Computational Imaging

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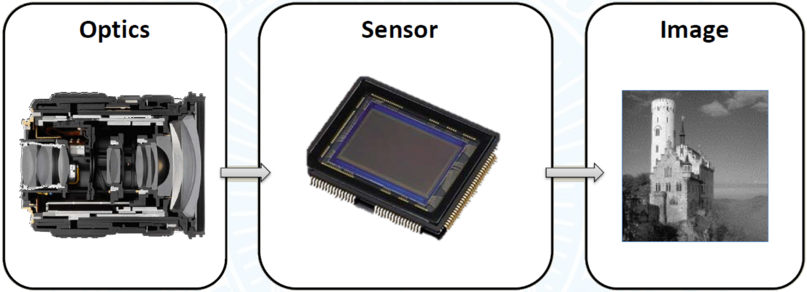
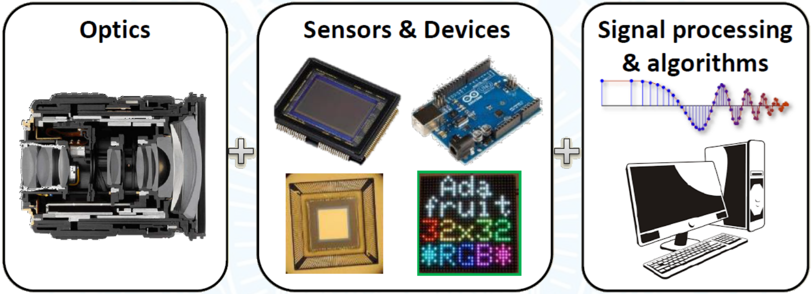
Traditional imaging: direct approach



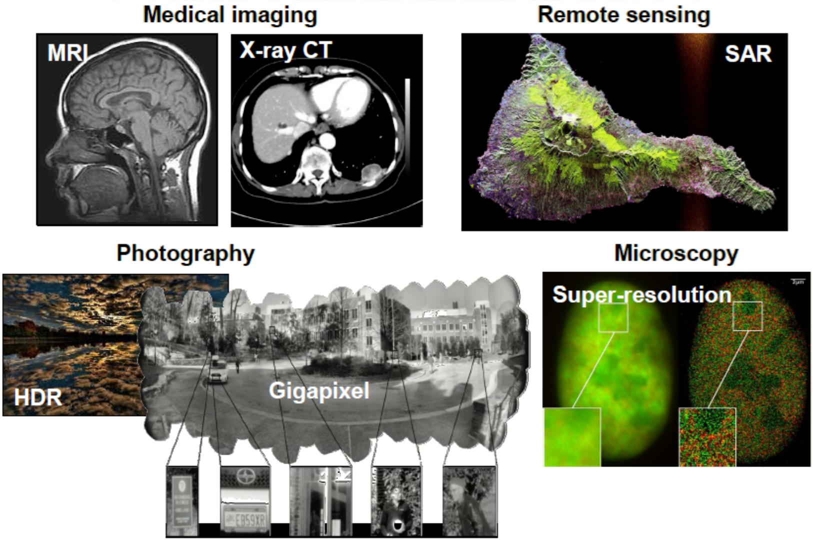
- Rely on optics
- Fundamental limitations due to physical laws, material constraints, manufacturing capabilities, etc.

Computational imaging: system approach

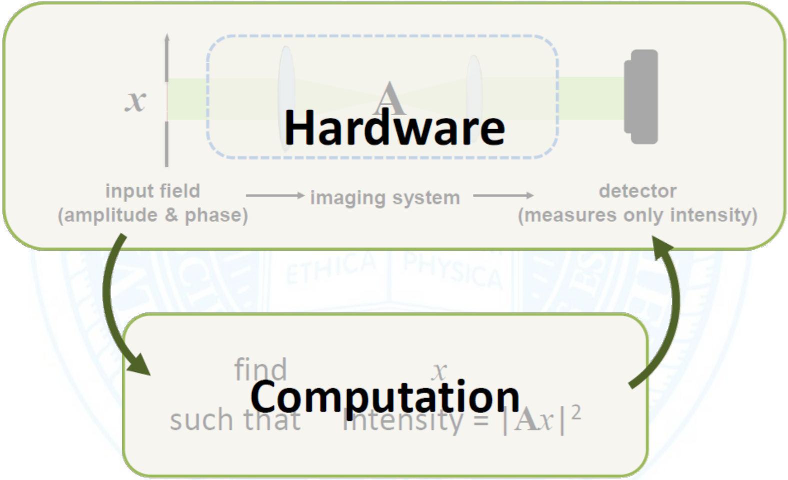


- System-level integration creates new imaging pipelines:
  - Encode information with hardware
  - Computational reconstruction
- Design flexibility
- Enable new capabilities, e.g. super-resolution, 3D, phase

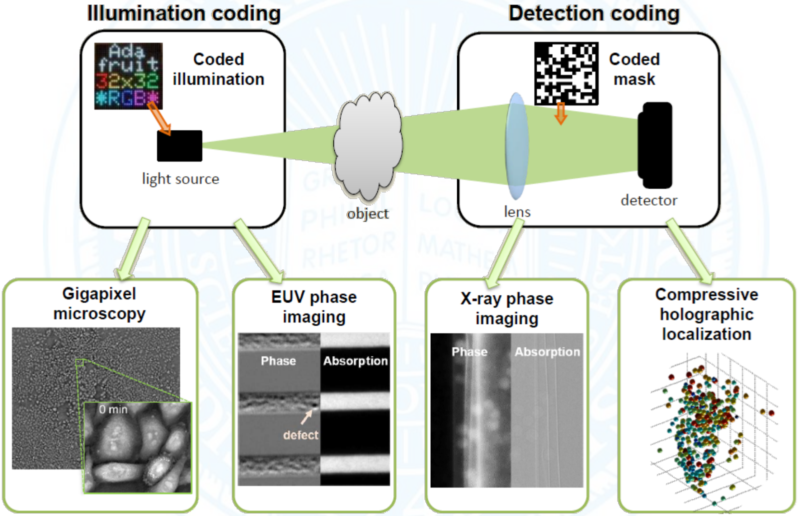
Computational imaging is revolutionizing many domains



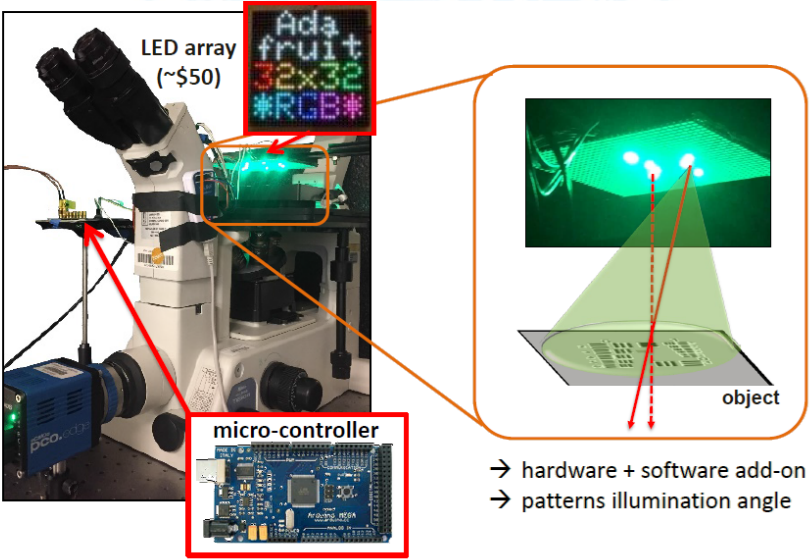
Computational wave-field imaging



Computational strategies in computational imaging

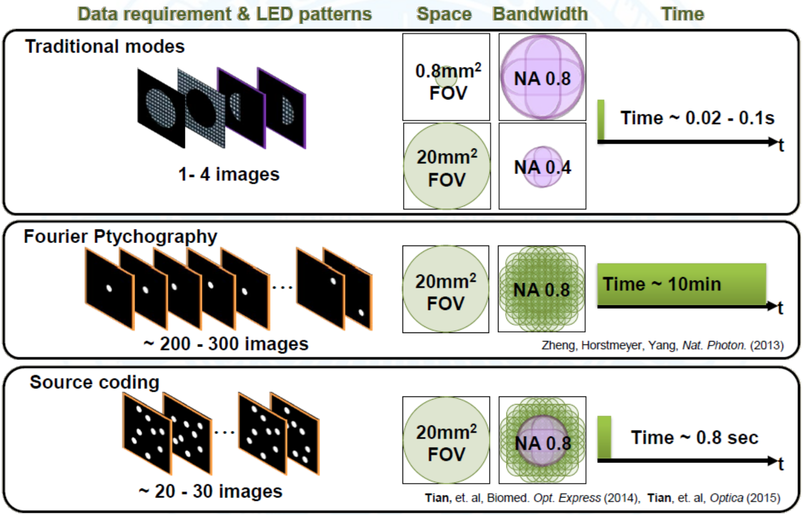


Computational microscopy using LED array

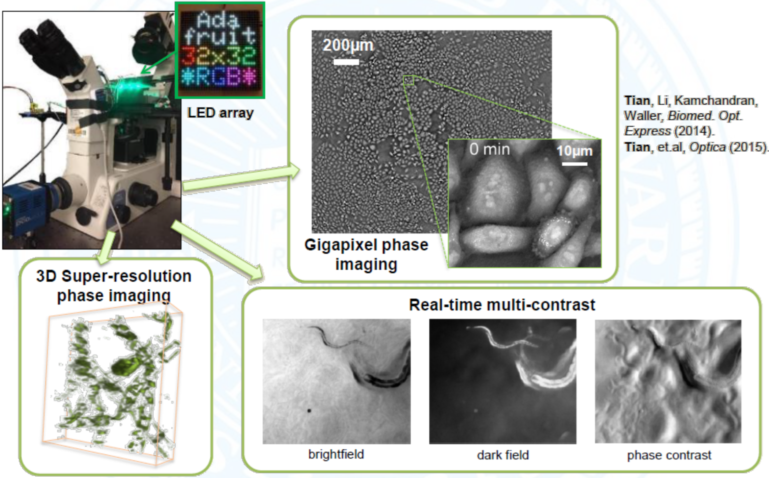


→ hardware + software add-on
→ patterns illumination angle

Tradeoff in space, bandwidth, and time



Computational imaging by coded illumination

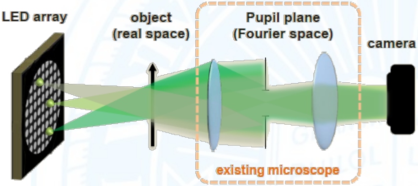


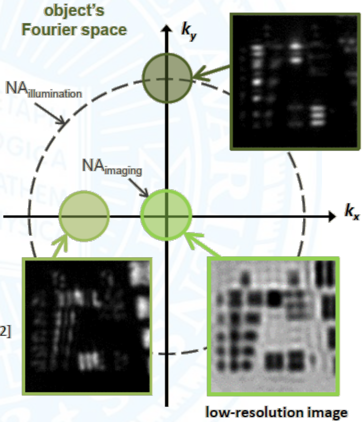
Tian, Li, Kamchandran, Waller, *Biomed. Opt. Express* (2014).
Tian, et.al, *Optica* (2015).

Tian, Waller, *Optica* (2015).
Tian, Wang, Waller, *Opt. Lett.* (2014)

Tian, Waller, *Opt. Express* (2015)
Liu, **Tian**, Liu, Waller, *J. Biomed. Optics* (2014).

Fourier Ptychography: synthetic aperture+phase retrieval





- Capture data with low magnification objective lens:
  - wide field-of-view
  - but... small bandwidth
- Improve resolution by synthetic aperture[1-2]
  - $NA_{final} = NA_{illumination} + NA_{imaging}$

[1] Zheng, Horstmeyer, Yang, *Nat. Photon.* (2013)
[2] Gutzler, Hillman, Alexandrov, Sampson, *Opt. Lett*, (2010)

Phase retrieval by nonlinear optimization

Stitch Fourier regions from
intensity-only measurements?

Forward model:

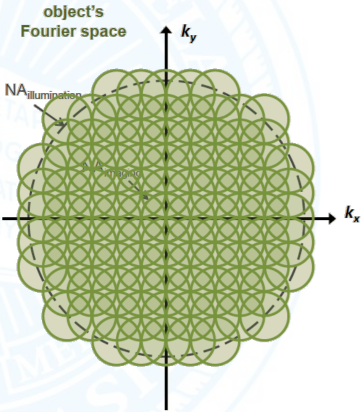
$$I_n(\boldsymbol{r}) = |\mathcal{F}^{-1}\{O(\boldsymbol{k}-\boldsymbol{k}_n)\cdot P(\boldsymbol{k})\}|^2$$

intensity from n^th LED — **object's Fourier transform** — **pupil function**

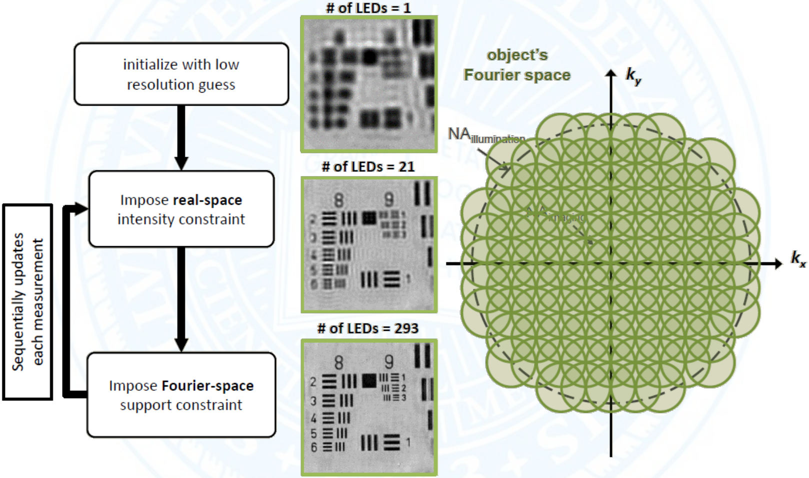
Inverse problem:

$$\min_{O(\boldsymbol{k})} \sum_n \sum_{\mathbf{r}} |I_n(\boldsymbol{r}) - |\mathcal{F}^{-1}\{O(\boldsymbol{k}-\boldsymbol{k}_n)\cdot P(\boldsymbol{k})\}|^2\ |^2$$

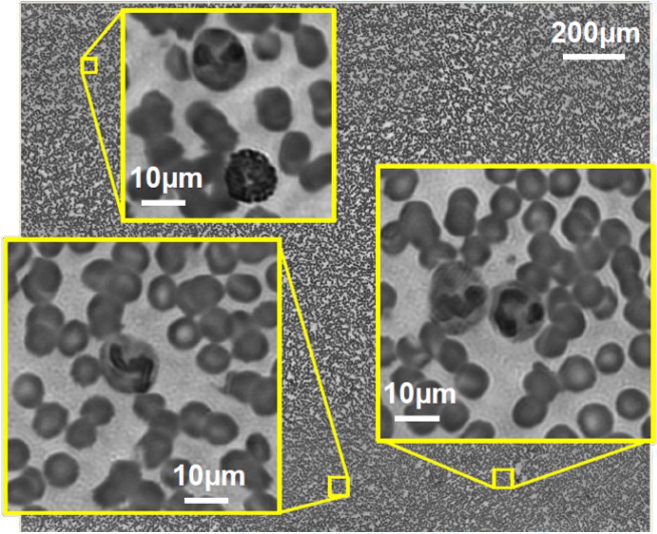
unknown



Phase retrieval by nonlinear optimization



Wide field-of-view high resolution for high-throughput screening



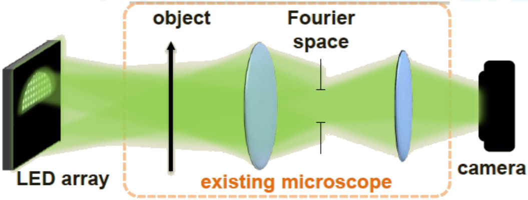
~40,000 cells

2.1mmx1.7mm
resolution ~400nm

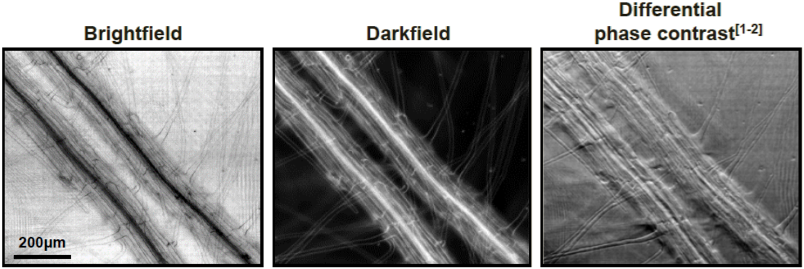
13k x 11k pixels
reconstructed

Stained Human
Blood Cell

Multi-contrast imaging with LED array



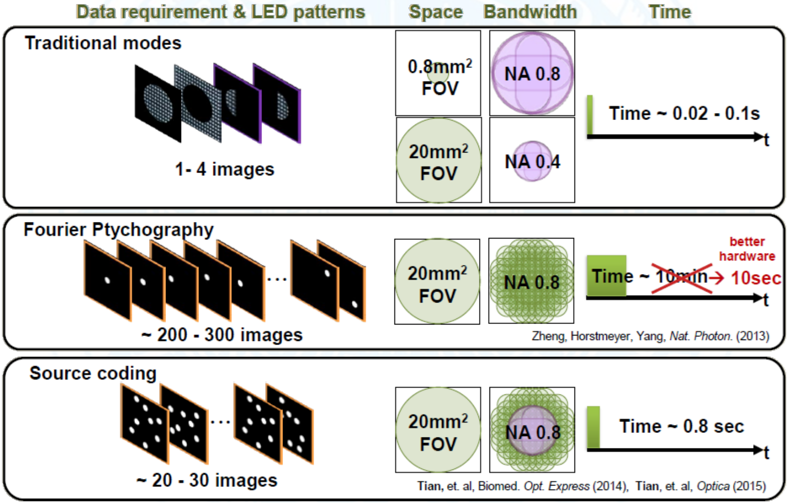
- No requirement for special inserts, polarization optics, and objective lens
- No mechanical movement



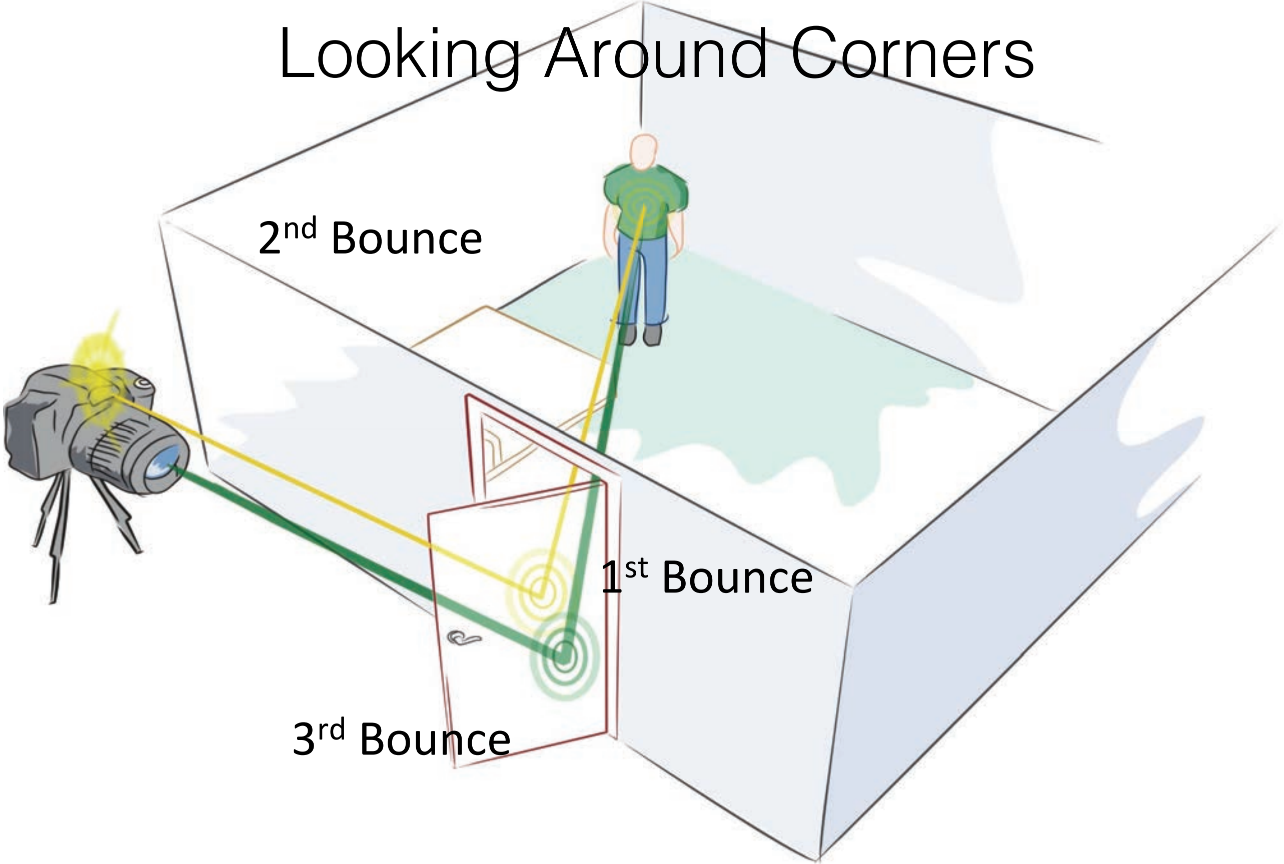
Tian, Wang, Waller, *Opt. Lett.* (2014).

[1] Mehta, Sheppard, *Opt. Lett.* (2009).
[2] Ford, Chu, Mertz, *Nat. Methods* (2012).

Tradeoff in space, bandwidth, and time

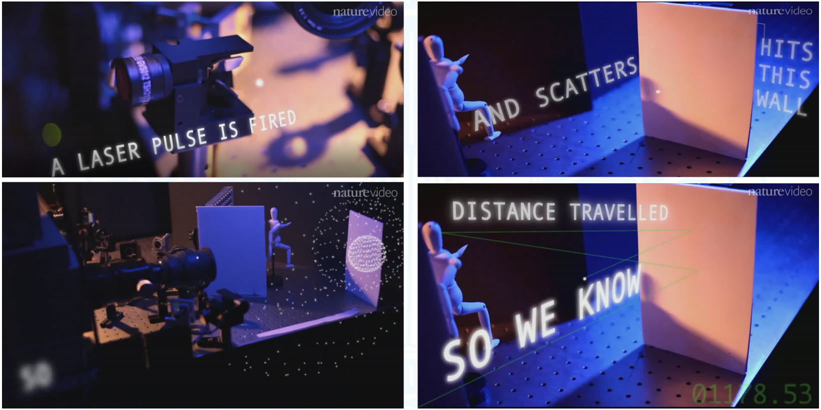


Looking Around Corners

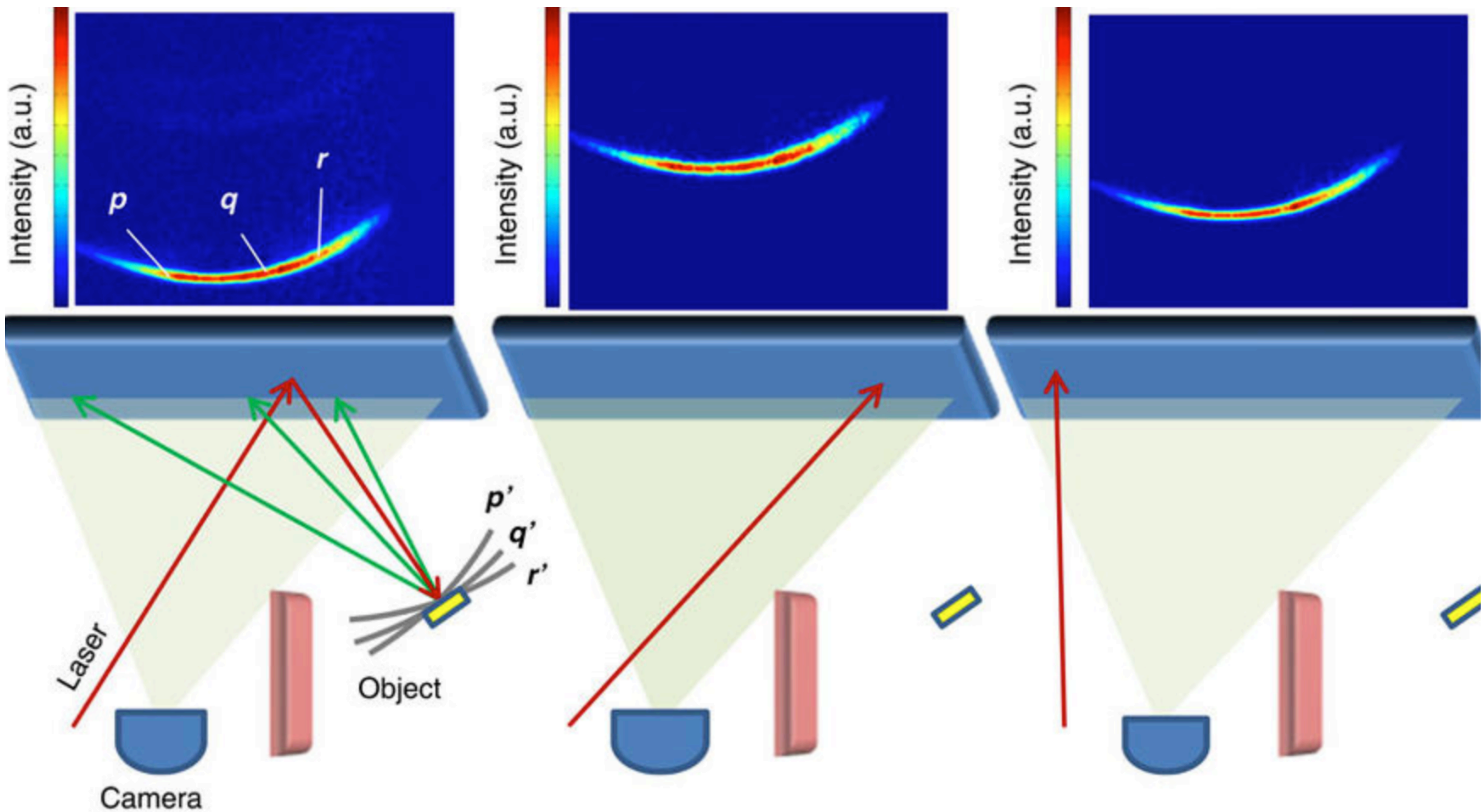


MIT Media Lab, Camera Culture Group


MIT Media Lab, Camera Culture Group
naturevideo

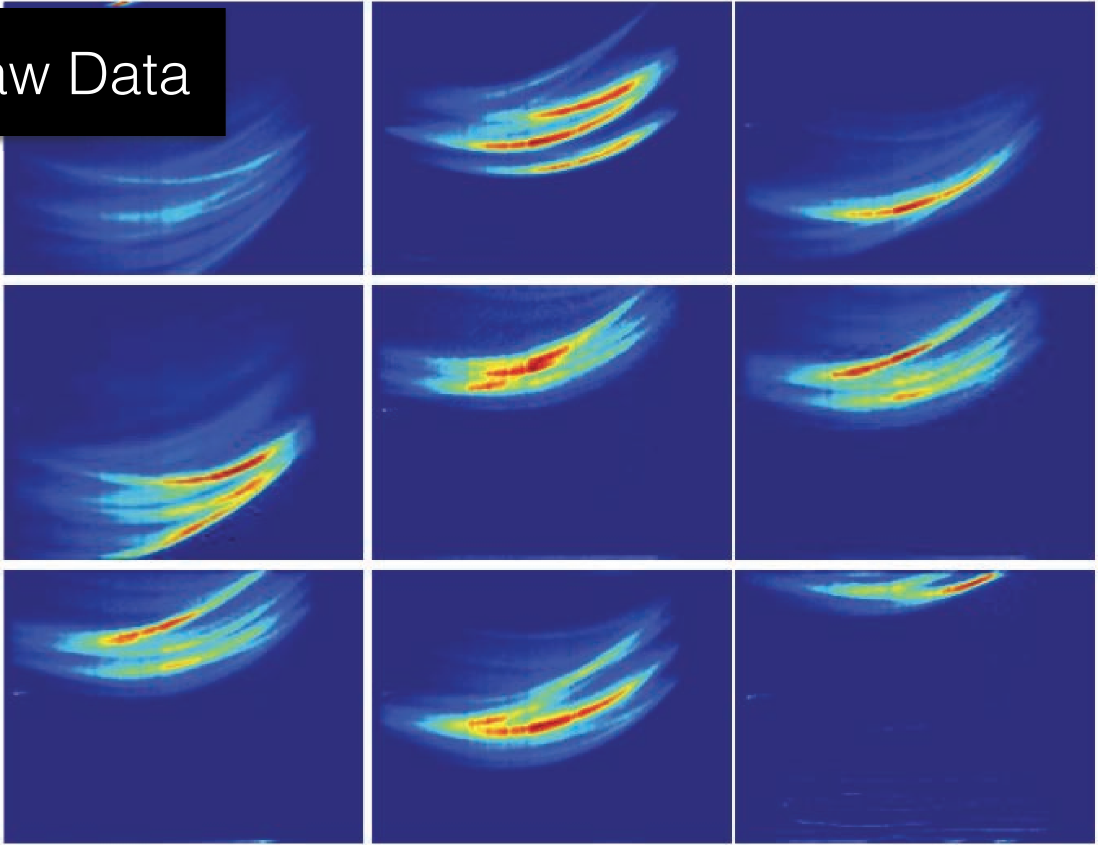


[0] A. Velten, T. Willwacher, O. Gupta, A. Veeraraghavan, M. G. Bawendi & R. Raskar, "Recovering three-dimensional shape around a corner using ultrafast time-of-flight imaging," in Nature Communications 3 2012.

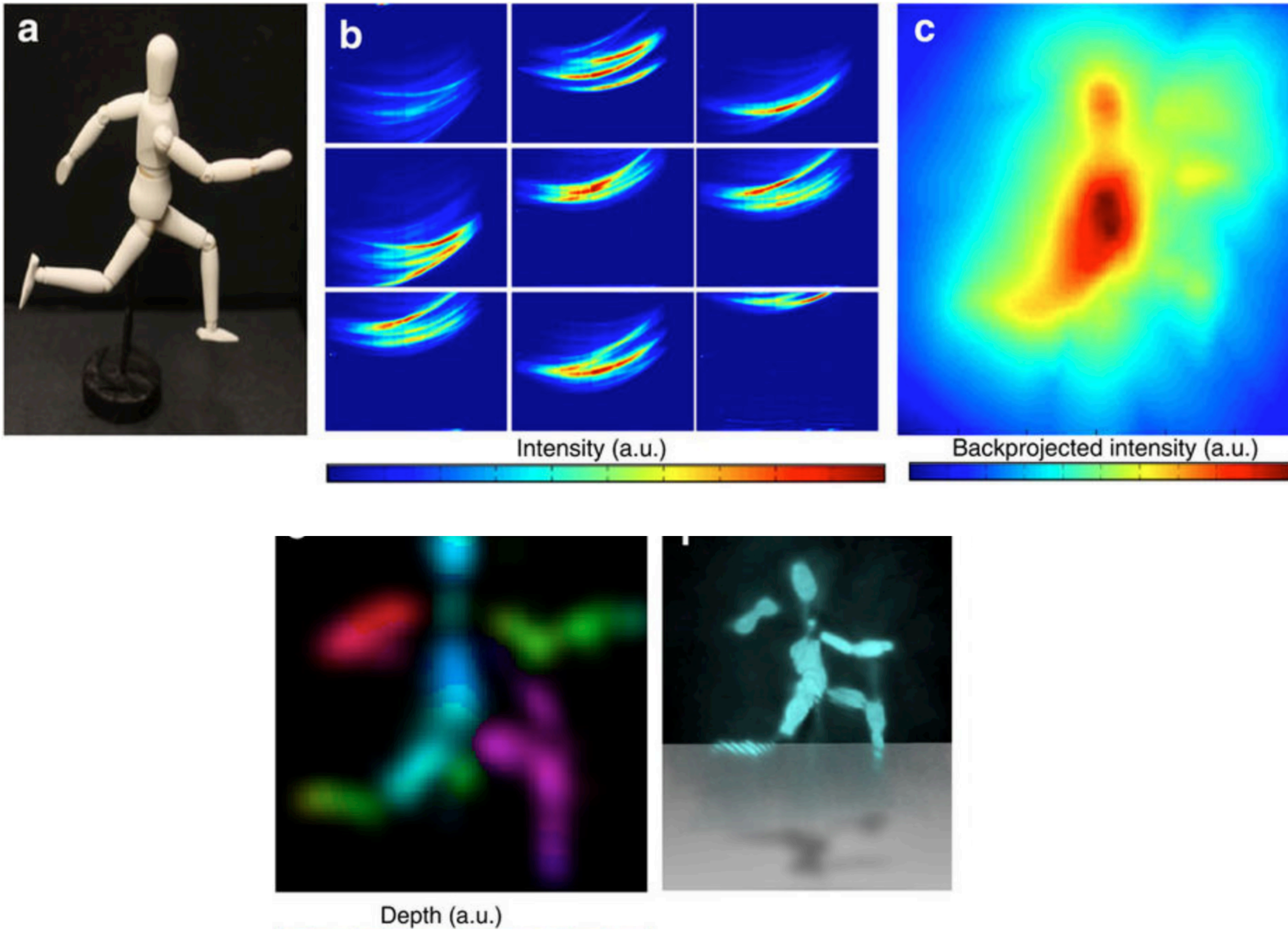


Intensity (a.u.)
p
q
r
Intensity (a.u.)
Intensity (a.u.)
p'
q'
r'
Laser
Object
Camera

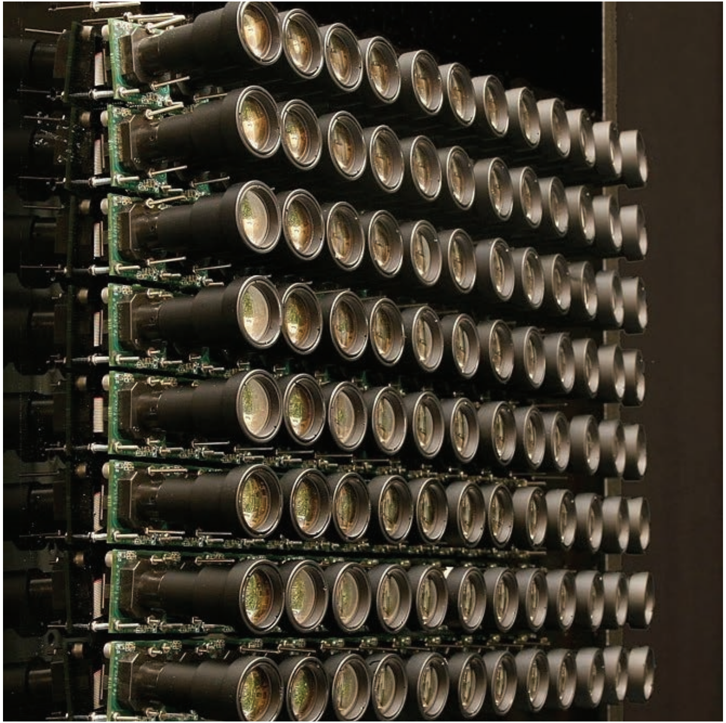
Raw Data



MIT Media Lab, Camera Culture Group

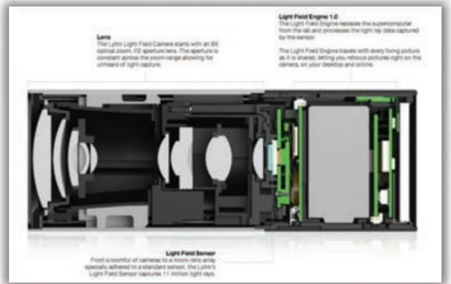

a
b
c
Intensity (a.u.)
Backprojected intensity (a.u.)
Depth (a.u.)

Light Fields and The Plenoptic Function



Stanford Camera Array

- camera arrays
- integral imaging
- coded masks
- refocus
- fourier slice photography


Lens
Light Field Engine 1.0
Light Field Sensor

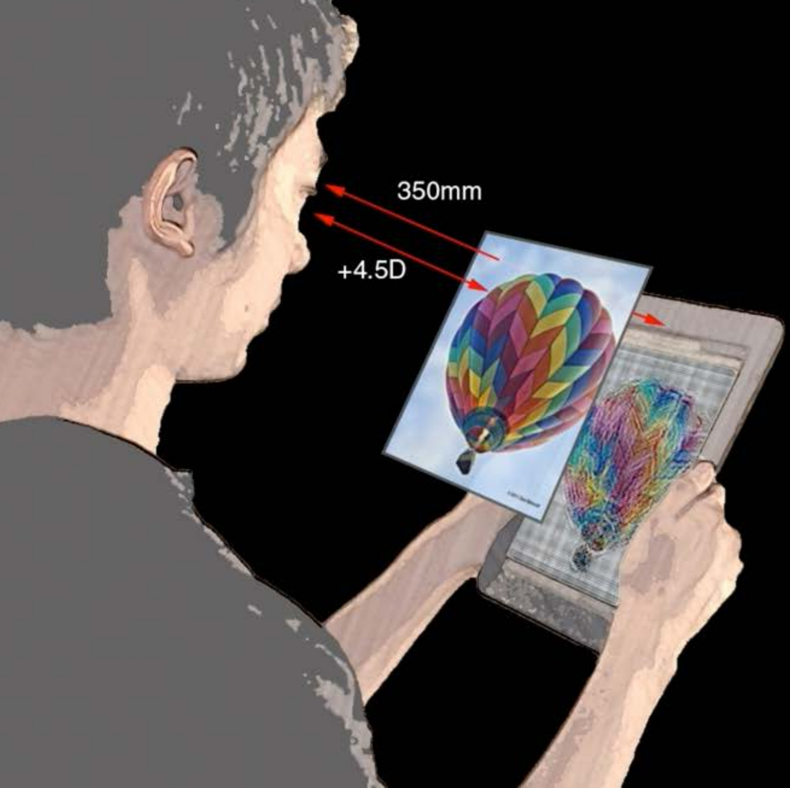

F/2.0 30 - 255 mm
0 mm - ∞

Lytro

Refocus

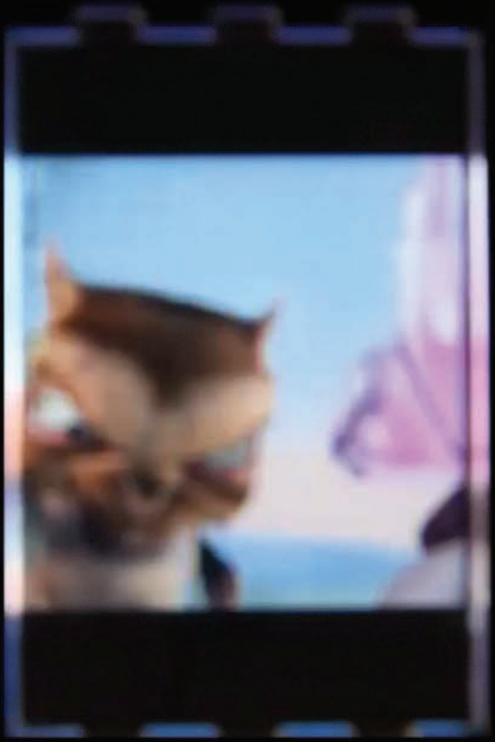
[Ng et al. 2005]

Vision-correcting Display



300 dpi or higher

prototype construction



conventional display

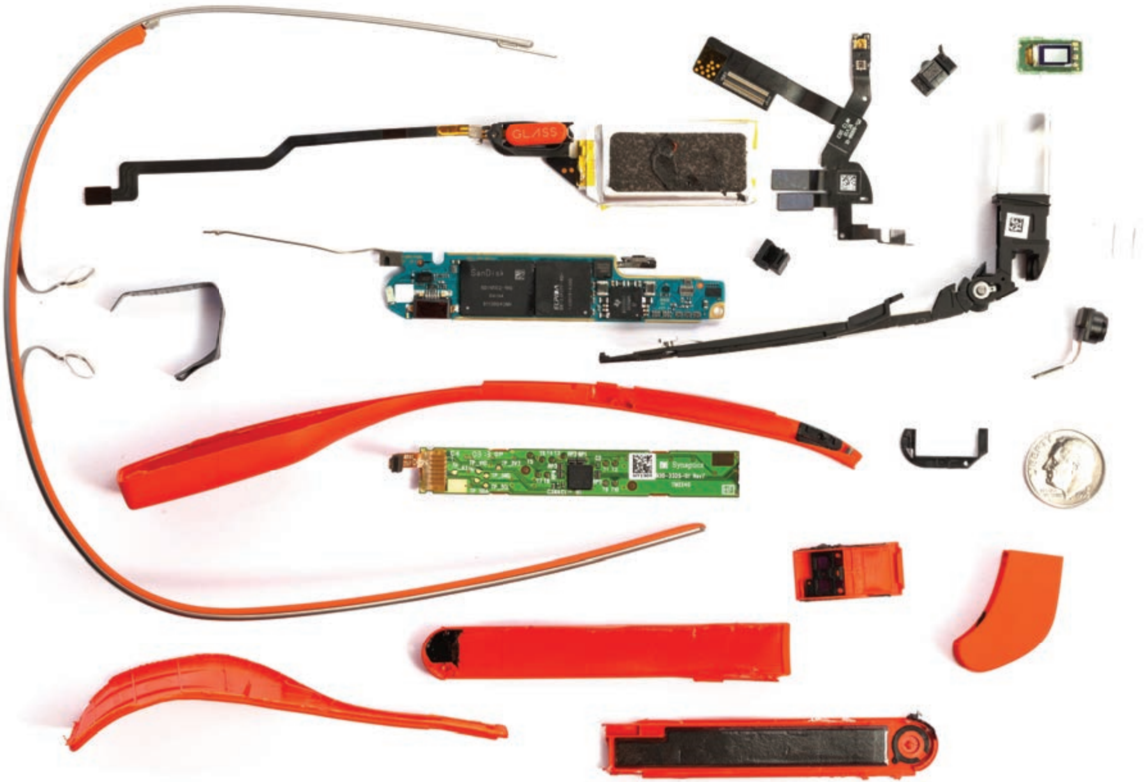
vision-correcting display

Digital Displays

displayblocks.org

- liquid crystal displays
- spatial light modulators
- gamut mapping
- stereo displays
- light field displays

Oculus Rift

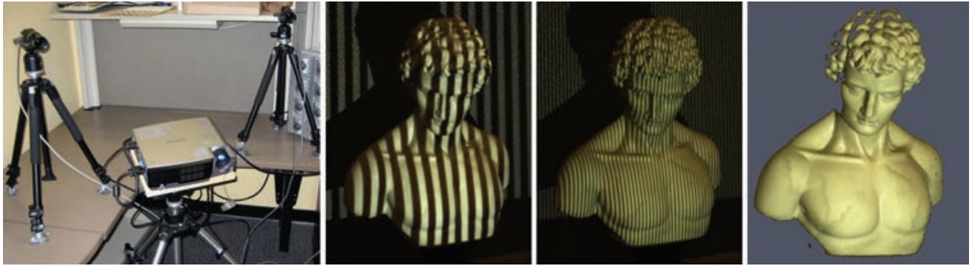


Google Glass

Computational Illumination

- time of flight
- structured illumination
- photometric stereo
- multi-flash photography
- microsoft kinect
- leap motion

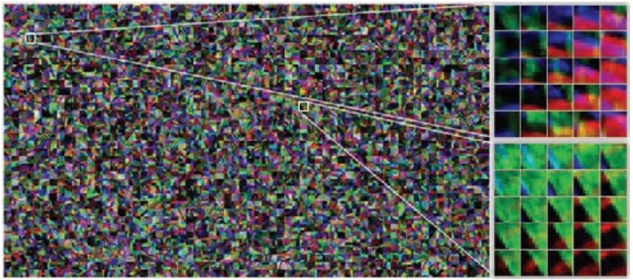
MS Kinect One

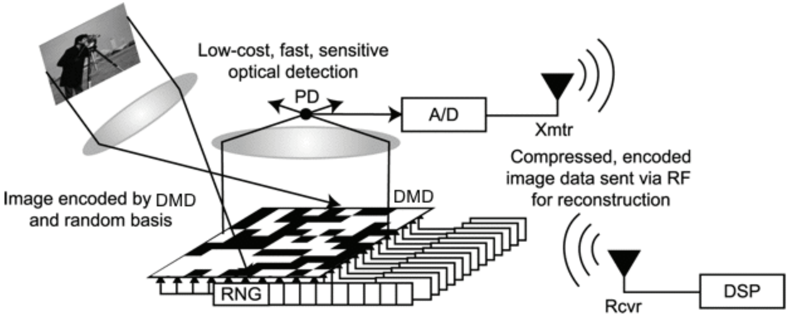


Taubin & Lanman , 2009

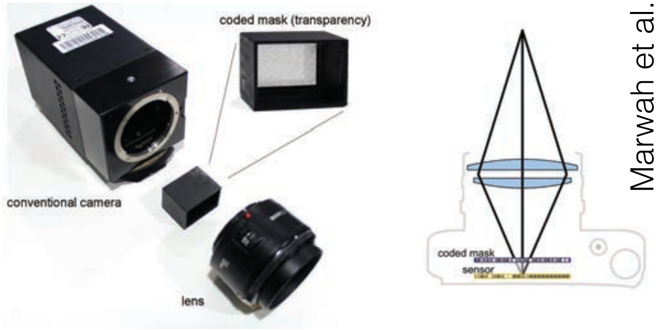
Compressive Imaging

- single pixel camera
- compressive hyperspectral imaging
- compressive light field imaging





Wakin et al. 2006



Marwah et al., 2013

A contemporary paradox

Raw: 15MB

JPEG: 150KB

- Massive data acquisition
- Most of the data is redundant and can be thrown away
- Seems enormously wasteful

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JPEG: 150KB

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- Most of the data is redundant and can be thrown away
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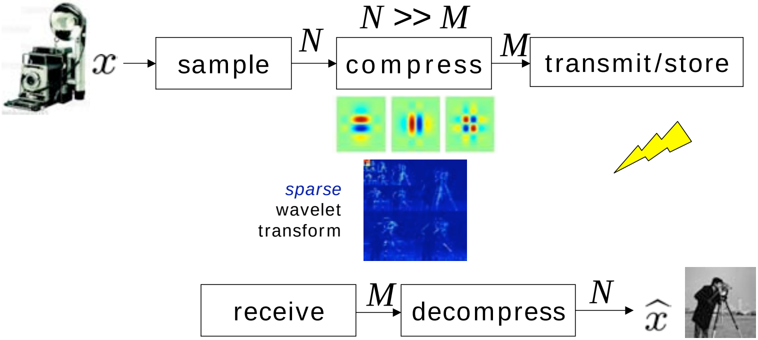
One can regard the possibility of digital compression as a failure of sensor design. If it is possible to compress measured data, one might argue that too many measurements were taken.

David Brady

Going against a long established tradition?

- Acquire/Sample (A-to-D converter, digital camera)
- Compress (signal dependent, nonlinear)



Fundamental question

Can we directly acquire just the useful part of the signal?

What Is Compressive Sensing?

In a nutshell...

- Can obtain super-resolved signals from just a few sensors
- Sensing is *nonadaptive*: no effort to understand the signal
- Simple acquisition process followed by numerical optimization

First papers

- Candès, Romberg and Tao, 2006
- Candès and Tao, 2006
- Donoho, 2006

By now, very rich mathematical theory

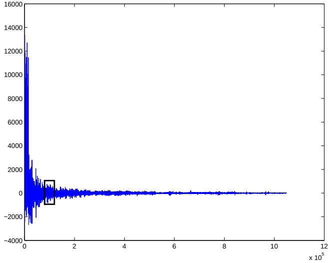
Sparsity: wavelets and images

1 megapixel image

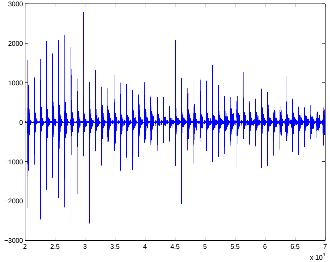
Sparsity: wavelets and images

1 megapixel image

wavelet coefficients



⇓



zoom in

Implication of sparsity: image “compression”

1. Compute 1,000,000 wavelet coefficients of mega-pixel image
2. Set to zero all but the 25,000 largest coefficients
3. Invert the wavelet transform

original image

Implication of sparsity: image "compression"

1. Compute 1,000,000 wavelet coefficients of mega-pixel image
2. Set to zero all but the 25,000 largest coefficients
3. Invert the wavelet transform

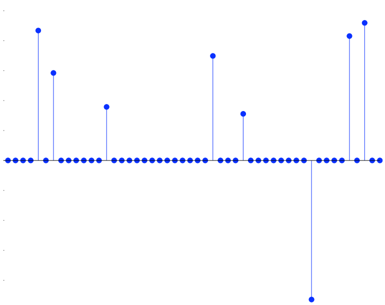
original image

after zeroing out smallest coefficients

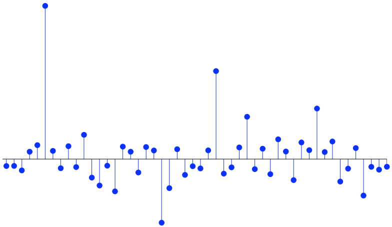
This principle underlies modern lossy coders (sound, still-picture, video)

Idealized sampling

- x: signal coefficients in our convenient representation
- collect information by measuring largest components of x



sparse x



nearly sparse x

Idealized sampling

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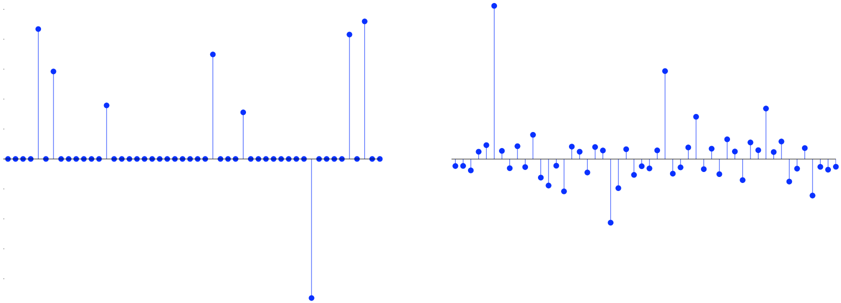


sparse x nearly sparse x

What if these positions are not known in advance?

- what should we measure?
- how should we reconstruct?

Incoherent/random sensing

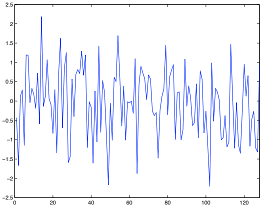
$$y = \langle a_k, x \rangle, \quad k = 1, \ldots, m$$

- Want sensing waveforms as spread out/"incoherent" as possible
- Span of $\{a_k\}$ should be as random as possible (general orientation)

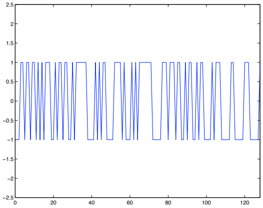
$$a_k \overset{\text{i.i.d.}}{\sim} F$$

$\mathbb{E}\, a_k a_k^* = I$ and a_k spread out

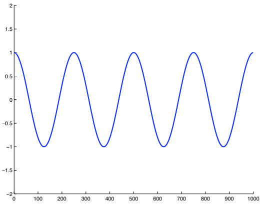
- a_k i.i.d. $\mathcal{N}(0,1)$ (white noise)
- a_k i.i.d. ± 1
- $a_k = \exp(i 2\pi \omega_k t)$ with i.i.d. frequencies ω_k
- ...



random waveform $N(0,1)$

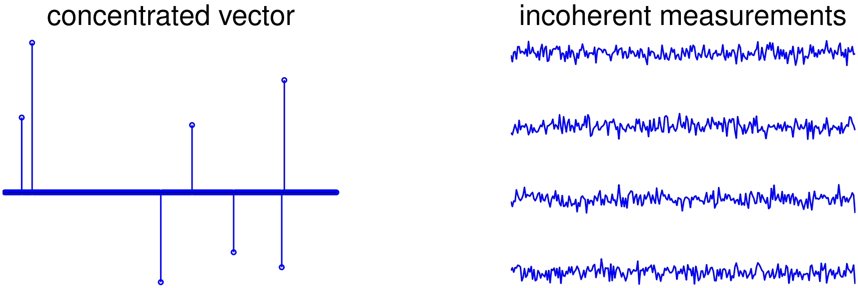


random waveform ± 1



random sinusoid

Incoherence



- Signal is local, measurements are global
- Each measurement picks up a little information about each component

Example of foundational result

Classical viewpoint

- Measure everything (all the pixels, all the coefficients)
- Keep d largest coefficients: distortion is $\|x - x_d\|$

Compressed sensing viewpoint

- Take m random measurements: $y_k = \langle x, a_k \rangle$
- Reconstruct by *linear programming*: ($\|x\|_{\ell_1} = \sum_i |x_i|$)

$$x^\star = \text{arg min } \|\tilde{x}\|_{\ell_1} \quad \text{subject to} \quad y_k = \langle \tilde{x}, a_k \rangle, \; k = 1, \ldots, m$$

Among all the objects consistent with data, pick min ℓ_1

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Among all the objects consistent with data, pick min ℓ_1

Same performance with about $m = d \log n/d$ (sketch)

$$\|x^\star - x\|_{\ell_2} \leq \|x - x_d\|_{\ell_2}$$

Example

- Take 96K incoherent measurements of "compressed" image
- Compressed image is perfectly sparse (25K nonzero wavelet coeffs)
- Solve ℓ_1

original (25k wavelets)

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- Compressed image is perfectly sparse (25K nonzero wavelet coeffs)
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original (25k wavelets)

perfect recovery

What is compressive sensing?

Possibility of compressed data acquisition protocols which directly acquire just the important information

- Incoherent/random measurements $\longrightarrow$ compressed description
- Simultaneous signal acquisition and compression!

All we need is to decompress...

Three surprises

- Sensing is ultra efficient and *nonadaptive*
- Recovery is possible by tractable optimization
- Sensing/recovery is robust to noise (and other imperfections)

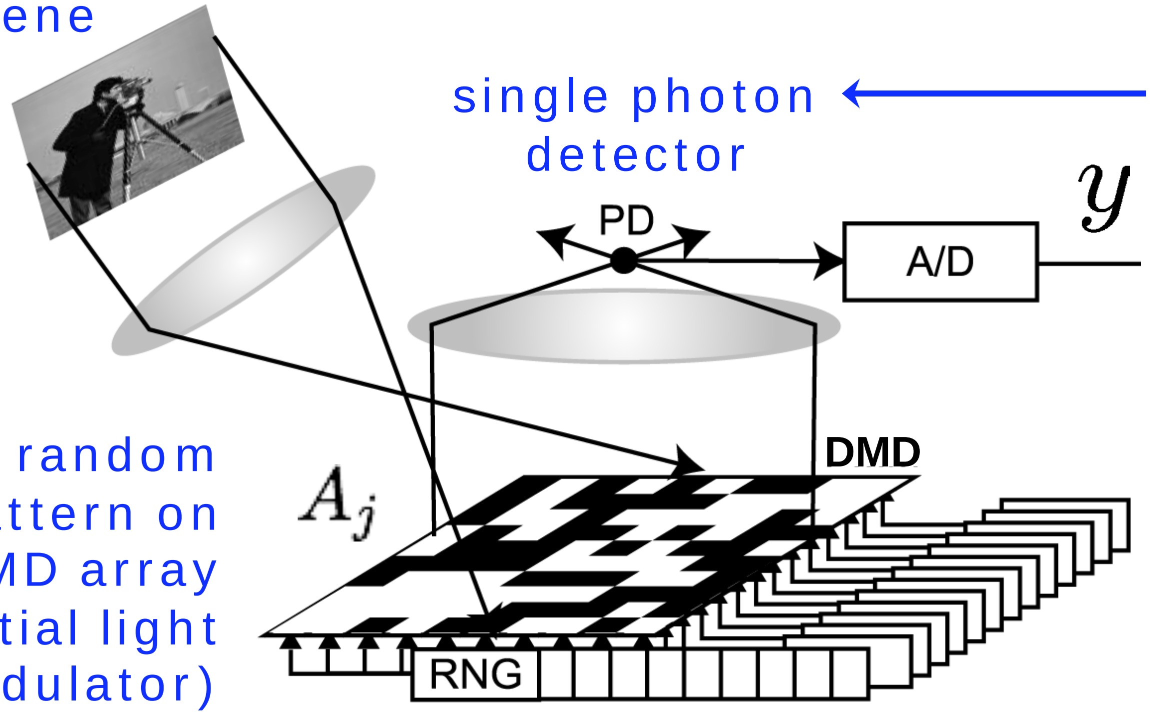
Applications and Opportunities

"Single-Pixel" CS Camera

Kevin Kelly
Richard Baraniuk
Rice University

scene

x



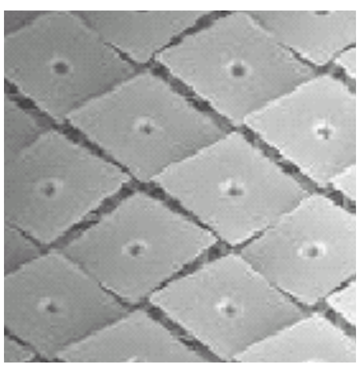
single photon detector

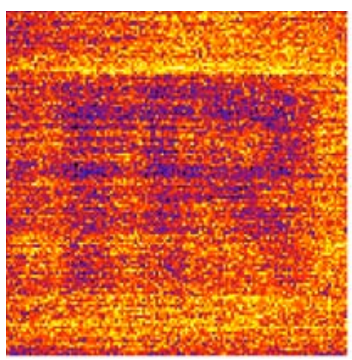
random pattern on DMD array (spatial light modulator)

can be exotic

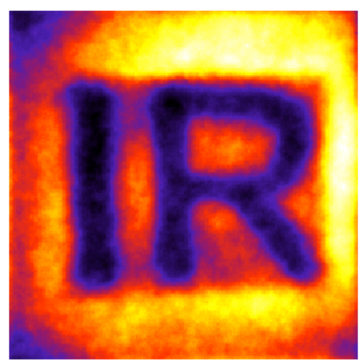
- IR, UV, THz, PMT, spectrometer, …

color target

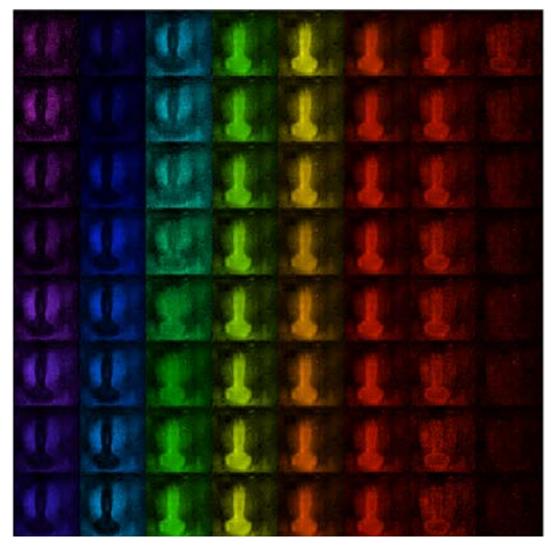




raster scan IR



CS IR

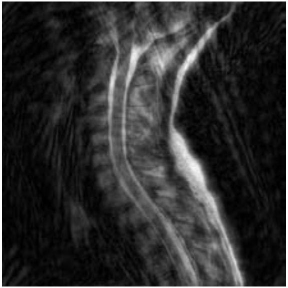


hyperspectral data cube

Fast Magnetic Resonance Imaging

Goal: sample less to speed up MR imaging process

Fully sampled

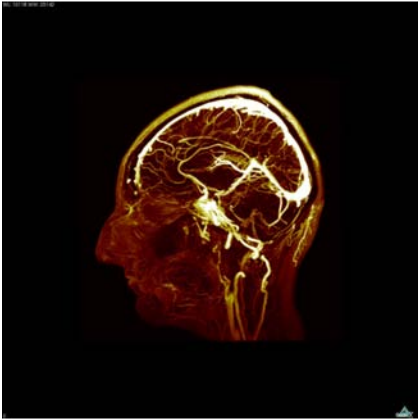


6 $\times$ undersampled
classical

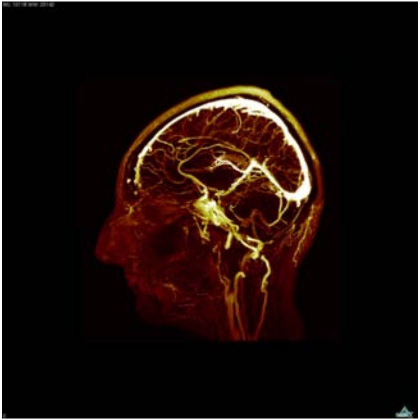
6 $\times$ undersampled
CS

Trzasko, Manduca, Borisch (Mayo Clinic)

MR angiography

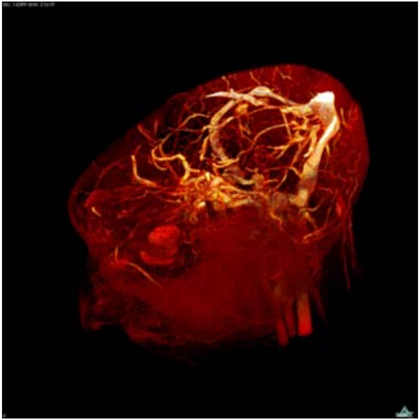


Fully sampled

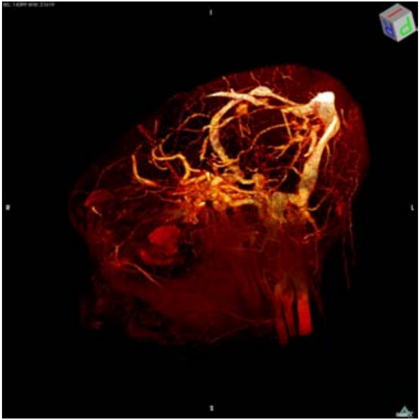


6 $\times$ undersampled

Trzasko, Manduca, Borisch



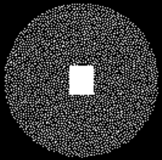
Fully sampled



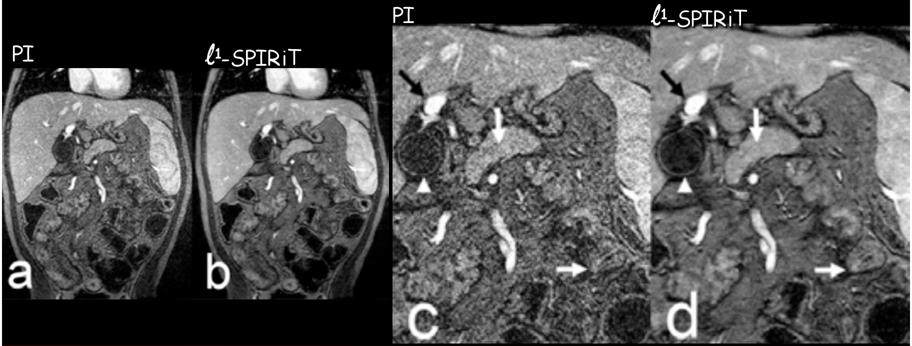
6 $\times$ undersampled

Trzasko, Manduca, Borisch

ℓ^1-SPIRiT, T1 3D SPGR

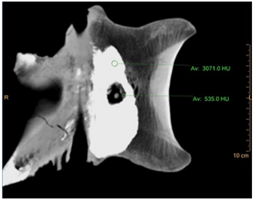


Submillimeter near-isotropic resolution MRI in an 8-year-old male. Post-contrast T1 imaging with an acceleration of 4. Standard (a, c) and compressed sensing reconstruction (b, d) show improved delineation of the pancreatic duct (vertical arrow), bowel (horizontal arrow), and gallbladder wall (arrowhead) with L1-SPIRiT reconstruction, and equivalent definition of the portal vein (black arrow)



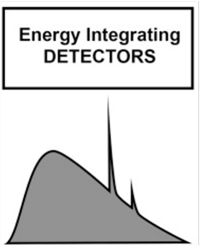
M. Lustig, Electrical Eng. Stanford & EECS UC Berkeley
S. Vasanawala, Radiology Stanford

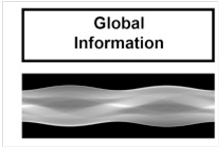
X-rays in Medical and Security Scanning

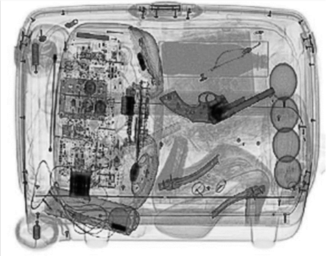


Conventional X-Ray CT Challenges

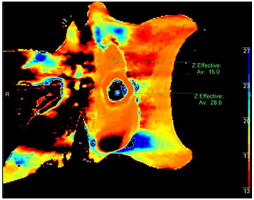
- Single view X-rays of overlapping objects create distorted shapes
- Cannot reveal chemical decomposition
- Time consuming (Security Applications)





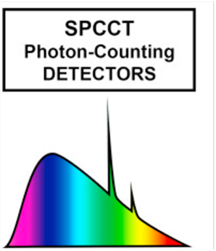


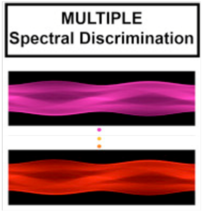
X-rays in Medical and Security Scanning

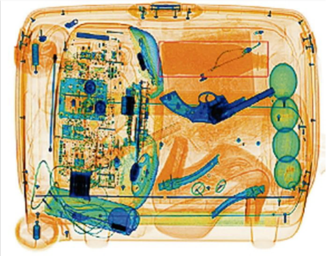


Spectral CT advantages

- Material differentiation
- Reveals chemical decomposition
- Asses tissue density





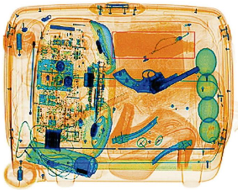


X-ray Imaging for Security Scanning

Imaging of baggage in rail and air travel, as well as cargo shipping, is a problem of global importance. Challenges hindering their broad application:

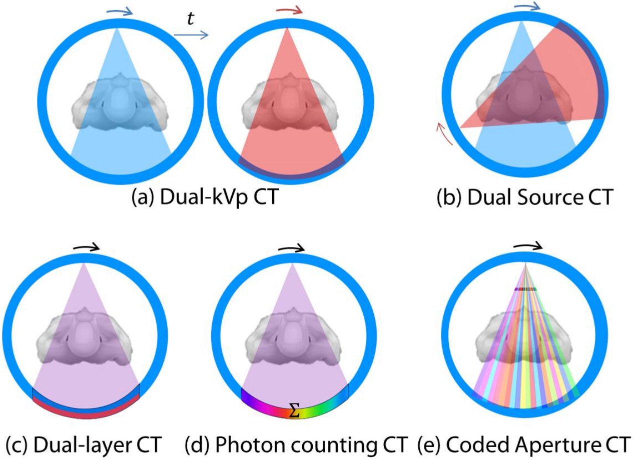
- Single view X-rays of overlapping objects create distorted shapes and their recognition becomes challenging.

- X-ray computerized tomography (CT) reconstructs 3D volumetric images but gray scale images cannot reveal different chemical composition.
- X- ray CT is time consuming. Used as a tier-two system, used only to check bags which are questionable by single look X-ray imaging.



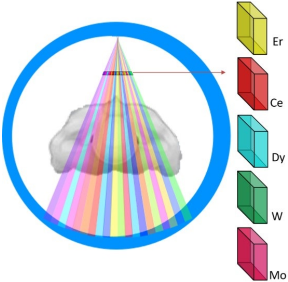
Spectral CT Measurement Systems

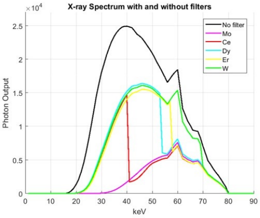
- Limited angle geometries needed for reduced complexity.
- Computational complexity of compressive CT reconstruction scales up rapidly with image resolution and object size.

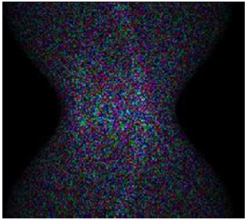


Pixelated K-edge Coded Apertures for Spectral Tomography

- Pixels of the coded apertures are composed by Ross filters.
- Ross filters consist of a pair of materials with adjacent atomic numbers whose transmitted spectra differs in the energy band between their K-edges.
- K-edge is the binding energy of the K shell electron of an atom.



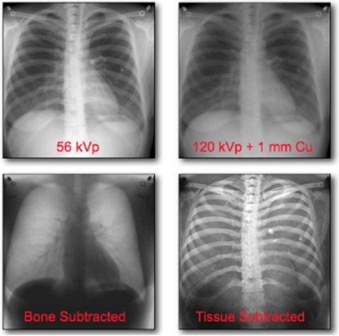




Commercial Applications and Markets

Homeland Security

Food Inspection

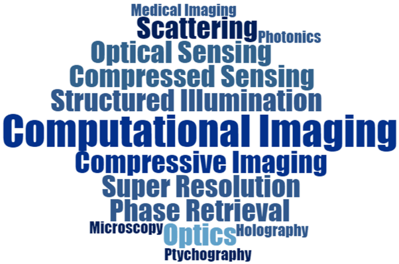


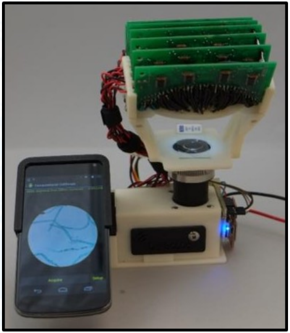
Medical Imaging


Image: National Geographic

Conclusion

- Computational imaging = convergence of applied mathematics, optics, human perception, high performance computing, and electronics.
- Use software and hardware to transcend the boundaries of camera and display technology
- Applications in consumer electronics, microscopy, human computer interaction, scientific imaging, health, and remote sensing.





References

- Lei Tian, UC Berkeley - Computational Imaging talk
- MIT Media Lab - Camera culture group
- Compressive sensing - A 25 minute tour - Emmanuel Candes

Acknowledgements

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