

Lecture 11 Image Reconstruction

(Compress Sensing)

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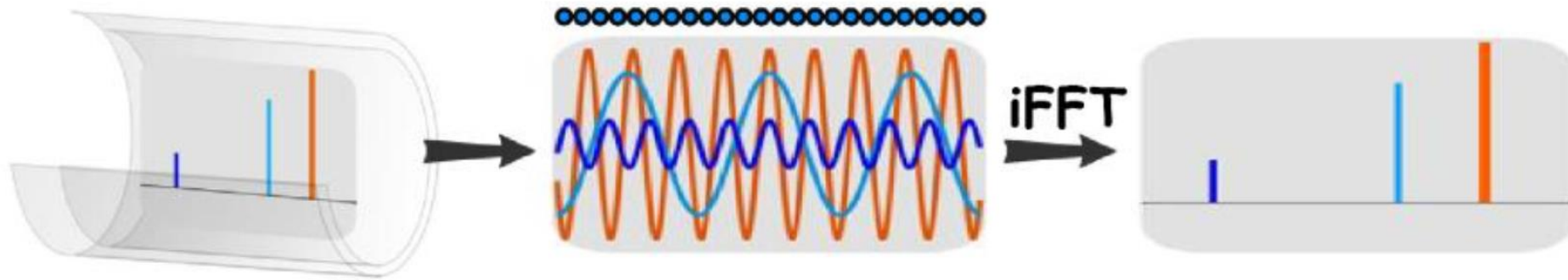
SIST Building-3 420

Outline

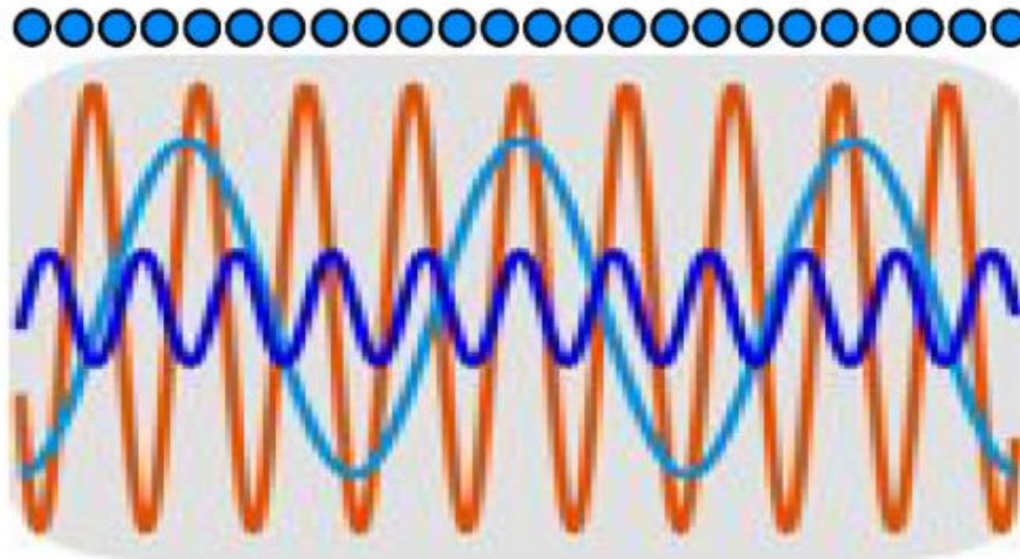
- Intuitive Example of Compress Sensing
- Compress Sensing
- Restricted Isometry Property
- Example in Image Reconstruction



Intuitive Example of Compress Sensing (CS)



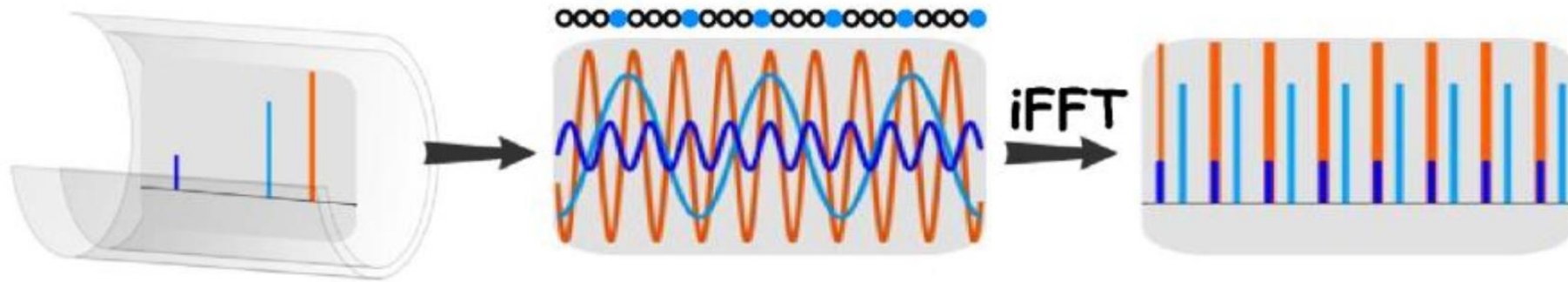
sampling →



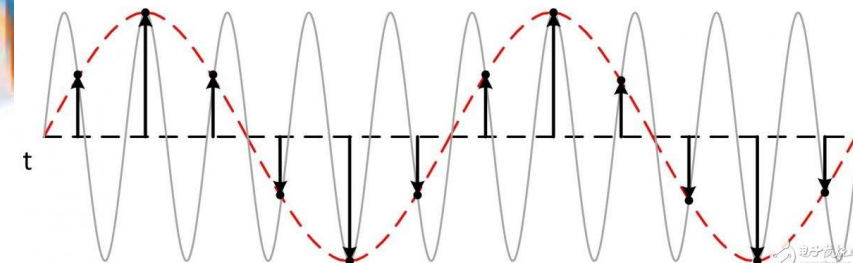
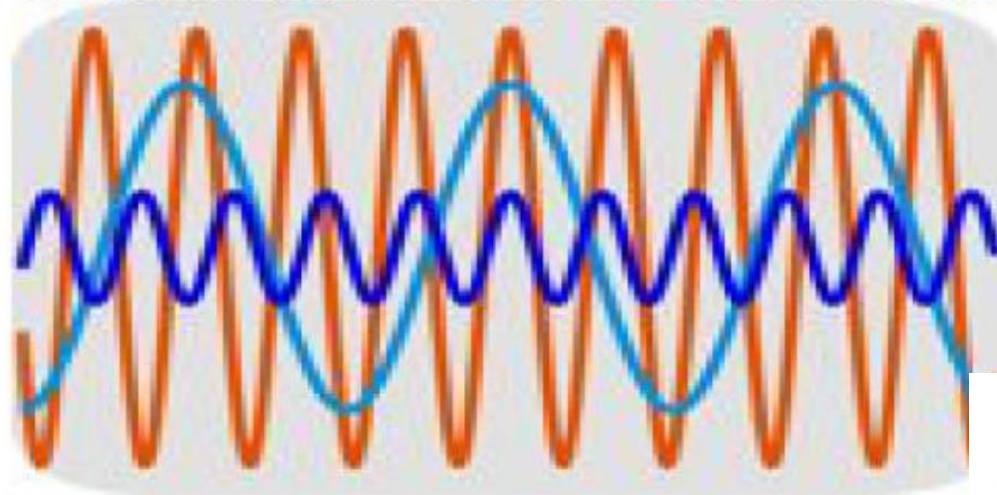
Nyquist



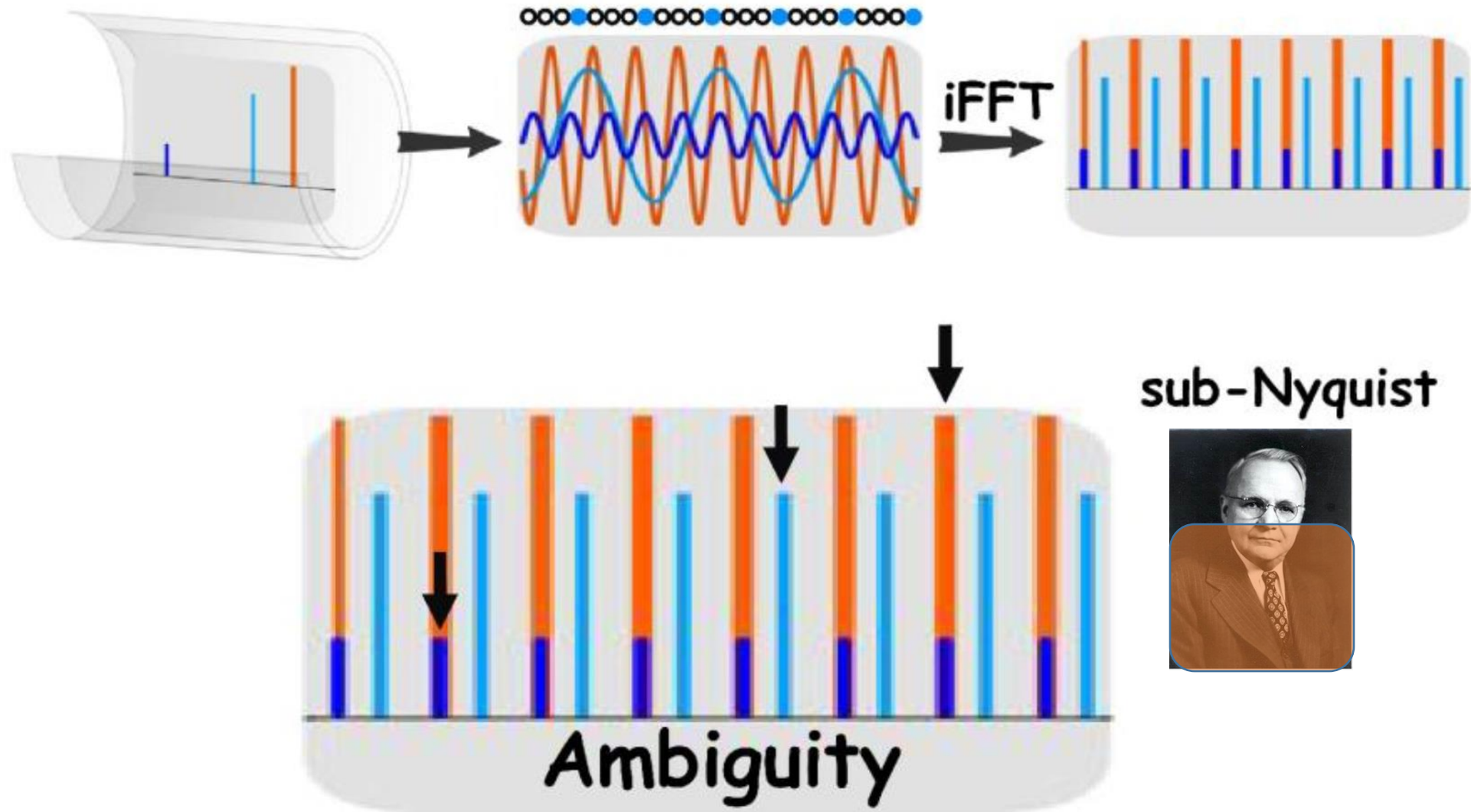
Intuitive Example of Compress Sensing (CS)



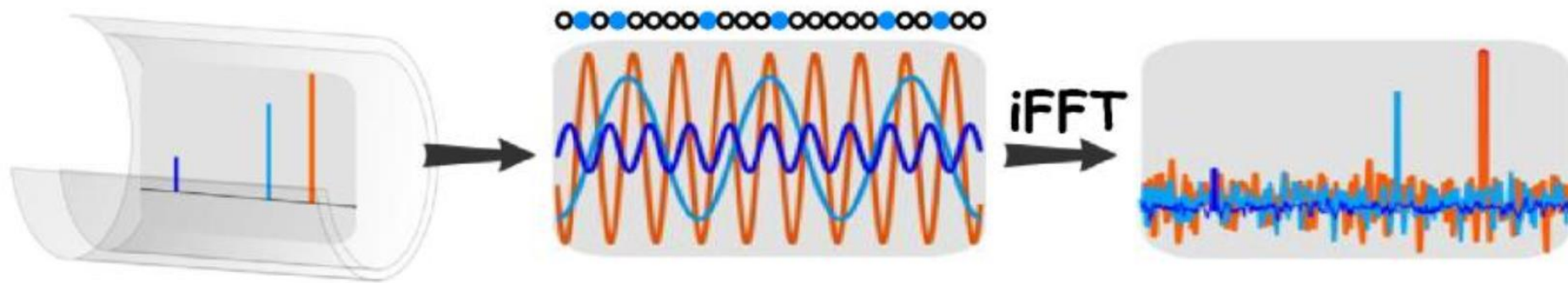
equispaced \rightarrow  sub-Nyquist



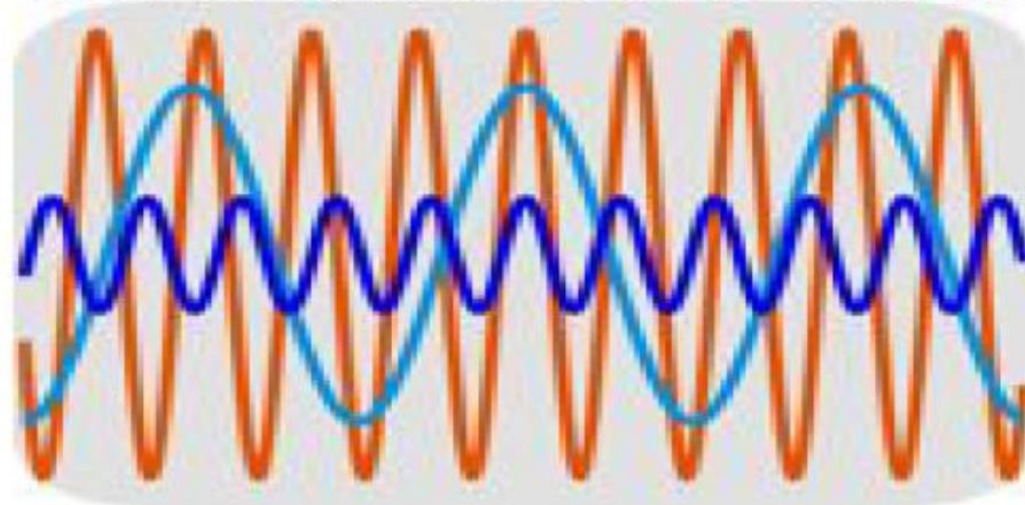
Intuitive Example of Compress Sensing (CS)



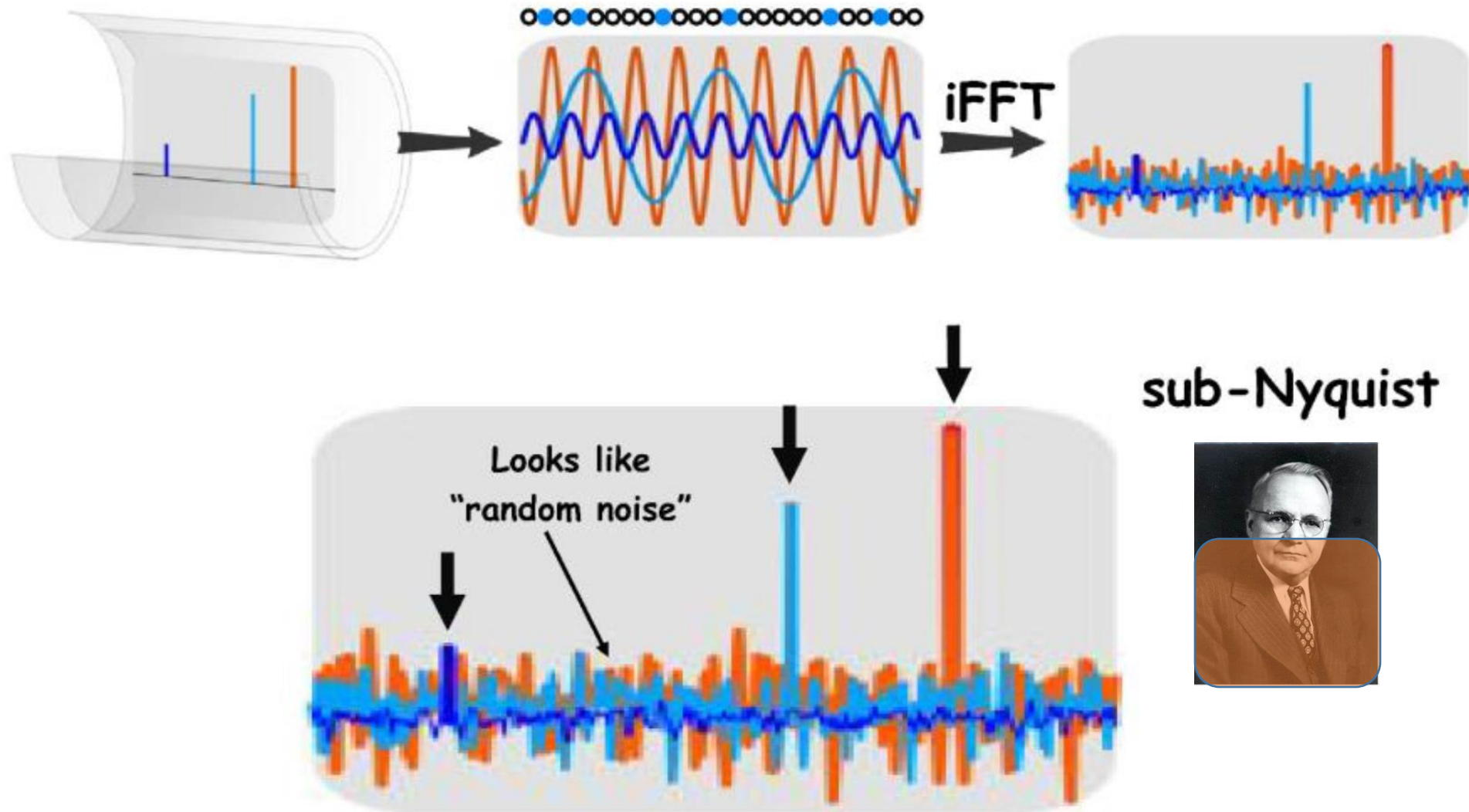
Intuitive Example of Compress Sensing (CS)



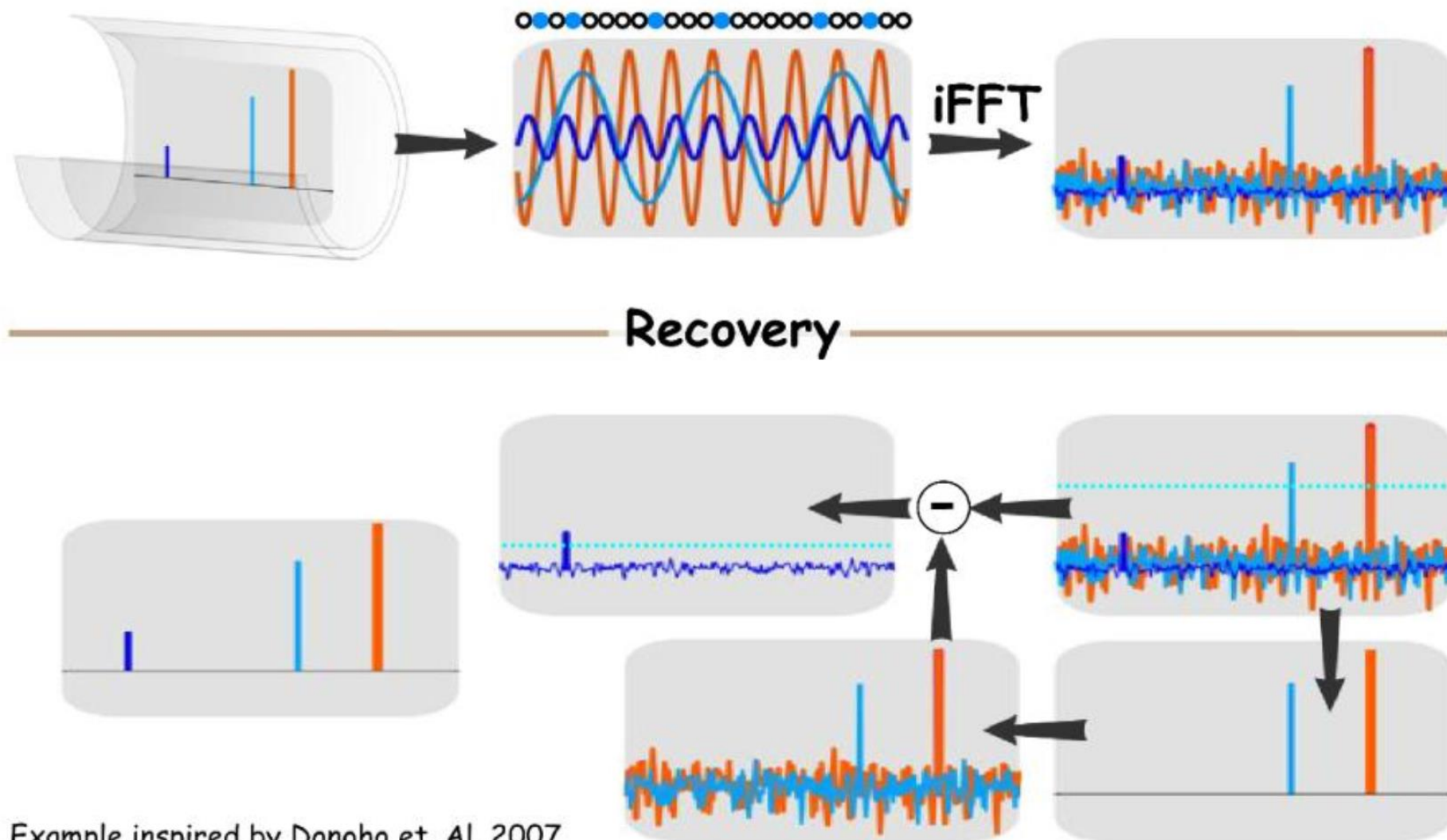
random \rightarrow  sub-Nyquist



Intuitive Example of Compress Sensing (CS)



Intuitive Example of Compress Sensing (CS)

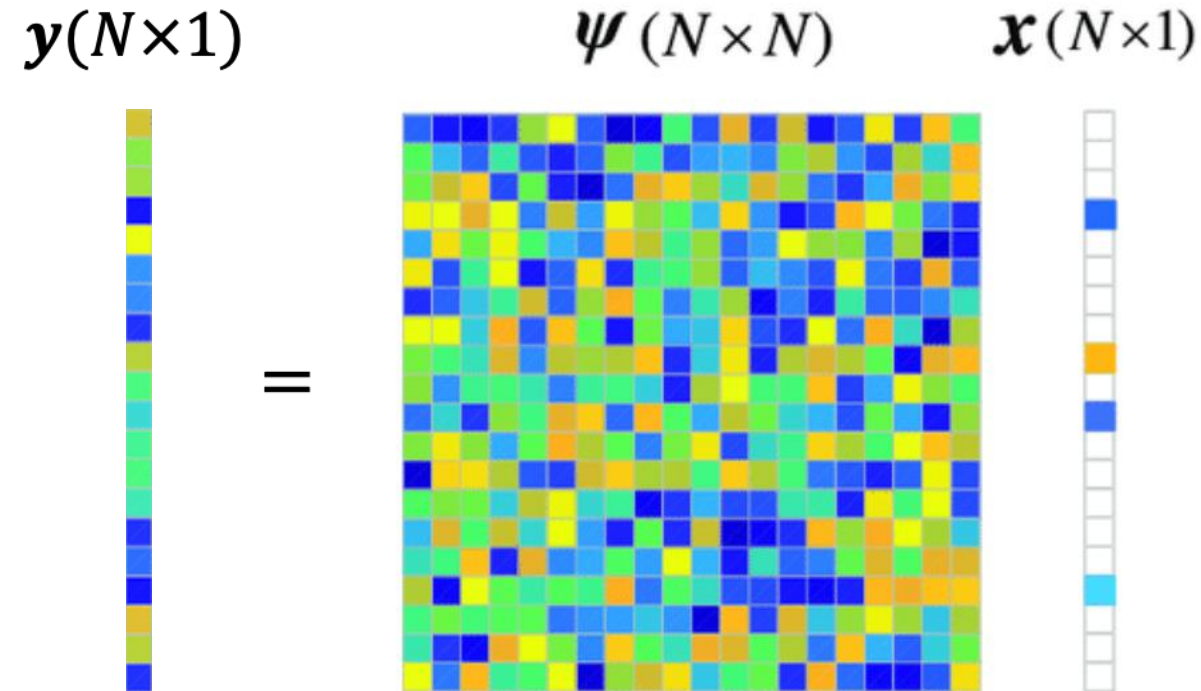


Example inspired by Donoho et. Al, 2007



Traditional Sensing

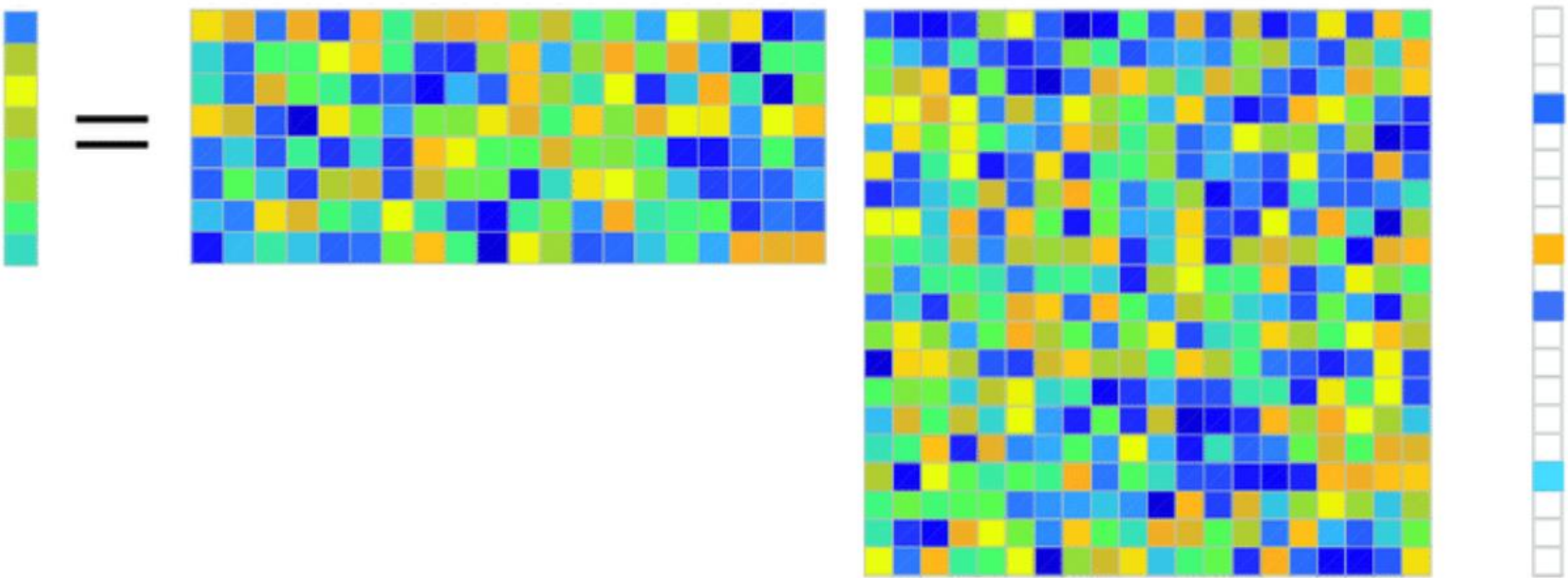
- $x \in \mathcal{R}^N$ is a signal
- Make N linear projections

$$\mathbf{y}(N \times 1) = \boldsymbol{\Psi}(N \times N) \mathbf{x}(N \times 1)$$




Compress Sensing

- $x \in \mathcal{R}^N$ is a K -sparse signal ($K \ll N$)
- Make $M(K < M \ll N)$ incoherent linear projections

$$\mathbf{y} \ (M \times 1) = \Phi \ (M \times N) \Psi \ (N \times N) \mathbf{x} \ (N \times 1)$$




Restricted Isometry Property (RIP)

Definition 1.1 (Restricted Isometry Constants): Let F be the matrix with the finite collection of vectors $(v_j)_{j \in J} \in \mathbf{R}^p$ as columns. For every integer $1 \leq S \leq |J|$, we define the S -restricted isometry constants δ_S to be the smallest quantity such that F_T obeys

$$(1 - \delta_S)\|c\|^2 \leq \|F_T c\|^2 \leq (1 + \delta_S)\|c\|^2 \quad (1.7)$$

for all subsets $T \subset J$ of cardinality at most S , and all real coefficients $(c_j)_{j \in T}$.



Restricted Isometry Property (RIP)

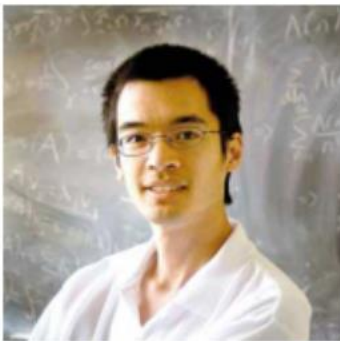
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Restricted Isometry Property (RIP)



陶哲轩和Candès于2005年给出了更为准确的要求：观测矩阵 Φ 应满足约束等距性条件 (Restricted Isometry Property, 简称RIP)：



即对于任意和常数，有：

$$(1 - \delta_k) \|c\|_2^2 \leq \|\phi c\|_2^2 \leq (1 + \delta_k) \|c\|_2^2$$



Restricted Isometry Property (RIP)

Baraniuk证明：

RIP的等价条件是观测矩阵和稀疏表示基**不相关**
(incoherent)



$$y = \Phi \Psi s$$
$$\Phi \longleftrightarrow \text{不相关} \longrightarrow \Psi$$

相关性的定义：

$$\mu(\Phi, \Psi) = \sqrt{n} \cdot \max_{1 \leq k, j \leq n} |\langle \varphi_k, \psi_j \rangle|.$$

μ 的范围： $\mu(\Phi, \Psi) \in [1, \sqrt{n}]$

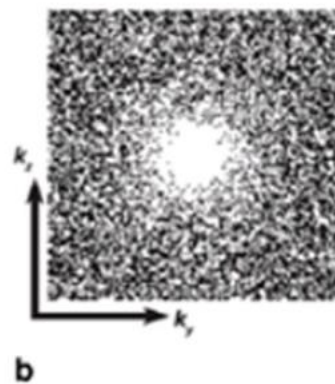
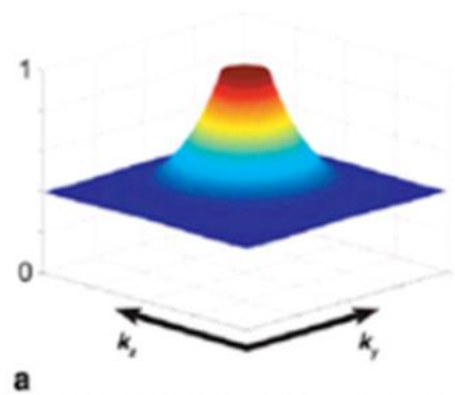
μ 越小， Φ 和 Ψ 越不相关



Restricted Isometry Property (RIP)

陶哲轩和Candès证明：

独立同分布的高斯随机测量矩阵可以成为普适的压缩感知测量矩阵。



CS recovery

- Given $y = \Phi x$ } Under-determined
find x
- But there's hope, x is sparse.

Enforce Sparsity

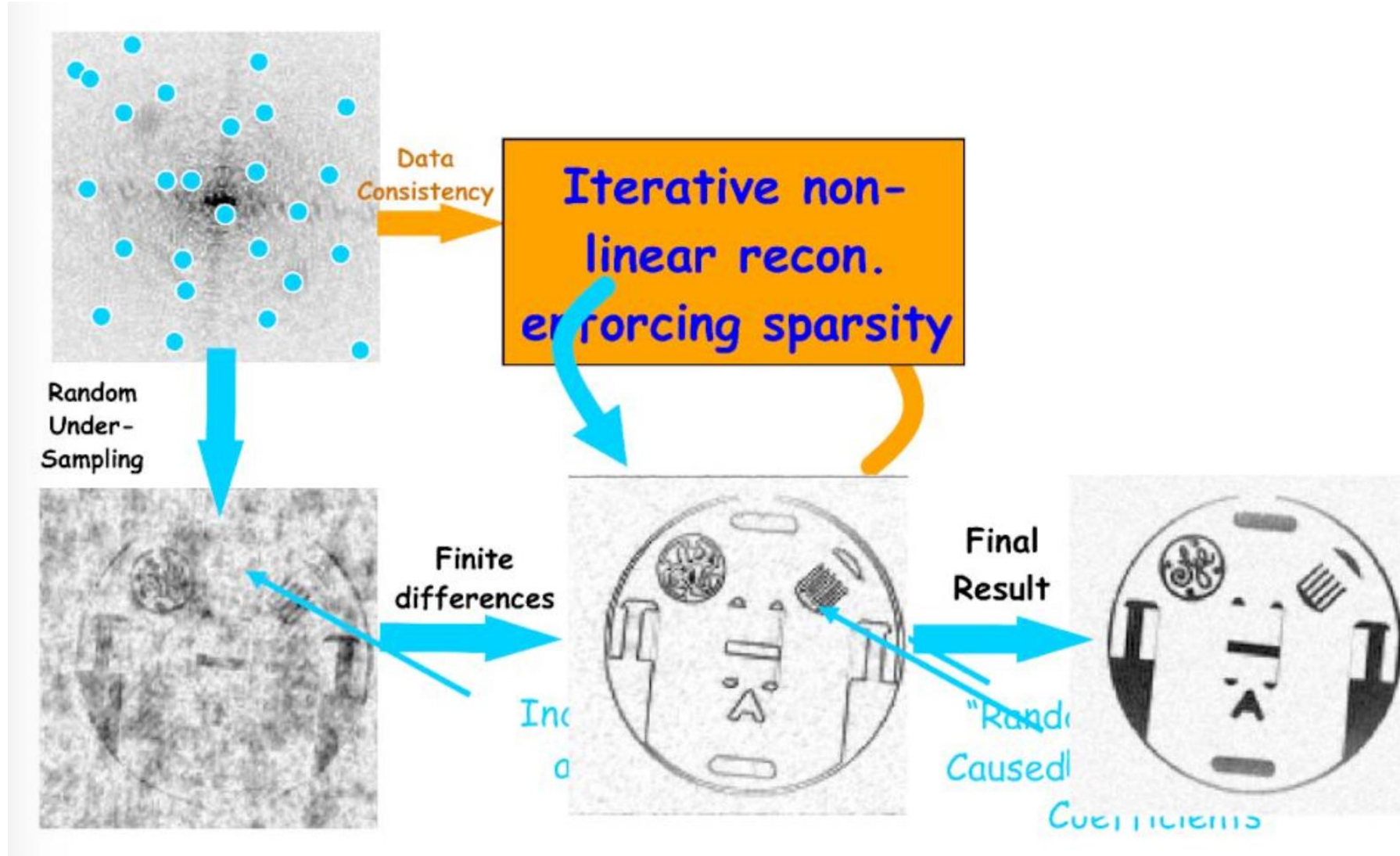
$$\min_x \|x\|_{L1}, s.t. \|\Phi \Psi x - y\| < \varepsilon$$

Enforce Data Consistency

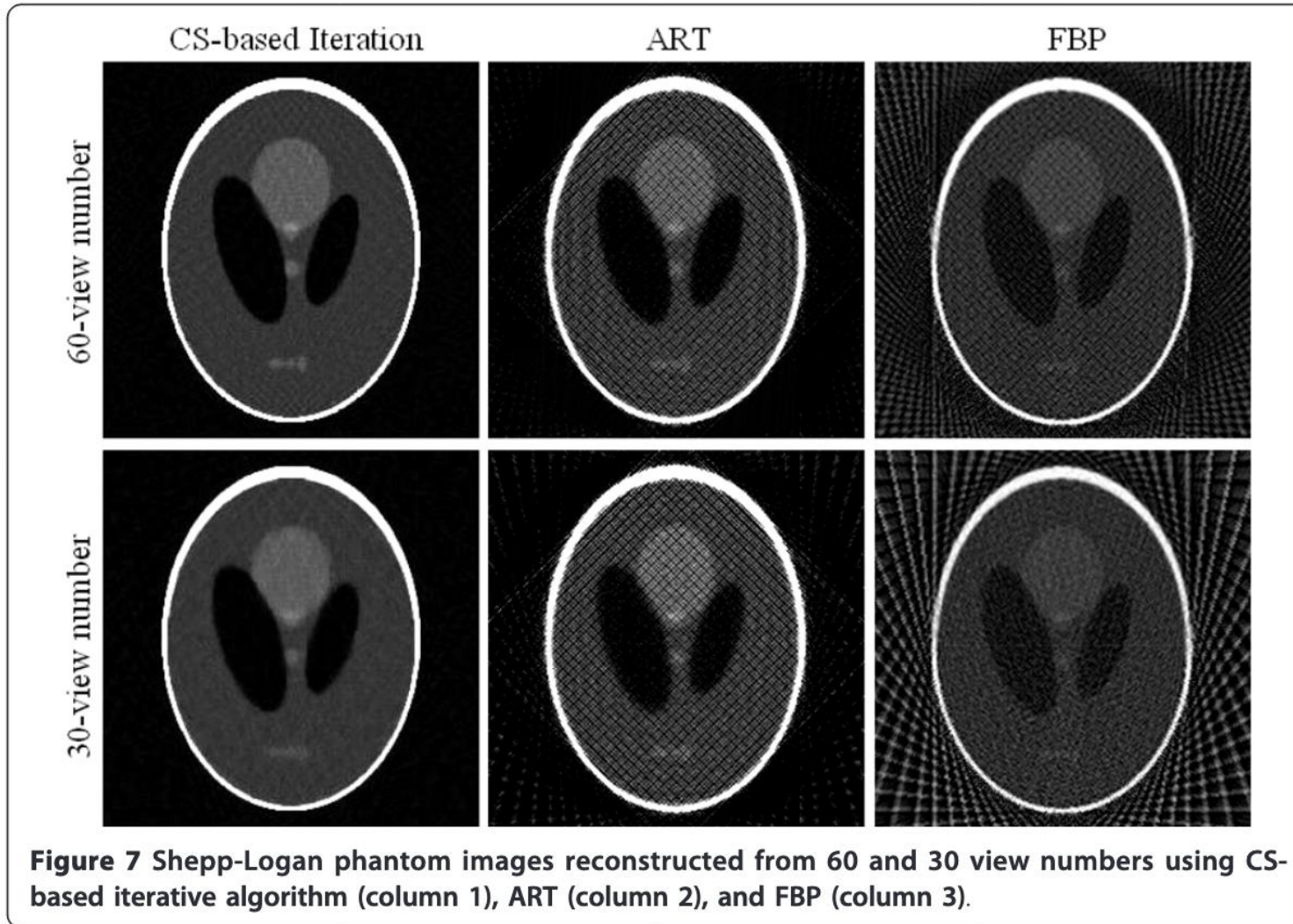
Need $M \approx K \log(N) \ll N$
Solved by linear-programming



CS recovery



Not a good idea for CT, why?



Magnetic Resonance Imaging (MRI): Fourier Encoding

A natural CS hardware

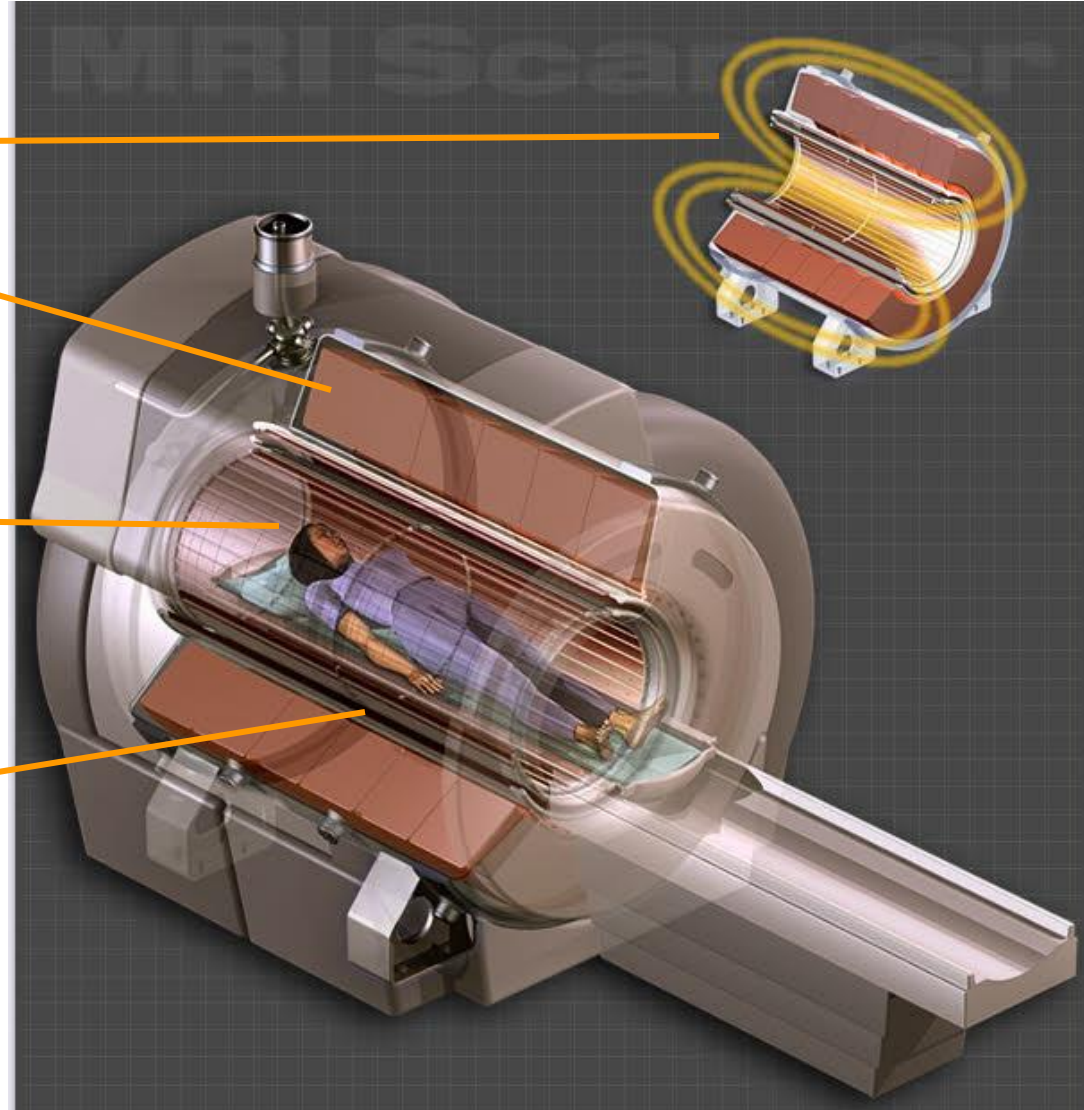


Basic Components of MRI System

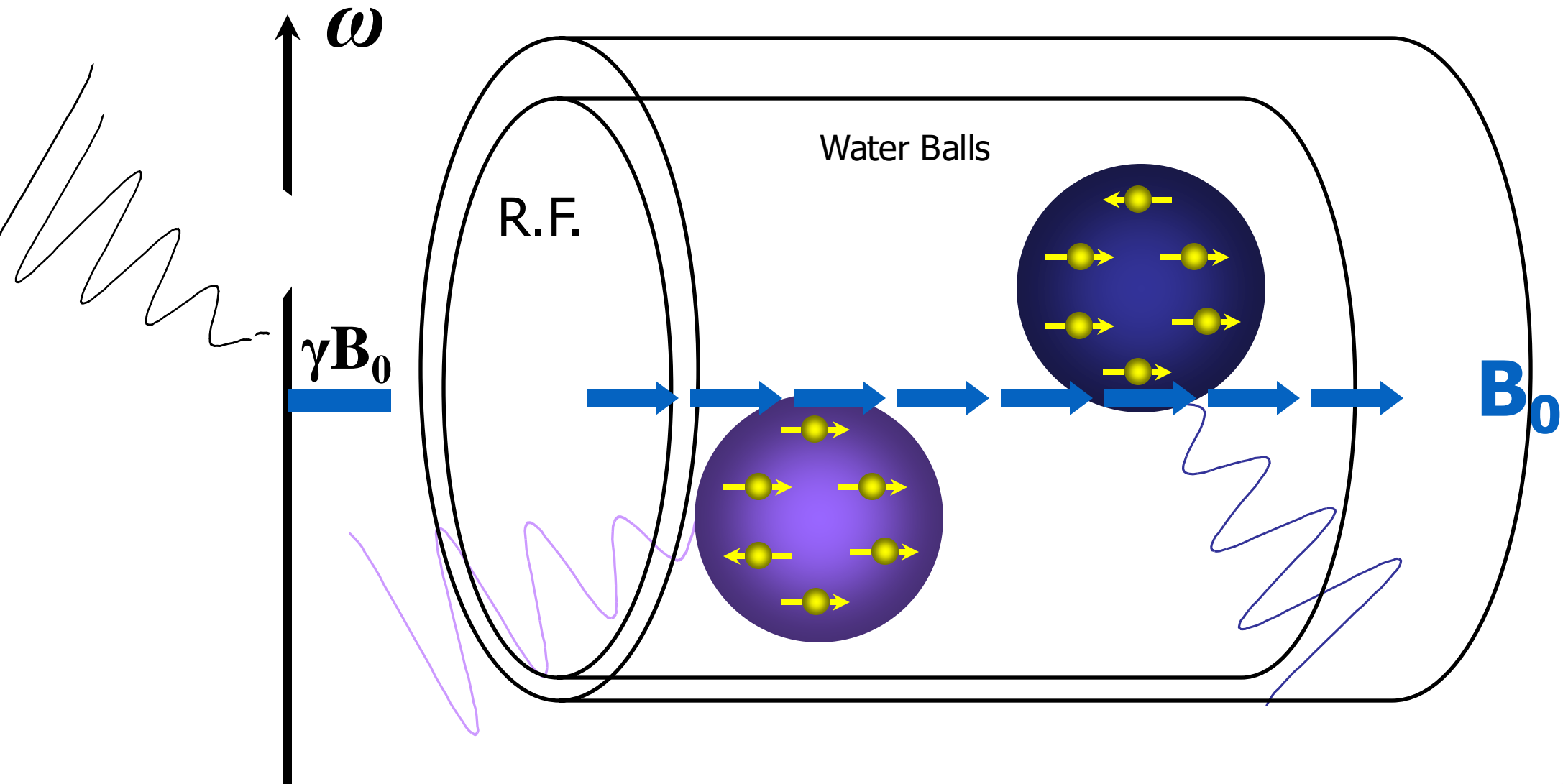
B_0 Field

RF Coil: B_1

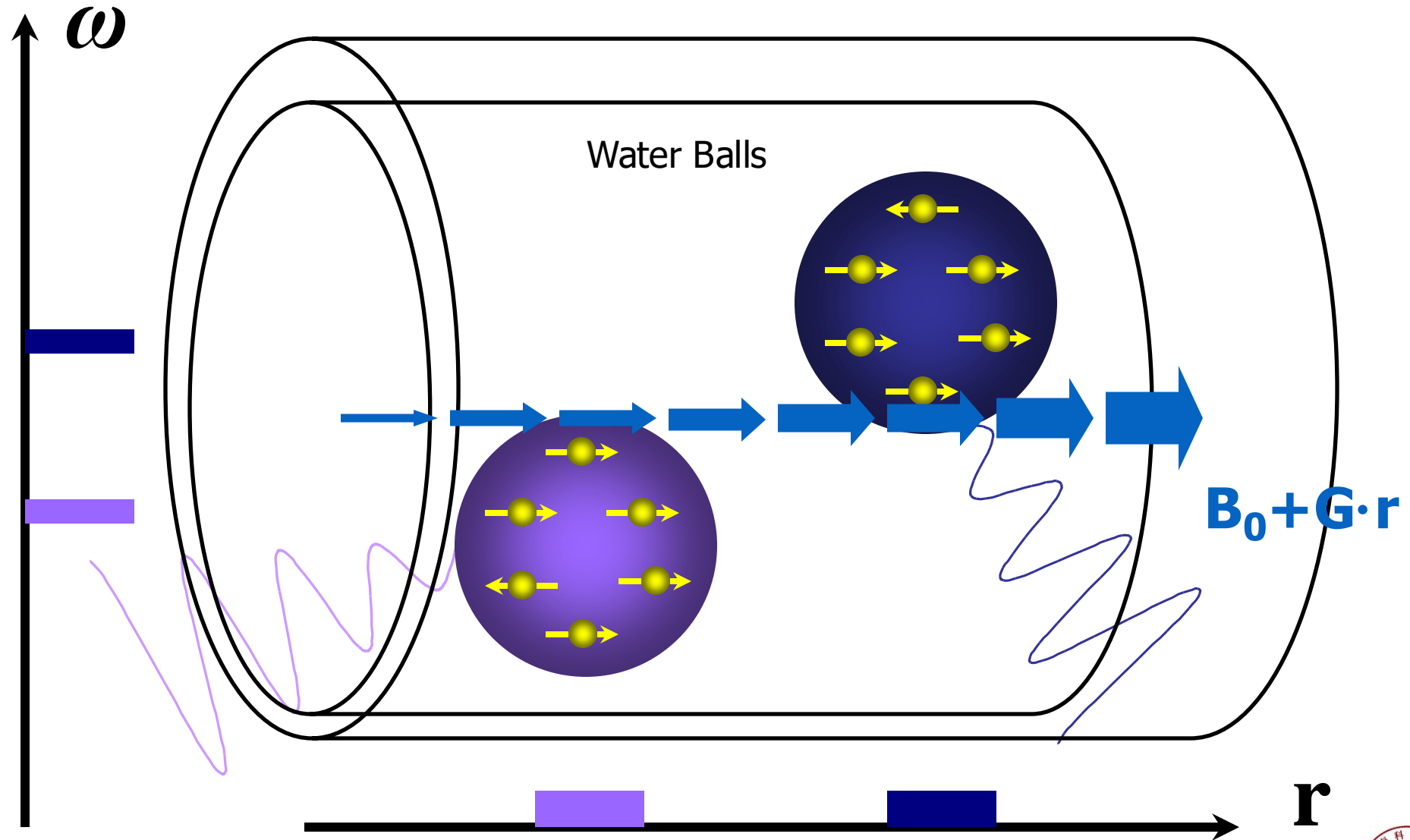
Gradient Coil: G



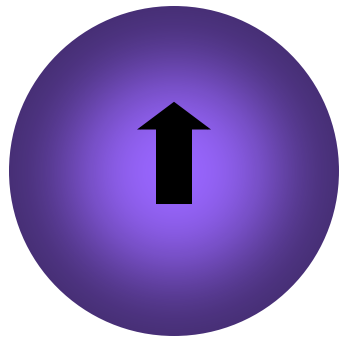
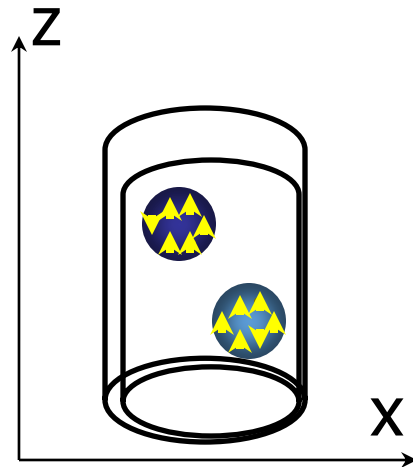
Magnetic Resonance Phenomenon



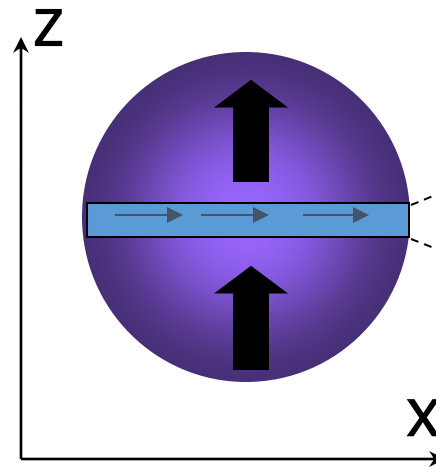
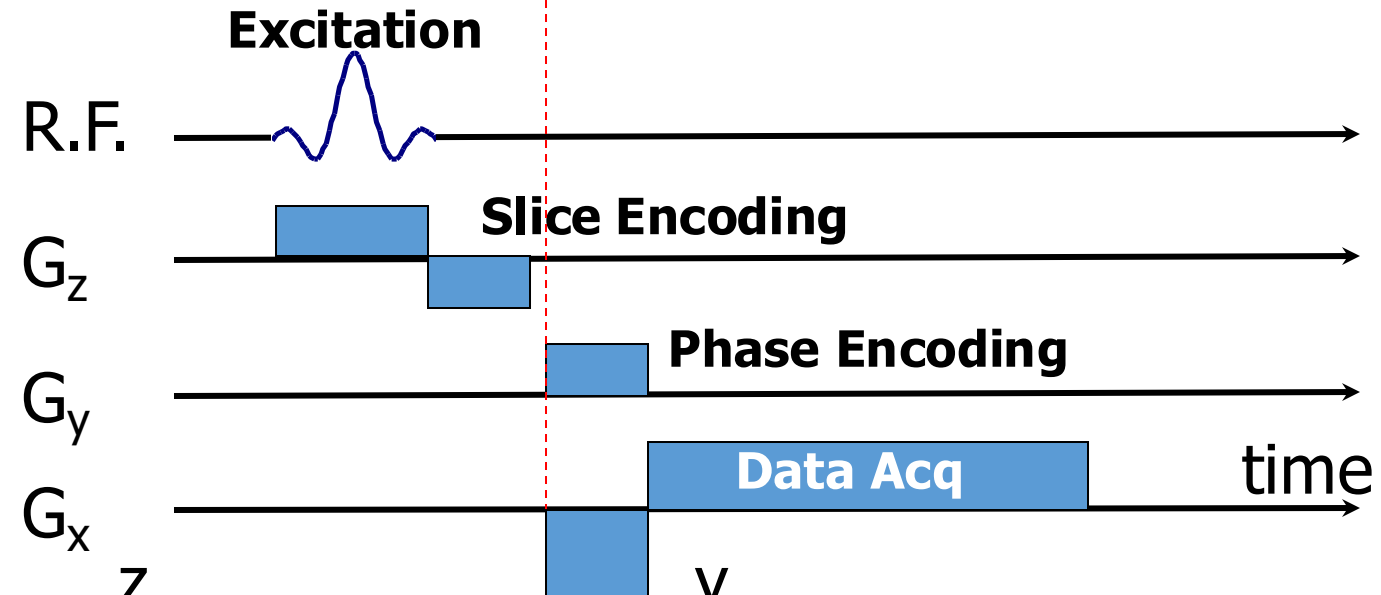
“Big” Idea: Magnetic Field Gradient



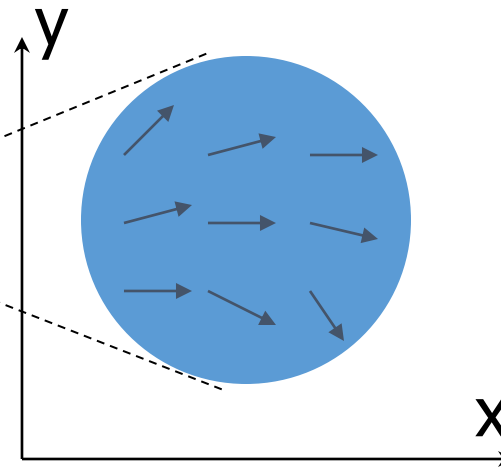
Pulse Sequence: Excitation, Encoding & Acquisition



$\mathbf{M}_z(\mathbf{r})$



$m(x, y)$



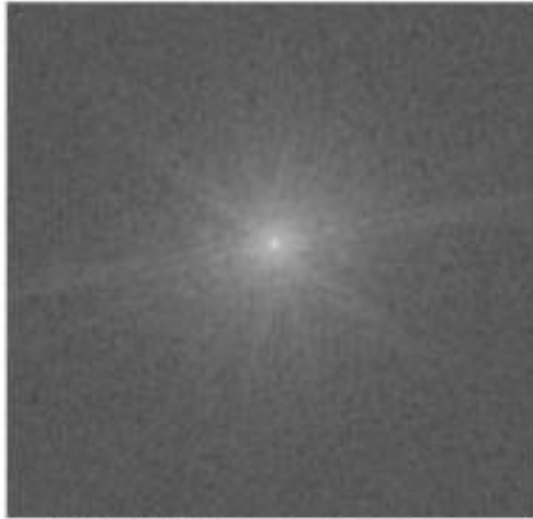
$$s(t) = \iint m(x, y) e^{i\varphi(x, y, t)} dx dy$$

<https://mriquestions.com/what-is-phase-encoding.html>

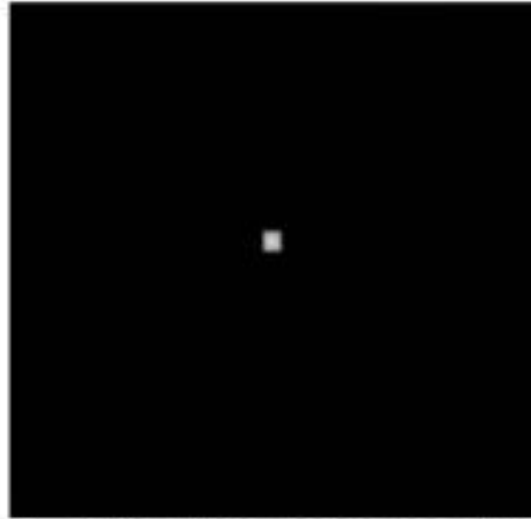


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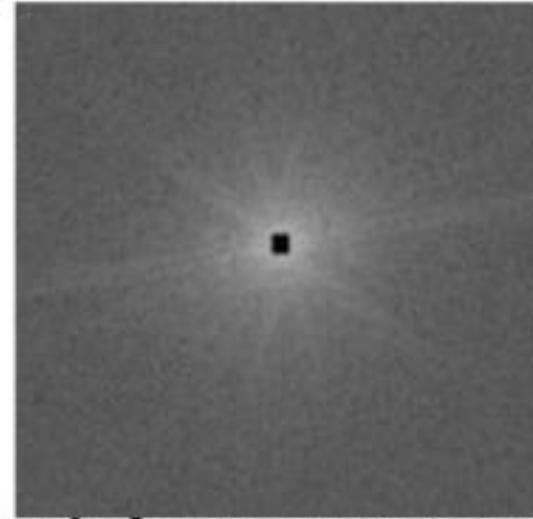
K-Space



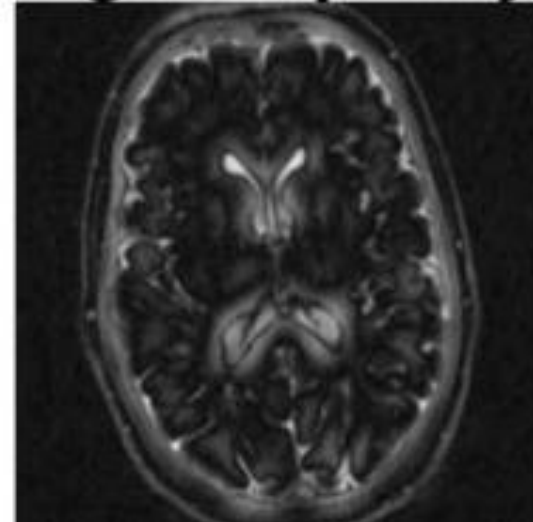
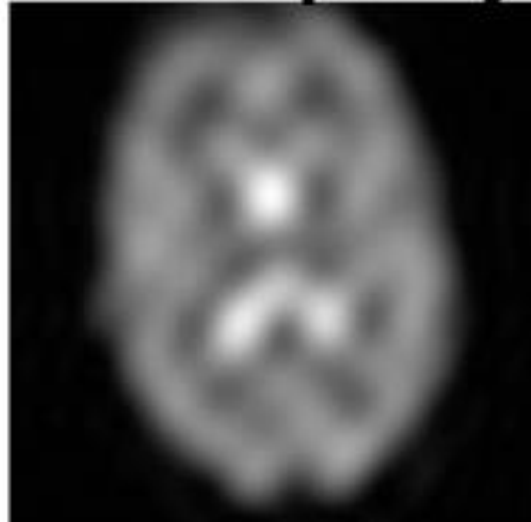
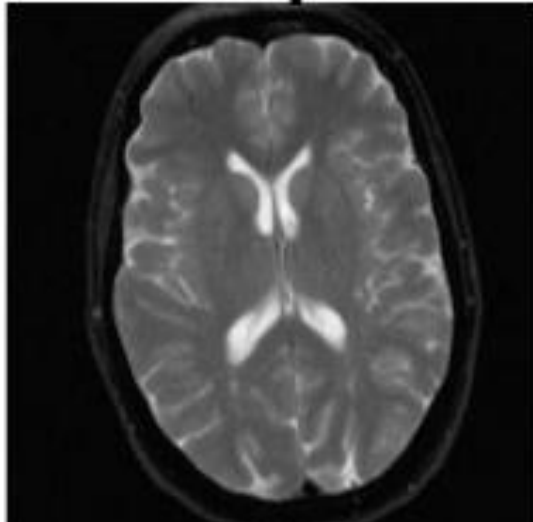
Full k-space



Low Frequency

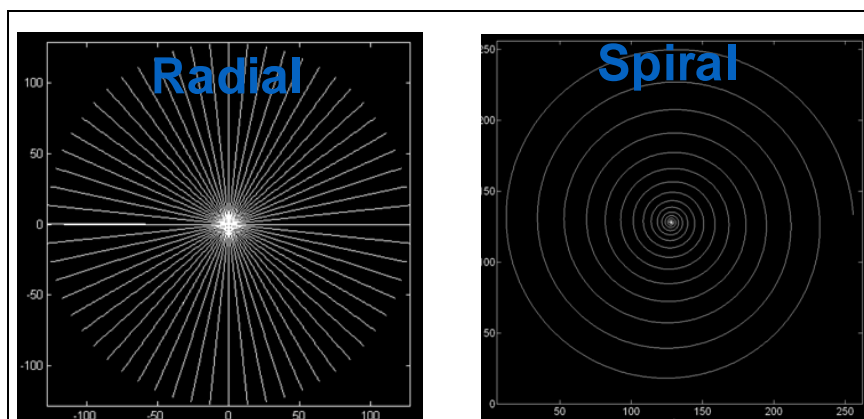
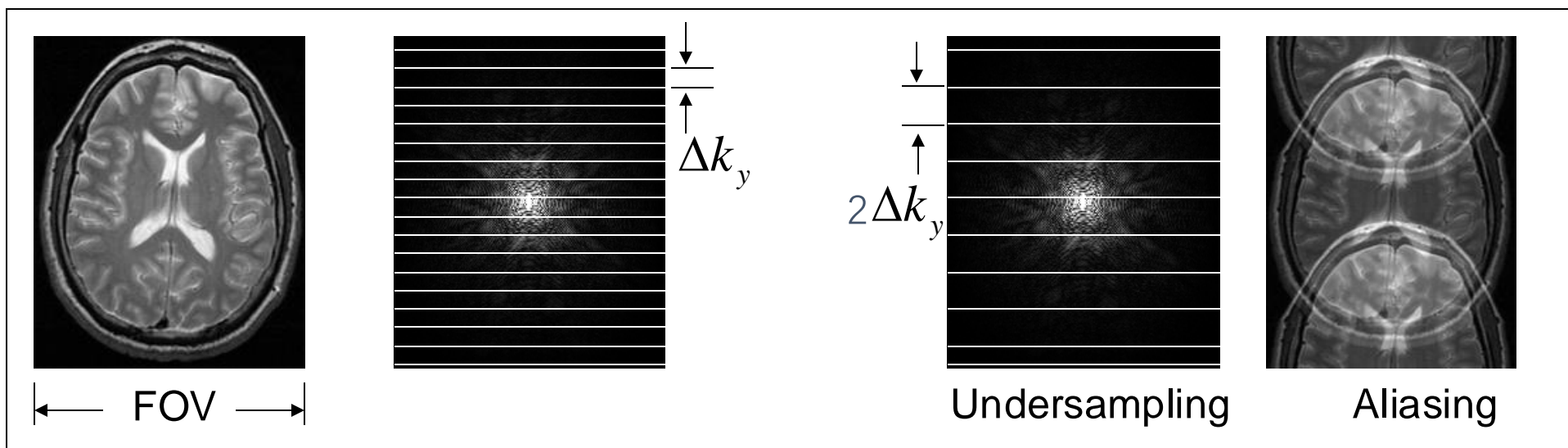


High Frequency



K-Space Sampling

Nyquist rate: $f = 2 \cdot B_w \rightarrow \Delta k_x = 1/FOV_x, \Delta k_y = 1/FOV_y$



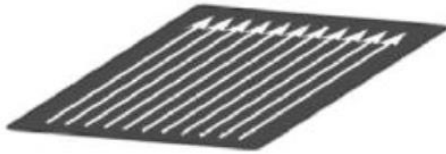
- Non-Cartesian Sampling
 - Design of gradient waveform
 - Image recon needs gridding



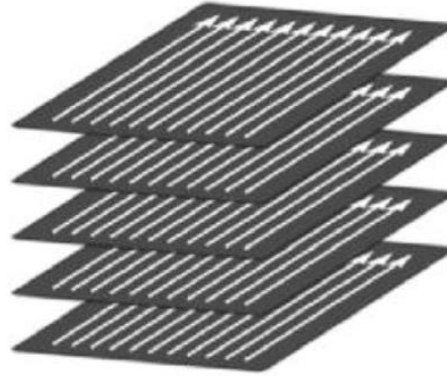
MRI – A Natural CS Hardware

Cartesian sampling:

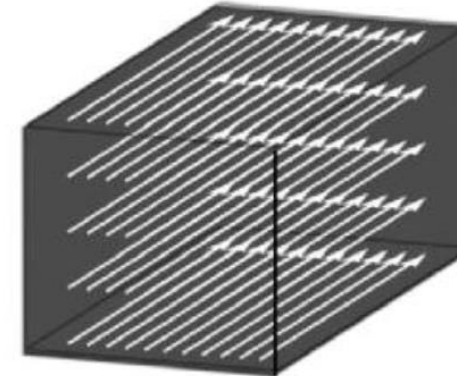
2DFT



Multi-slice

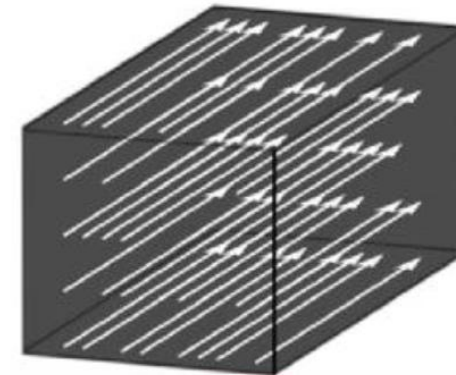
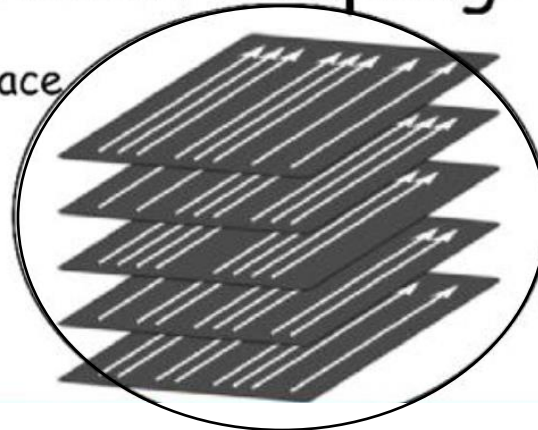
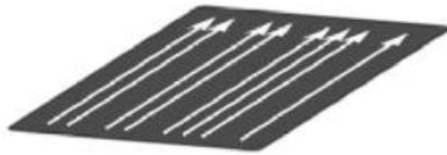


3DFT

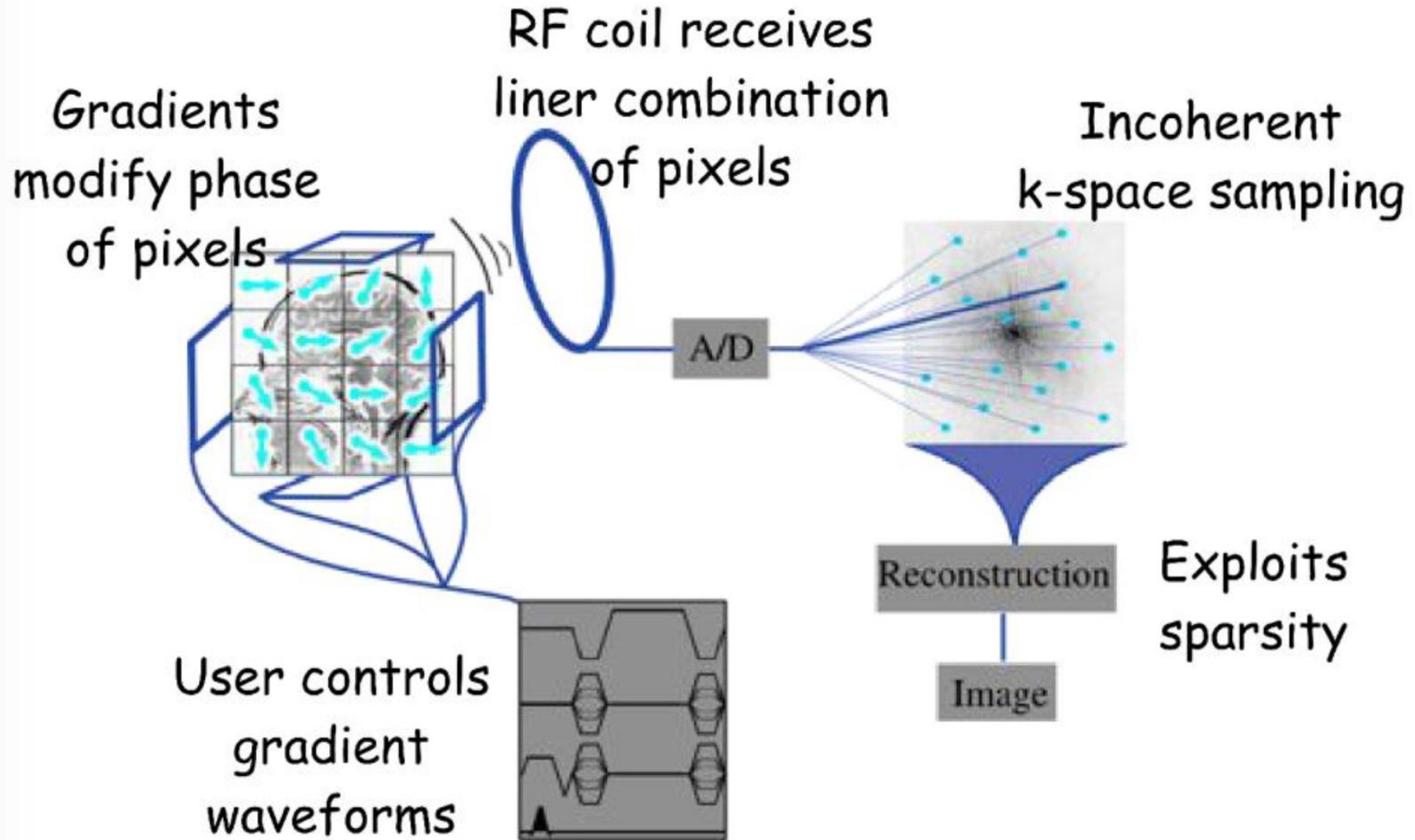


Incoherent Cartesian sampling:

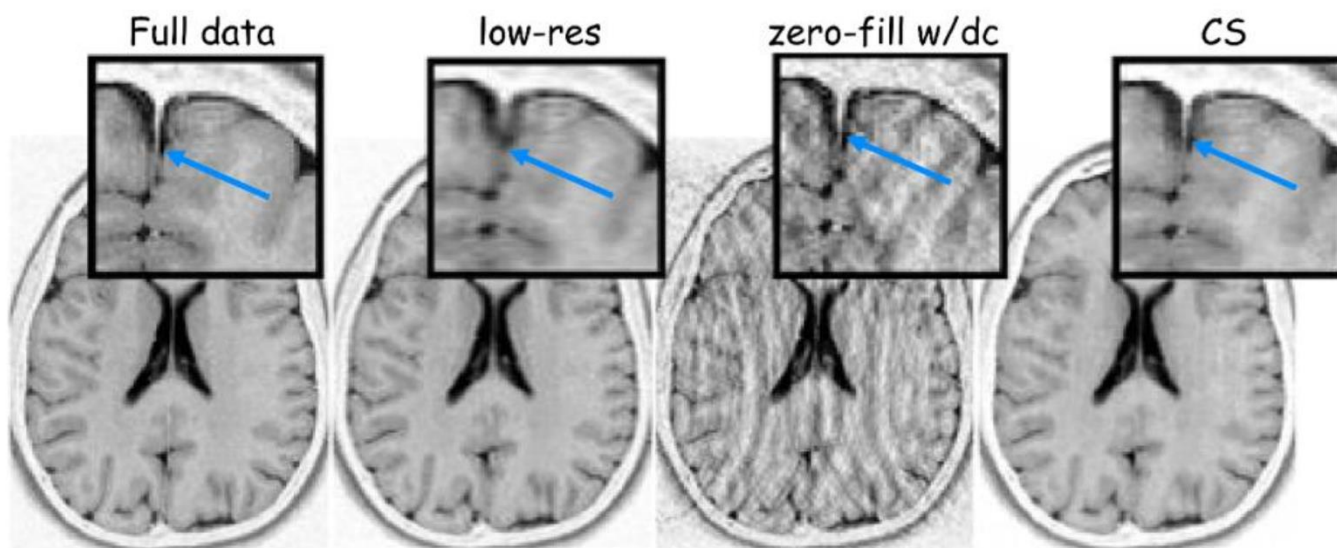
Hybrid space



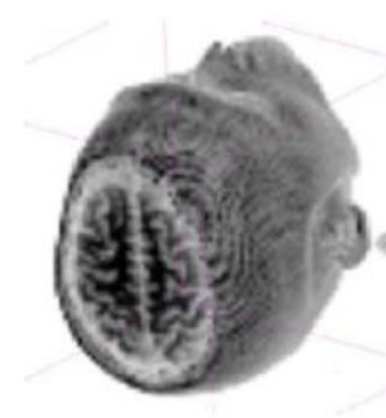
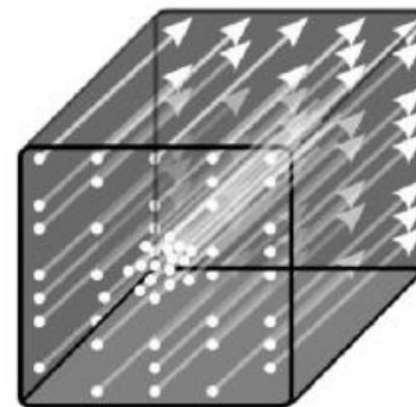
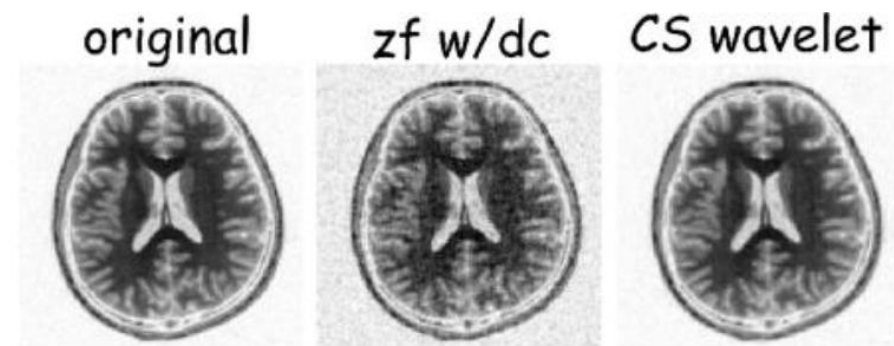
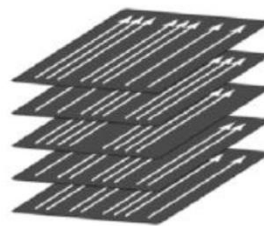
Incoherent Sampling



- Scan time reduction: 2.4 times
- Transform: Wavelet



- Scan reduction: x2.4
- Transform: wavelet



Resources

- SparseMRI V0.2: matlab code, examples
<http://www.stanford.edu/~mlustig/SparseMRI.html>
- Rice University CS page: papers, tutorials, codes,
<http://www.dsp.ece.rice.edu/cs/>
- IEEE Signal Processing Magazine, special issue on compressive sampling 2008;25(2)
- Blog:
<http://nuit-blanche.blogspot.com/>