Sparse MRI – The Application of Compressed Sensing in Rapid MRI

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Presented by Wenwen Jiang

Outline

- Recap Compresses Sensing (CS)
- Introduction to MRI (Motivation)
- Framework of Using CS in MRI
- Examples

Recap CS (Compressed Sensing)

- **Three key ingredients:**

❖ Sparsity

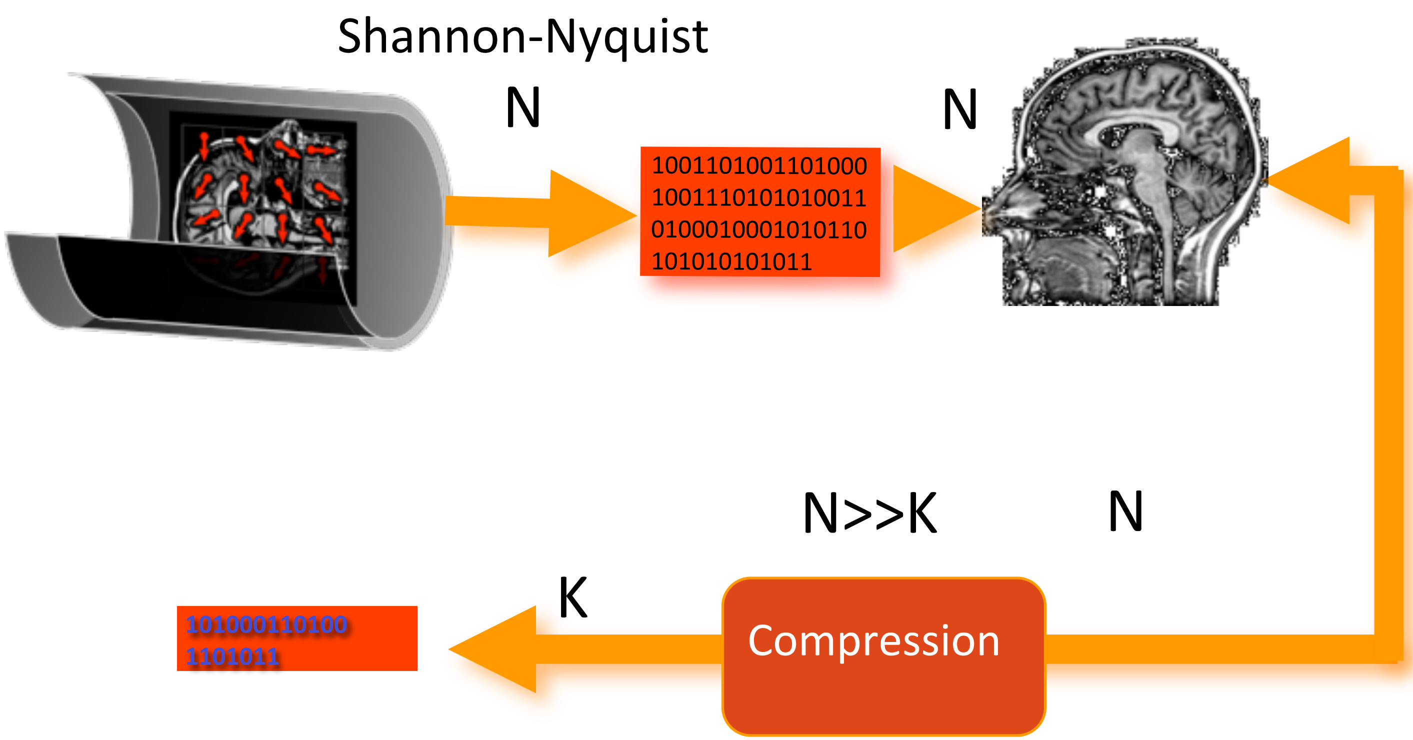
❖ Incoherence of Measurements

❖ Non-linear Reconstruction

Redundancy: Compression

Most images are compressible

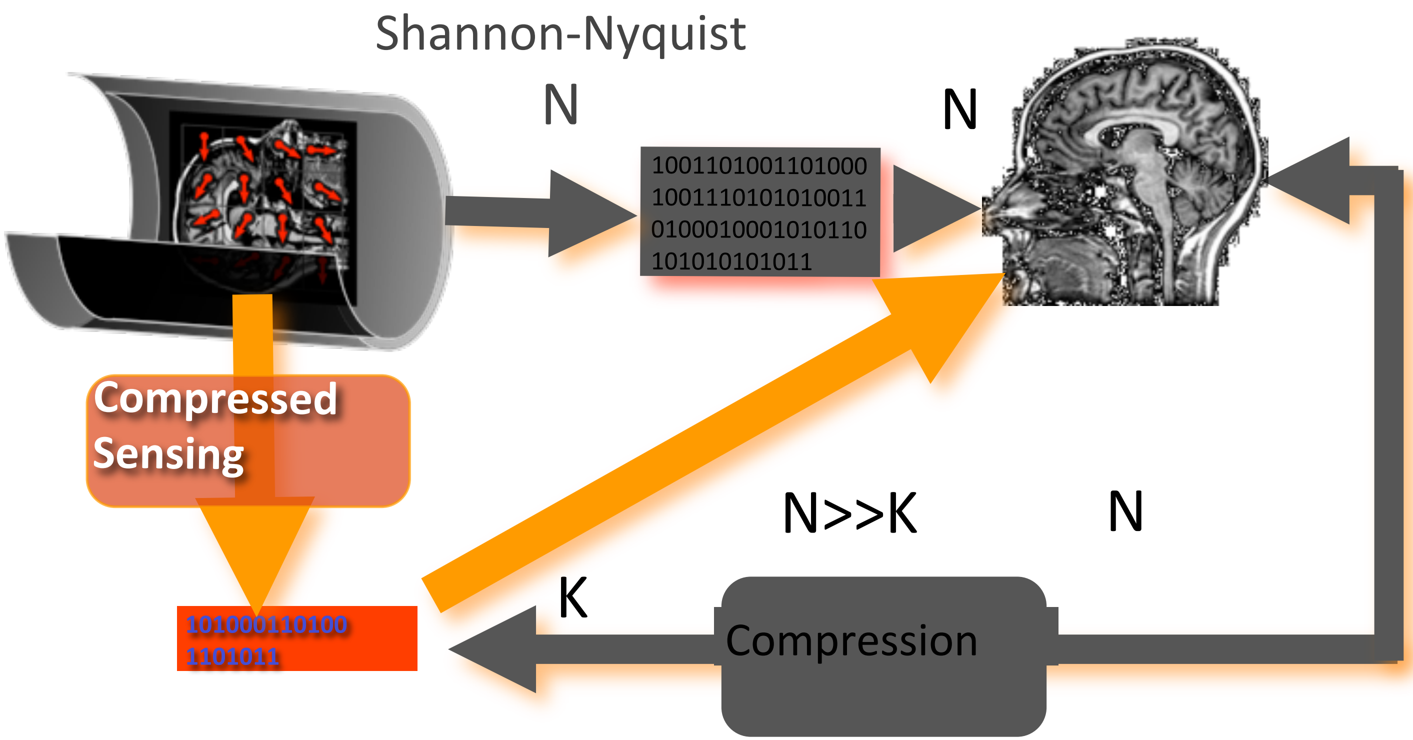
- Standard approach: First collect, then compress



Compressed Sensing

Instead: Compressed Sensing (CS)

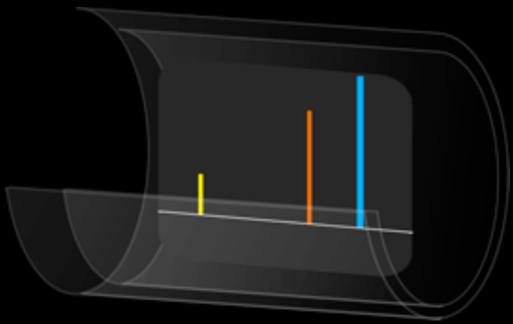
First Compress, then reconstruct.

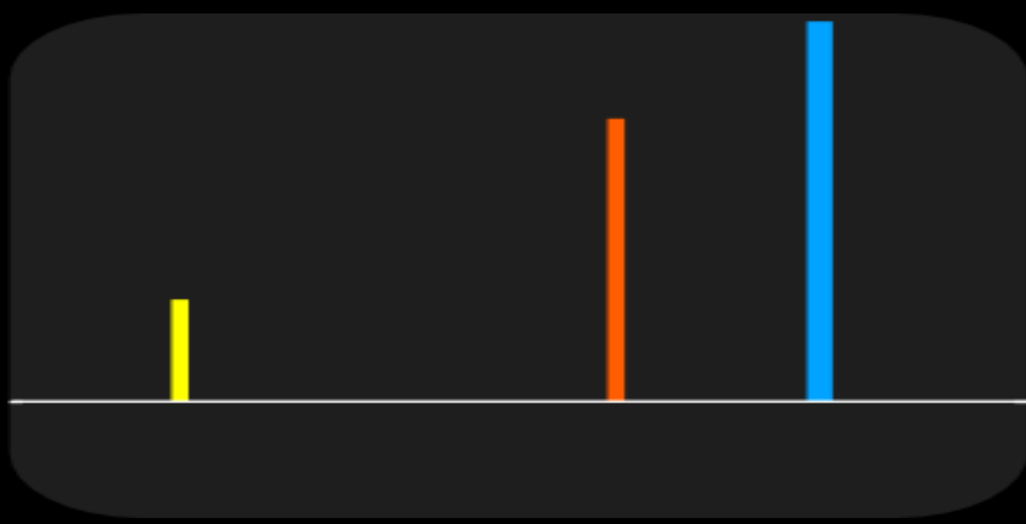


Candes et al.
IEEE TIF '06

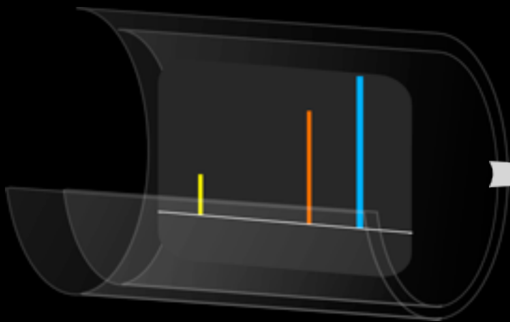
Donoho
IEEE TIF '06

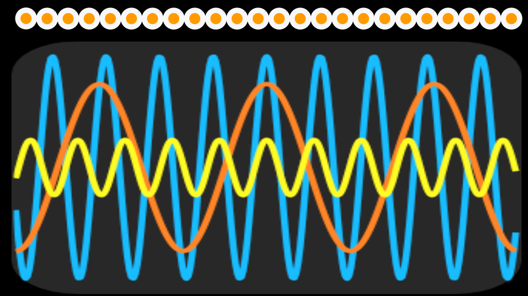
Intuitive example of CS



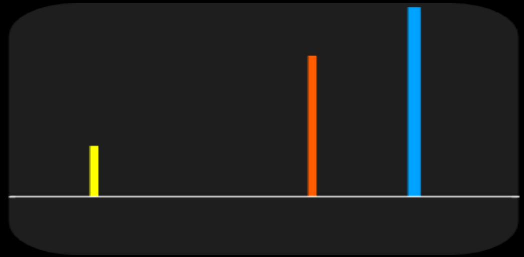


Intuitive example of CS

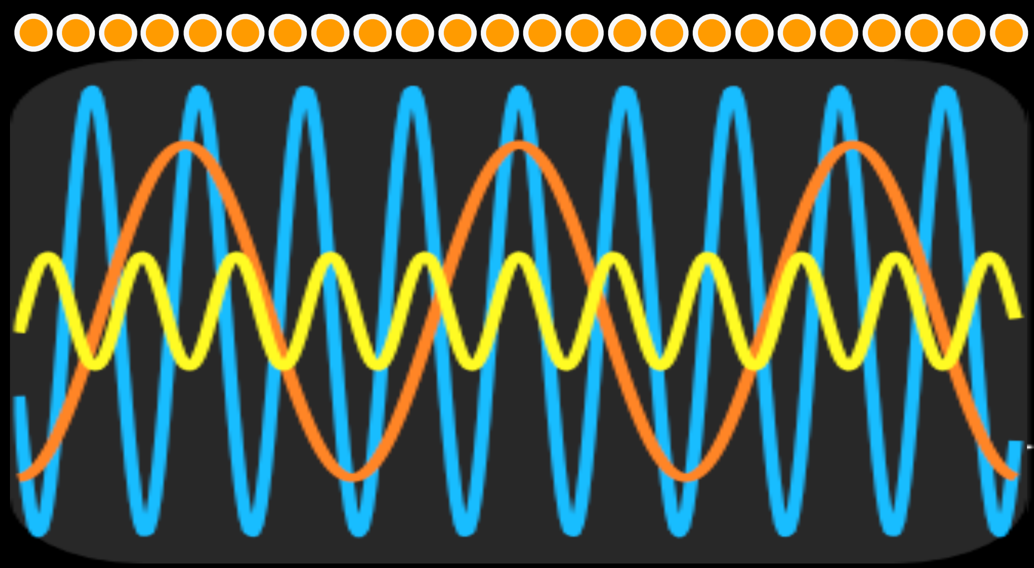




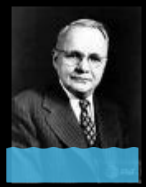
iFFT



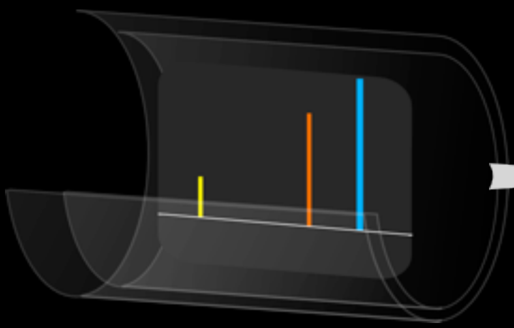
sampling

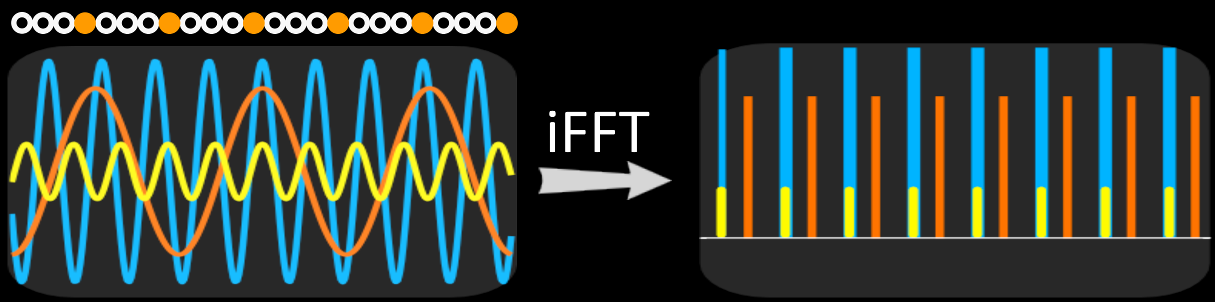


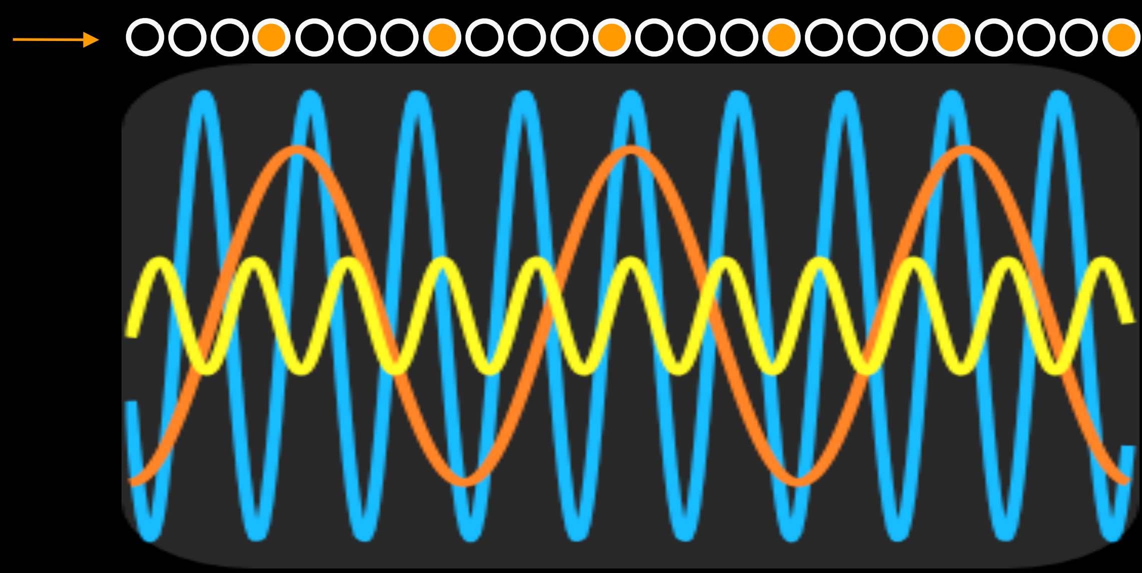
Nyquist



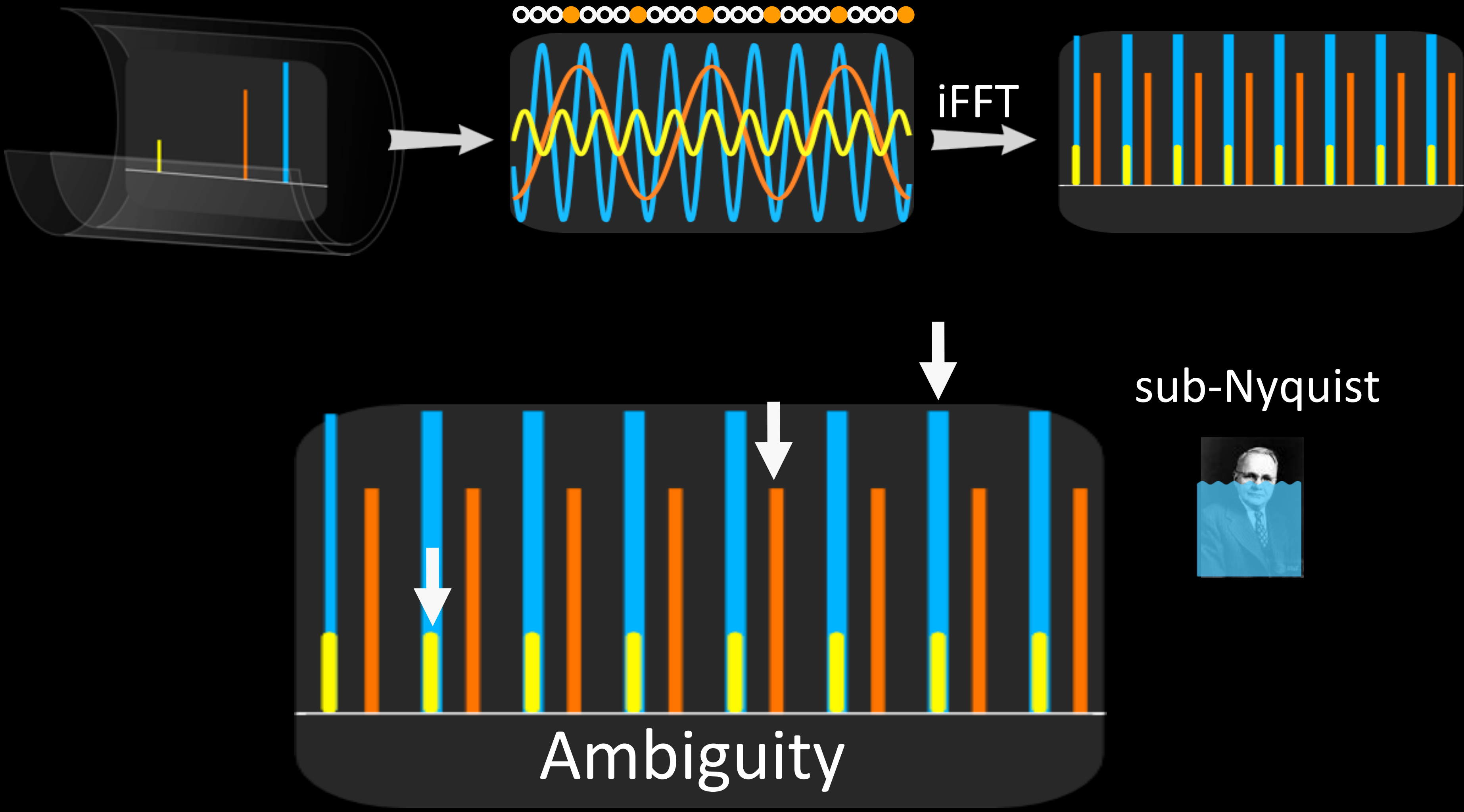
Intuitive example of CS



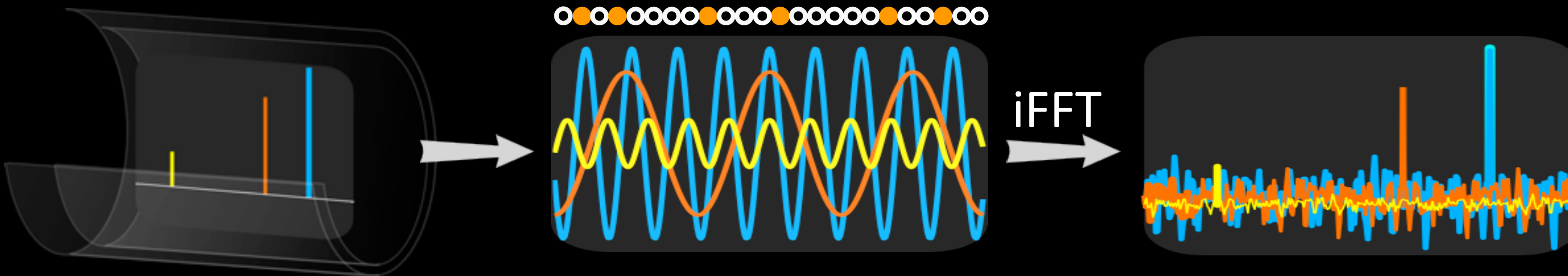




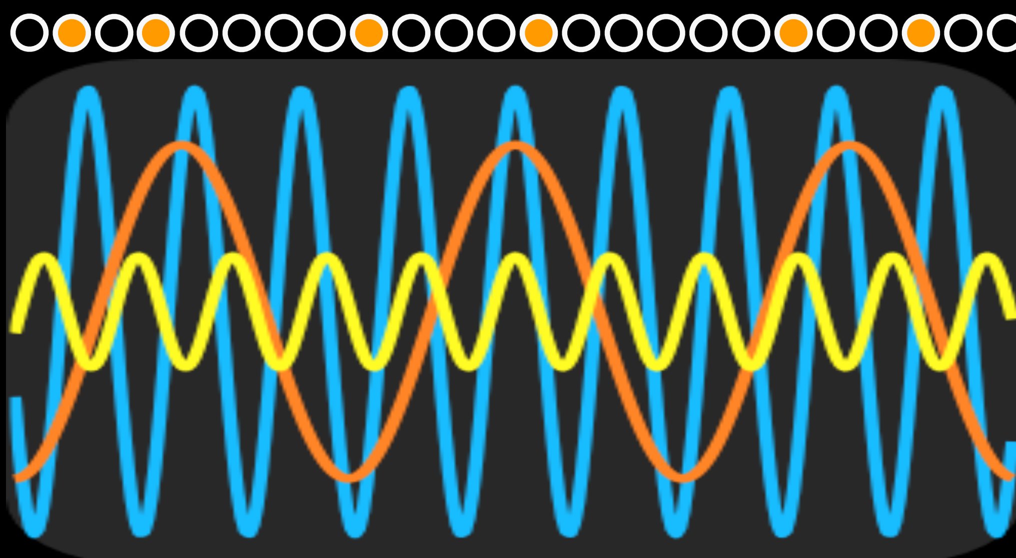
Intuitive example of CS



Intuitive example of CS

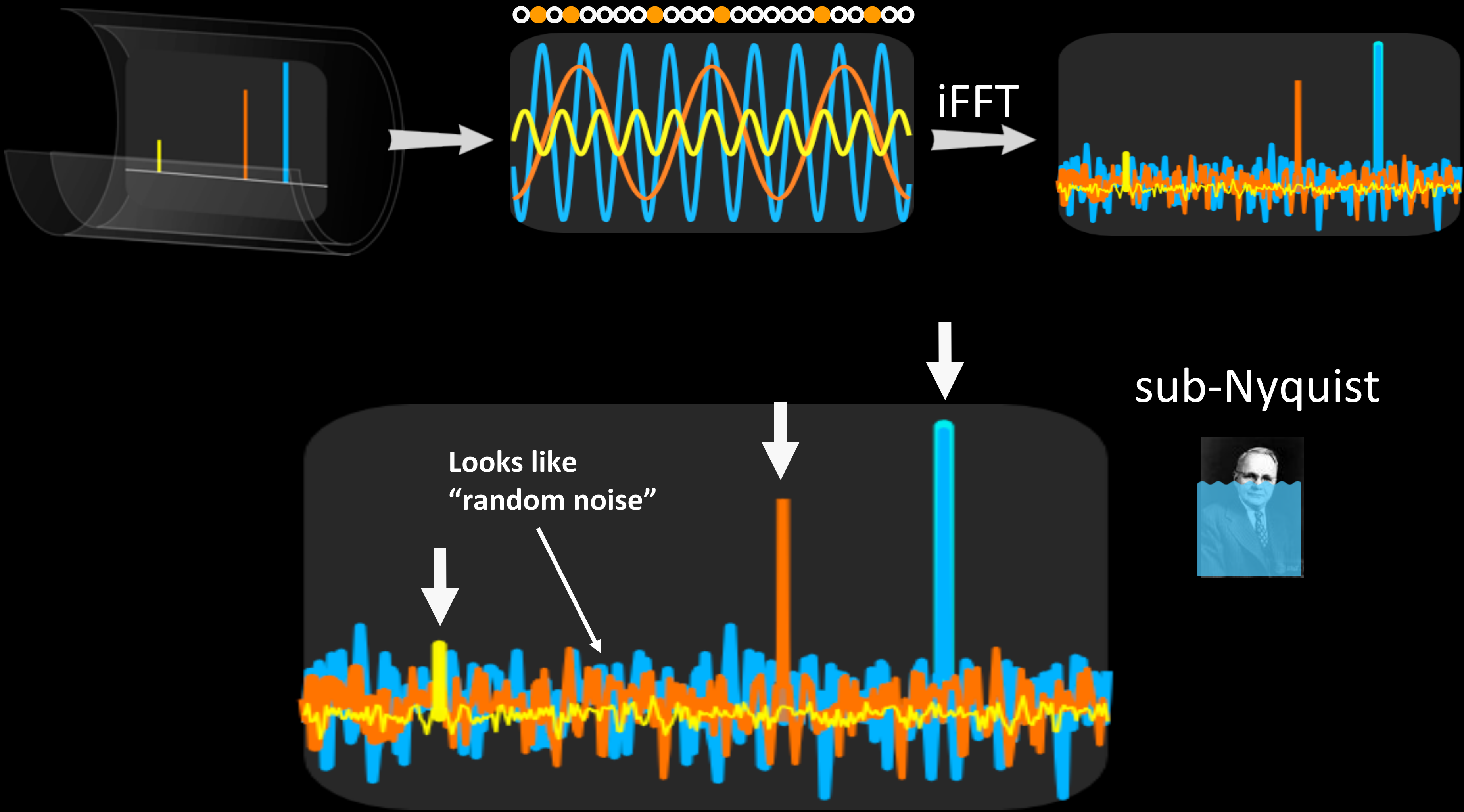


random

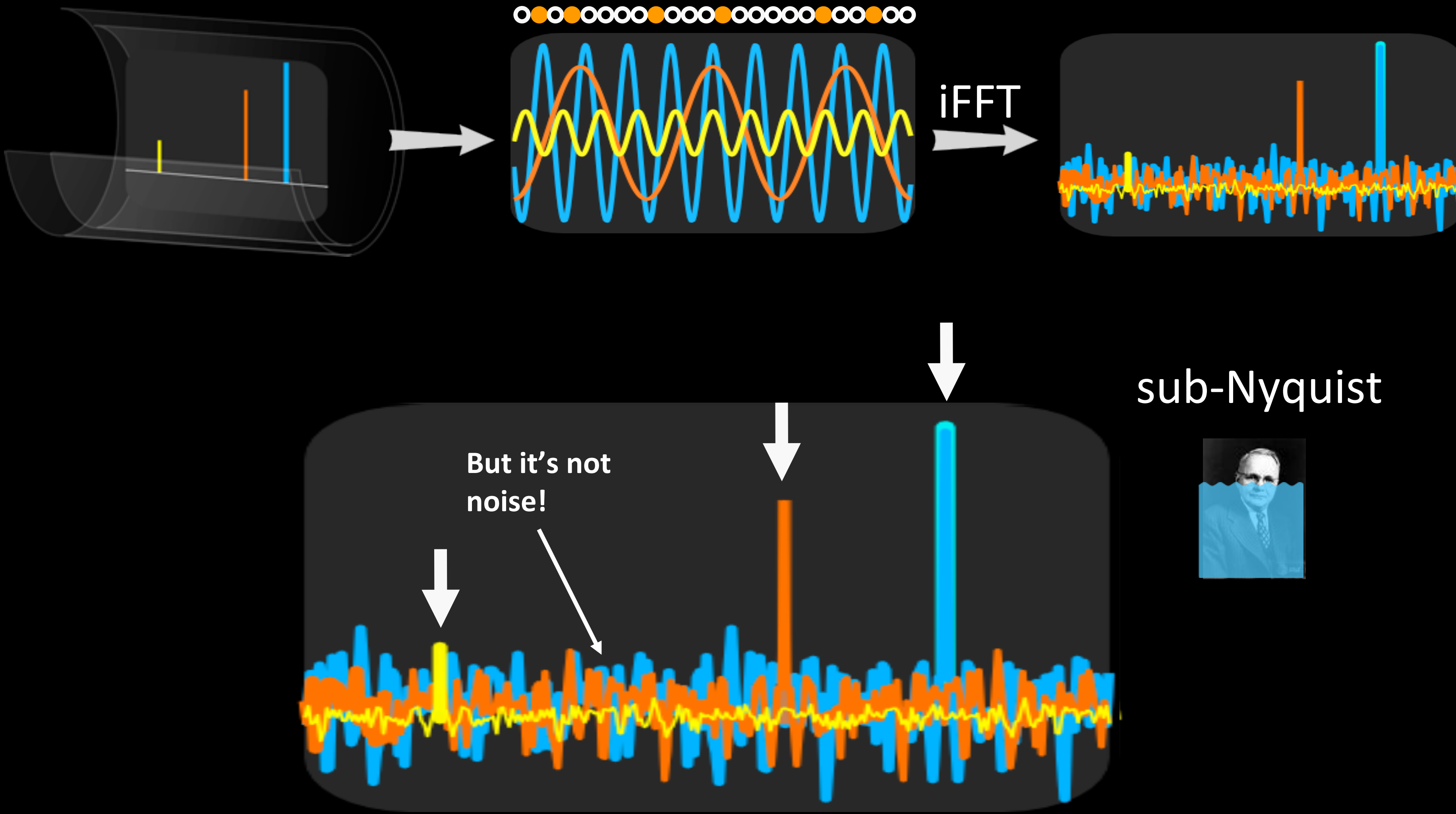


sub-Nyquist

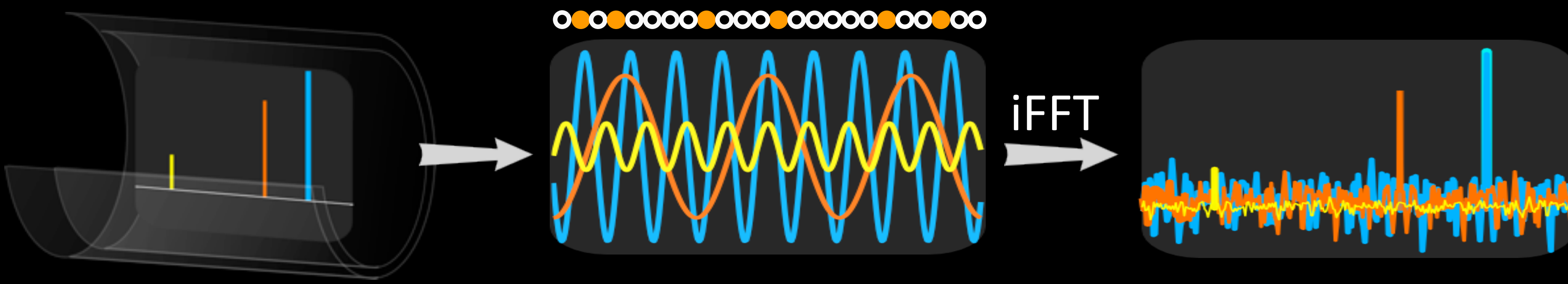
Intuitive example of CS



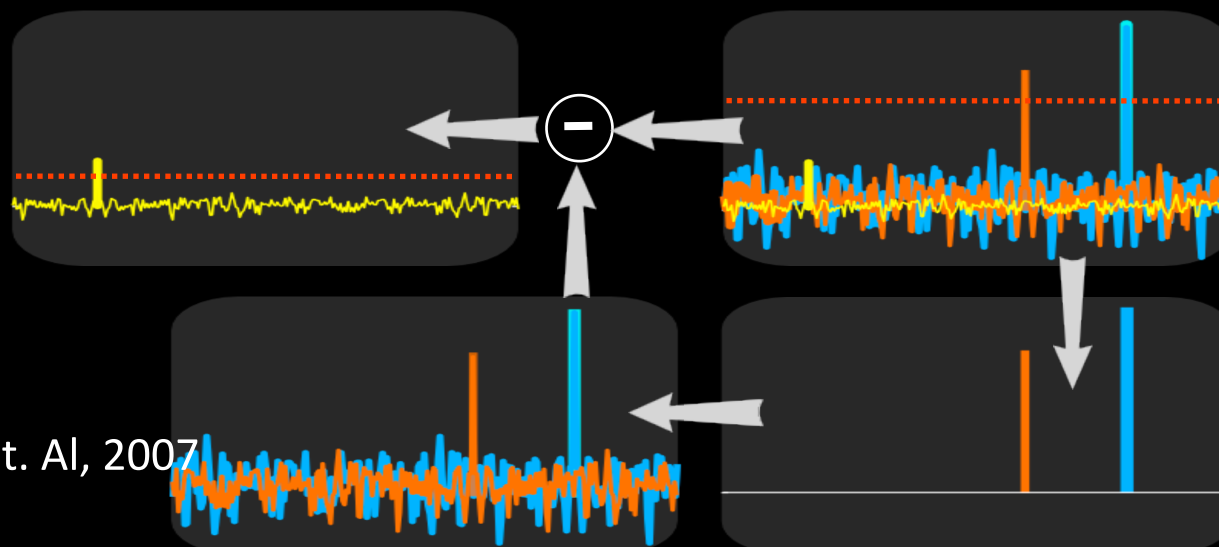
Intuitive example of CS



Intuitive example of CS



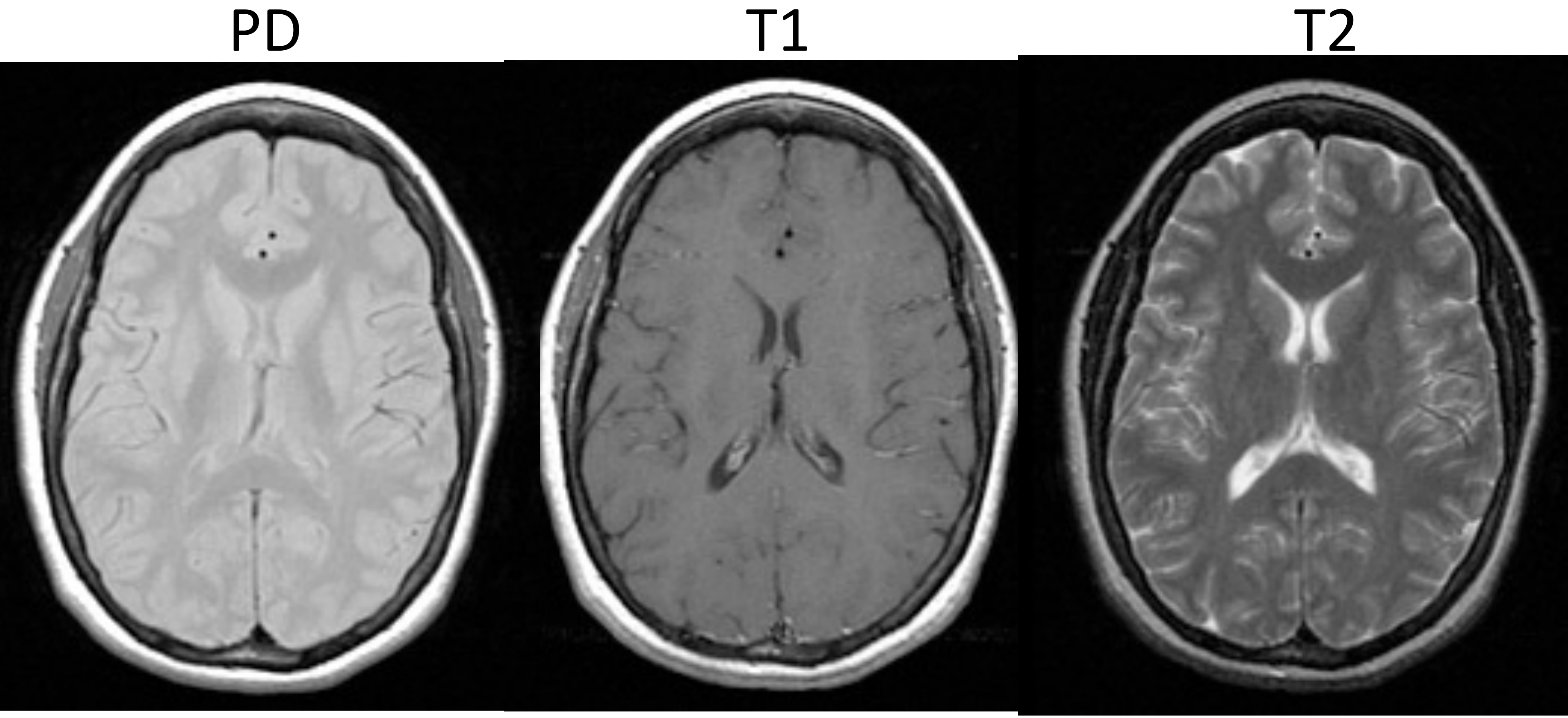
Recovery



Example inspired by Donoho et. Al, 2007
Similar to CLEAN algorithm

Intro to MRI

Neuro Examples of MRI



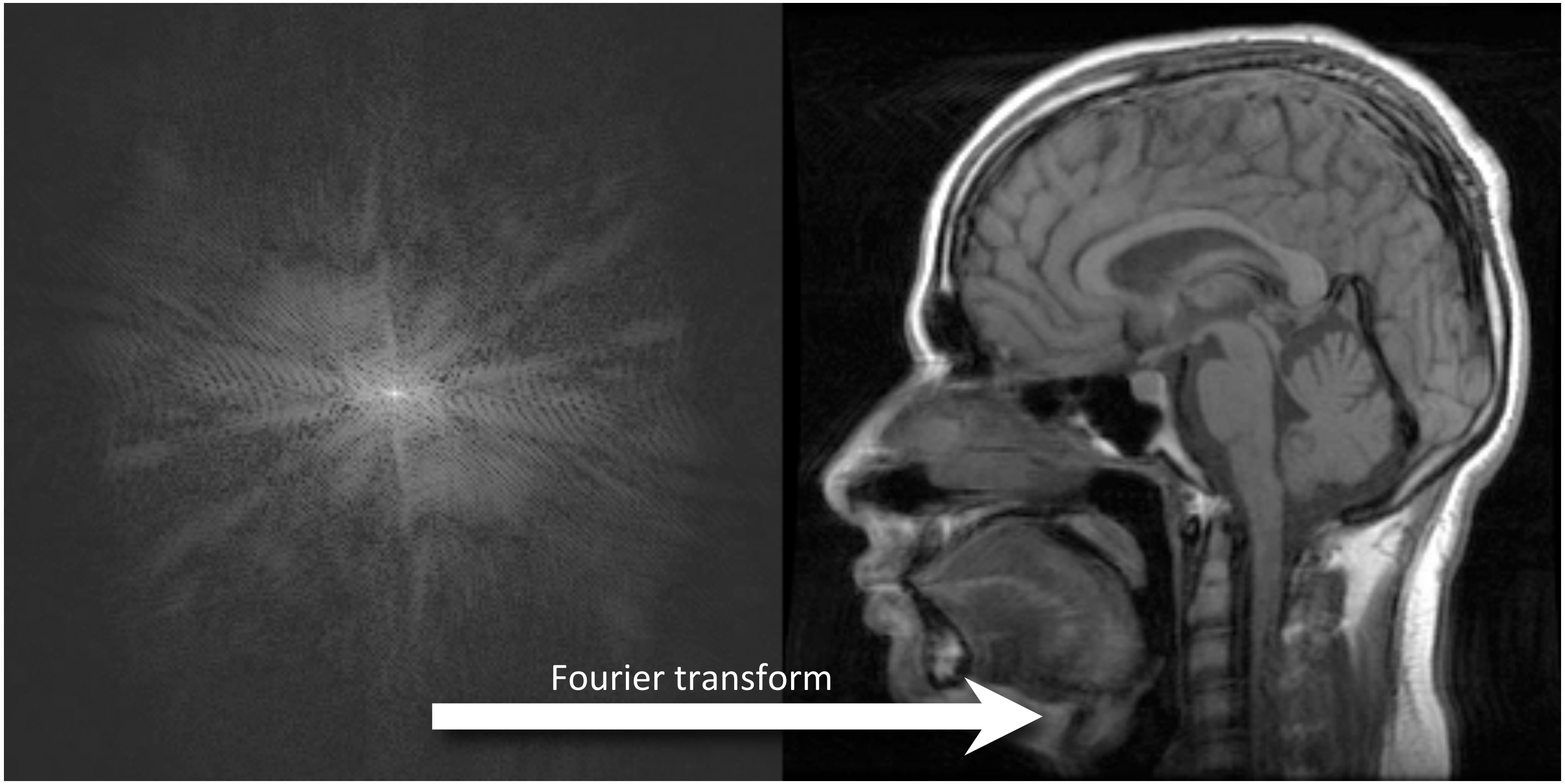
Many different contrasts available

Image courtesy: K. Pauly, G. Gold
Stanford Rad 220

MR Imaging

Fourier

k-space (Raw Data) Image



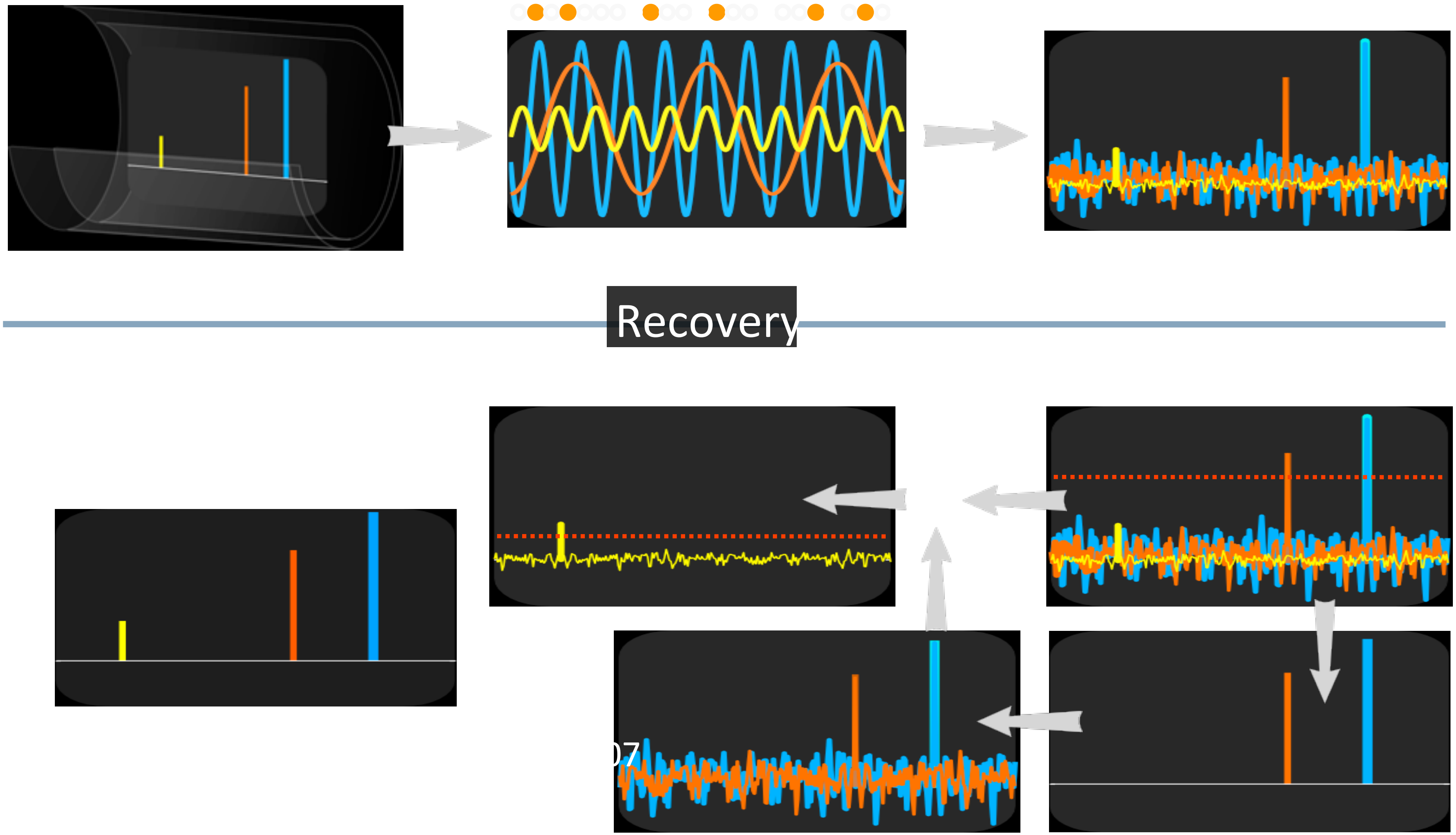
Key MRI Idea

- MR scanner makes your body put out a signal that is its own Fourier Transform (k-space)
- Data is acquired directly in spatial frequency space (**coded nature of MRI**)
- Limits to how fast this can be done

Motivation: The Need for Speed

- **MRI data collection is inherently slow!!**
- Rapid MR imaging would
  - Decrease scan time
  - Reduce image artifacts
  - Increase spatial/temporal resolution
  - Increase coverage

Recall Example of CS



Recap CS (Compressed Sensing)

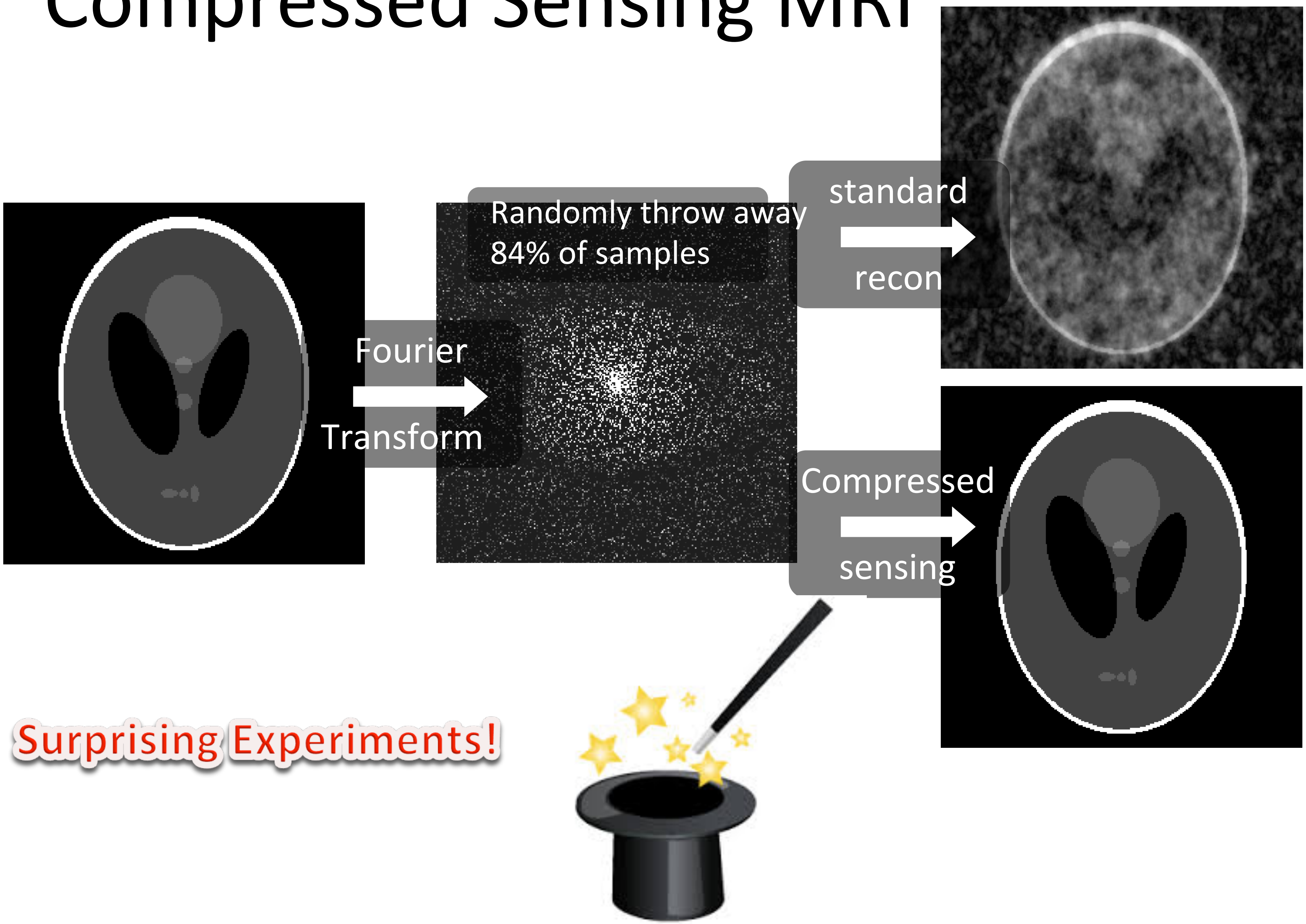
- **Three key ingredients:**

❖ Sparsity

❖ Incoherence of Measurements

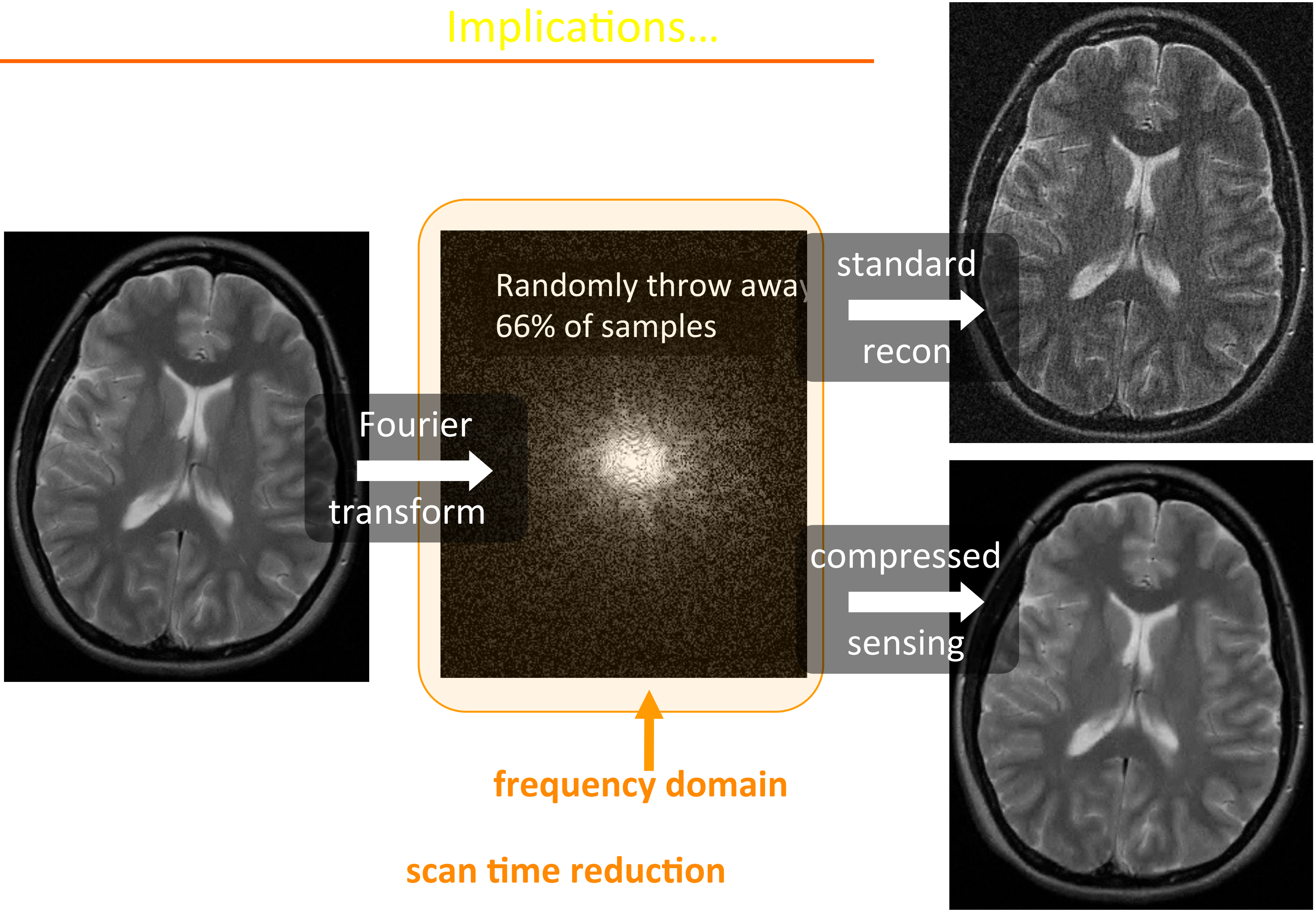
❖ Non-linear Reconstruction

Compressed Sensing MRI



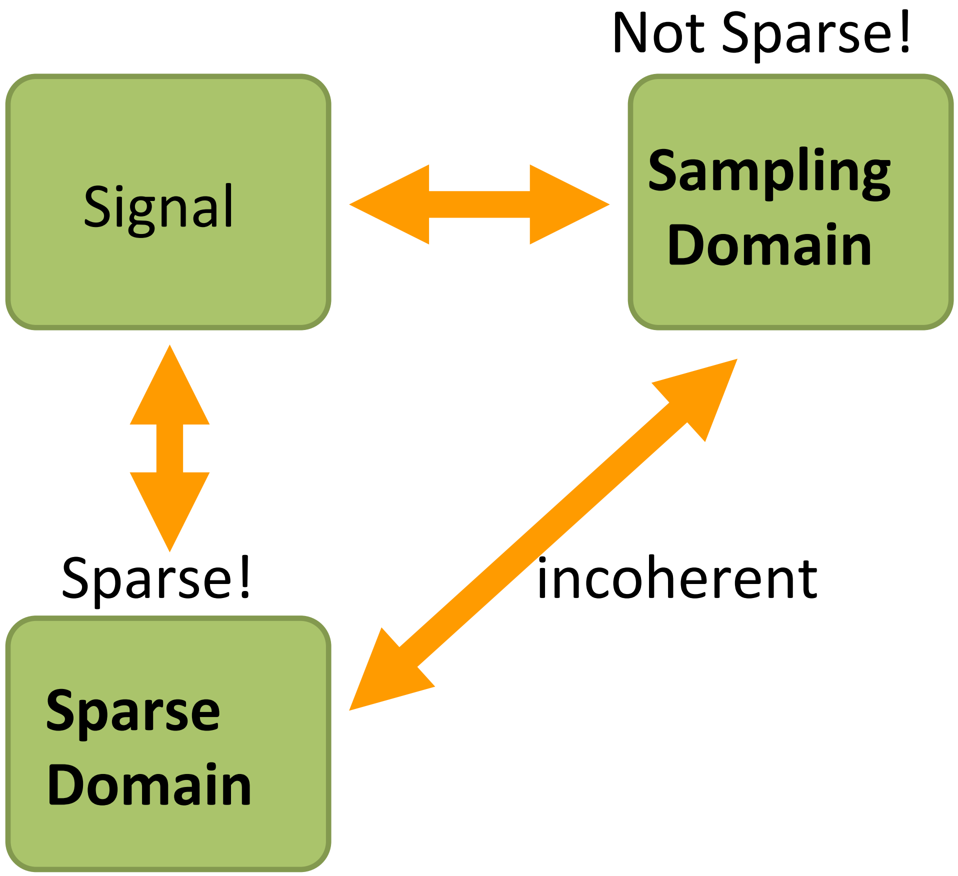
Surprising Experiments!

Implications...



scan time reduction

Domains in Compressed Sensing



Three Key Ingredients of CS also works in MRI!

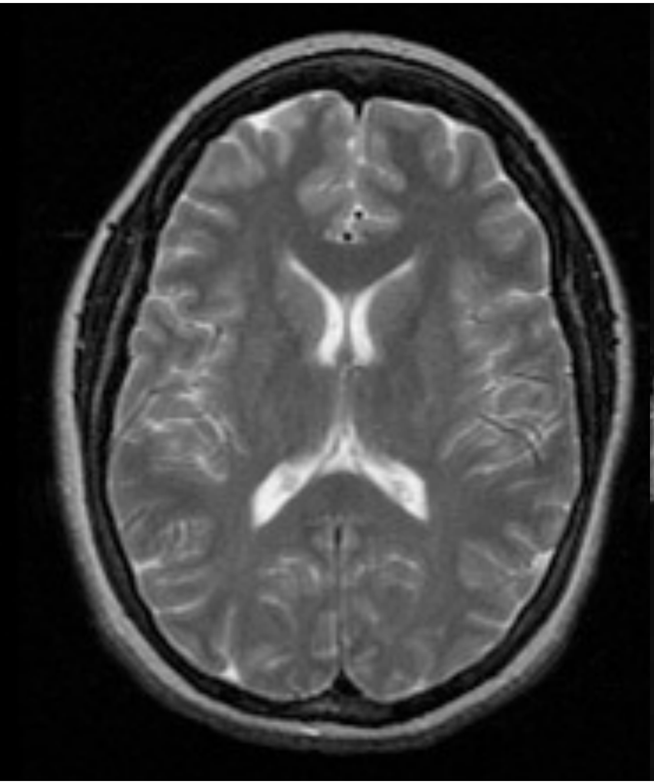
- Sparse Representation (compressibility)
- Incoherent Measurement
- Recovery with non-linear convex optimization

Framework on Compresses Sensing in MRI

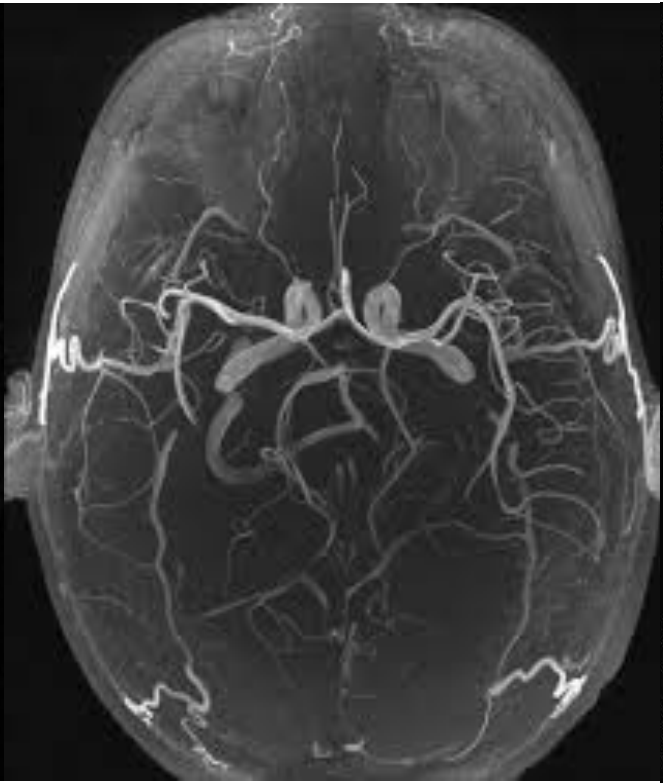
- <u>Sparse Representation of Signals</u>
- Incoherent Measurement
- Recovery with non-linear convex optimization

MR Images – difference applications

T2 weighted brain image



Brain angiogram



T2 spinal cord image

Image courtesy: K. Pauly, G. Gold
And google images

Sparsifying Transform

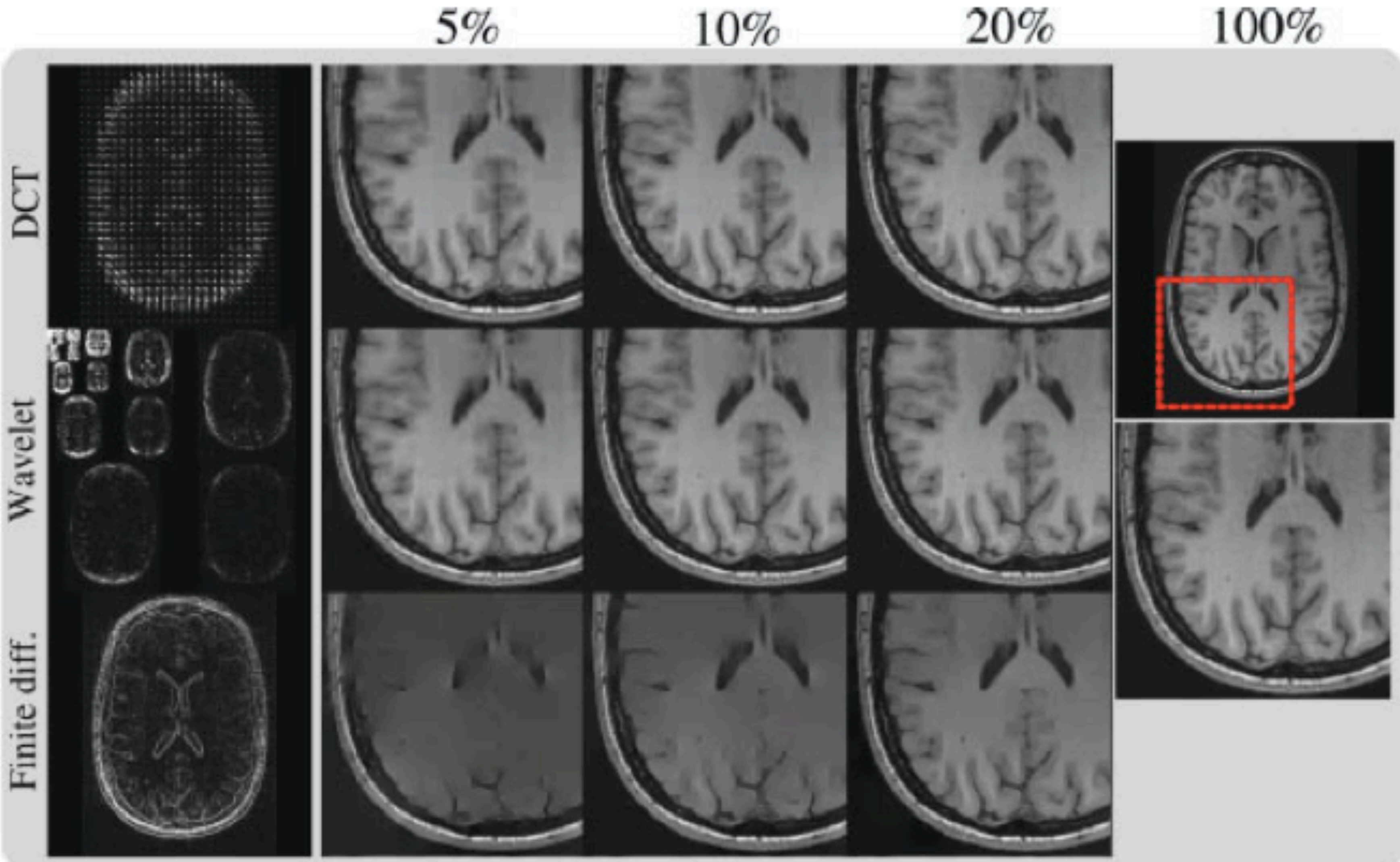
- Real-life images known to be sparse in discrete cosine transform (DCT) and wavelet transform domains

✓ DCT is central to JPEG image compression and MPGE

✓ Wavelet transform is used for JPEG-2000 compression standard

- Finite-difference Transform (not always work for MR images)

Compare Sparse Transforms



The images were reconstructed from a subset of 5,10 and 20% of the largest transform coefficients

Framework of Compresses Sensing in MRI

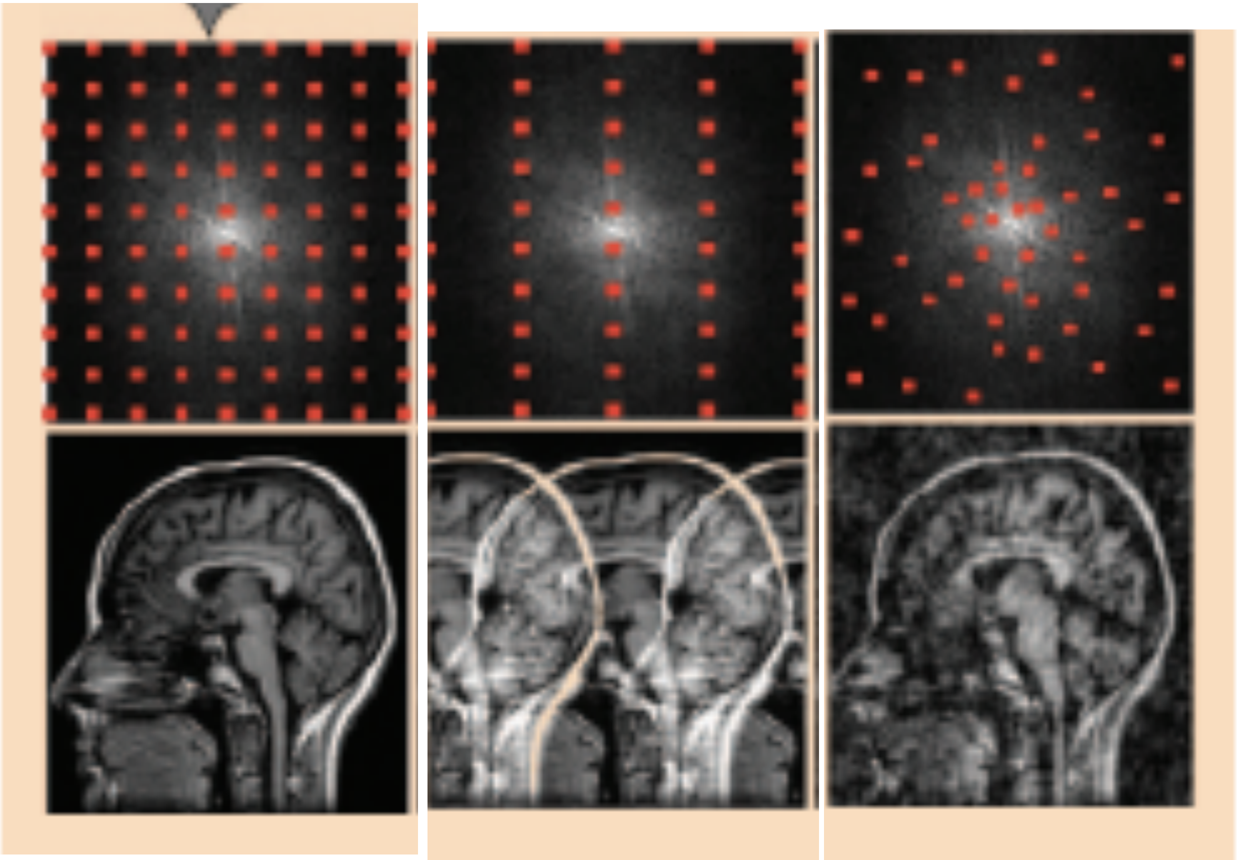
- Sparse Representation of Signals
- <u>Incoherent Measurement</u>
- Recovery with non-linear convex optimization

Compresses Sensing MRI- Incoherence

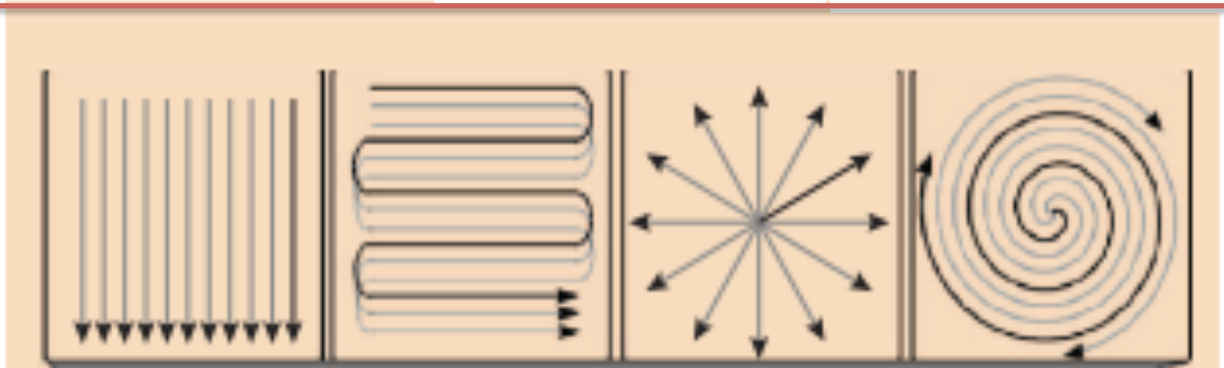
"randomness is too important to be left to chance*"

*R. Conveyo, Oak Ridge National Laboratory

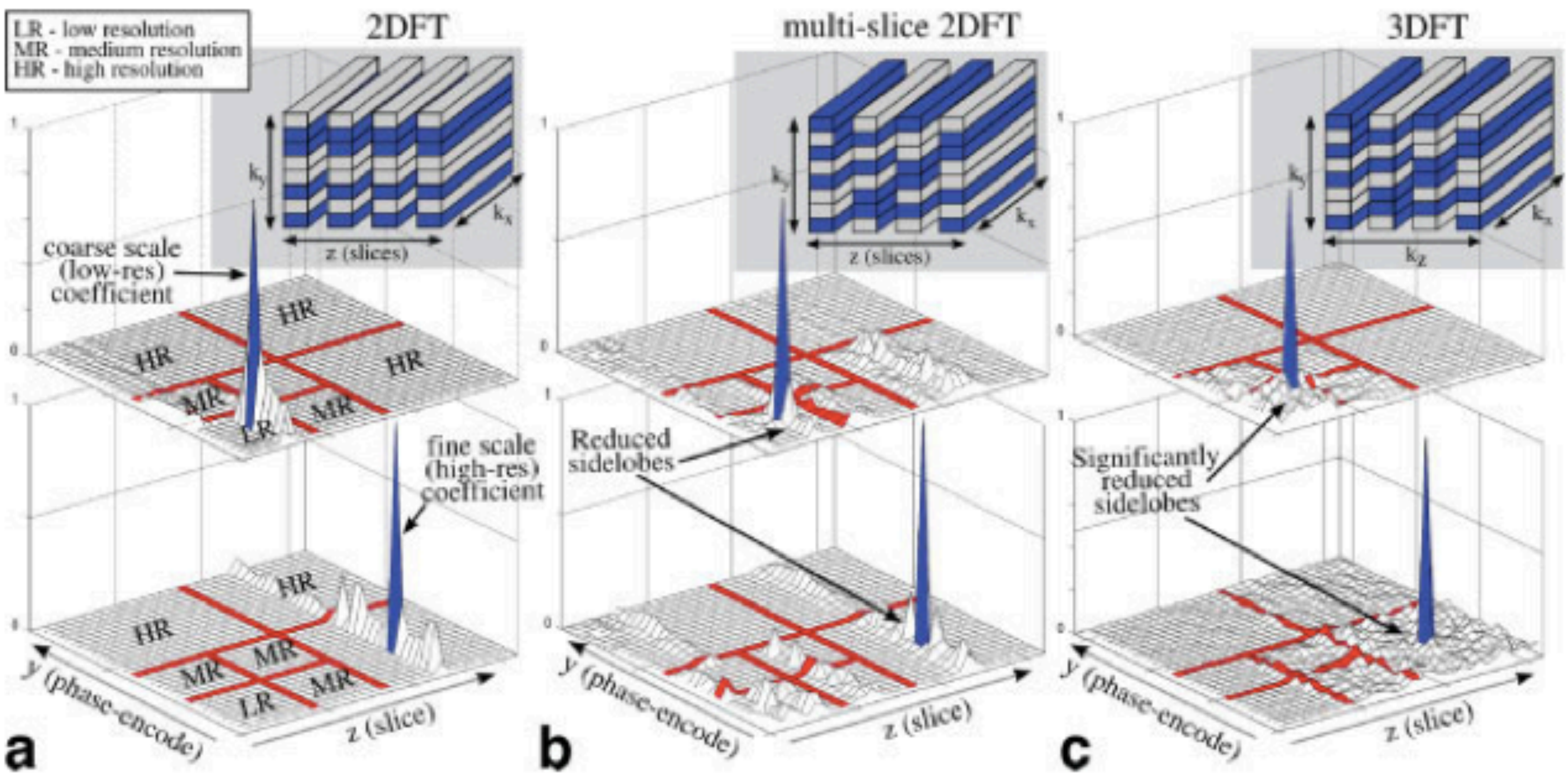
Incoherent Measurement (sampling)



To create noise-like interference



Incoherence Analysis



Incoherent aliasing interference in the sparse transform domain is an essential ingredients for CS

Framework of Compresses Sensing in MRI

- Sparse Representation of Signals
- Incoherent Measurement
- <u>Recovery with non-linear convex optimization</u>

Reconstruction Model

Tool: Convex Optimization

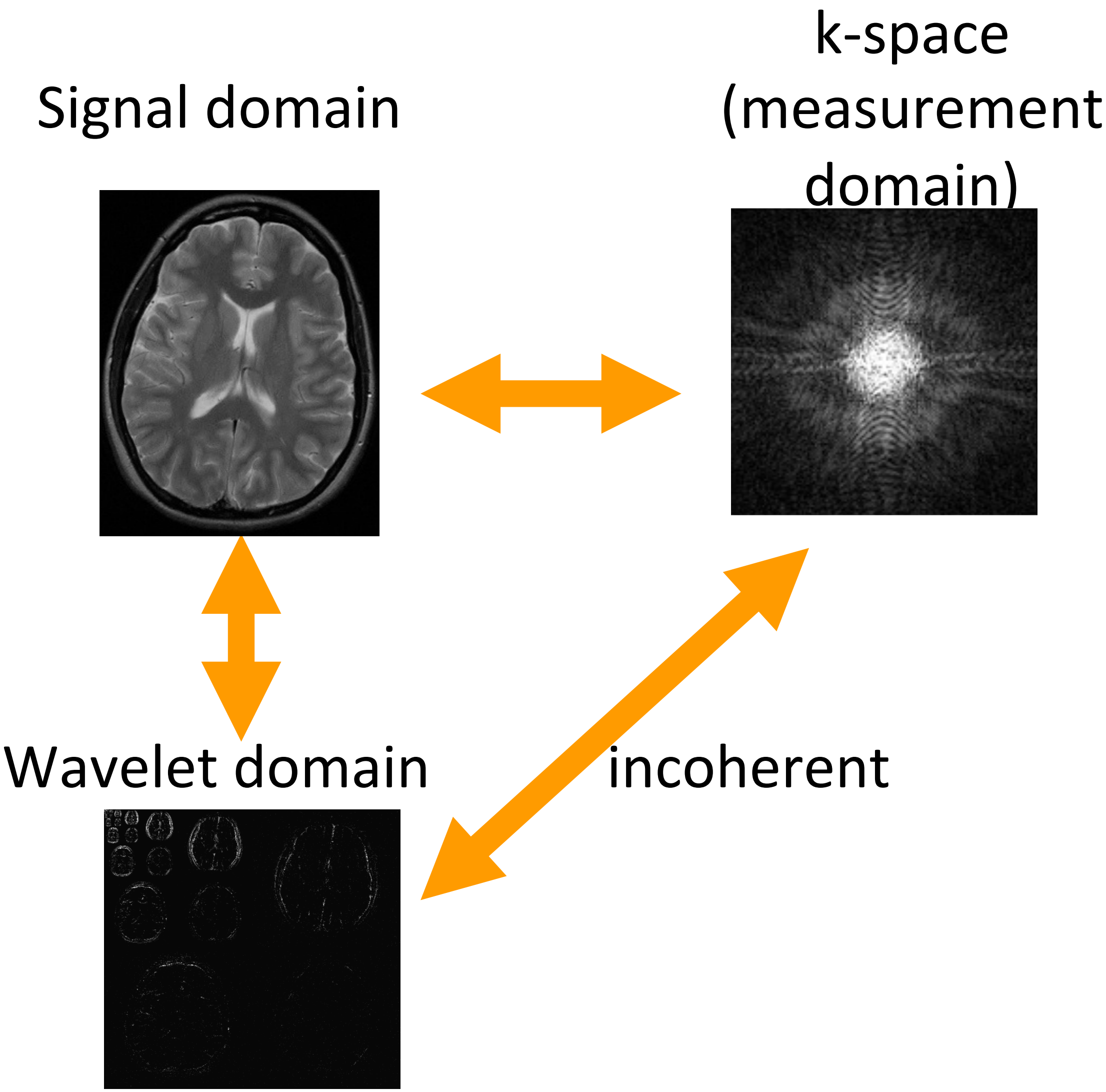
$$min\ \|\psi m\|_1$$
$$s.t.\ \|F_u m - y\|_2 \leq \epsilon$$

L1 norm promotes Sparsity

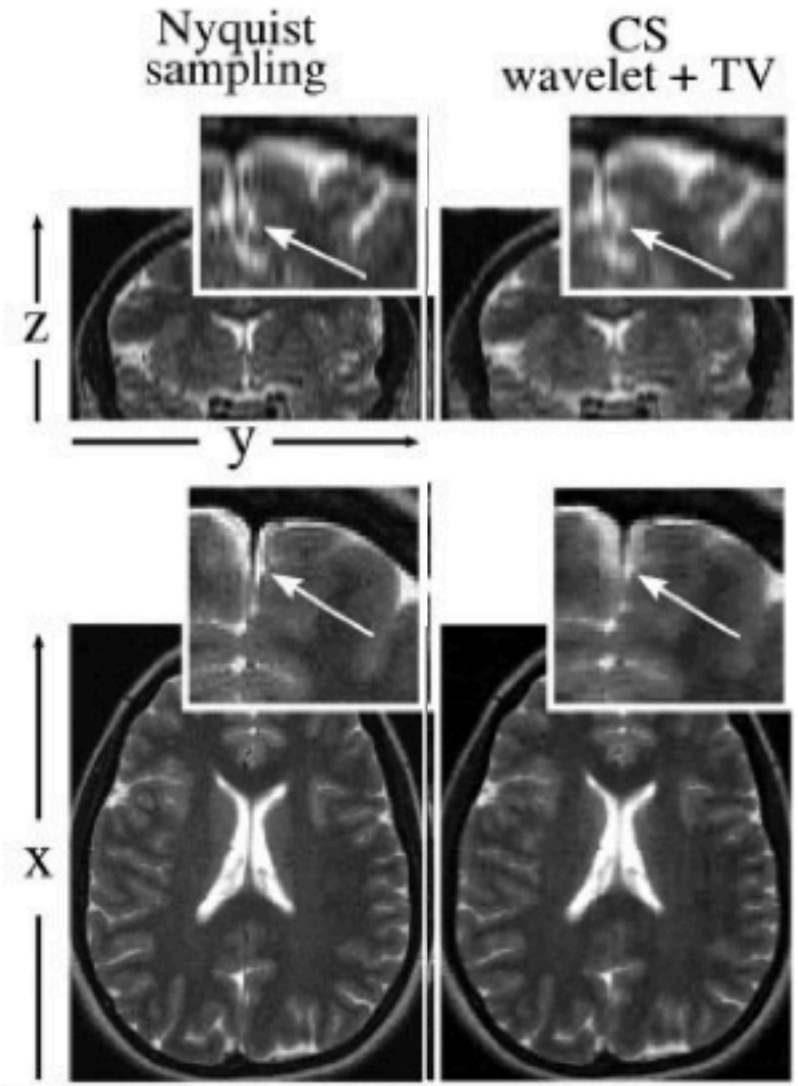
Enforce data consistency

m is the reconstructed image, ***ψ*** is the sparsifying transform, ***Fu*** is the undersampled Fourier Transform, ***y*** is the measurements

Domains in CS MRI



CS works very well in MRI



(left) Nyquist sampled image;
(right) CS reconstructed image
with 2.4-fold acceleration

CS works very well in MRI

(left)Nyquist sampled image; (right) CS reconstructed image with 5-fold acceleration

Conclusions and General Commnets

- MRI acquisition is slow
- Can be accelerated by collecting less data
- Compressed sensing exploits sparsity
- Many avenues for research:
  - Applications,Applications, Applications, and: signal representation, algorithms, computation, ...

To play with that

http://www.eecs.berkeley.edu/~mlustig/CS.html