Computational Imaging for better ML & ML for better Computational Imaging

Typical cameras are optim... ...tion

ML pipeline with a standard c...

3D
hyperspectral
polarization
world
camera
RGB
2D image
ML n...
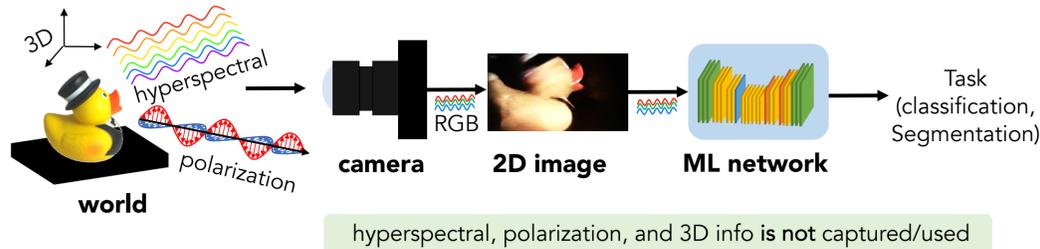
...onal scene information (3D, hyper...ctral, polarization) can be more ...tan color images for many tasks, but is ...t captured by typical cameras

task ...sification
...mentation

...ng this information often requires ...ulky, expensive hardware, e.g. $25k+ for a hype...ctral camera

hyperspectral, polarization, and 3D info **is not** captured/used

Computational cameras are designed to capture higher dimensional information

Conceptual ML pipeline with a computational camera:

3D
hyperspectral
polarization
world
reconstruction network
recovered image
computational camera
encoded image
ML network
Task (classification, segmentation)

hyperspectral, polarization, and 3D info **is** captured/used
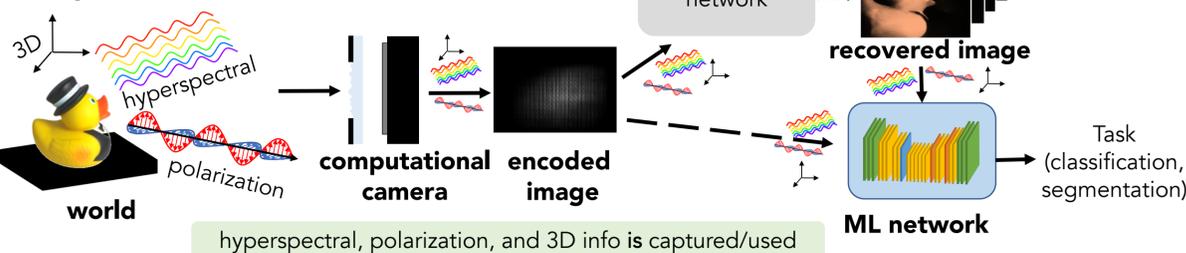
- Computational cameras can be compact and cheap
- These cameras could be designed to capture the most useful information for a given task

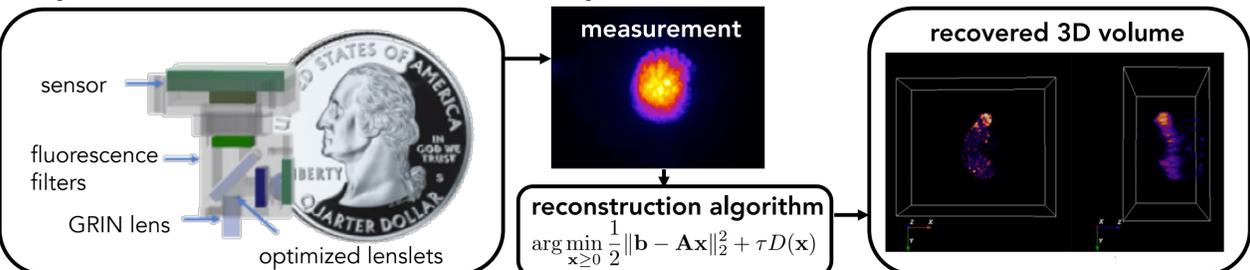## Our computational cameras are tiny, cheap, and capture 3D & hyperspectral images

Snapshot hyperspectral imager[1]

diffuser
x
y
λ
scene
spectral filter array
sensor

measurement

recovered hyperspectral volume
reconstruction
1 super-pixel
400nm 600nm

reconstruction algorithm
$$\arg\min_{\mathbf{x}\geq 0}\frac{1}{2}\|\mathbf{b}-\mathbf{A}\mathbf{x}\|_2^2+\tau D(\mathbf{x})$$
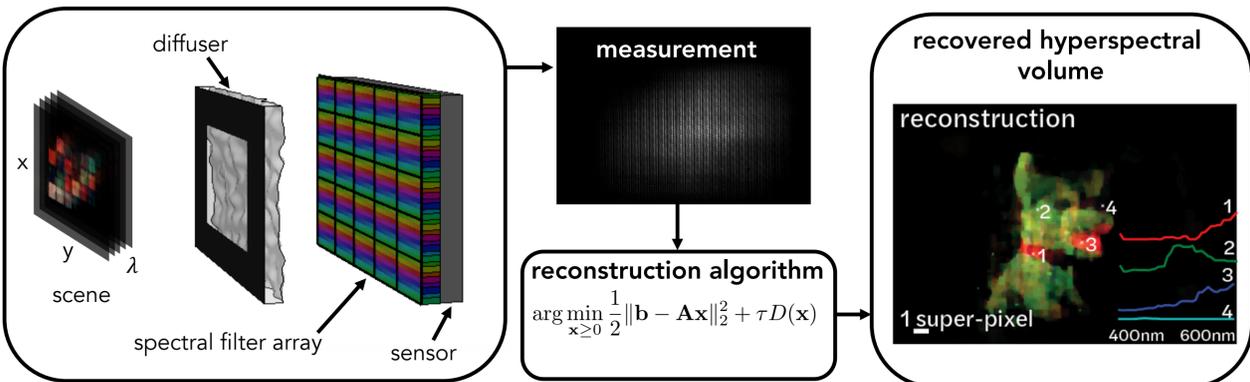
- Low cost system ($5 for filter array and diffuser)
- 64 spectral channels
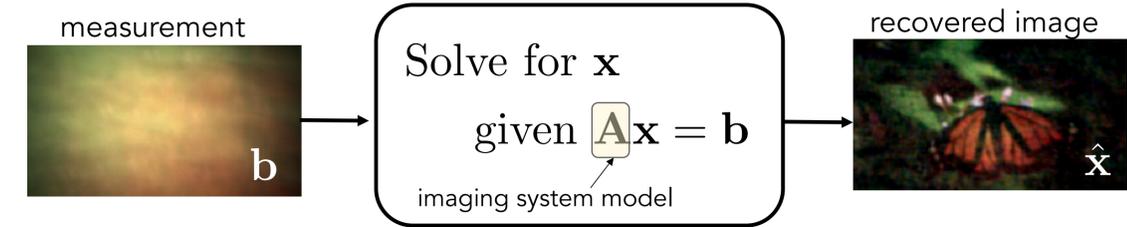- Compressive measurement system – higher resolution than possible with a lens

Snapshot 3D fluorescence microscope[2]

sensor
fluorescence filters
GRIN lens
optimized lenslets

measurement

recovered 3D volume

reconstruction algorithm
$$\arg\min_{\mathbf{x}\geq 0}\frac{1}{2}\|\mathbf{b}-\mathbf{A}\mathbf{x}\|_2^2+\tau D(\mathbf{x})$$
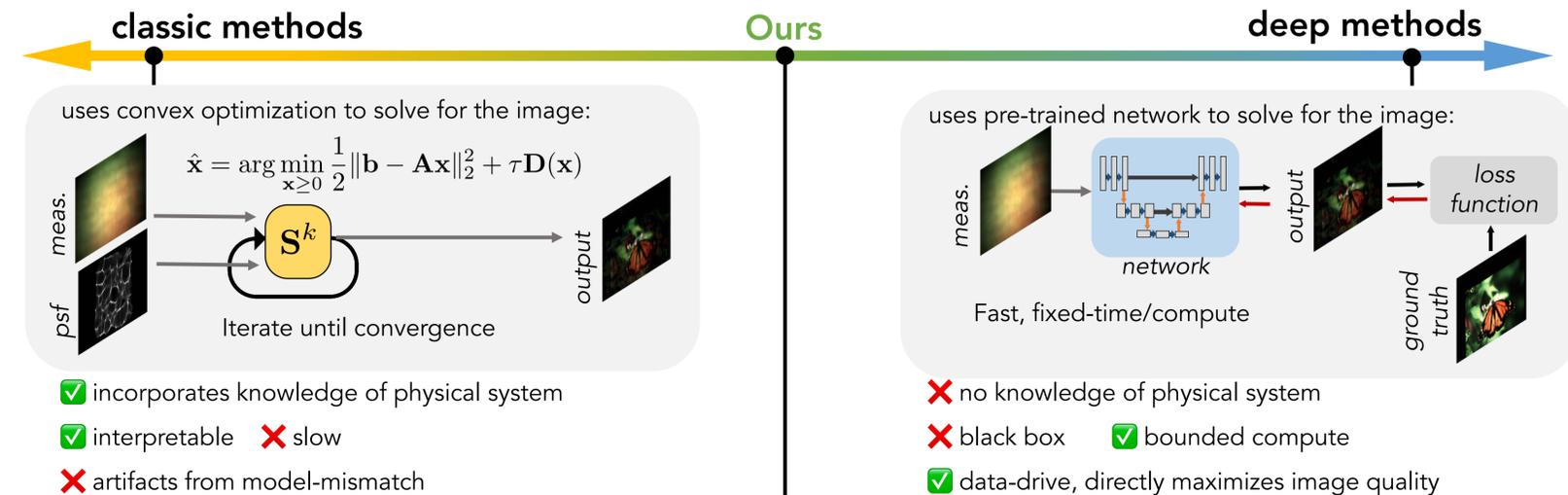
- Tiny: 2.5 grams
- Recovers 3D volumes from encoded measurement
- Achieves 2.74 μm lateral and 15 μm axial resolution across 900 x 700 x 390 μm^3 volume

Computational cameras solve an inverse problem to recover images
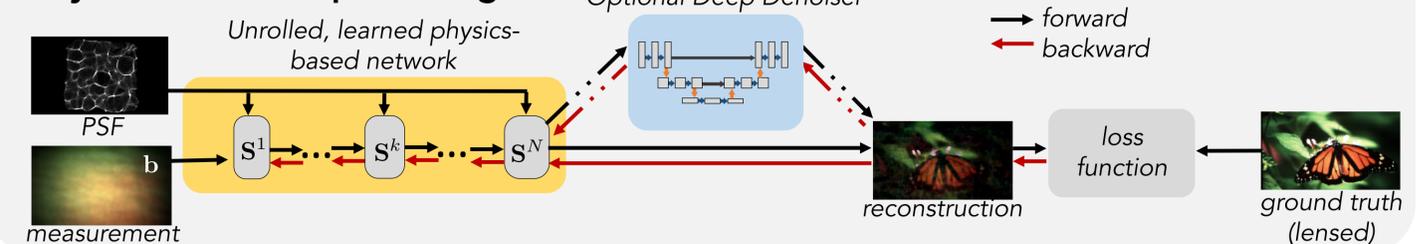
measurement
b

Solve for **x**
given $\mathbf{A}\mathbf{x}=\mathbf{b}$
imaging system model

recovered image
$\hat{\mathbf{x}}$

Optimization or deep learning can be used to solve imaging inverse problems

classic methods   Ours   **deep methods**

uses convex optimization to solve for the image:
$$\hat{\mathbf{x}}=\arg\min_{\mathbf{x}\geq 0}\frac{1}{2}\|\mathbf{b}-\mathbf{A}\mathbf{x}\|_2^2+\tau\mathbf{D}(\mathbf{x})$$
meas.
psf
$\mathbf{S}^k$
output
Iterate until convergence

uses pre-trained network to solve for the image:
meas.
network
output
loss function
ground truth
Fast, fixed-time/compute

✅ incorporates knowledge of physical system
✅ interpretable ❌ slow
❌ artifacts from model-mismatch

❌ no knowledge of physical system
❌ black box ✅ bounded compute
✅ data-drive, directly maximizes image quality

Physics-based deep learning

Unrolled, learned physics-based network
Optional Deep Denoiser
PSF
measurement
b
$\mathbf{S}^1$ ⋯ $\mathbf{S}^k$ ⋯ $\mathbf{S}^N$
→ forward
→ backward
reconstruction
loss function
ground truth (lensed)

Our physics-based deep learning outperforms classic and deep methods[3]

ADMM (71ms)
ADMM (1.5s)
Classic

71ms, 100 training
75ms, 24k training
Ours

10ms, 24k training
Deep

[1] K. Monkhova*, K. Yanny*, N. Aggarwal, L. Waller 'Spectral DiffuserCam: lensless snapshot hyperspectral imaging with a spectral filter array', Optica (2020)
[2] K. Yanny, N. Antipa, W. Liberti, S. Dehaeck, K. Monakhova, et al. 'Miniscope3D: optimized single-shot miniature 3D fluorescence microscopy', Nature LSA (2020)
[3] K. Monakhova, J. Yurtsever, G. Kuo, N. Antipa, K. Yanny, L. Waller, 'Learned reconstructions for practical mask-based lensless imaging', Optics Express (2019)