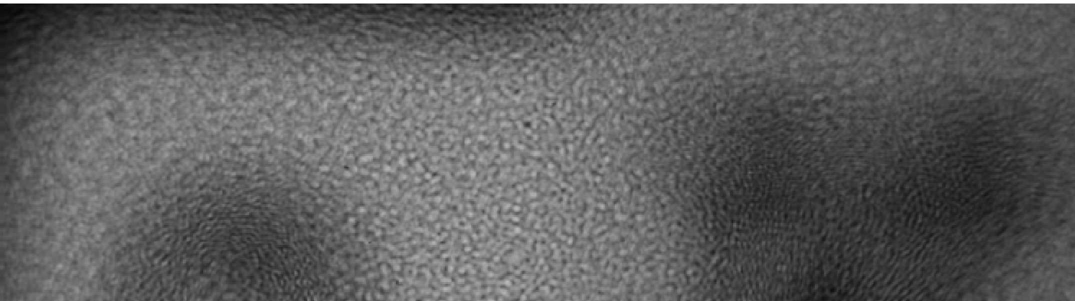
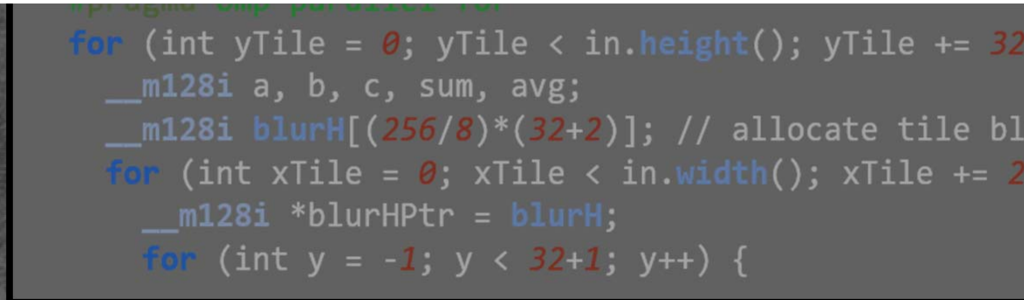
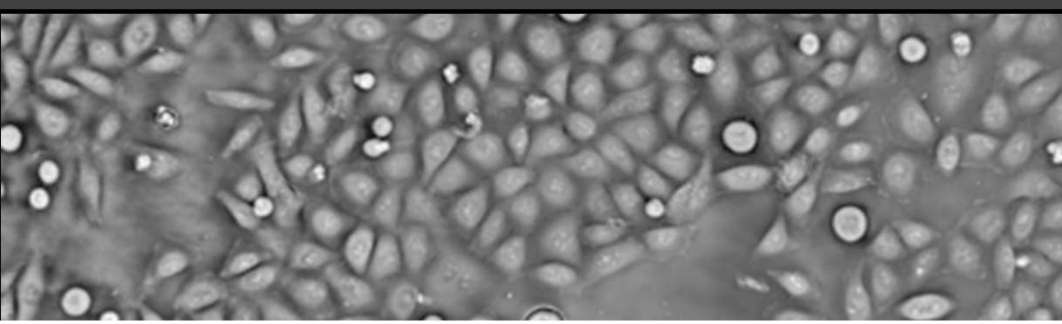
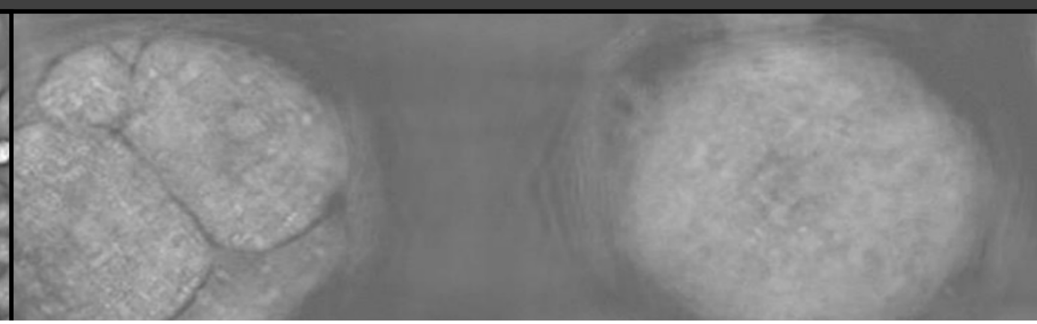




Computational Microscopy

Laura Waller
Ted Van Duzer Associate Professor
Electrical Engineering and Computer Sciences
UC Berkeley





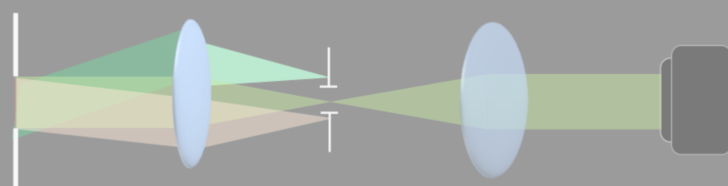
Computational Imaging

joint design of hardware and software

Image System Design

$\mathbf{x}$

object



$\mathbf{y}$

measurements

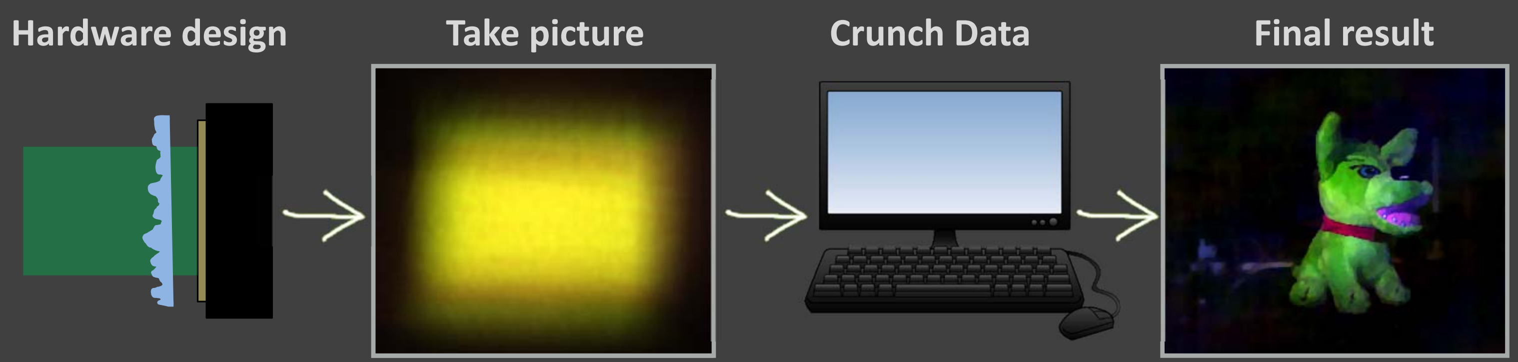
$\mathbf{A}$

Algorithm

find $\mathbf{x}$

such that $\mathbf{y} = \mathbf{A}\mathbf{x}$

Computational imaging pipeline



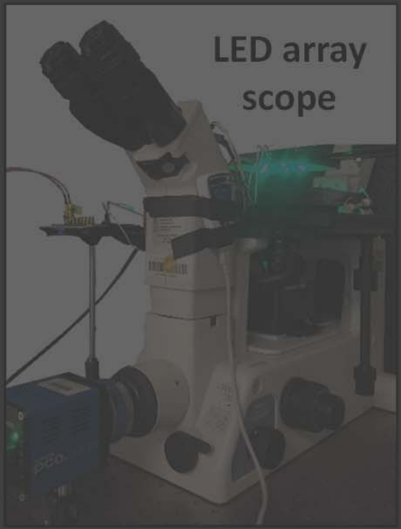
The hard part is *integration*

Hardware Toolbox

Computational Toolbox

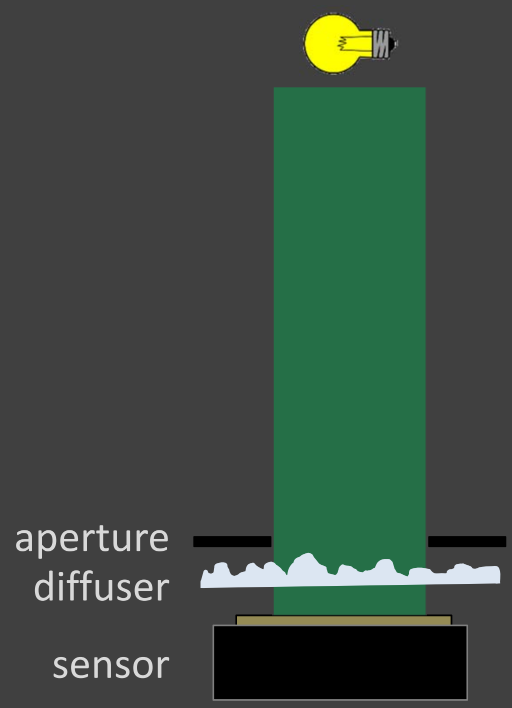
Pushing the limits of imaging can be done with existing physics and commodity hardware.

This talk:



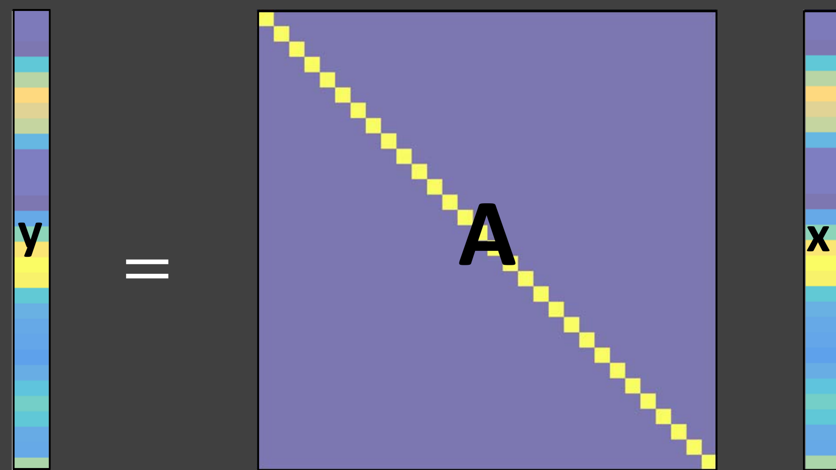
- » ***scalable*** hardware
- » ***efficient*** data capture
- » ***advanced computation***

DiffuserCam: tape a diffuser onto a sensor

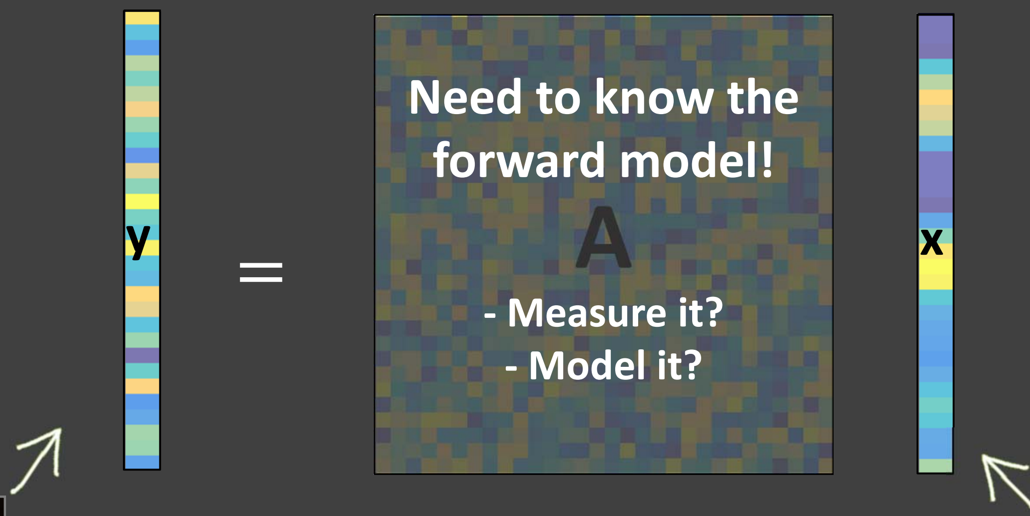


Grace Kuo
Nick Antipa

Traditional cameras take direct measurements



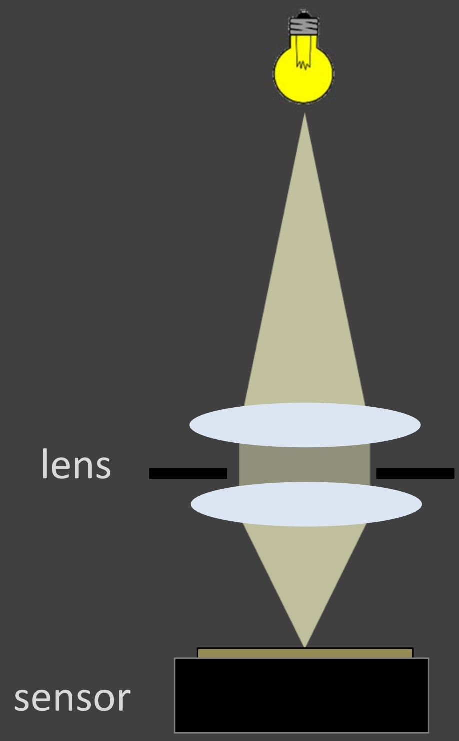
Computational cameras can multiplex

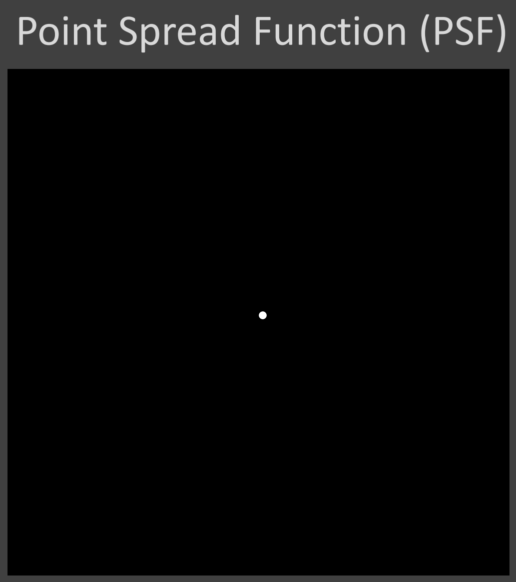


measurement

object

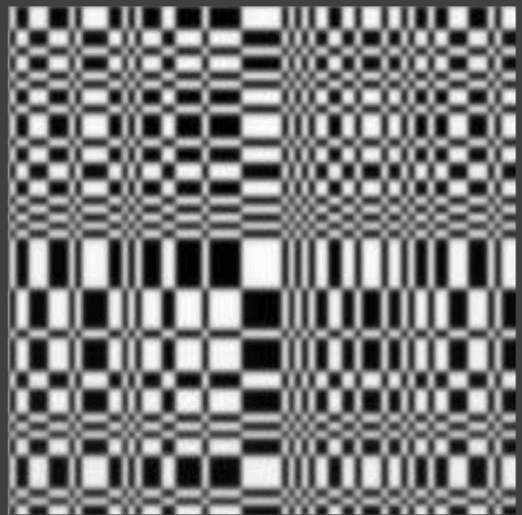
Lenses map points to points





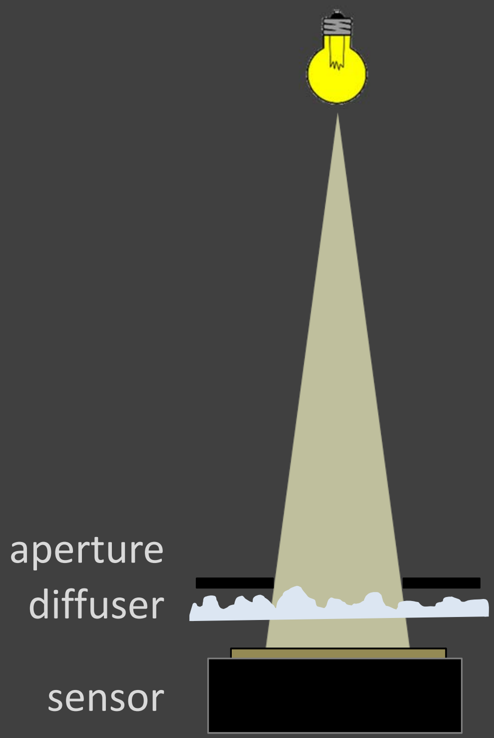
Mask-based cameras multiplex

Point Spread Function (PSF)

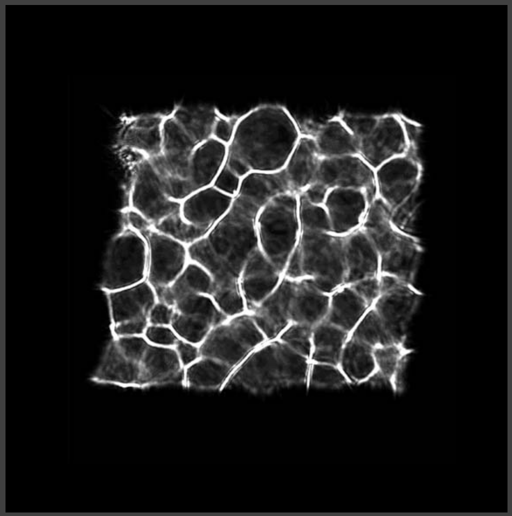


M. S. Asif, et al. *ICCVW* (2015)
J. Tanida, et al. *Applied optics* (2001)
K. Tajima, et al. *ICCP* (2017)
D. G. Stork, et al. *Int. J. Adv. Systems and measurements* (2014)

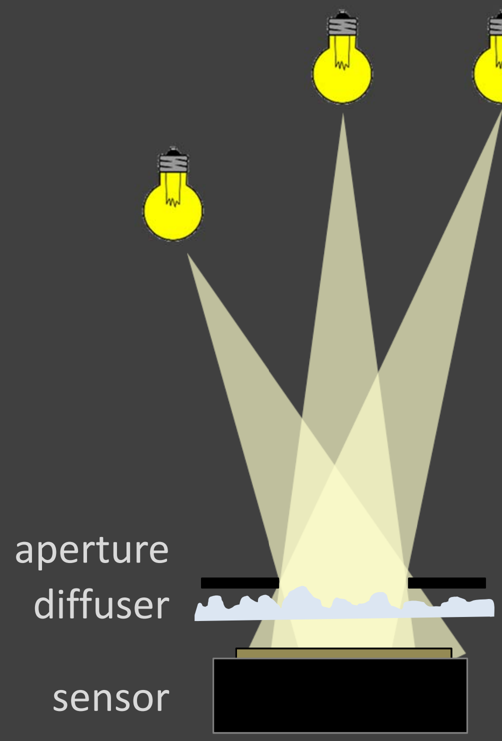
Diffuser indirectly encodes information



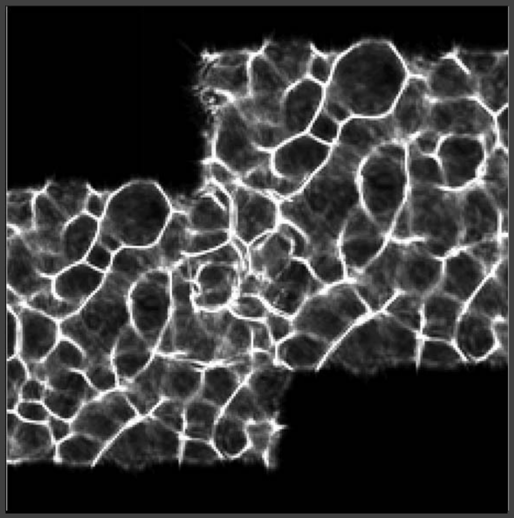
Point Spread Function (PSF)



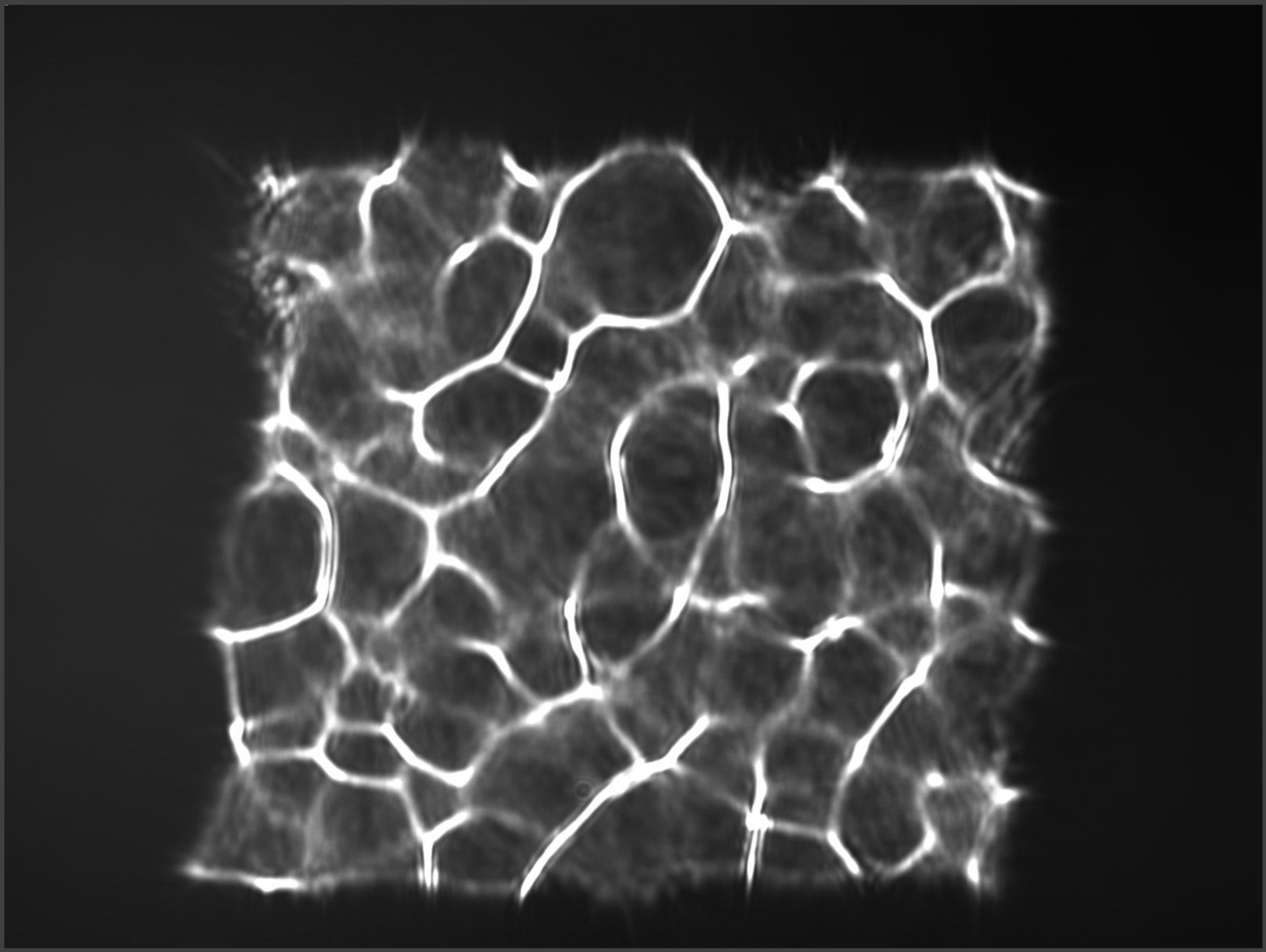
Diffuser indirectly encodes information



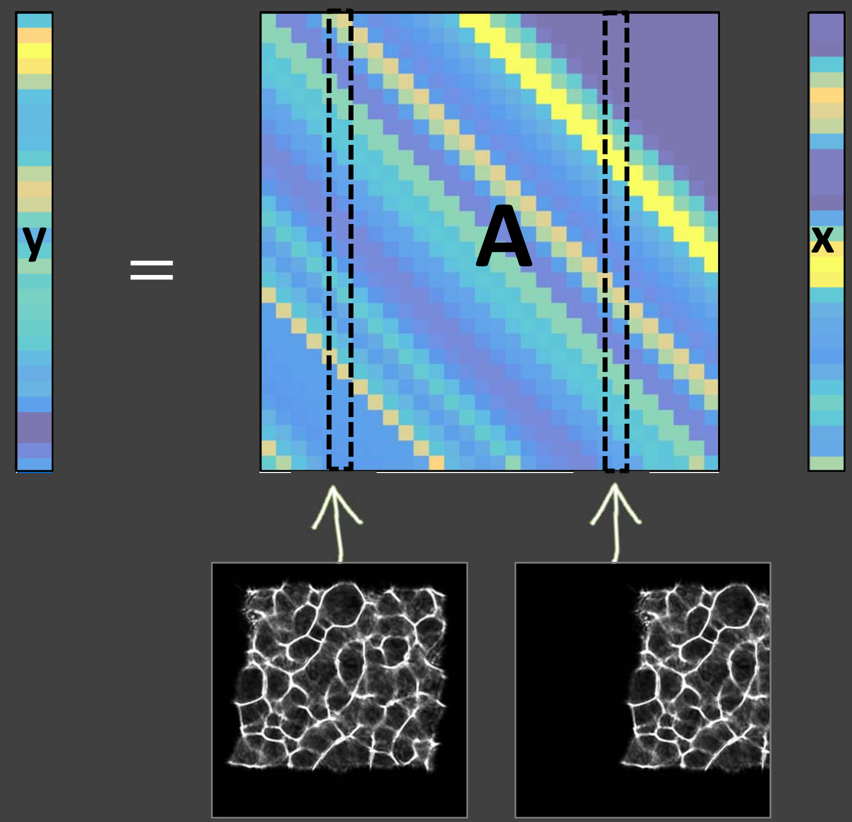
Point Spread Function (PSF)



Point spread function shifts with the object



DiffuserCam forward model is a convolution

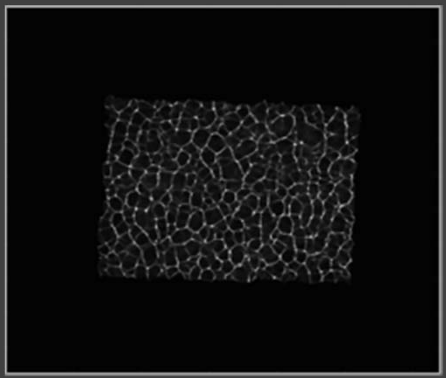


Point Spread Function(s)

DiffuserCam forward model is a convolution

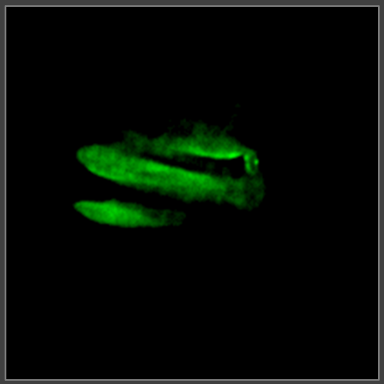
Measurement

=

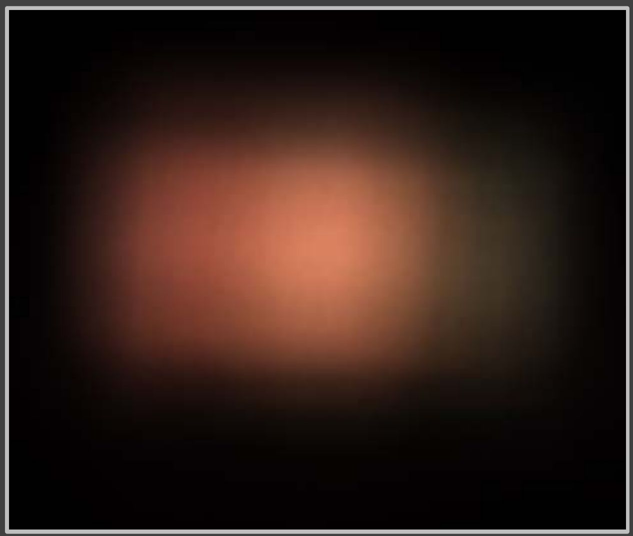


Point Spread Function

*



Object



raw sensor data

recovered scene

*solver is ADMM with TV reg in Halide

raw sensor data

recovered scene

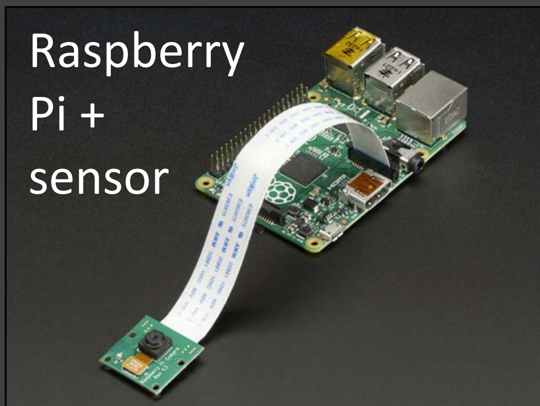
*solver is ADMM with TV reg in Halide

raw sensor data

recovered scene

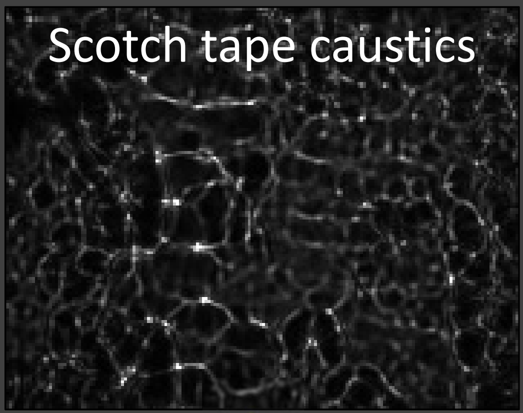
*solver is ADMM with TV reg in Halide

El cheapo version – ScotchTapeCam!



+

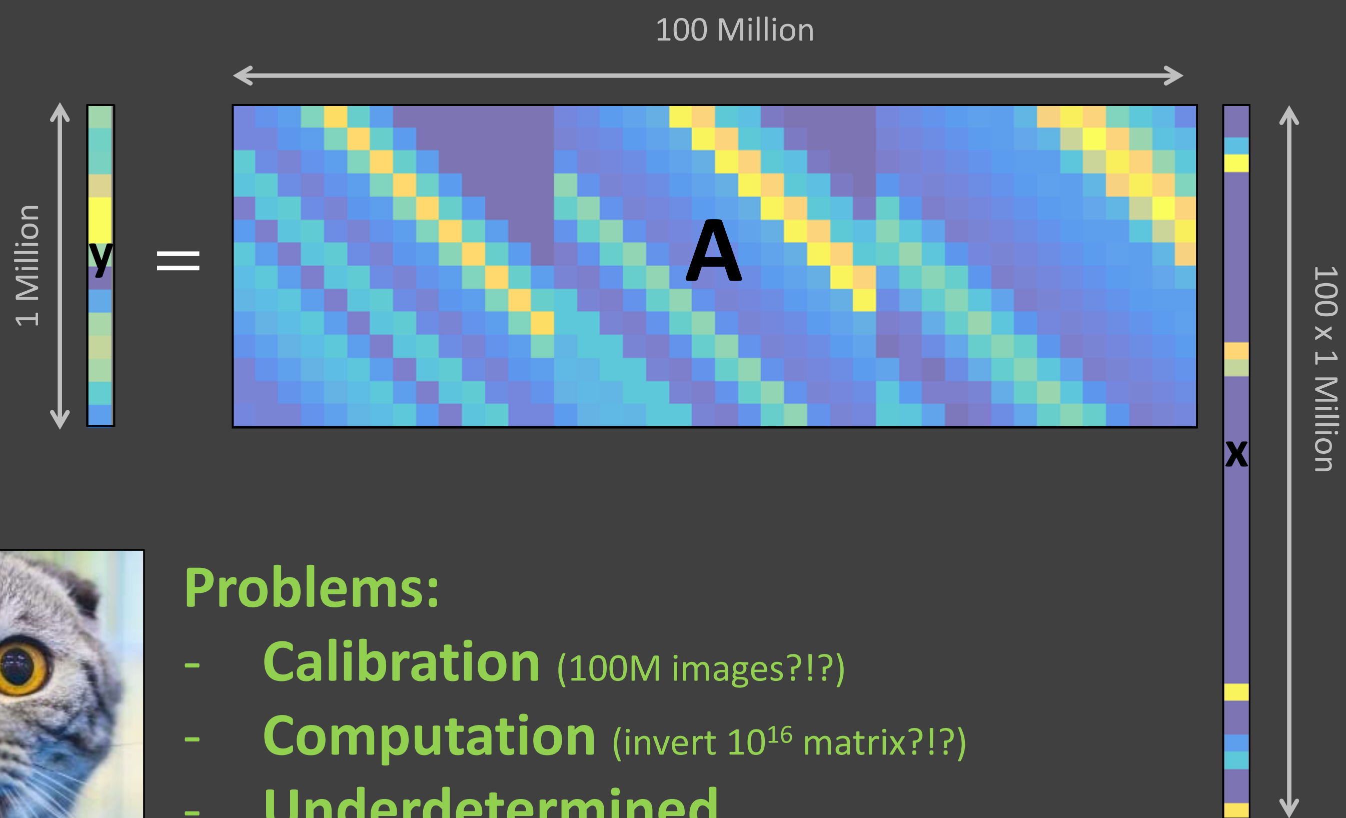
=

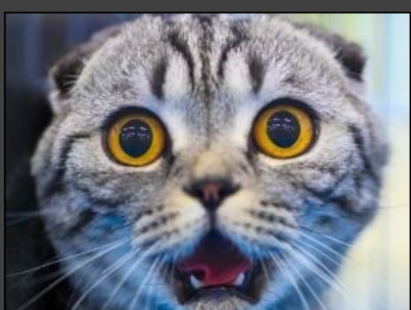



Camille Biscarrat
Shreyas Parthasarathy

2D → 3D

3D is not so easy

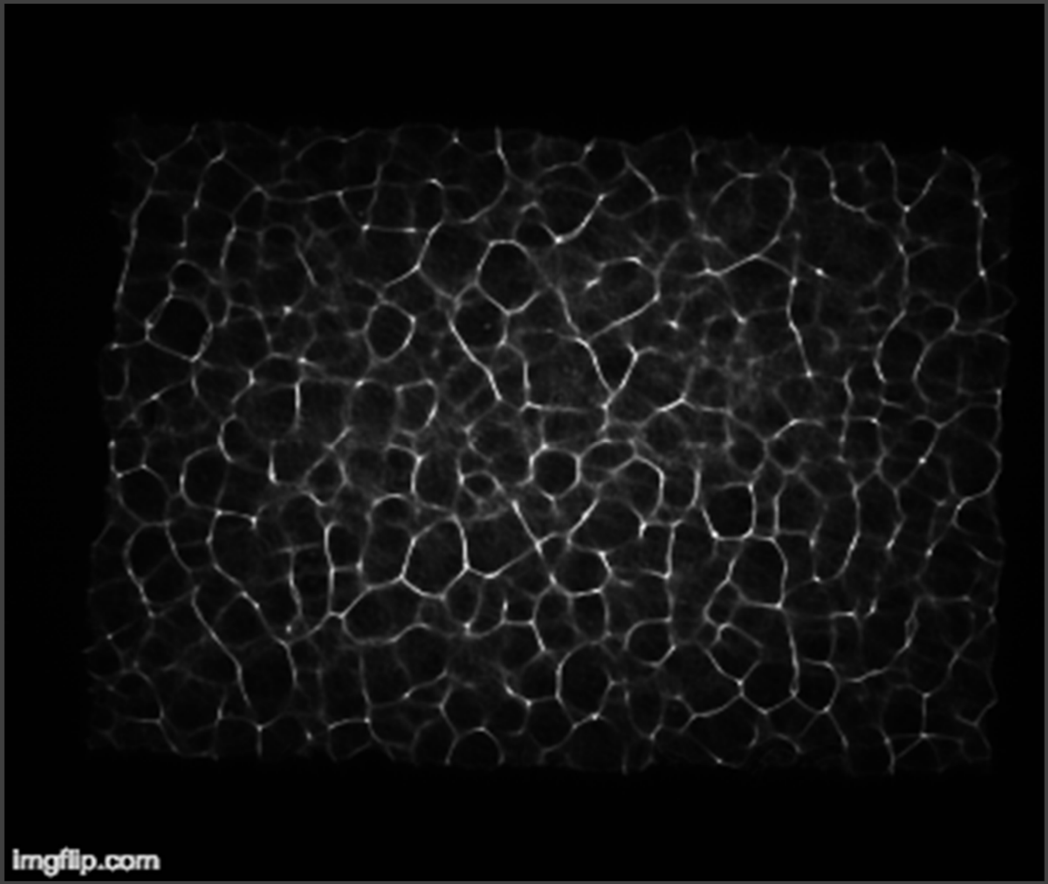




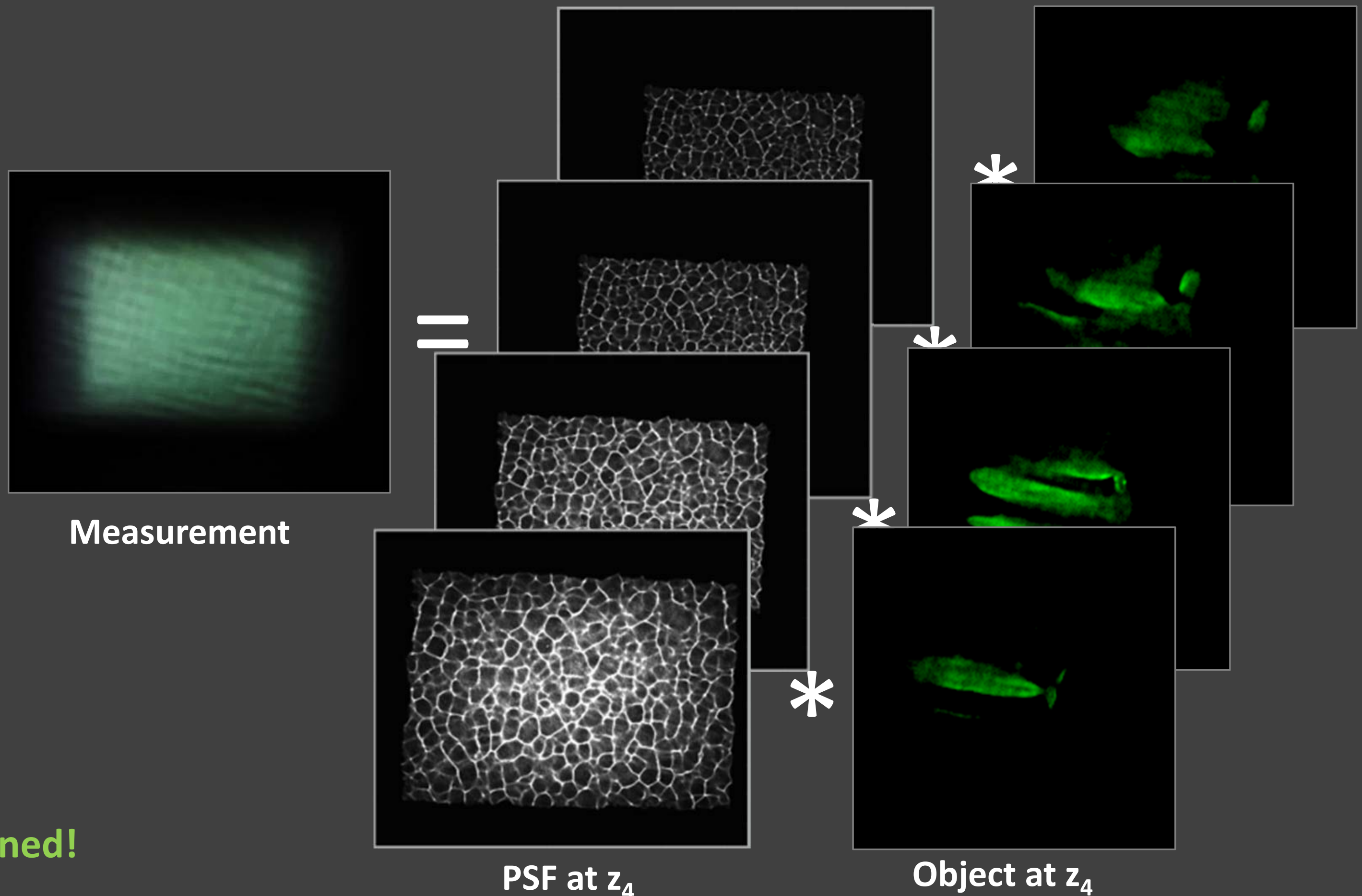
Problems:

- **Calibration** (100M images?!?)
- **Computation** (invert 10^{16} matrix?!?)
- **Underdetermined**

The PSF scales with depth

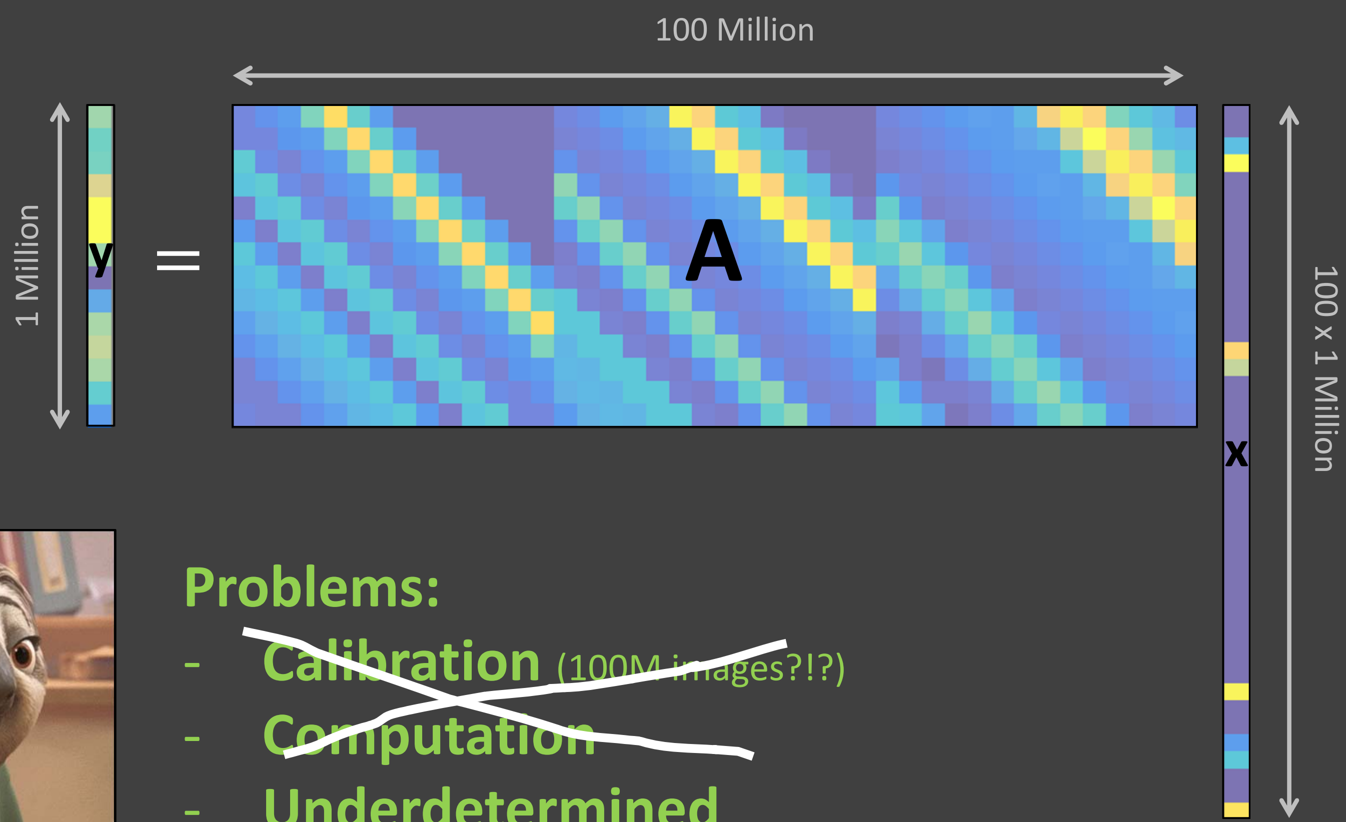


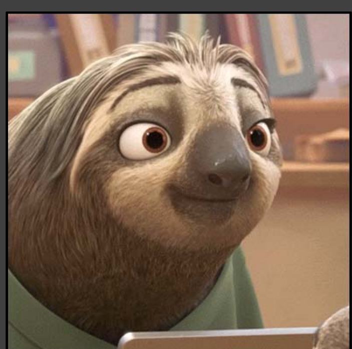
3D forward model is a sum of convolutions



<u>very</u>
underdetermined!

3D is not so easy



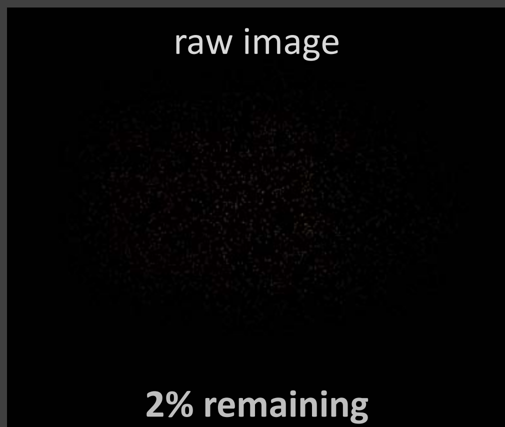


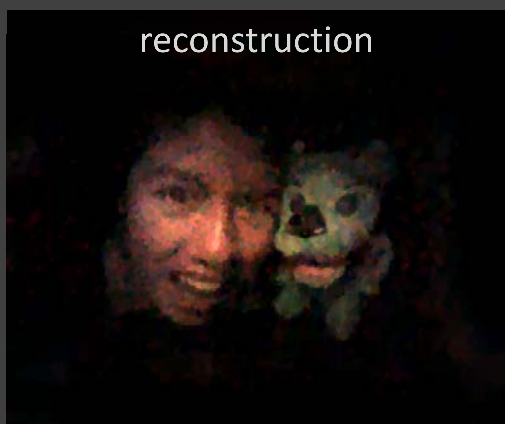
Problems:

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

Compressed sensing to the rescue!

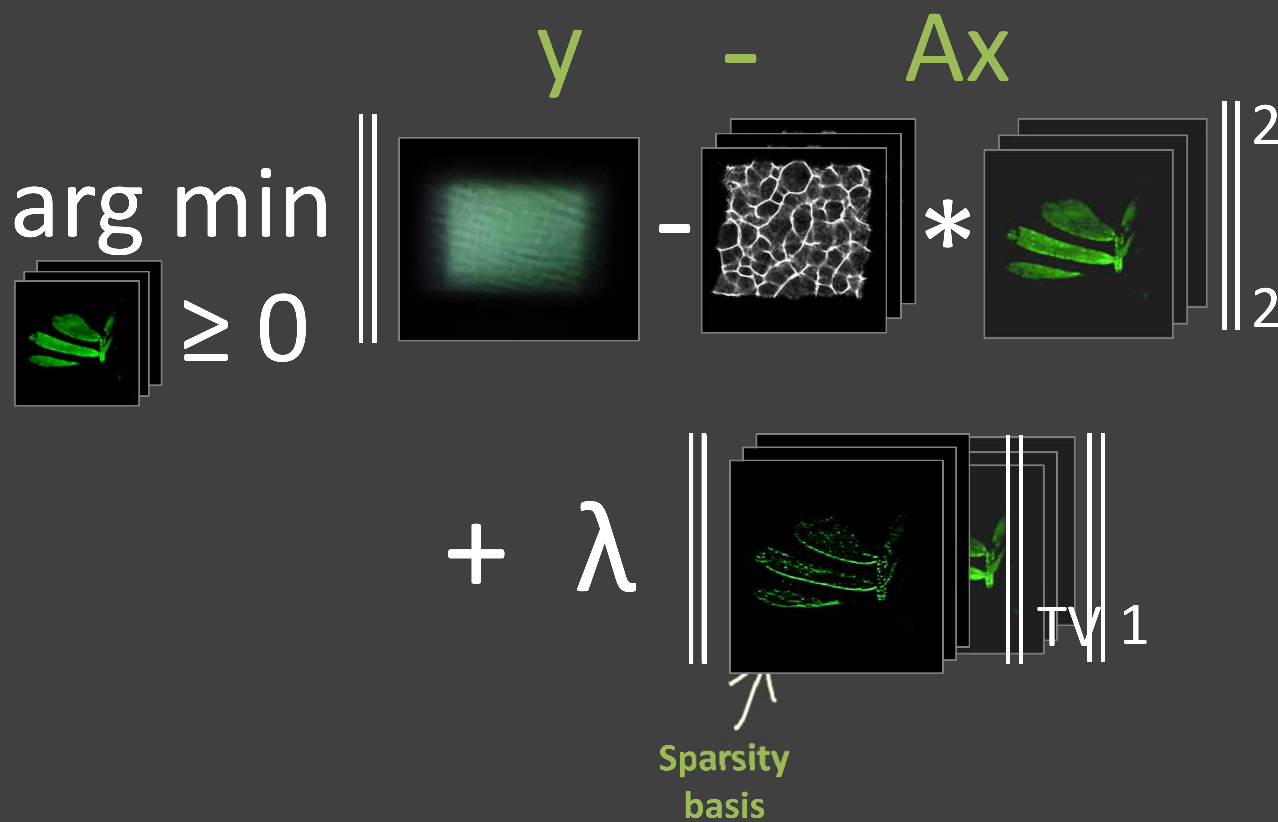
solves under-determined problems via a sparsity prior





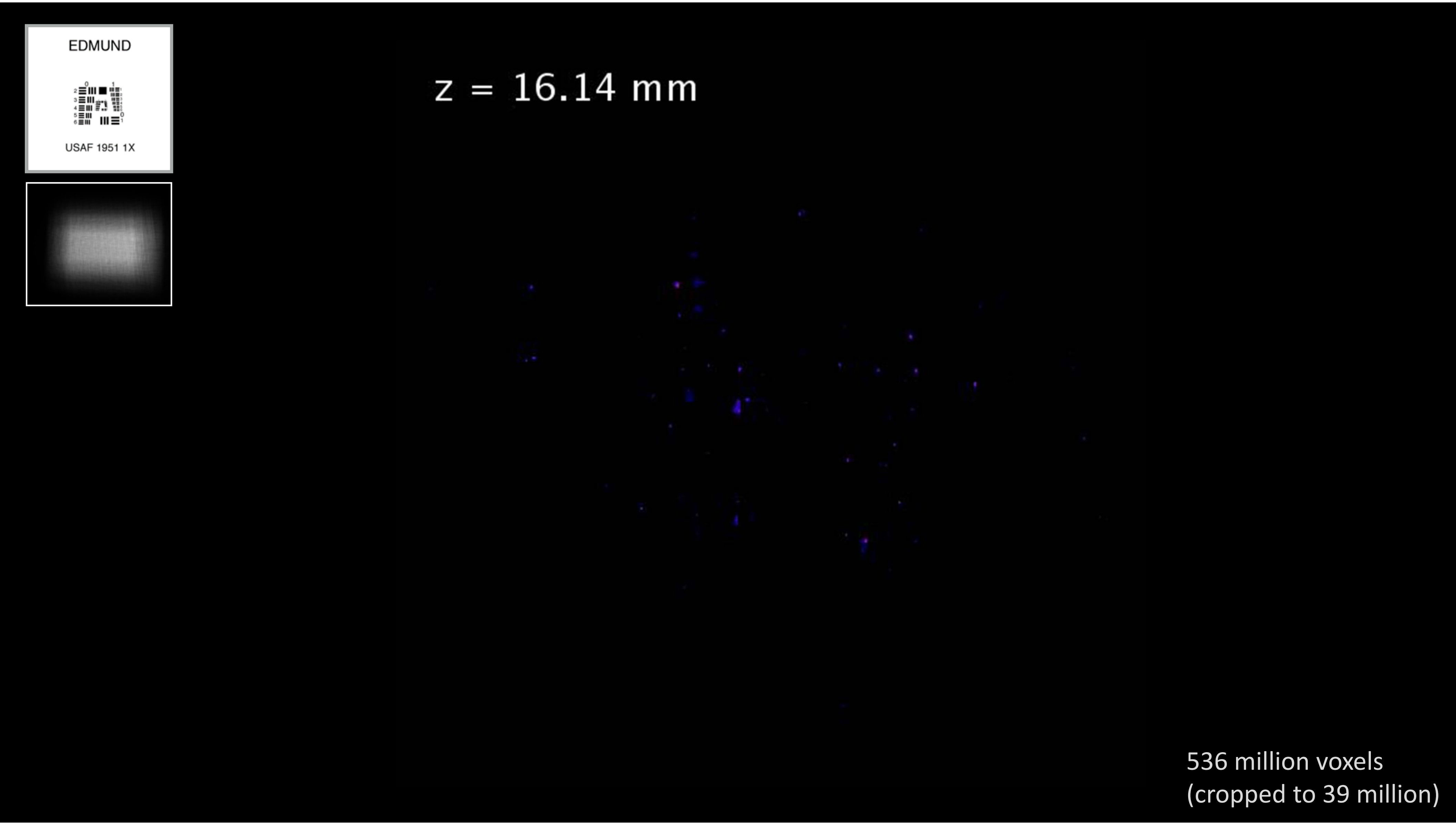
E. J. Candes, et al. *IEEE Signal Processing* (2008)
L. I. Rudin, et al. *Physica D: Nonlinear Phenomena* (1992)

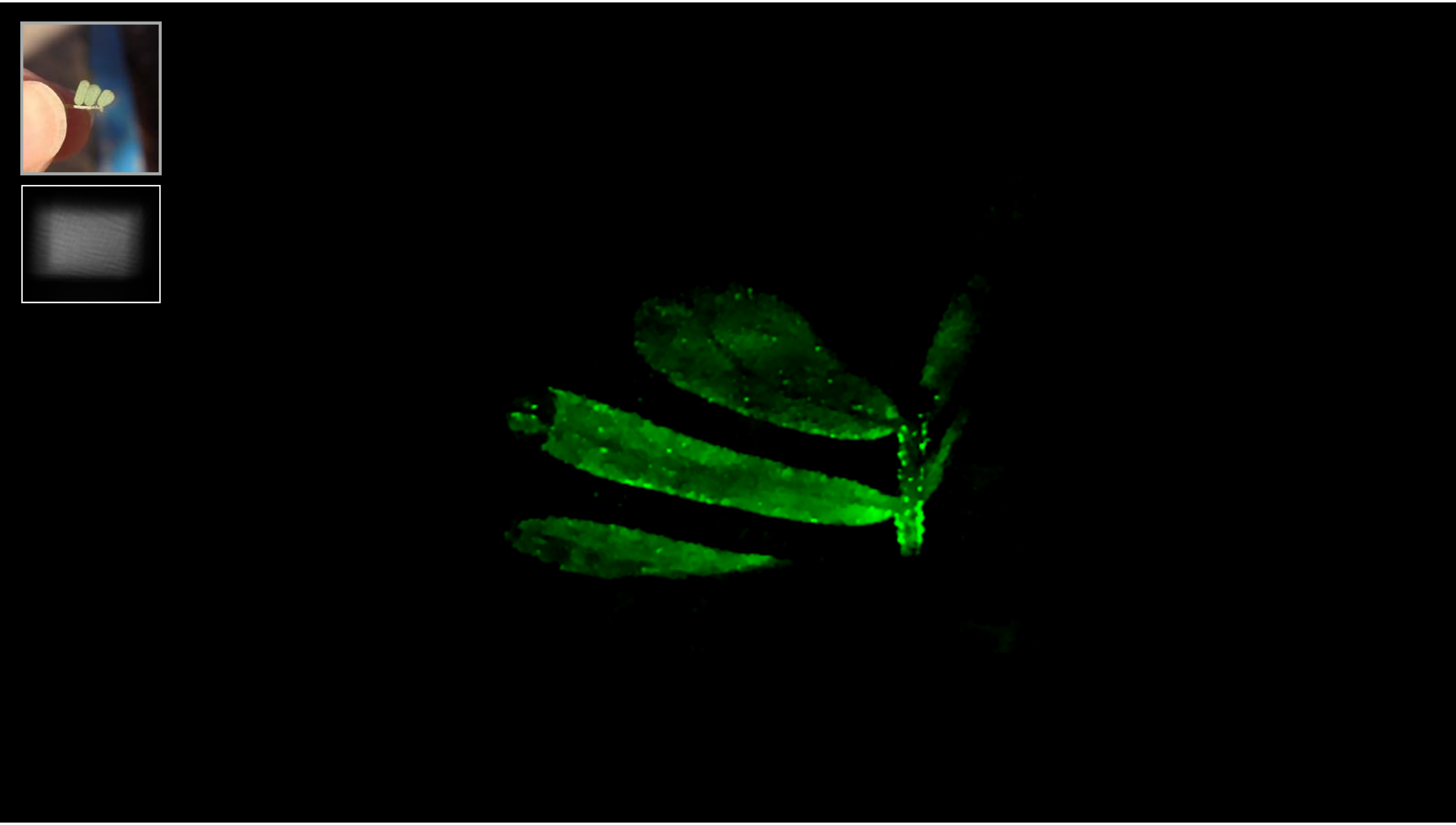
Image Reconstruction with Sparsity Prior

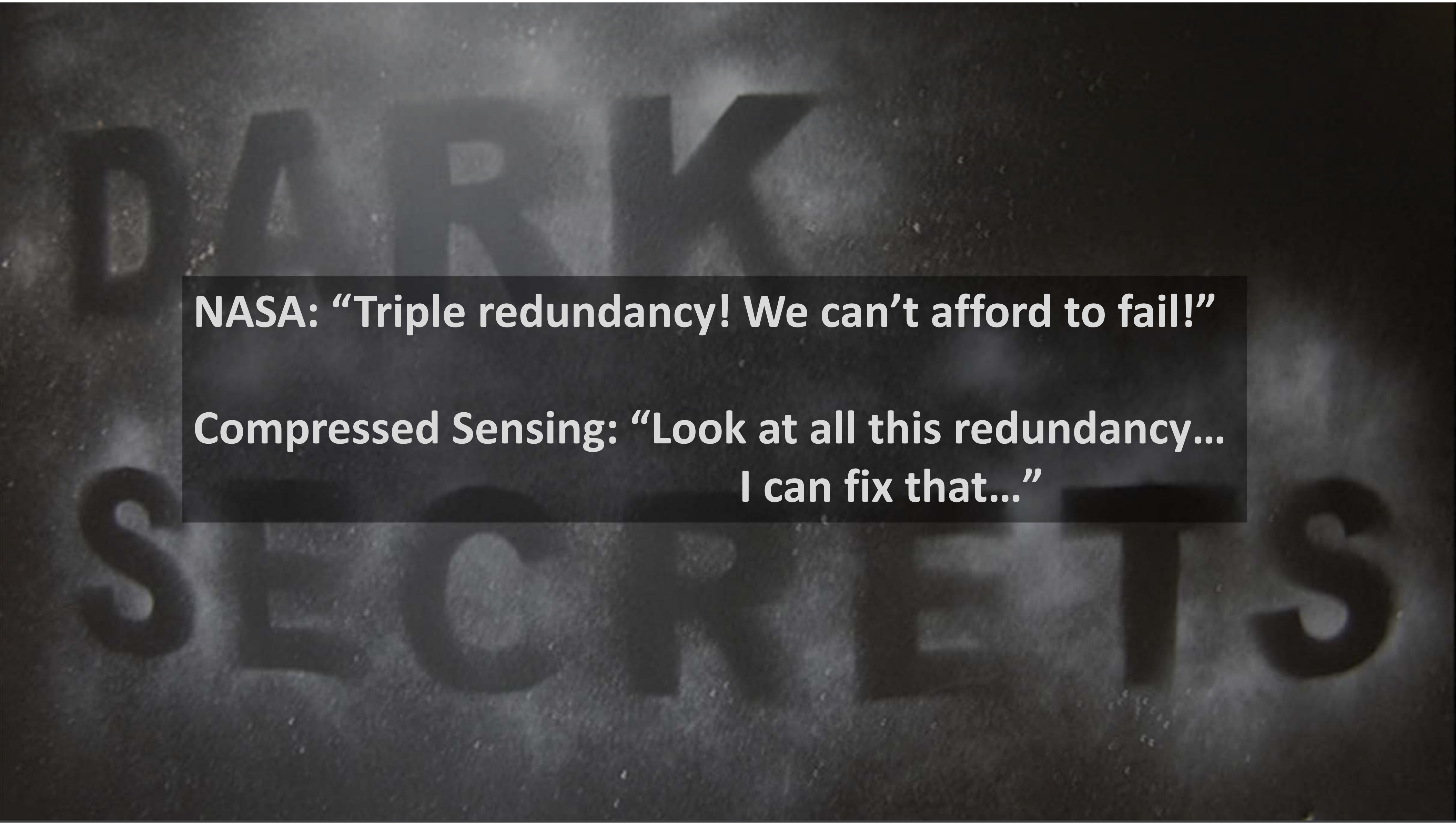


*solved with ADMM in Halide

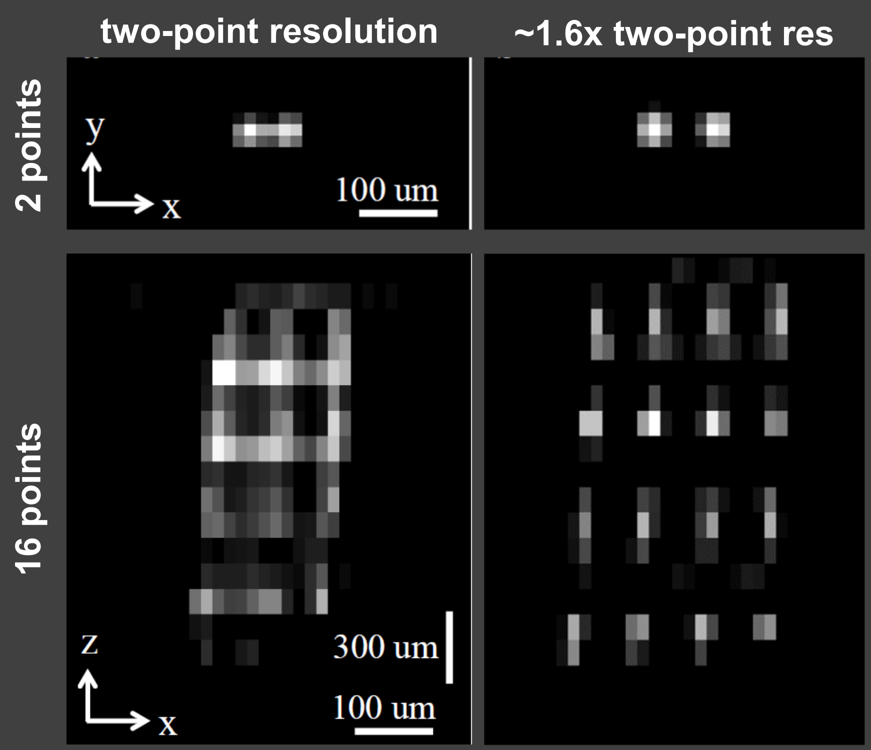
S. Boyd, et al. *Foundations and Trends in Machine Learning* (2011)
J. Ragan-Kelley, et al. *AMC SIGPLAN* (2013)


EDMUND
USAF 1951 1X
z = 16.14 mm
536 million voxels
(cropped to 39 million)




DARK
SECRETS
NASA: “Triple redundancy! We can’t afford to fail!”
Compressed Sensing: “Look at all this redundancy…
I can fix that…”

Challenge: object-dependent resolution

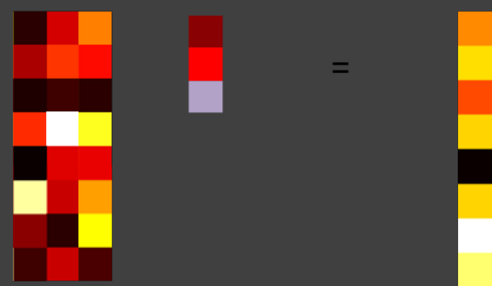


Two-point resolution only predicts *best case* scenario.

Solution?: use condition number of sub-problem

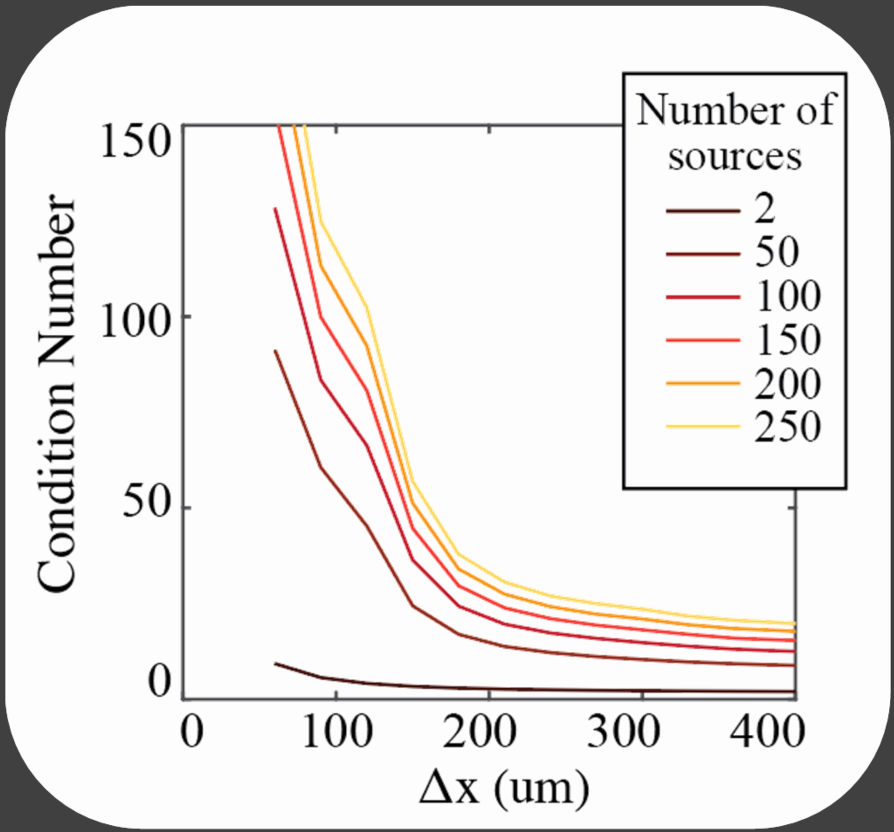
Assume we know where non-zero elements are:

Solution?: use condition number of sub-problem

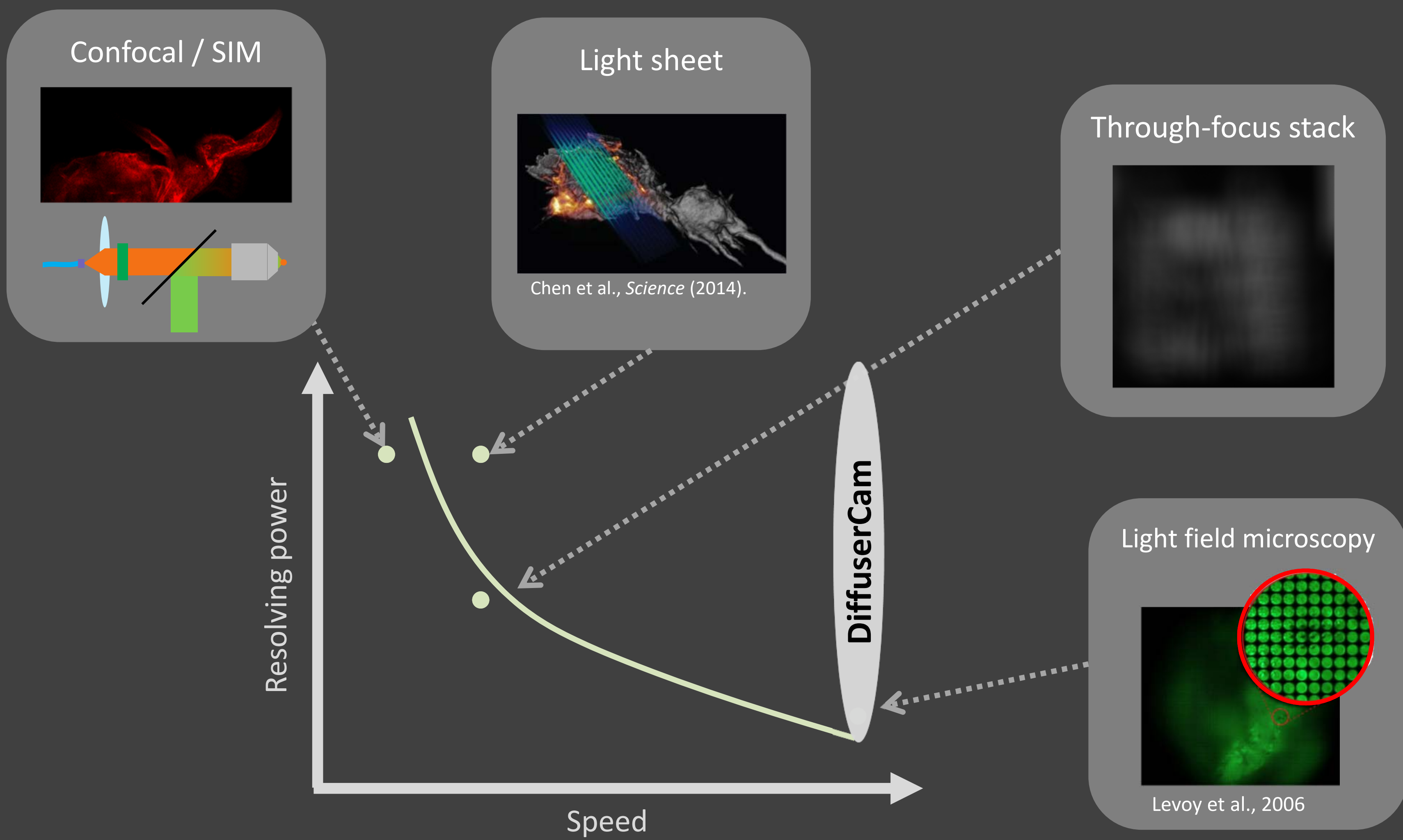


Now it is a small least squares problem

Solution?: use condition number of sub-problem



Local condition number sort of
gives worst case scenario


Confocal / SIM
Light sheet
Chen et al., *Science* (2014).
Through-focus stack
Light field microscopy
Levoy et al., 2006
DiffuserCam
Resolving power
Speed

Scanning Microscopy

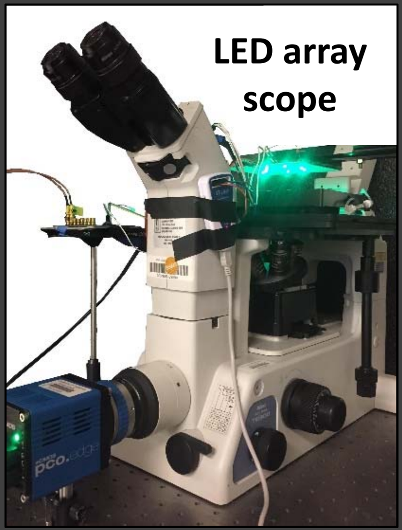
vs.

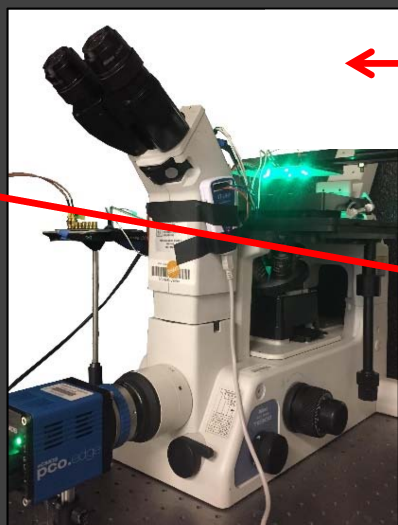
Compressed Sensing

speed scales with # voxels in image

speed scales with *sparsity* of sample

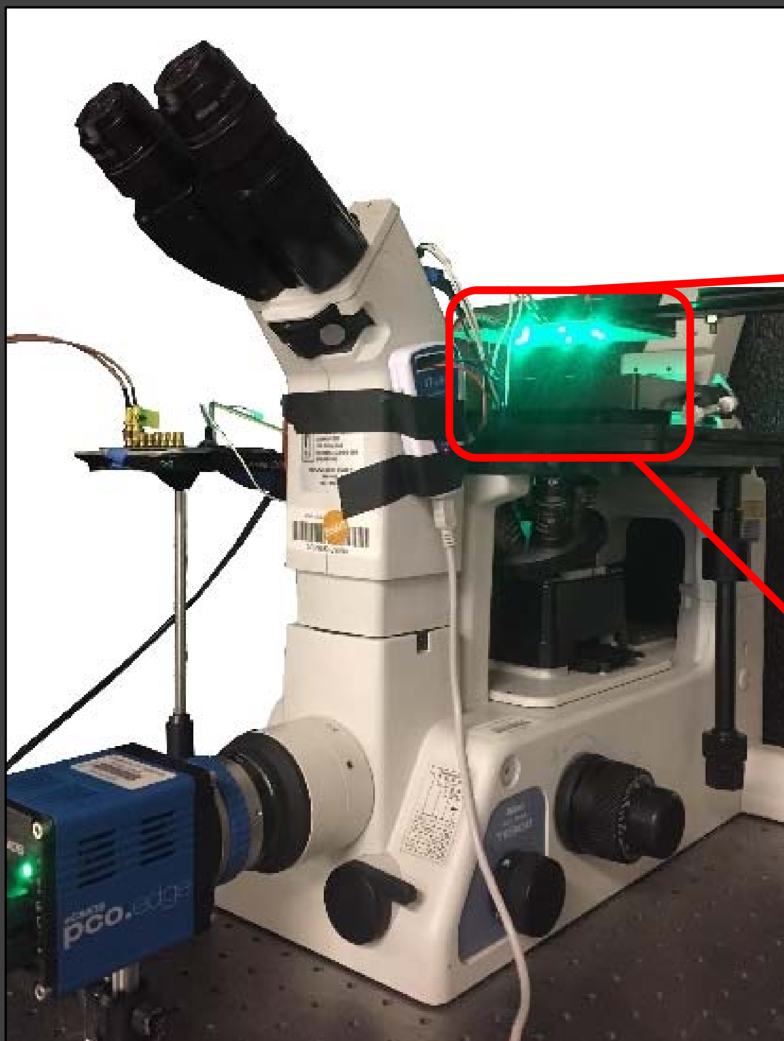
This talk:

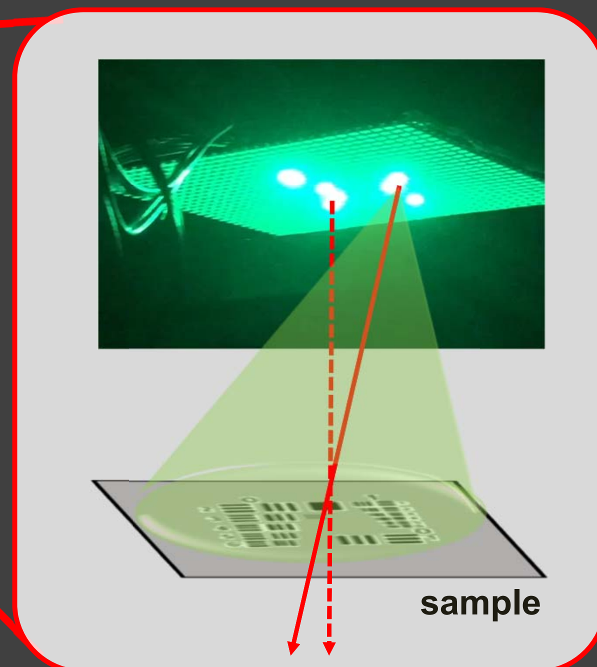




micro-controller

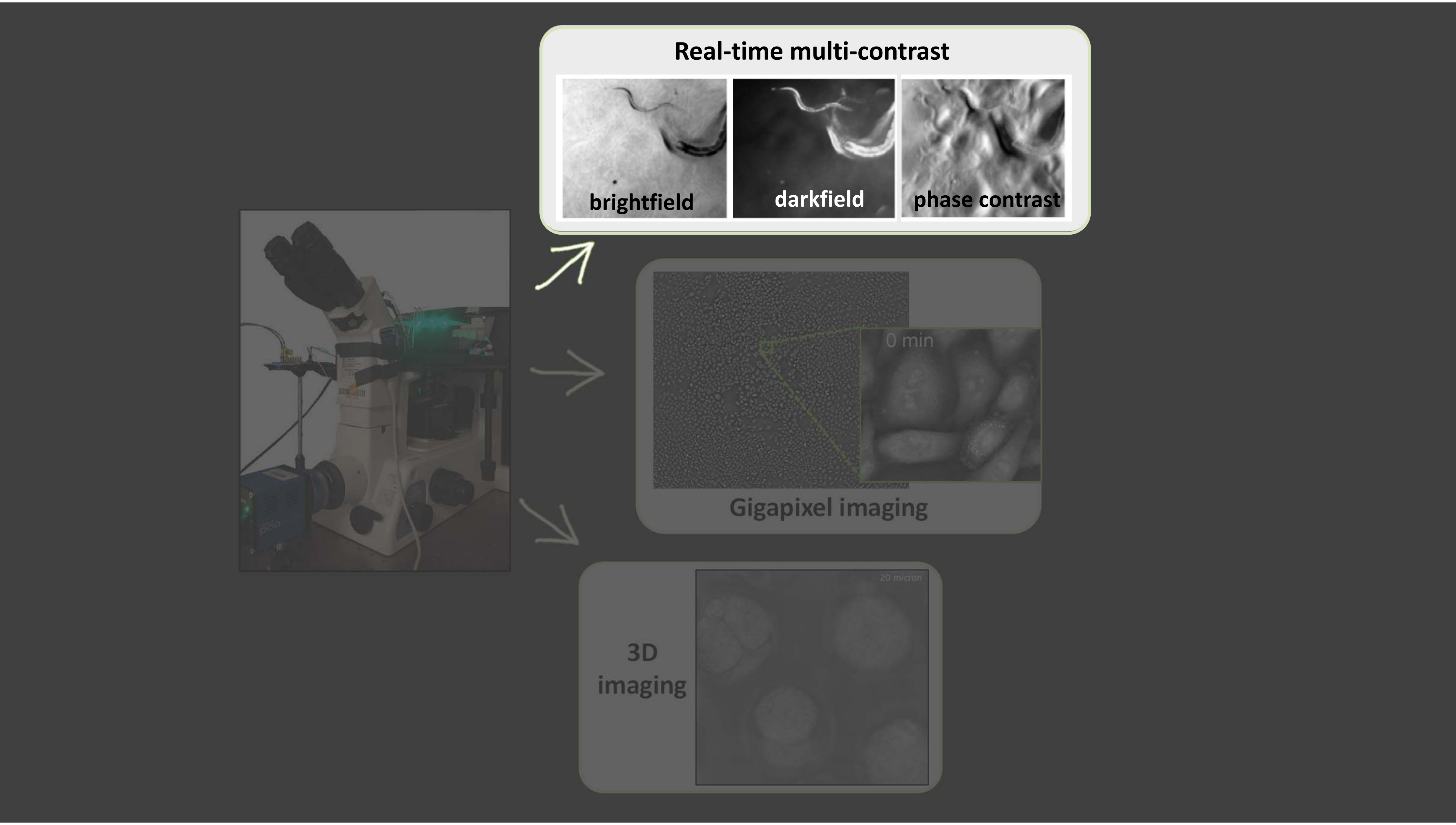
Our version of: G.Zheng, C. Kolner, C. Yang, *Opt. Lett.*. (2011).





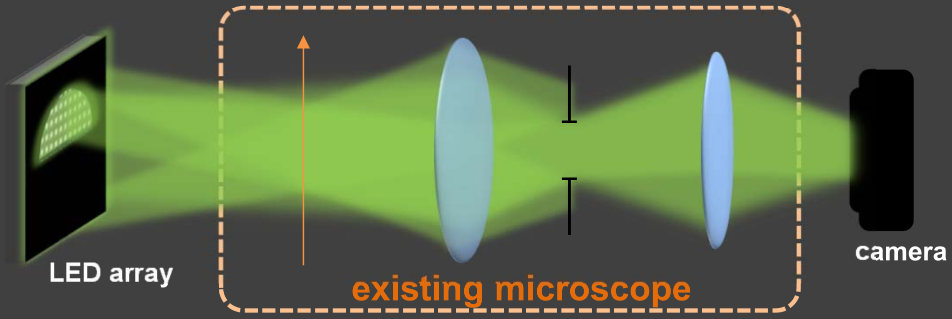
LEDs pattern illumination angles

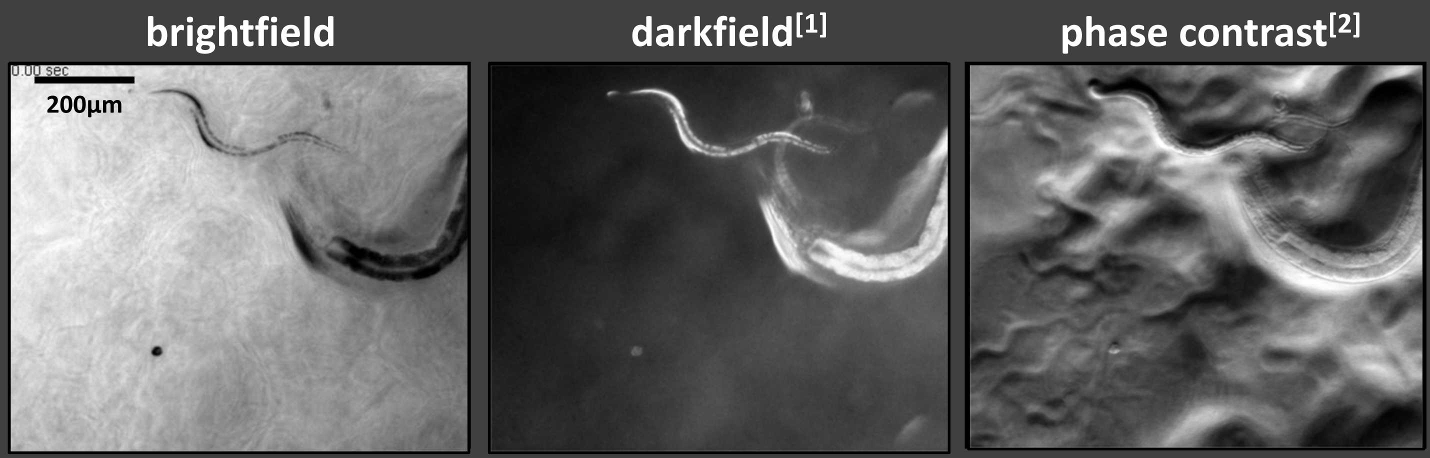
Our version of: G.Zheng, C. Kolner, C. Yang, *Opt. Lett.*. (2011).


Real-time multi-contrast
brightfield
darkfield
phase contrast
0 min
Gigapixel imaging
20 micron
3D imaging

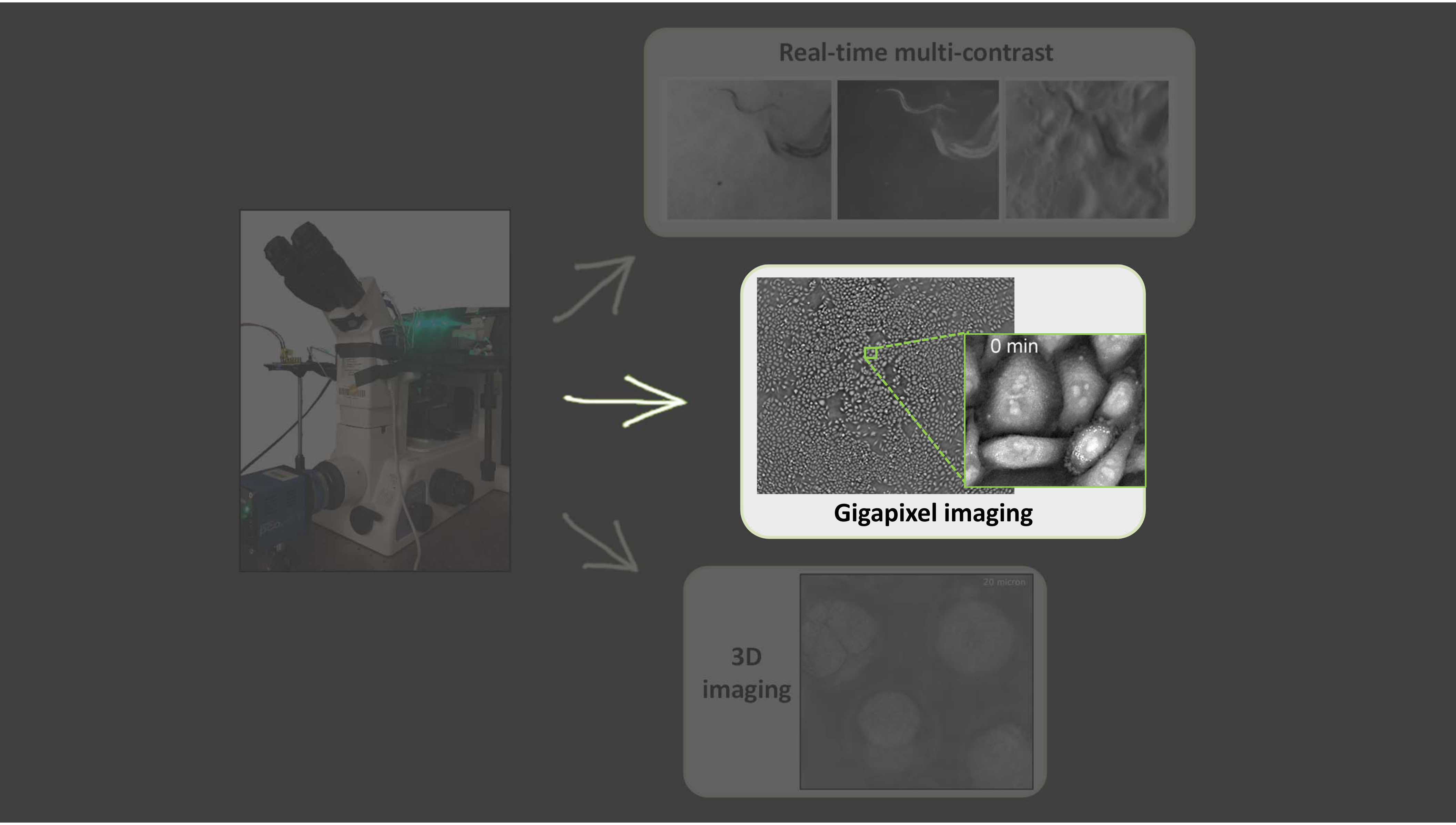
darkfield means
indirect illumination

Multi-contrast with an LED array microscope

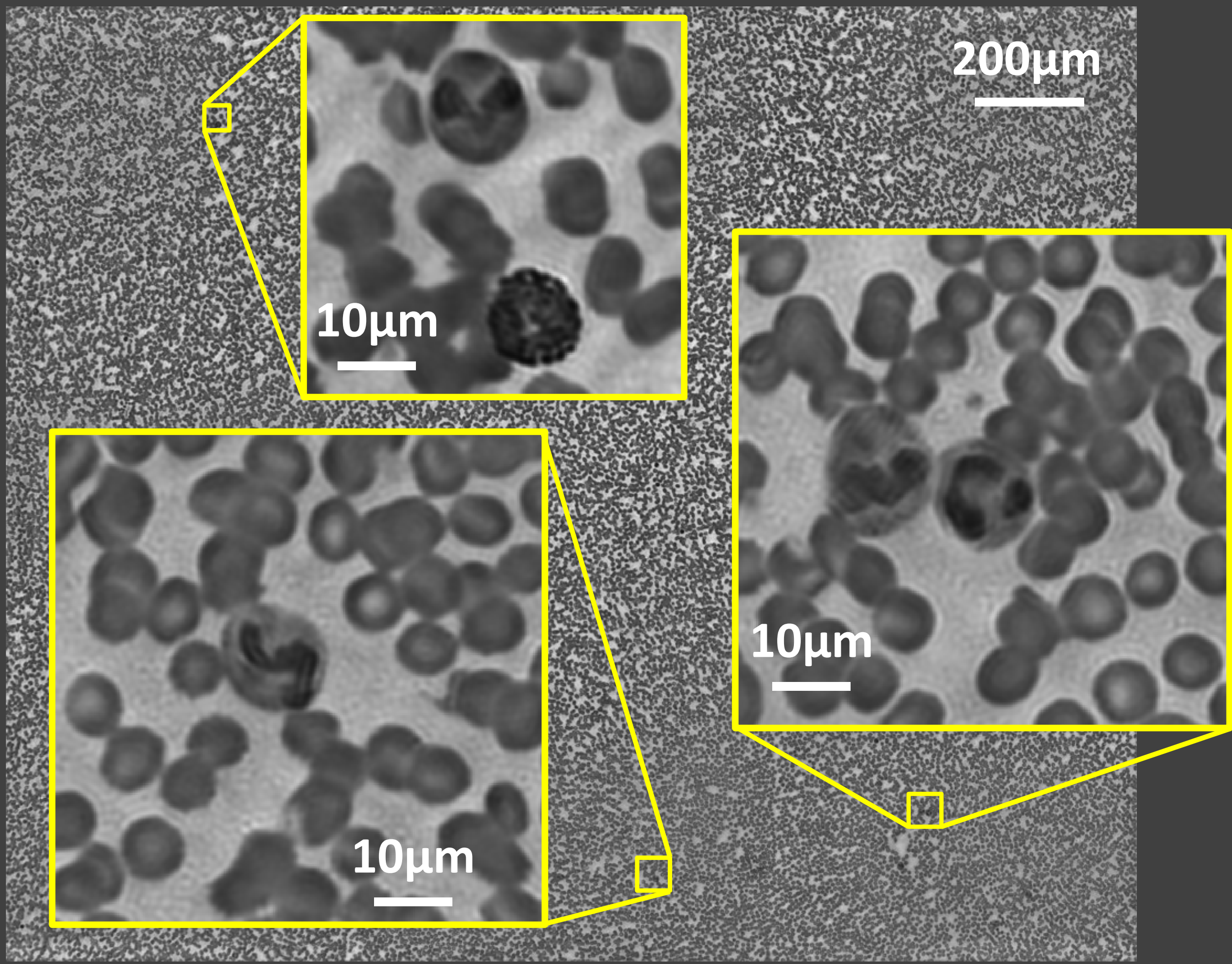




[1] G.Zheng, C. Kolner, C. Yang, *Opt. Lett.*. (2011).
[2] L. Tian, J. Wang, L. Waller, *Opt. Lett.* (2014).


Real-time multi-contrast
0 min
Gigapixel imaging
20 micron
3D imaging

Gigapixel imaging for disease screening



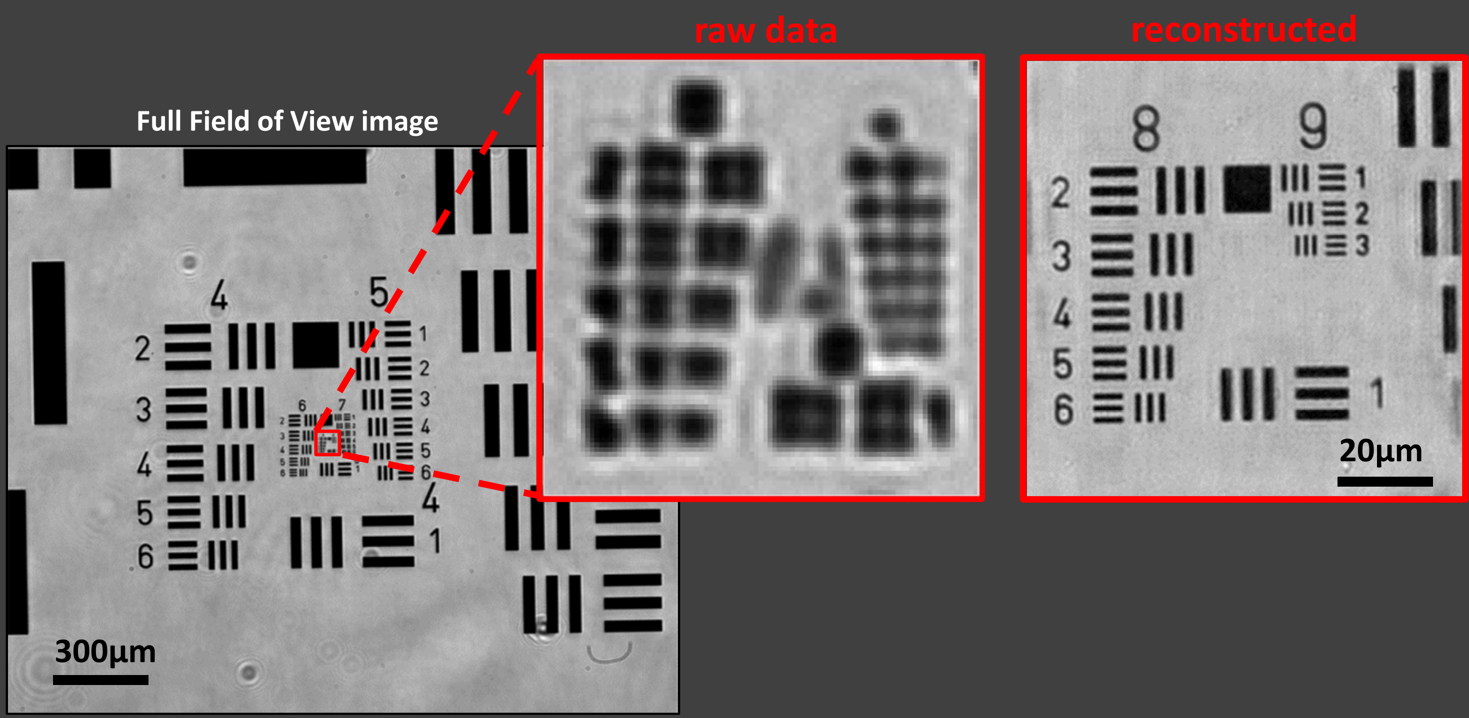
Stained Human Blood Cells

FoV~2.1mmx1.7mm
resolution ~0.4um

26k x 22k pixels

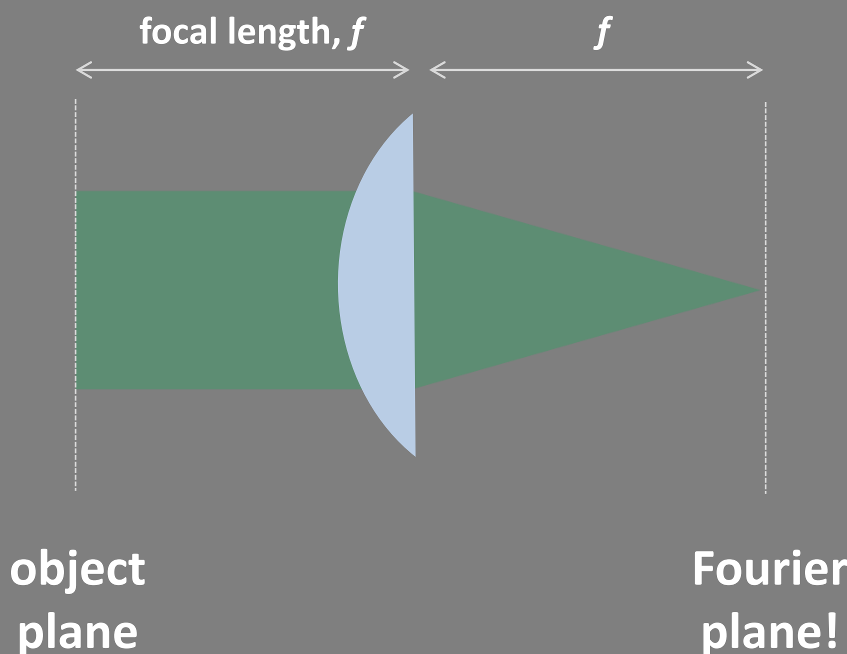
G.Zheng, R. Horstmeyer, C. Yang, *Nat. Photon.* (2013).
L.Tian, X.Li, K.Ramchandran, L. Waller, *Biomed. Opt. Express* (2014).

Super-resolution from coded illumination

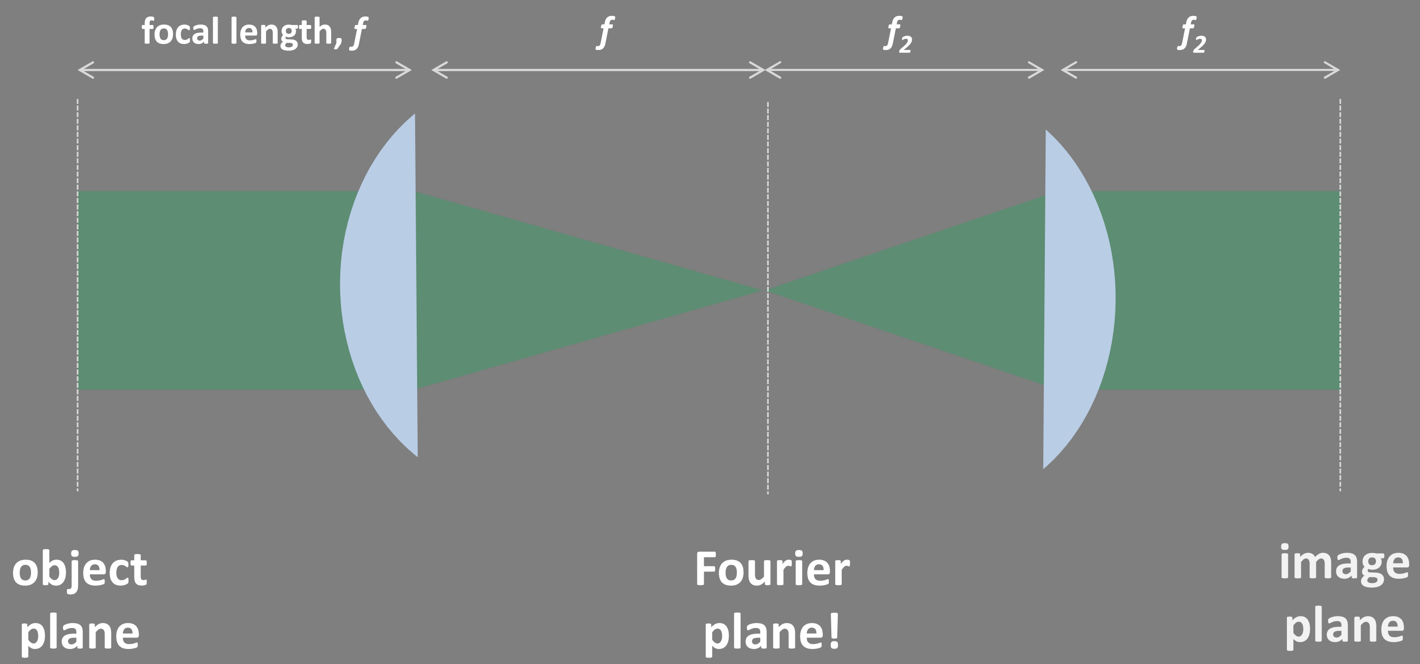


G.Zheng, R. Horstmeyer, C. Yang, *Nat. Photon.* (2013).
L.Tian, X.Li, K.Ramchandran, L. Waller, *Biomed. Opt. Express* (2014).

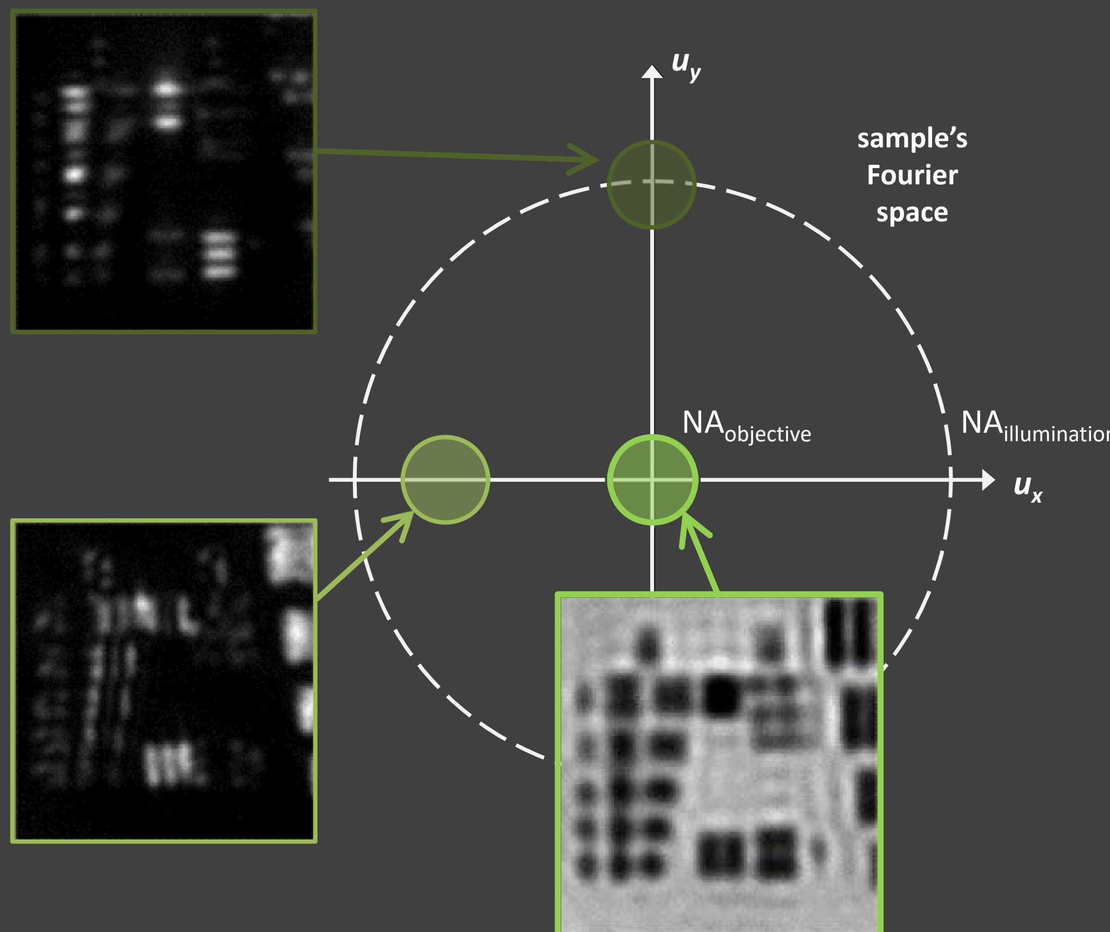
A lens can perform a Fourier transform!



A microscope does TWO Fourier transforms!



Synthetic aperture: filling in frequency space



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

Fourier Ptychography: synthetic aperture + phase retrieval

Forward model:

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

measurements

system matrix

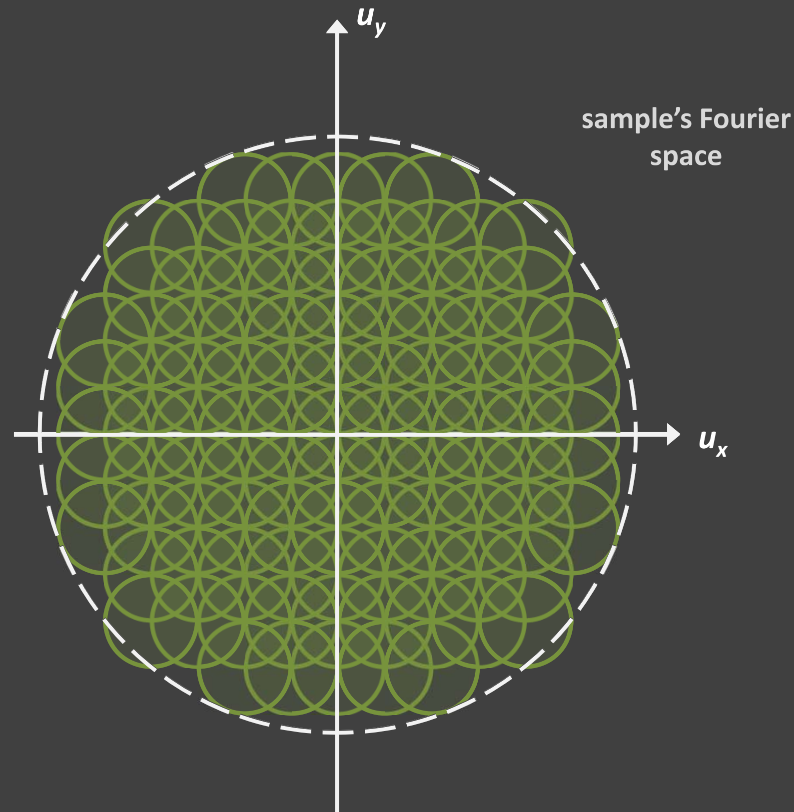
object

Inverse problem:

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

Solve for me!

And me!

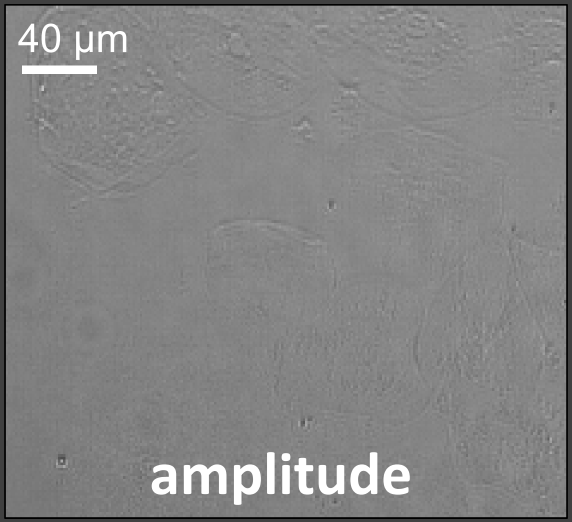


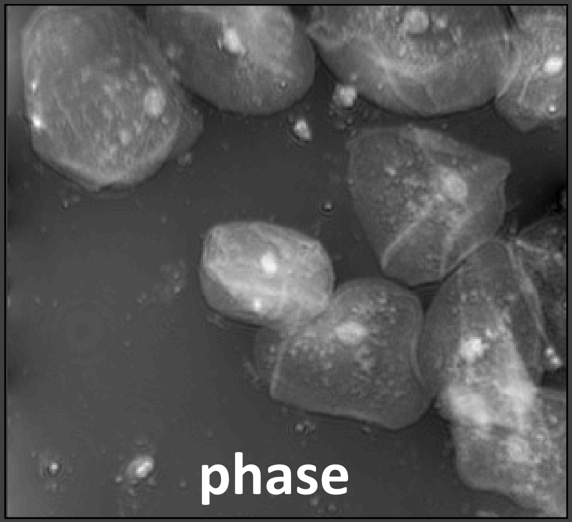
J. Rodenburg, H. Faulkner, *Appl. Phys. Lett*. 85 (2004).
M. Guizar-Sicairos, J. Fienup, *Opt. Express* 16 (2008).
L.Tian, X.Li, K.Ramchandran, L. Waller, *Biomed. Opt. Express* (2014).
S. Alexandrov, T. Hillman, T. Gutzler, D. Sampson, *Phys. Rev. Lett*. 97 (2006).
A. Kirkland, et al., *Ultramicroscopy*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

Computational $\wedge$ imaging

Phase

phase imaging *must* be computational

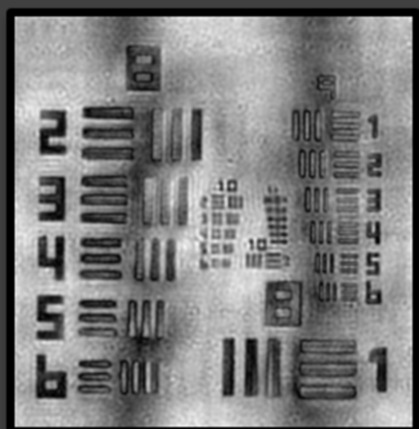




We can only measure intensity $\mathbf{y} = |\mathbf{Ax}|^2$

2^{nd} order optimization is better

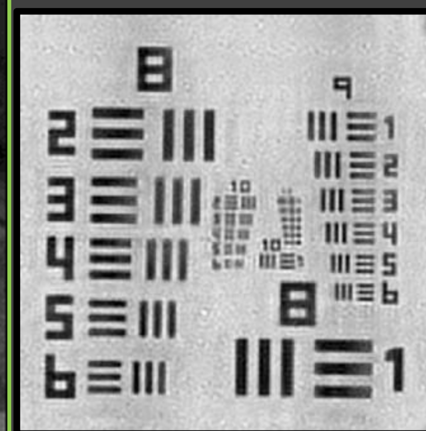
1^{st} order
(Gradient descent)



3 seconds

quasi 2^{nd} order

2^{nd} order
(Newton)

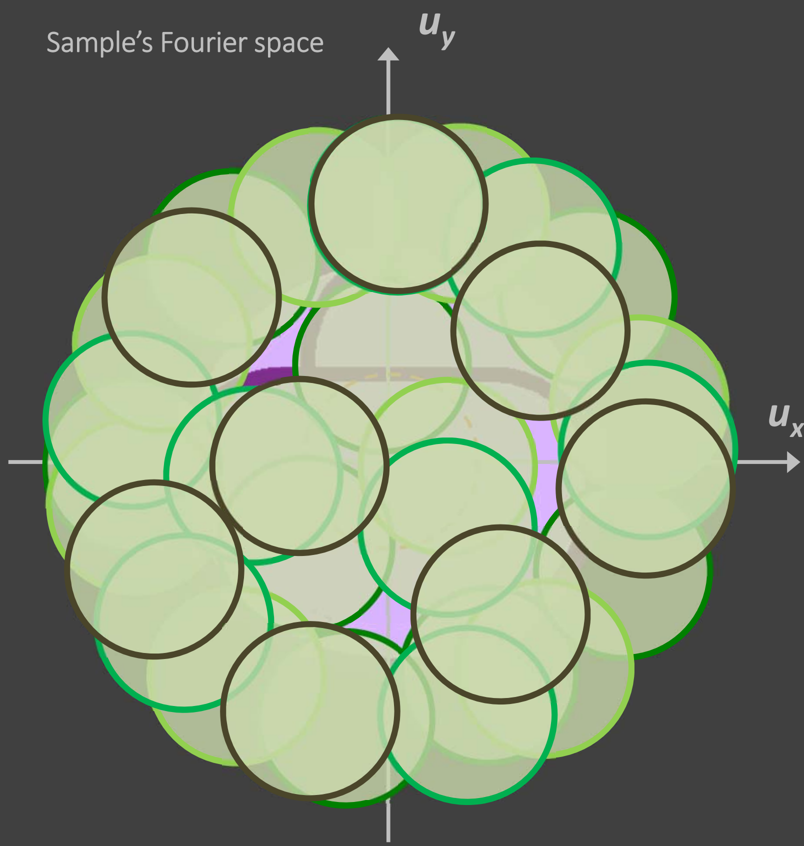


100 seconds

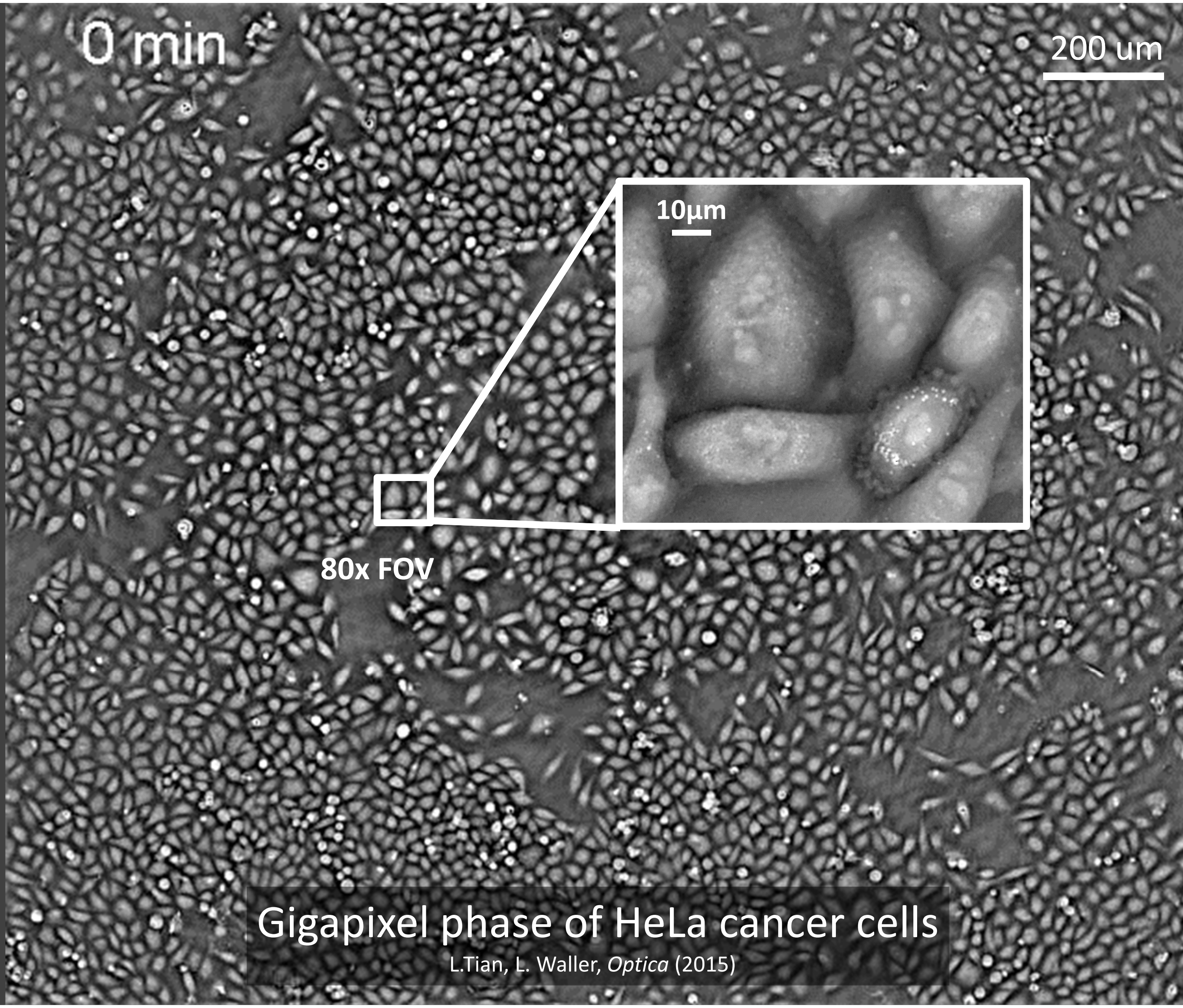
Li-Hao Yeh

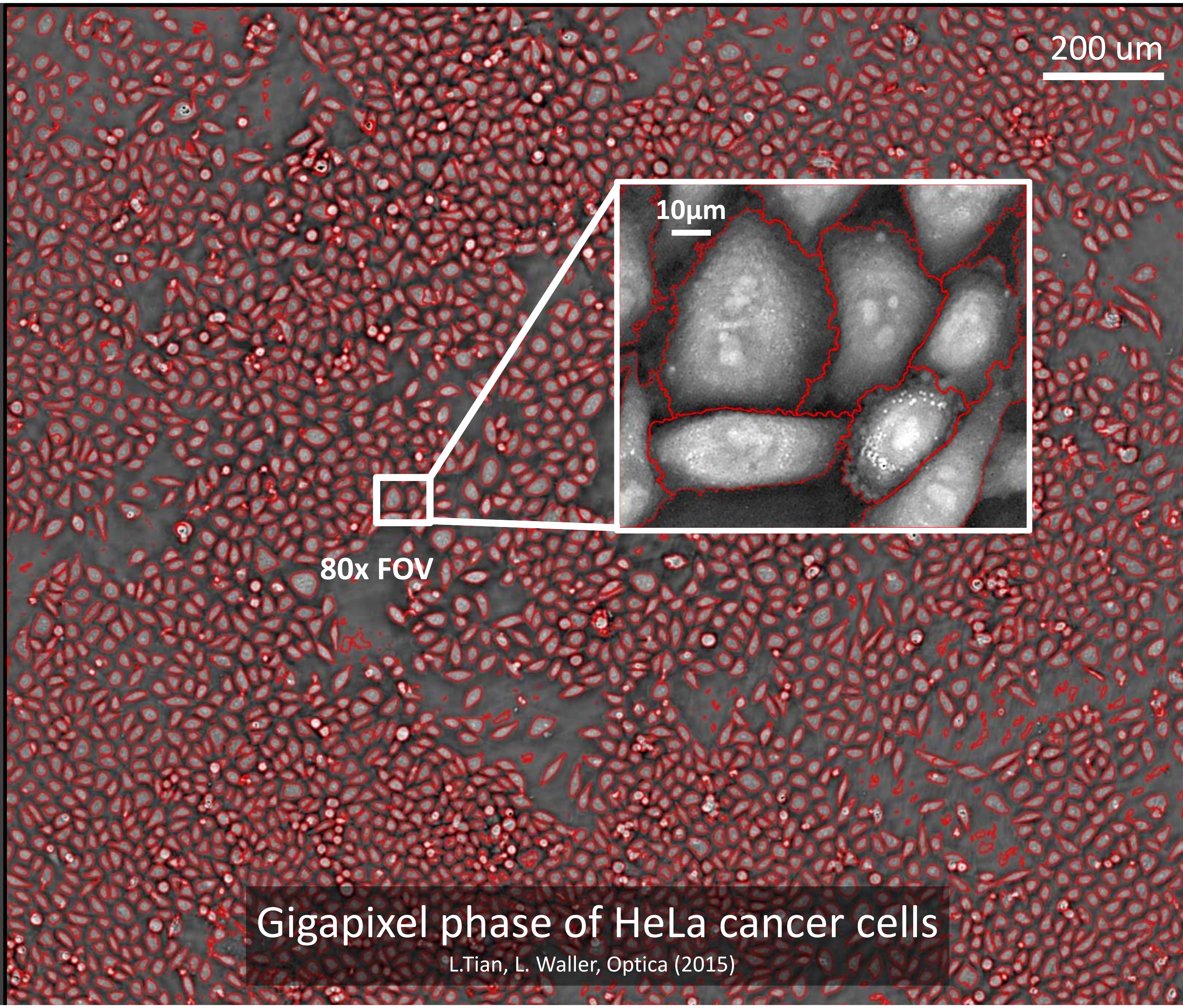
L. Yeh, Dong, Zhong, Tian, Chen, Tang, Soltanolkotabi, Waller, *Opt. Express* (2015)

Designer illumination codes for fast acquisition



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


0 min
200 um
10μm
80x FOV
Gigapixel phase of HeLa cancer cells
L.Tian, L. Waller, *Optica* (2015)



Segmentation by CellProfiler


DARK
SECRETS

Recipe for computational imaging

$$y = \underbrace{A}_{}x$$

1 **Physics**

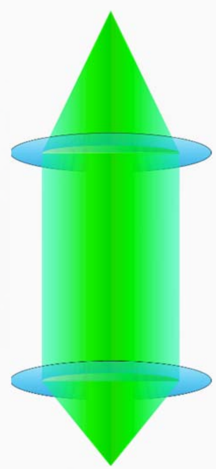
$$\nabla \cdot \mathbf{D} = \rho_V$$

$$\nabla \cdot \mathbf{B} = 0$$

$$\nabla \times \mathbf{E} = -\frac{\partial \mathbf{B}}{\partial t}$$

$$\nabla \times \mathbf{H} = \frac{\partial \mathbf{D}}{\partial t} + \mathbf{J}$$

2 **Optical Design**



3 **CALIBRATION**

Laura's Law:

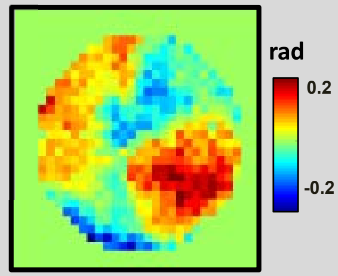
$$\text{Reproducibility} \;\; \alpha \;\; \frac{1}{\text{\# of critical pieces of duct tape}}$$

Algorithmic self-calibration

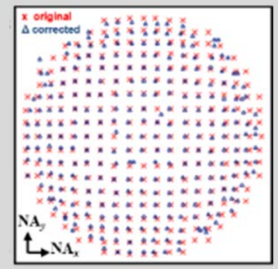
$$y = |Ax|^2$$

measurements — system matrix — object

Experimental errors:

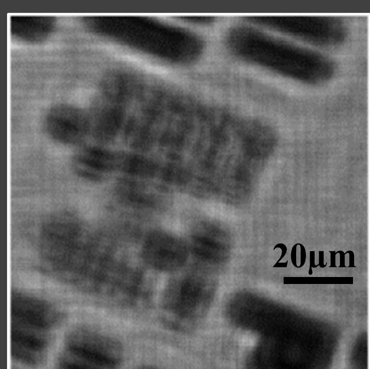


Aberrations

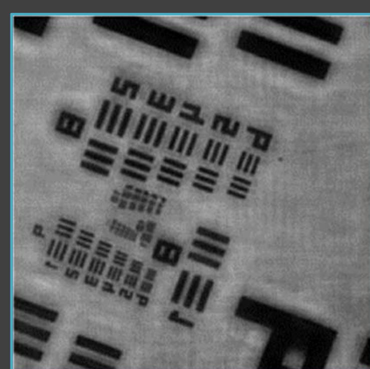


LED positions

not calibrated



calibrated



calibration parameters

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

Regina Eckert

Ou, et. al, *Opt. Express* (2014).
Yeh, Dong, …Waller, *Opt. Express* (2015).

Algorithmic self-calibration

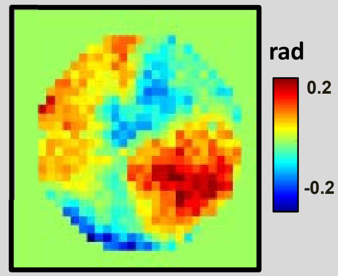
$$\mathbf{y} = |\mathbf{A}\mathbf{x}|^2$$

measurements

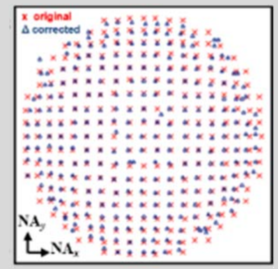
system matrix

object

Experimental errors:



Aberrations



LED positions

I don't wanna calibrate anymore!

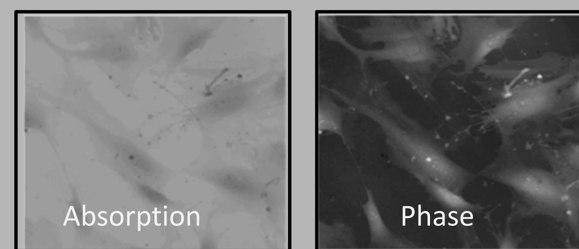
$$\min_{\mathbf{x},\boldsymbol{\theta}} \left\| \mathbf{y} - \left| \mathbf{A}(\boldsymbol{\theta})\mathbf{x} \right| \right\| + \lambda_1 \|\mathbf{x}\|_1 + \lambda_2 \|\boldsymbol{\theta}\|_2$$

calibration parameters

Regina Eckert

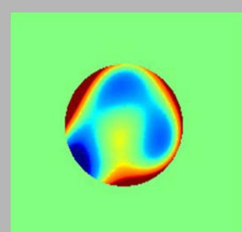
If it's critical, then let's design around it!

Solve for Object



Solve for Calibration

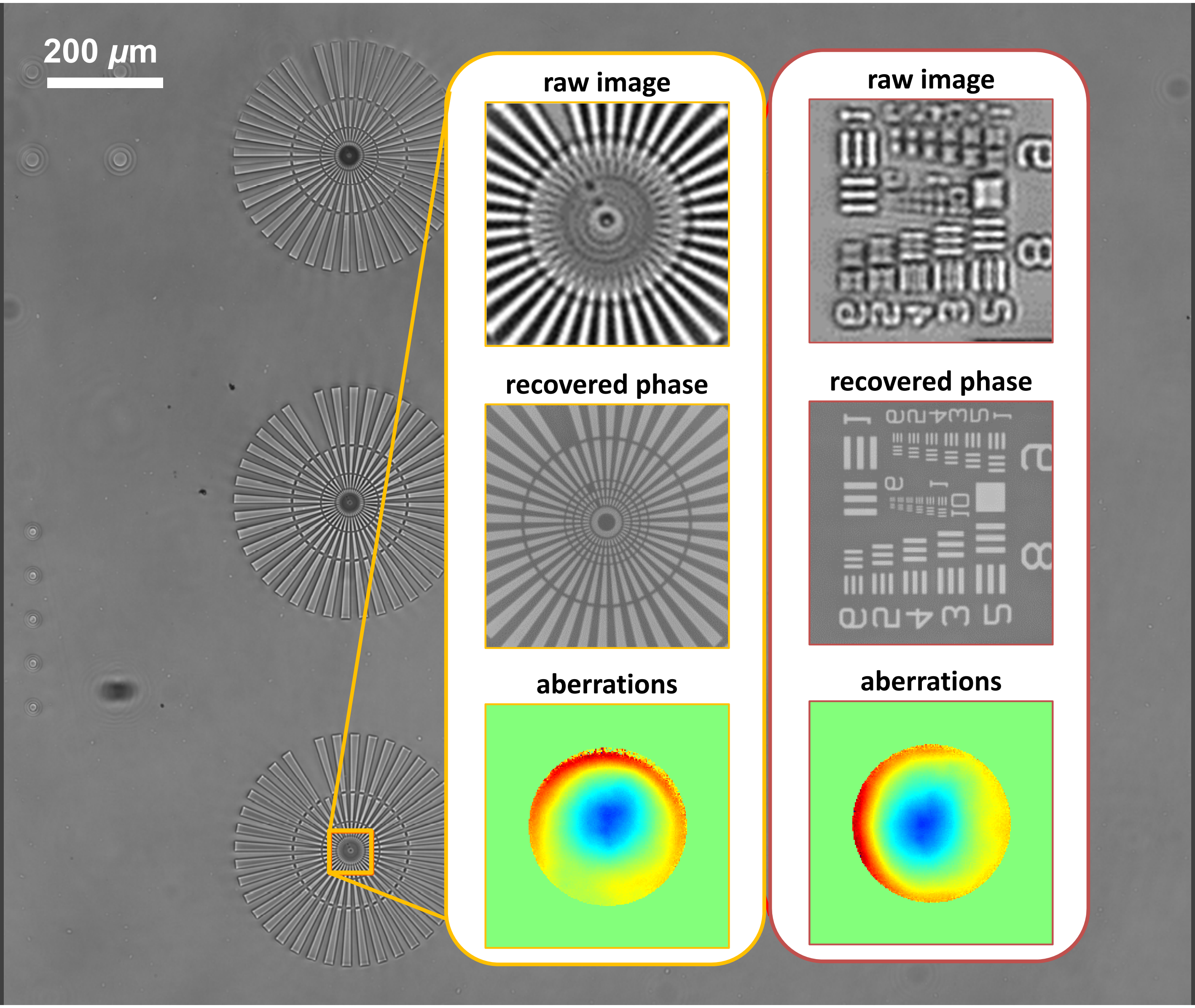
- Illumination Probe[1]
- Pupil Function[2]
- System Alignment



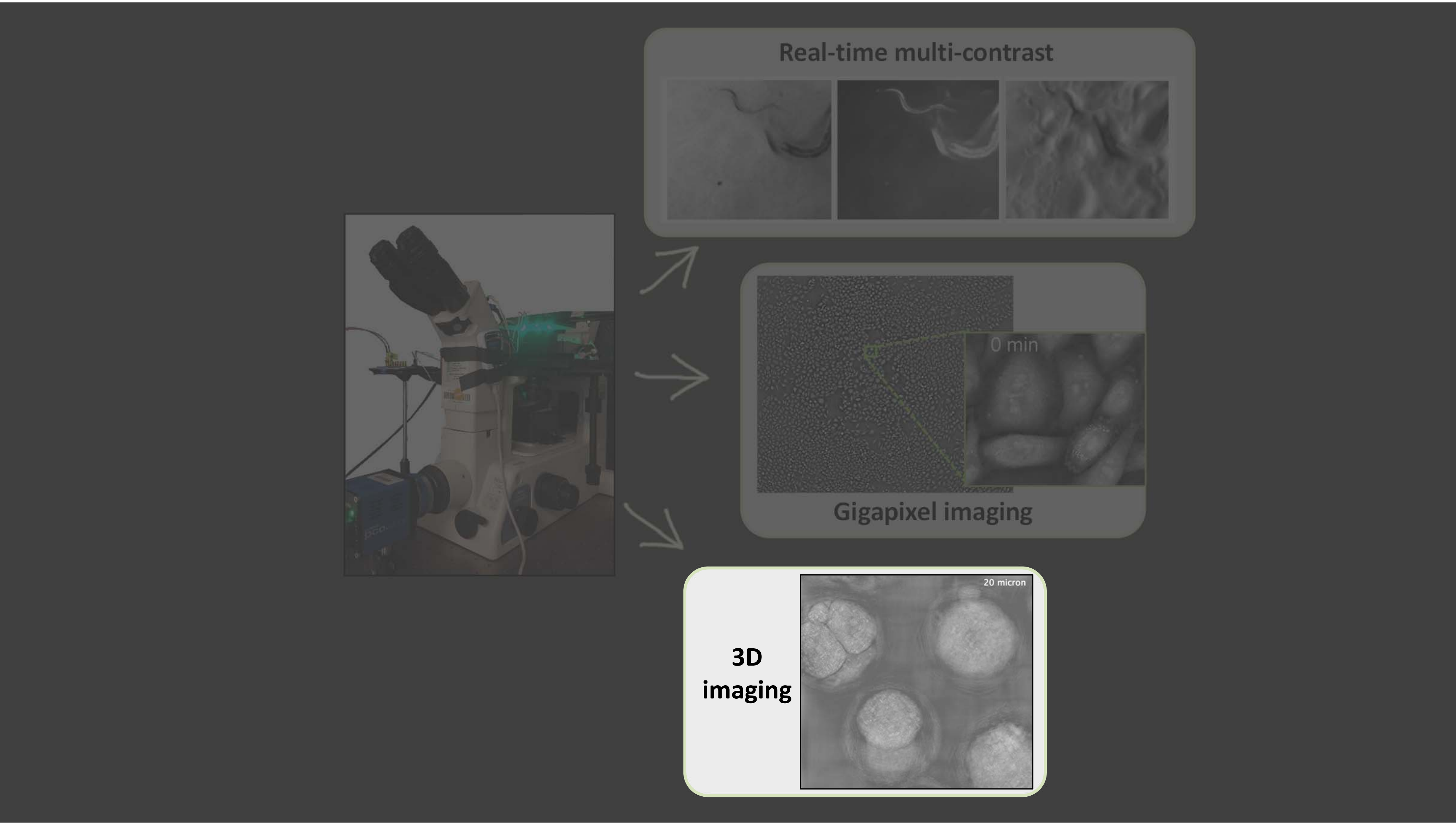
Joint Estimation

+ Guaranteed not to diverge
- Non-convex

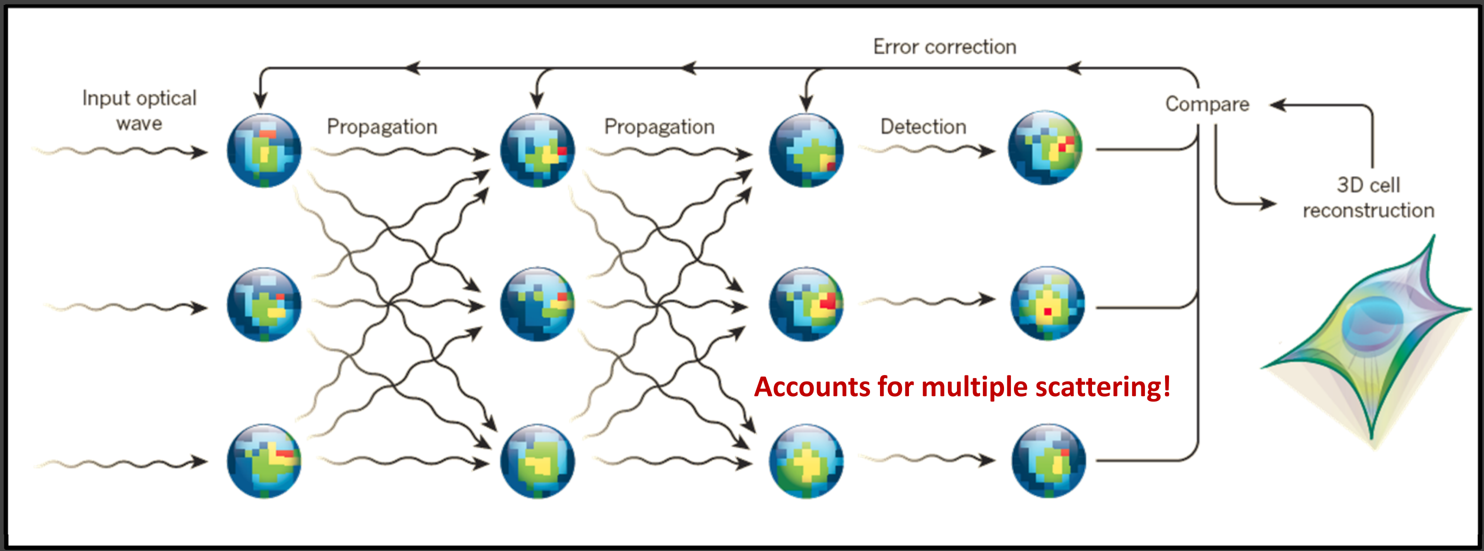
[1] M. Guizar-Sicairos and Fienup J. R. Opt. Exp. (2008)   [2] X. Ou et al., Opt Exp. (2014).



test object from Benchmark Technologies


Real-time multi-contrast
0 min
Gigapixel imaging
3D imaging
20 micron

3D phase imaging as a neural network

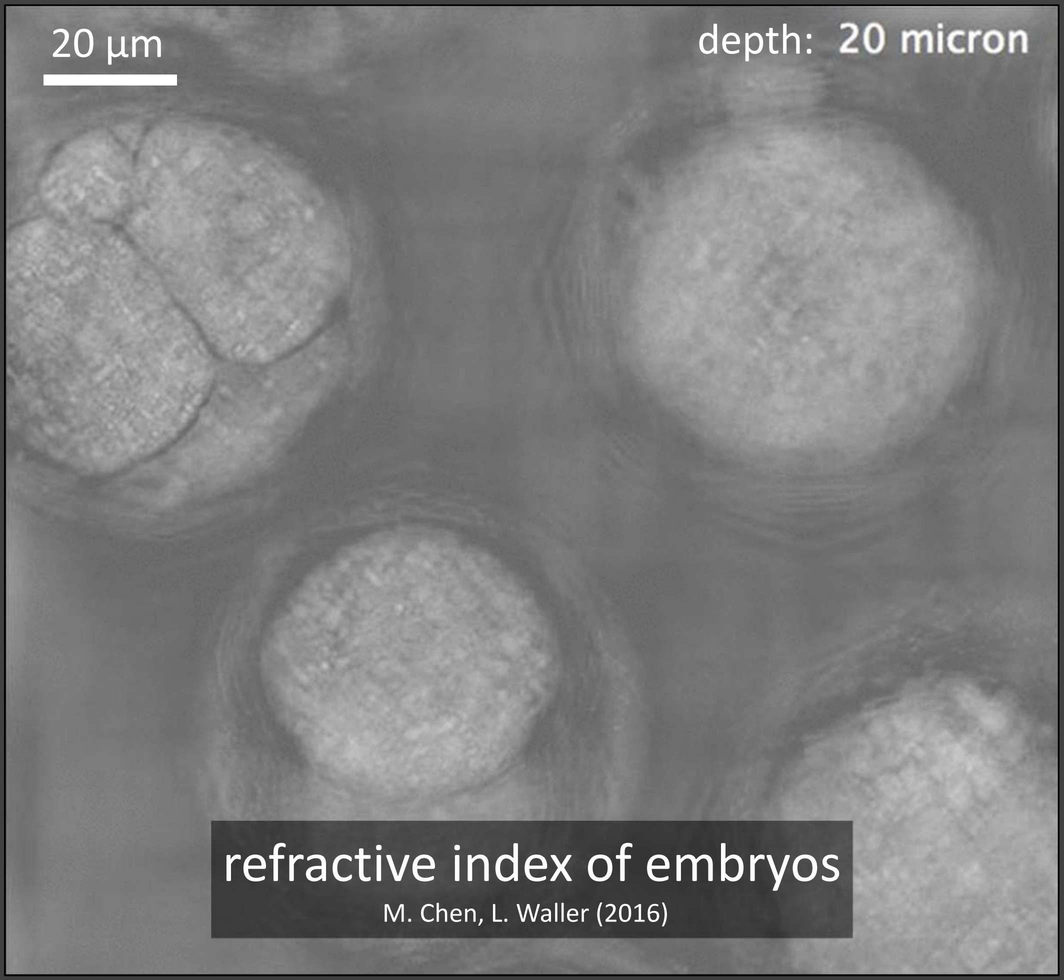


Nonlinear, nonconvex…
so will it converge?

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

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

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