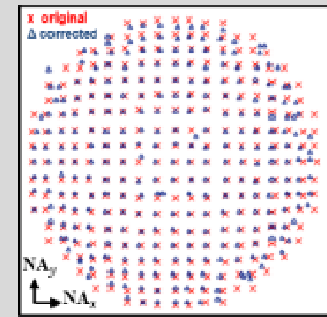
$$\mathbf{y} = |\mathbf{A}\mathbf{x}|^2$$

measurements system matrix object

Experimental errors:



Aberrations



LED positions

Learn more:

Tues 5pm (JTU5A.2)

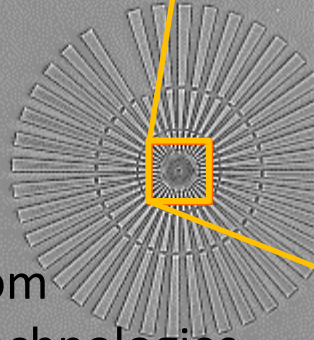
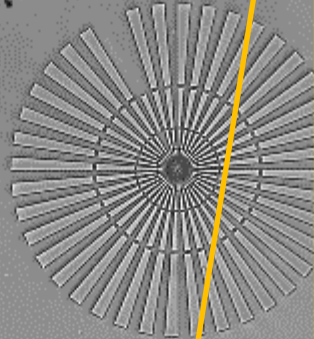
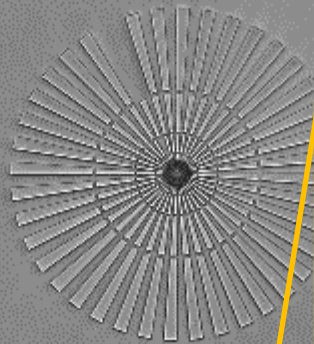
But I don't want to calibrate!

$$\min_{\mathbf{x}, \boldsymbol{\theta}} \left\| \mathbf{y} - \left\| \mathbf{A}(\boldsymbol{\theta}) \mathbf{x} \right\| \right\| + \lambda_1 \|\mathbf{x}\|_1 + \lambda_2 \|\boldsymbol{\theta}\|_2$$

calibration parameters

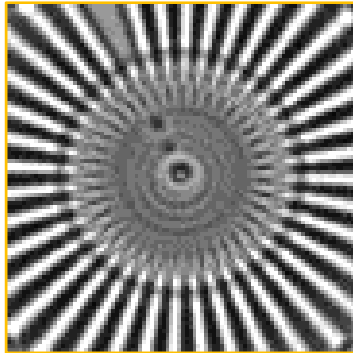


200 μm

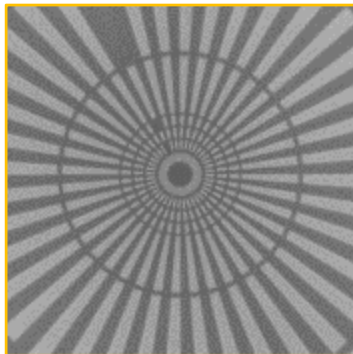


test object from
Benchmark Technologies

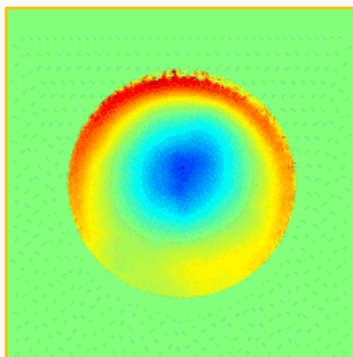
raw image



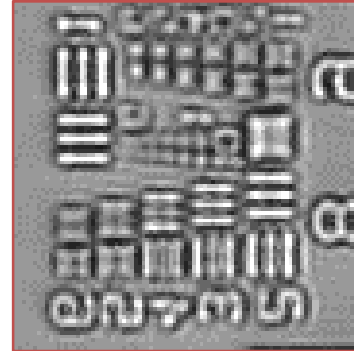
recovered phase



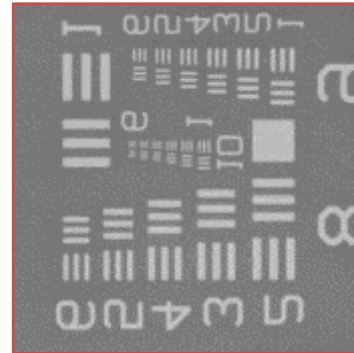
aberrations



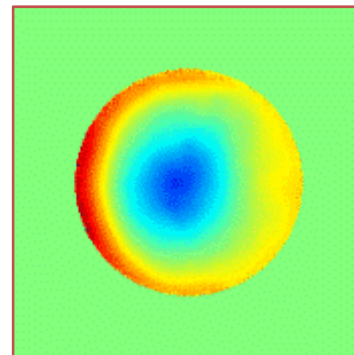
raw image



recovered phase

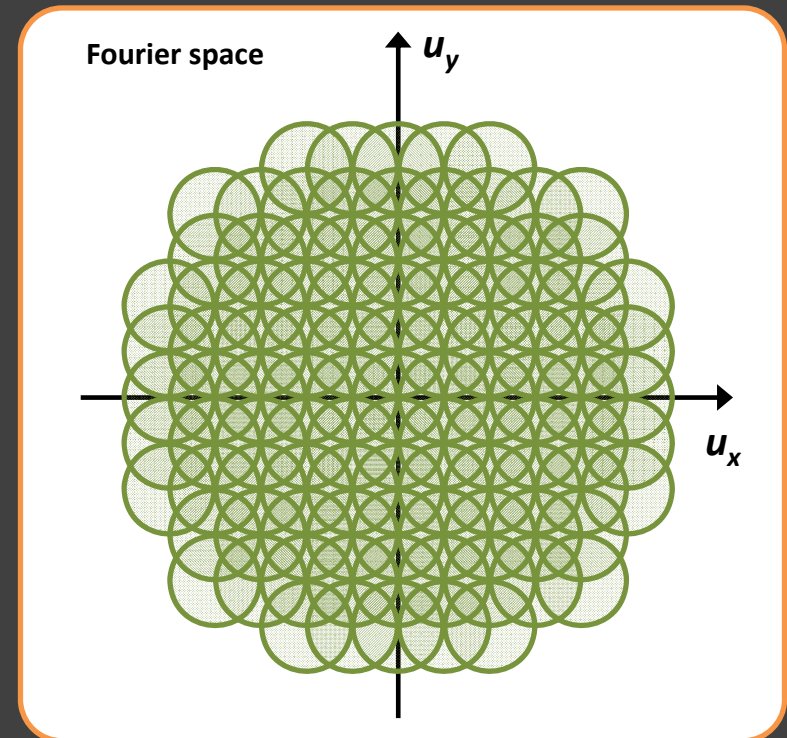


aberrations

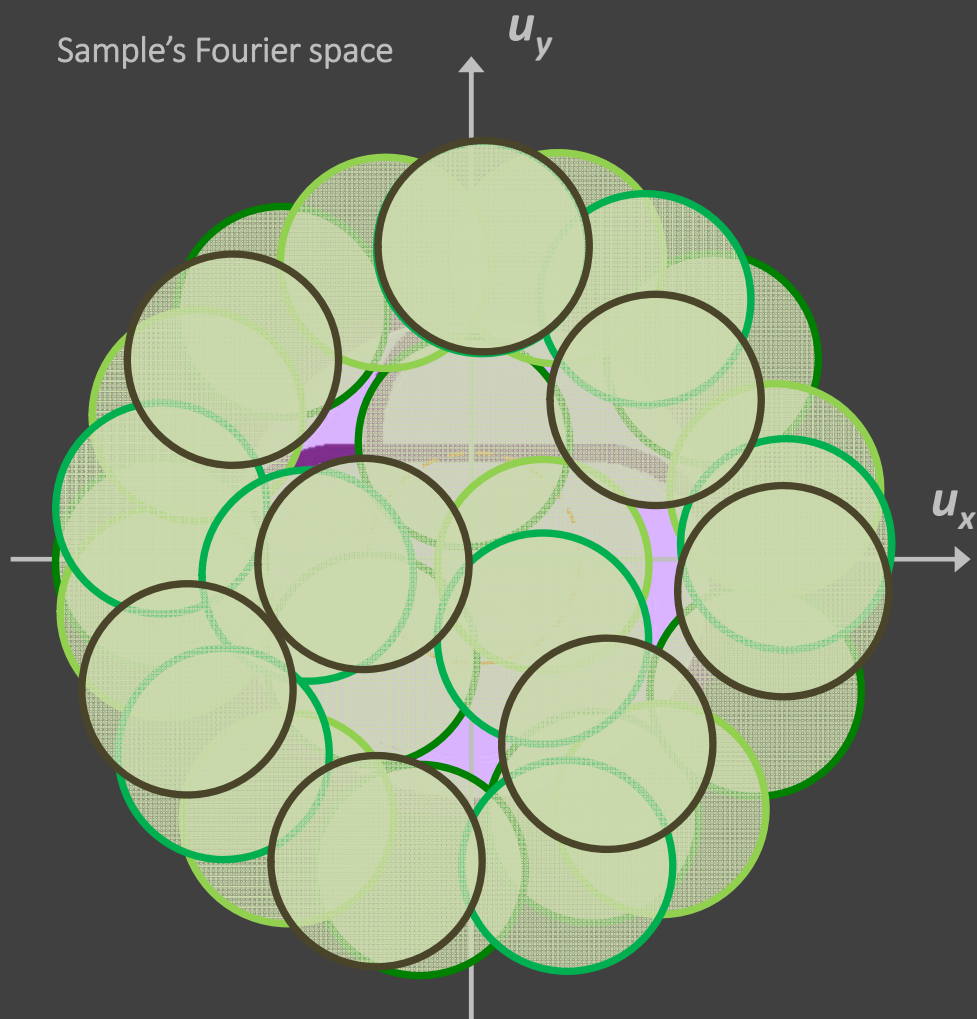


Redundancy is necessary, but inefficient...

requires **~10x** more data
collected than reconstructed

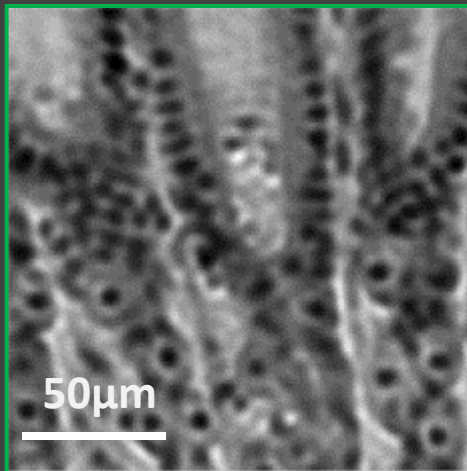


Multiplexed measurements are faster



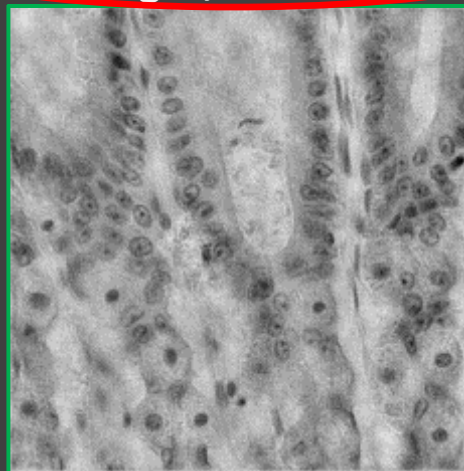
Multiplexing reduces time *and* data size

low resolution zoom-in



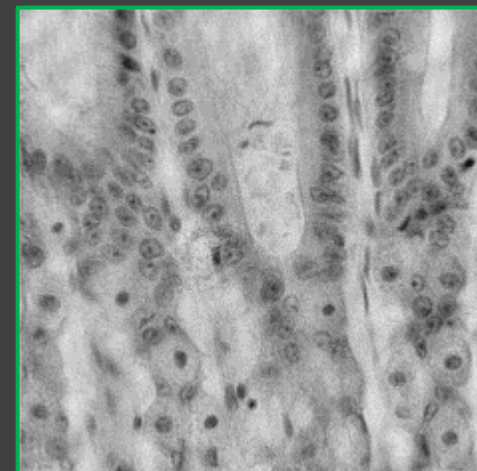
Original method

293 images, Time ~10min



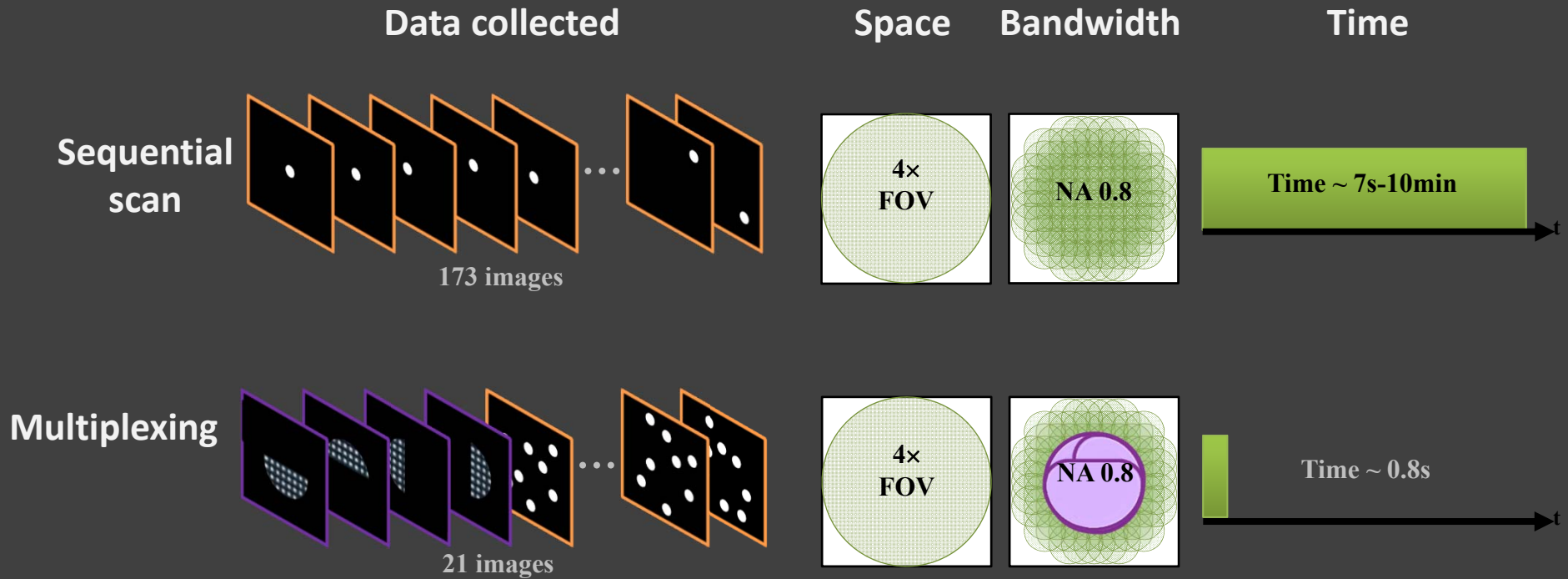
Multiplexing

40 images, Time 0.4s



Only uses 17% of data!

Space-bandwidth-time product



0 min

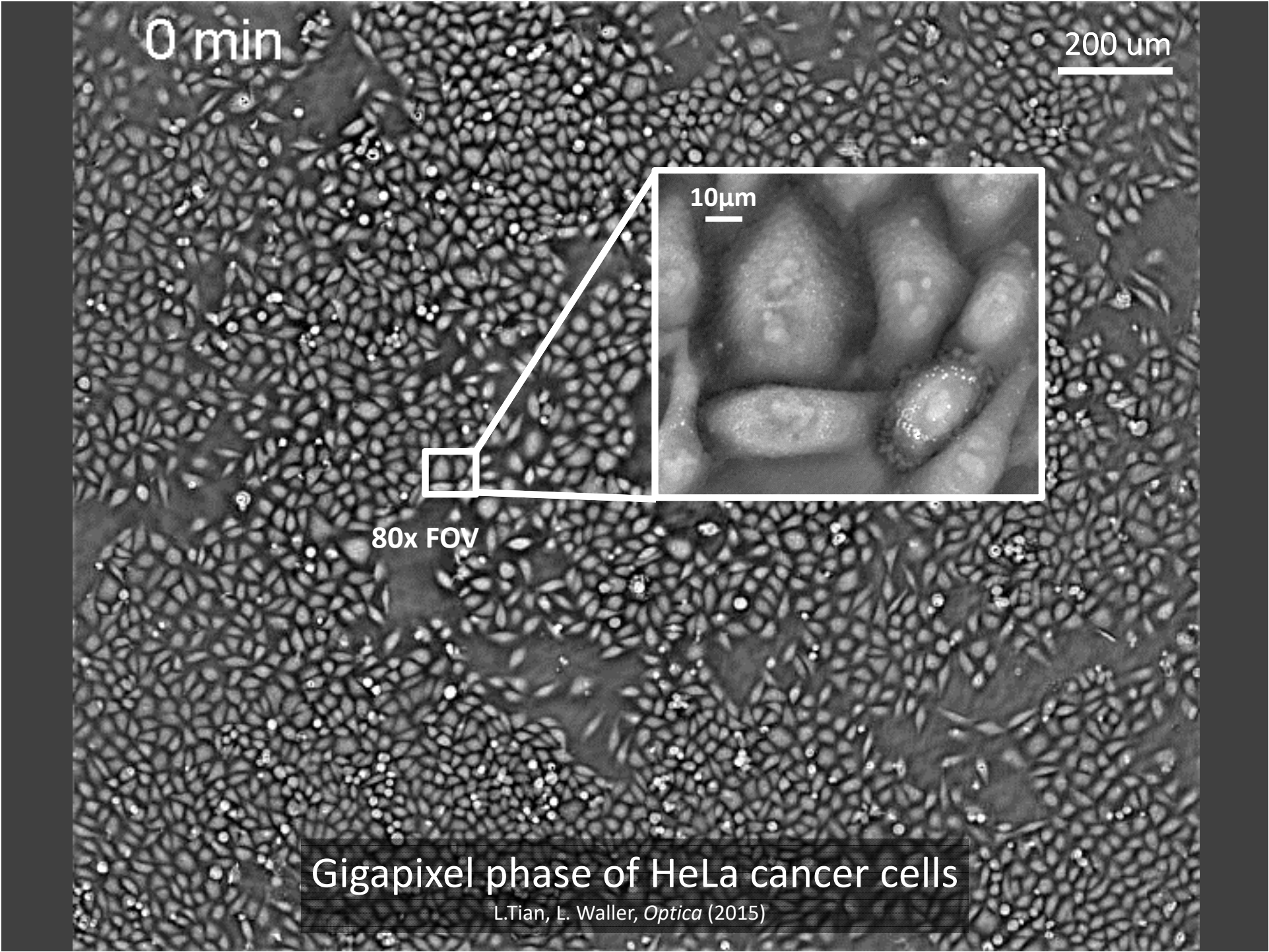
200 μm

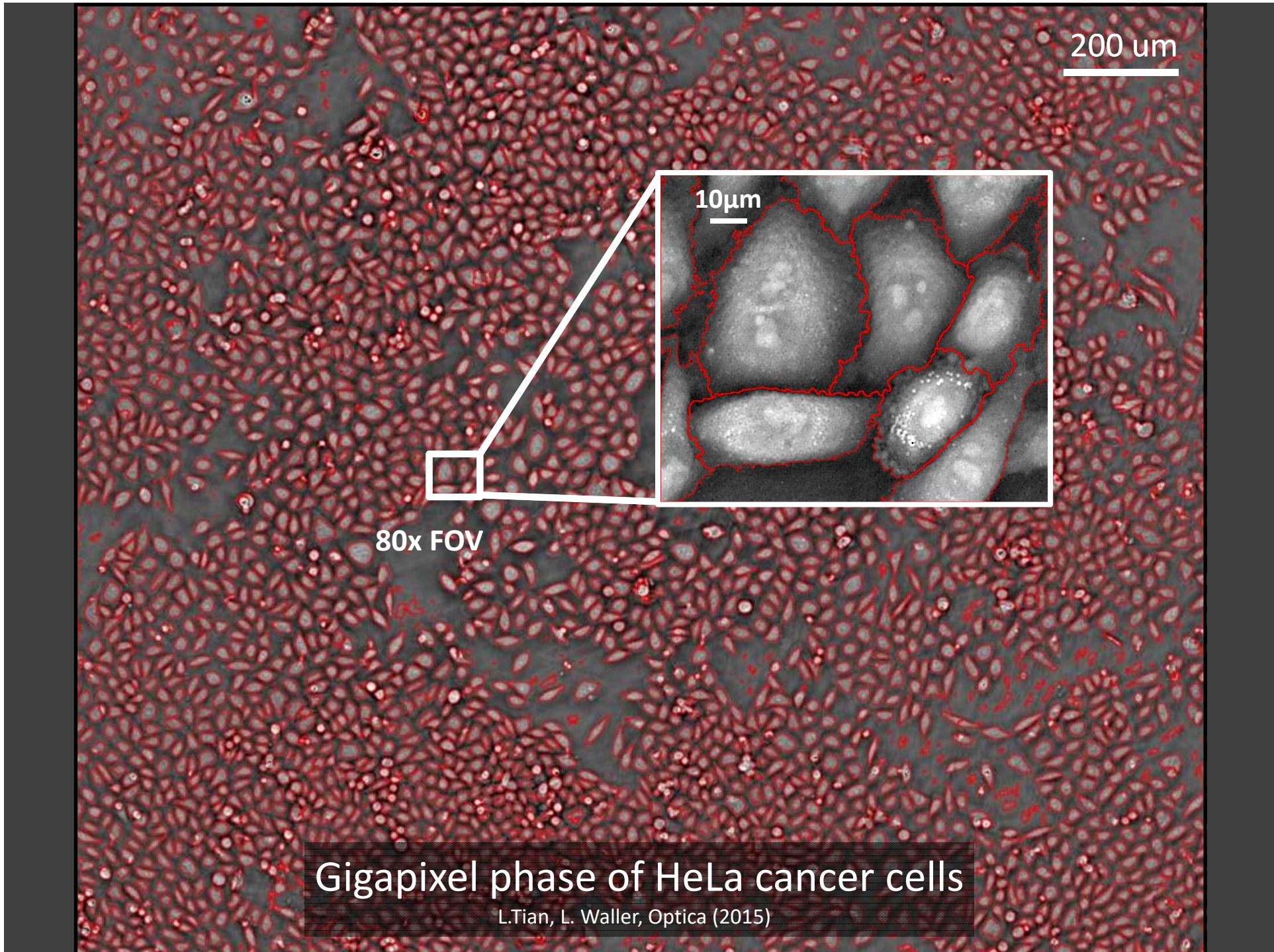
10 μm

80x FOV

Gigapixel phase of HeLa cancer cells

L.Tian, E. Waller, *Optica* (2015)





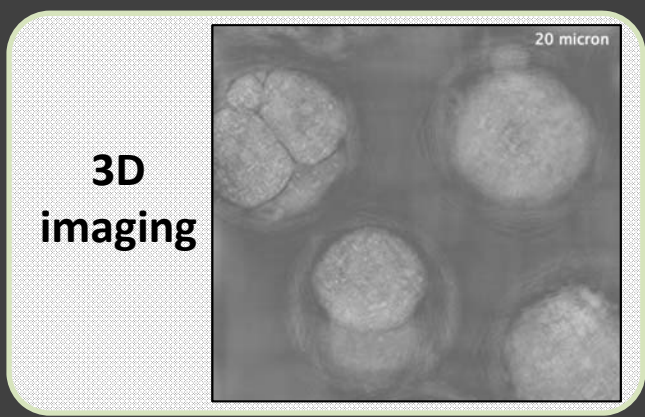
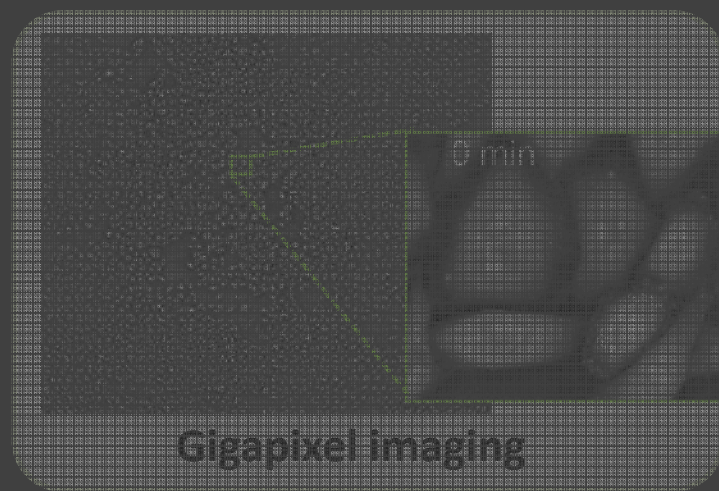
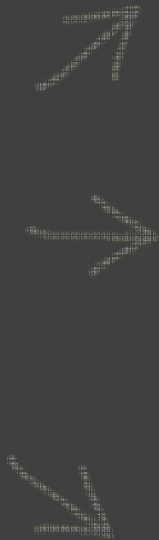
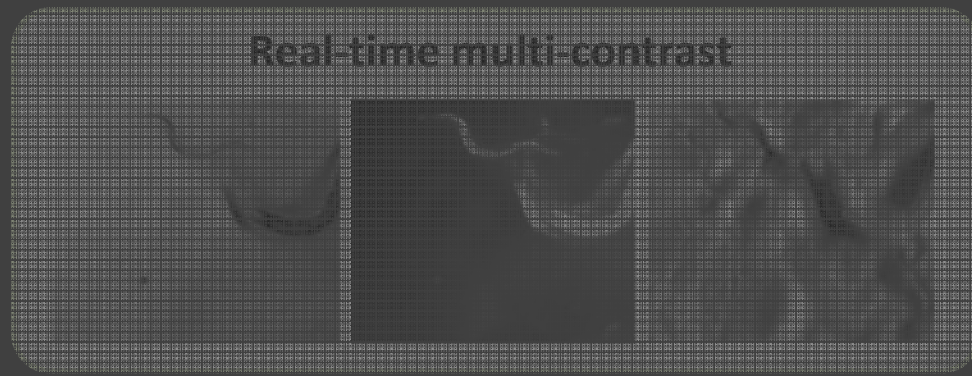
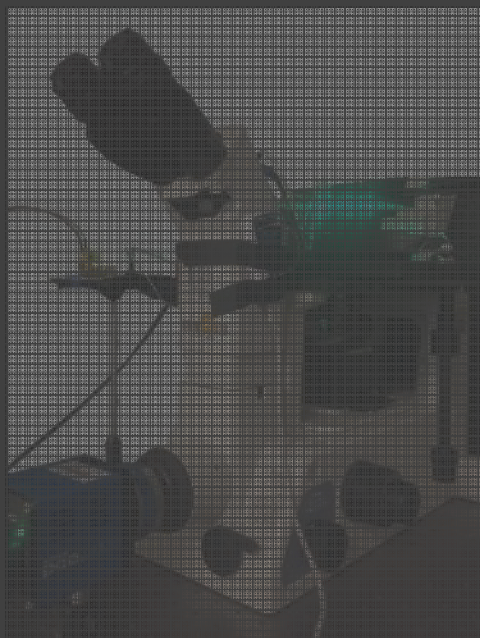
200 μm

10 μm

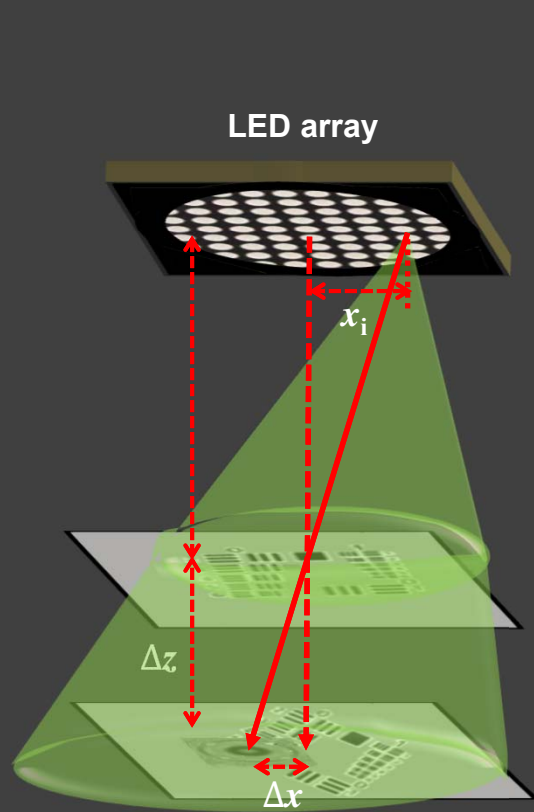
80x FOV

Gigapixel phase of HeLa cancer cells

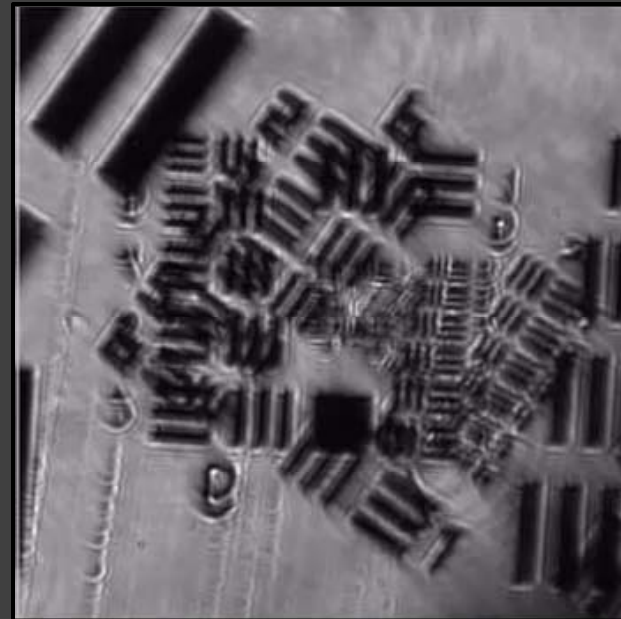
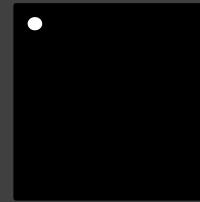
L.Tian, L. Waller, Optica (2015)

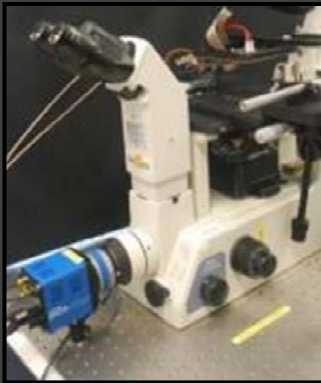


Angle scanning gives 3D information

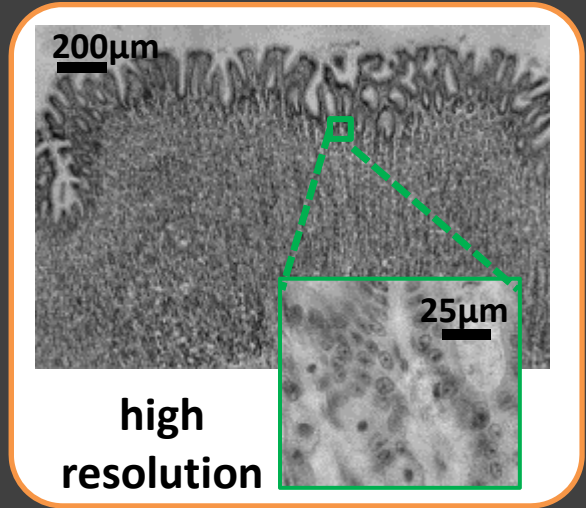
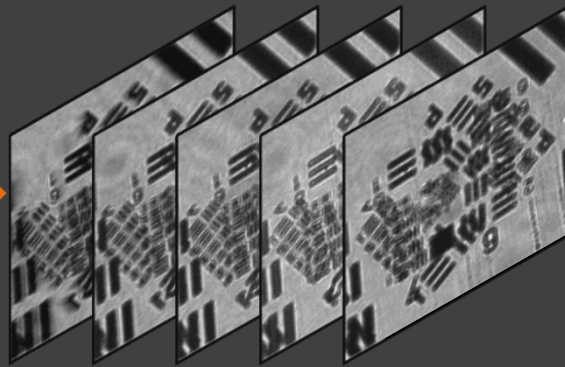


scan illumination
in (θ_x, θ_y)

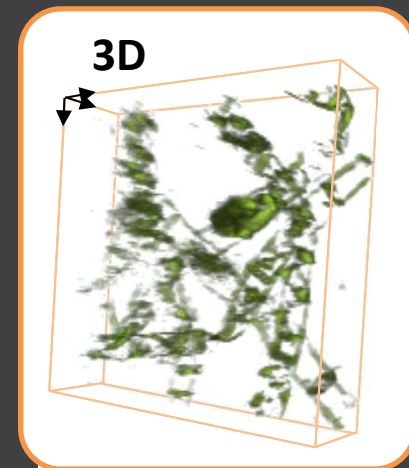




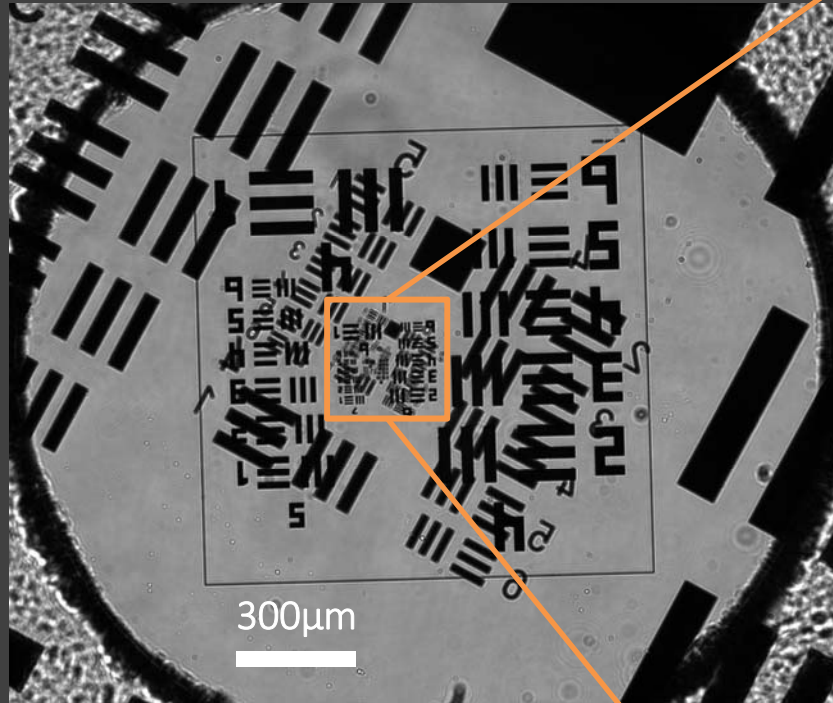
vary illumination angle



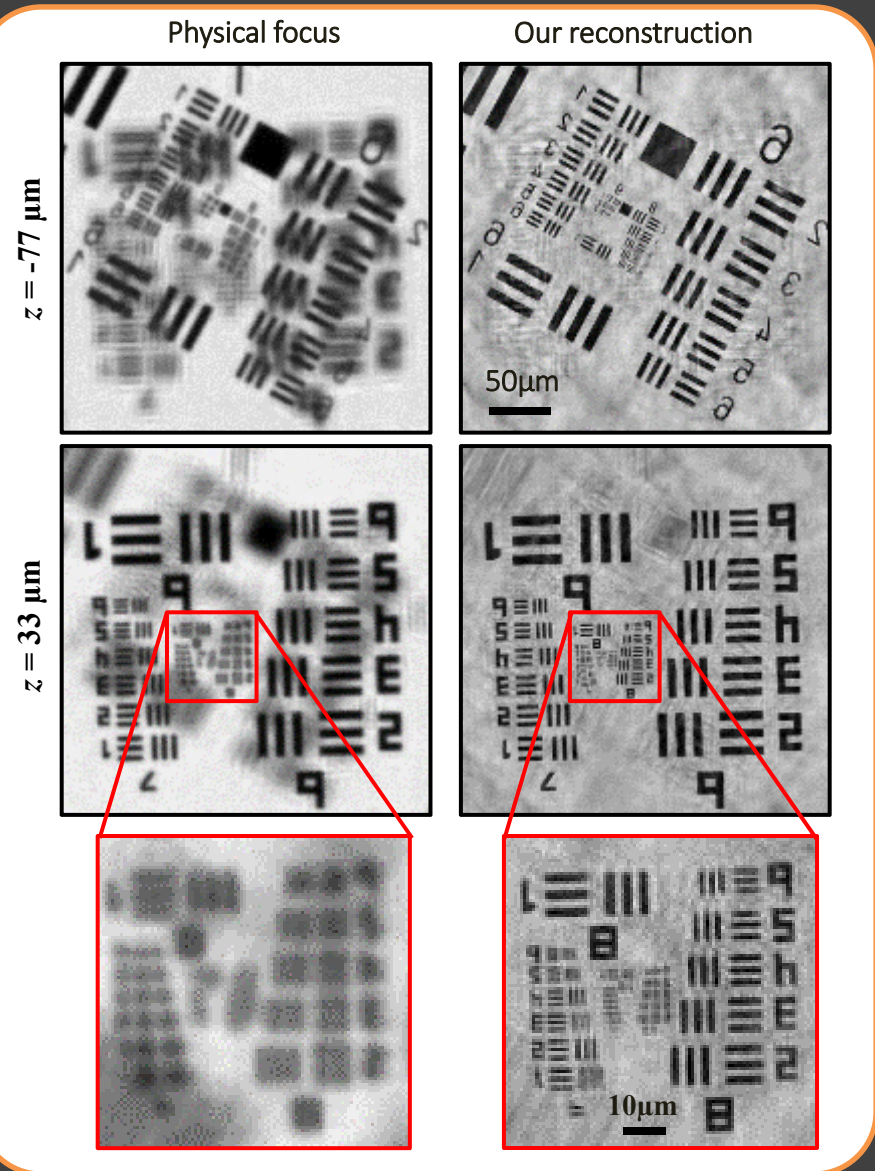
OR? AND?



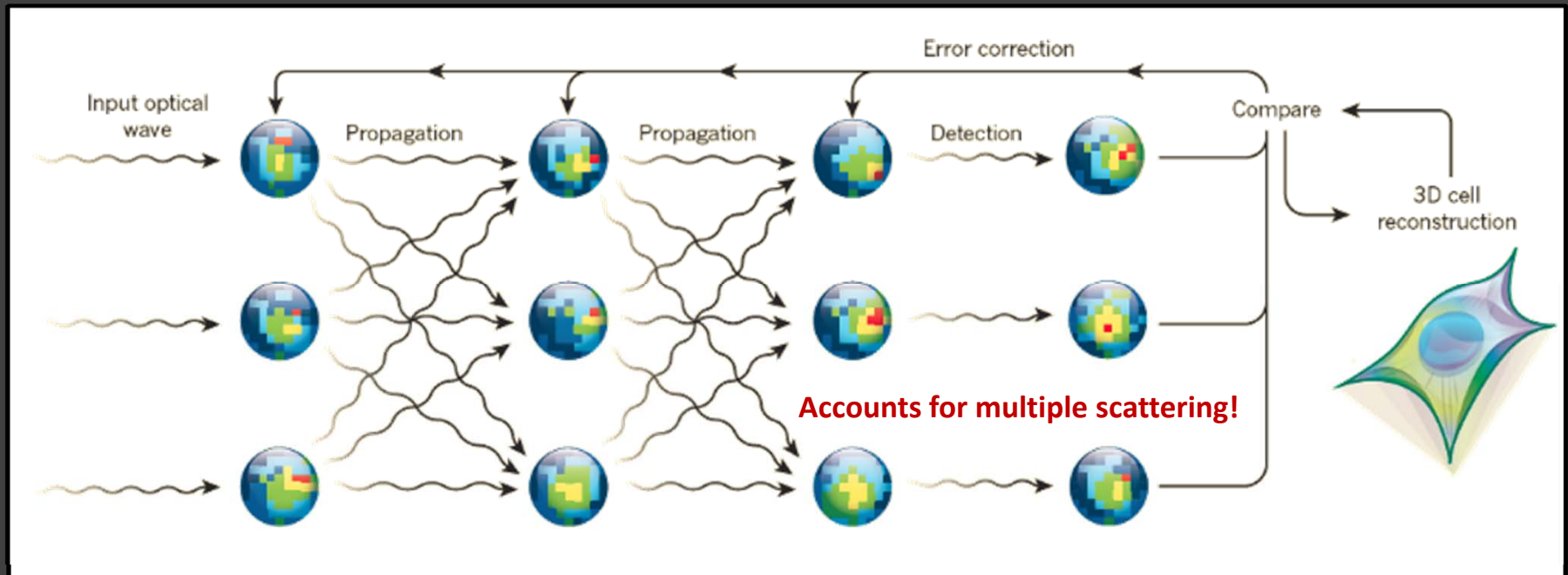
Can we super-resolution and 3D?



Low-resolution full FoV image
from 4× 0.1 NA objective



3D phase imaging as a neural network

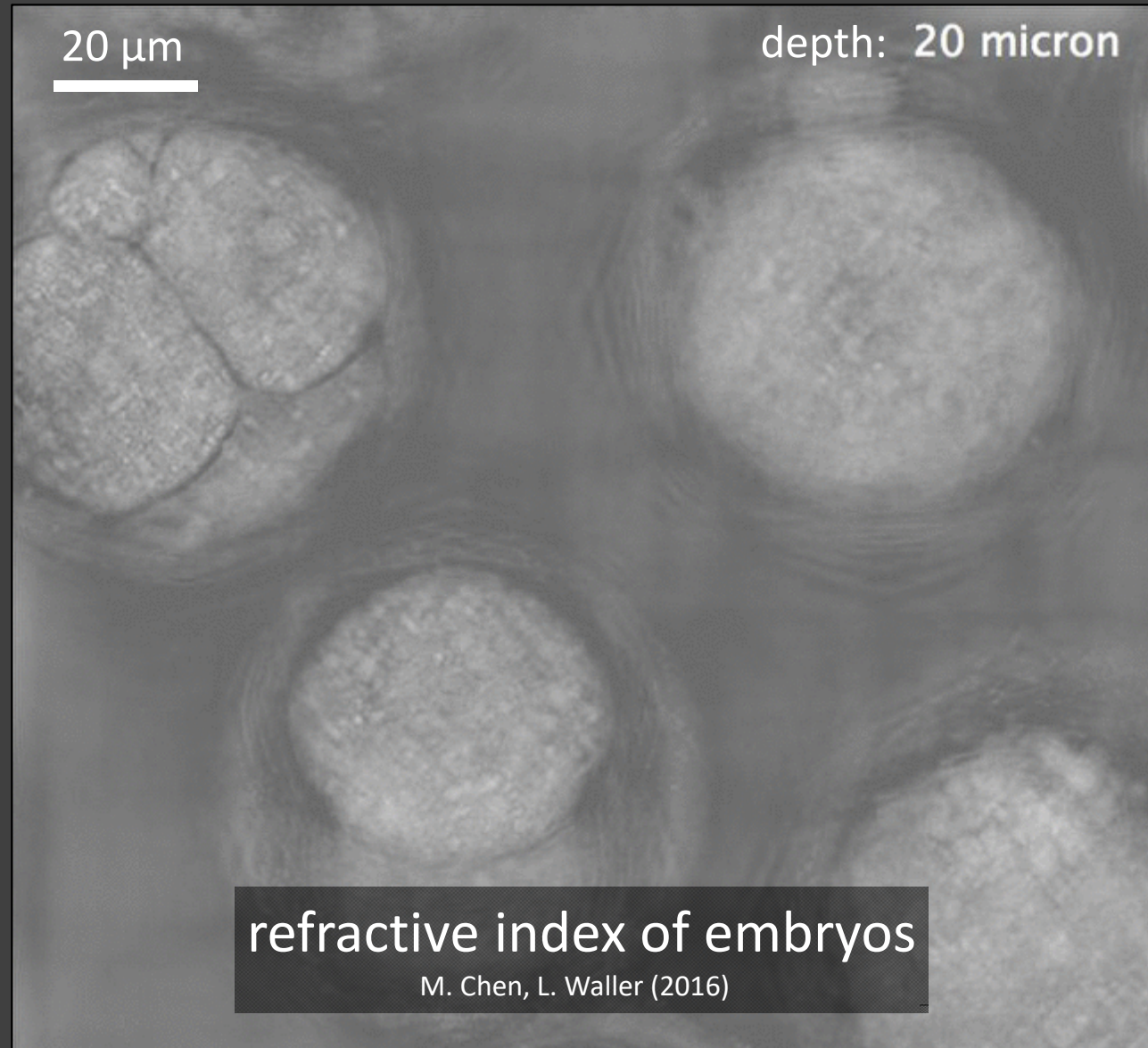


Nonlinear, nonconvex...
so will it converge?

- Van Roey, van der Donk, Lagasse, *J. Opt. Soc. Am.* (1981)
- Cowley, Moodie, *Acta Crystallogr.* (1957).
- Maiden, Humphry, Rodenburg, *J. Opt. Soc. Am. A* (2012).
- Tian, Waller, *Optica* (2015)
- Van den Broek, Koch, *Phys. Rev. Lett.* (2012)
- Van den Broek, Koch, *Phys. Rev. B* (2013)
- Kamilov, Papadopoulos..., Psaltis, *Optica* (2015)
- Waller, Tian, *Nature* (2015).

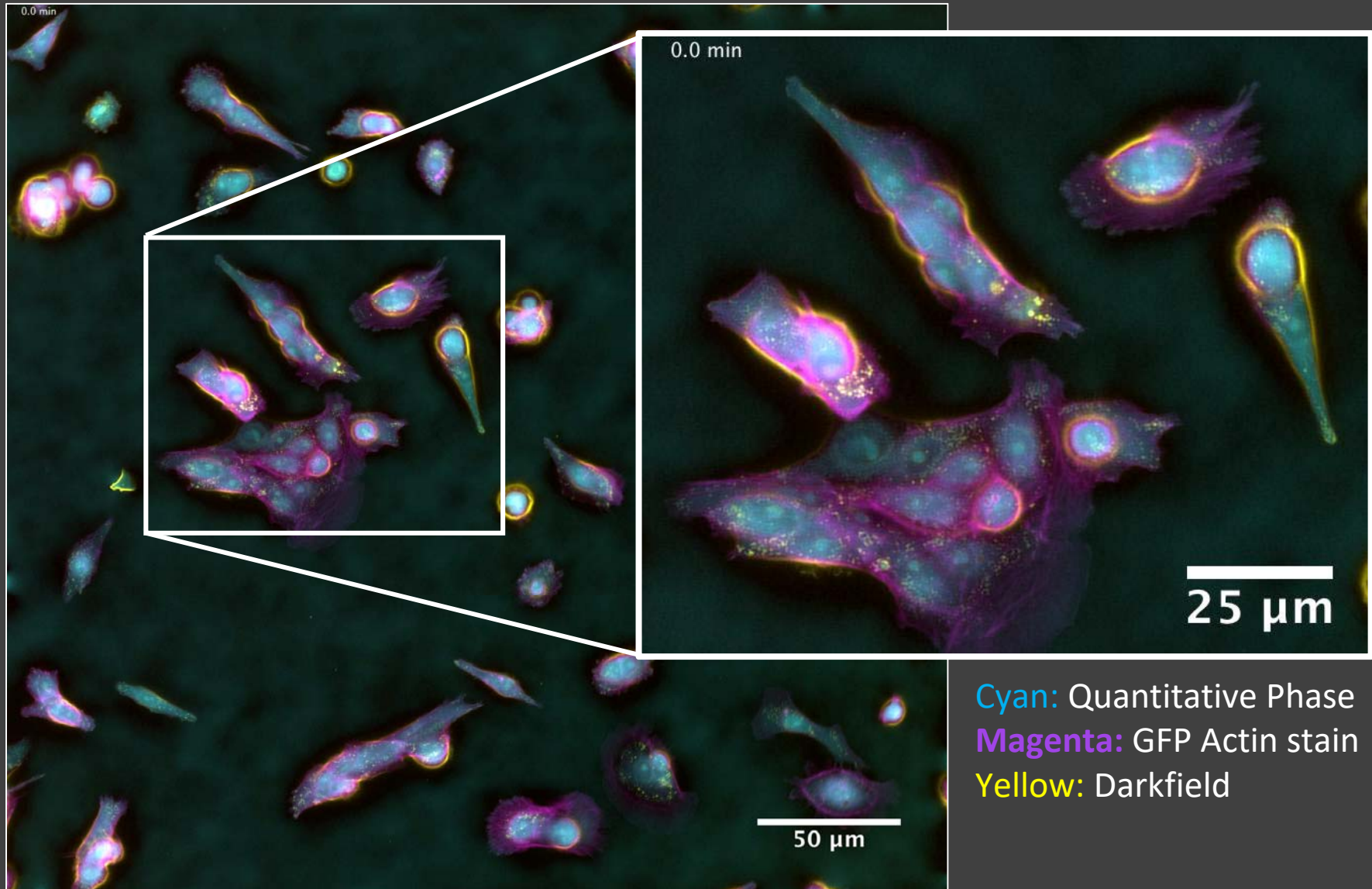
Analogy to Artificial Neural Networks

3D refractive index measurement



Michael
Chen

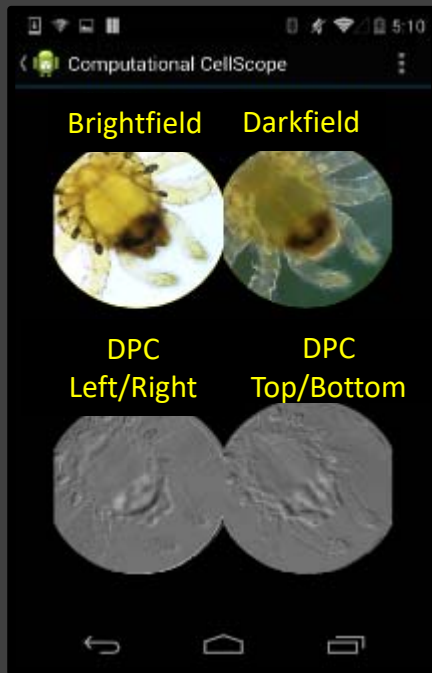
All together: phase + darkfield + fluorescence



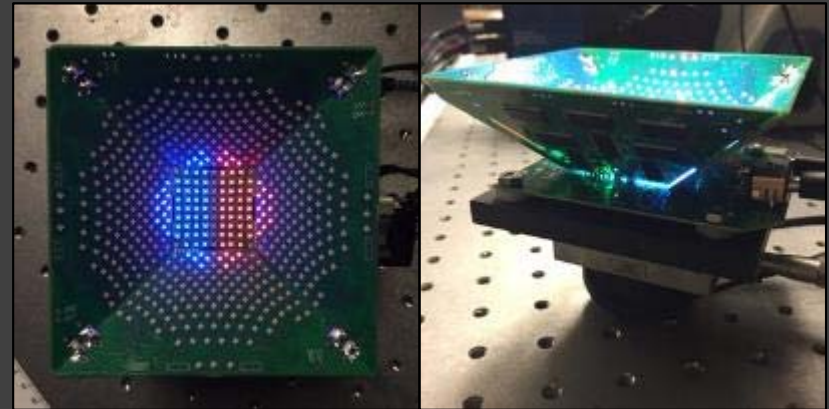
Cyan: Quantitative Phase
Magenta: GFP Actin stain
Yellow: Darkfield

Open-source hardware + software

Computational CellScope



Quasi-dome



ScotchTape Cam



Outlook

Hardware Toolbox



Computational Toolbox



Computers + Optics should talk more!



Collaborators:

Hillel Adesnik (Neuro)

Ben Recht, Ren Ng (EECS)

David Schaffer, Lydia Sohn, Dan Fletcher (BioE)

GigaPan: WallerLab_Berkeley

Open-source : www.laurawaller.com

Twitter: @optrickster

Github: Waller_Lab



Bakar Fellows Program

