



Medical Image Reconstruction

Term II – 2010

Topic 2: Reconstruction from Nonuniformly Sampled k-Space (2)

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Kadah's Method

Progressive Magnetic Resonance Image Reconstruction Based on Iterative Solution of a Sparse Linear System

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- ▶ Algebraic Solution
 - ▶ Iterative reconstruction method that provides an optimal solution in the least-squares sense
 - ▶ Based on a practical imaging model
 - ▶ Progressive reconstruction capability
 - ▶ Simple mechanism to control trade-off between accuracy and speed
 - ▶ Embedded inhomogeneity correction and spatial domain constraints
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Disadvantages of Previous Methods

- ▶ Reconstructed images do not represent optimality in any sense
- ▶ Variation of performance with form of k-space trajectory
- ▶ Lack of explicit methodology to trade-off accuracy and speed of reconstruction
- ▶ Not possible to progressively improve the accuracy of reconstruction
- ▶ Not possible to embed field inhomogeneity correction or constraints into the reconstruction



Theory

- ▶ Assume a piecewise constant spatial domain representing display using pixels
 - ▶ Image composed of pixel each of uniform intensity
 - ▶ Image can be represented by a sum of 2D RECT functions
- ▶ Assume spatial domain to be compact
 - ▶ Field of view is always finite in length
- ▶ The image can be expressed in terms of gate functions as,

$$f(x, y) = \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} \alpha_{n,m} \cdot \Pi(x - x_n, y - y_m)$$



Theory

- ▶ Applying **continuous Fourier transform**,

$$F(k_x, k_y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} \alpha_{n,m} \cdot \Pi(x - x_n, y - y_m) \cdot e^{-j2\pi(k_x x + k_y y)} dx dy,$$

- ▶ Hence,

$$F(k_x, k_y) = \text{Sinc}(w_x k_x) \cdot \text{Sinc}(w_y k_y) \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} \alpha_{n,m} \cdot e^{-j2\pi(k_x x_n + k_y y_m)}.$$

- ▶ This can be expressed in the form of a linear system as

$$\vec{b} = \mathbf{A} \vec{v}$$

- ▶ A matrix is $\sim N^2 \times N^2$ and complex-valued
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Theory

- ▶ Observation: A matrix is $\sim N^2 \times N^2$ and complex-valued
 - ▶ Solve a $|6384 \times 6384|$ linear system to get a $|28 \times 28|$ image
 - ▶ Very difficult to solve in practice because of size

$$\begin{aligned}
 & \begin{bmatrix} \frac{F(k_x^0, k_y^0)}{\text{Sinc}(w_x k_x^0) \cdot \text{Sinc}(w_y k_y^0)} \\ \frac{F(k_x^1, k_y^1)}{\text{Sinc}(w_x k_x^1) \cdot \text{Sinc}(w_y k_y^1)} \\ \vdots \\ \frac{F(k_x^{L-1}, k_y^{L-1})}{\text{Sinc}(w_x k_x^{L-1}) \cdot \text{Sinc}(w_y k_y^{L-1})} \end{bmatrix}_{L \times 1} \\
 &= \vec{b} = A \cdot \vec{v} \\
 &= \begin{bmatrix} e^{-j\pi(k_x^0 \cdot x_0 + k_y^0 \cdot y_0)} & e^{-j\pi(k_x^0 \cdot x_0 + k_y^0 \cdot y_1)} & \dots & e^{-j\pi(k_x^0 \cdot x_{N-1} + k_y^0 \cdot y_{M-1})} \\ e^{-j\pi(k_x^1 \cdot x_0 + k_y^1 \cdot y_0)} & e^{-j\pi(k_x^1 \cdot x_0 + k_y^1 \cdot y_1)} & \dots & e^{-j\pi(k_x^1 \cdot x_{N-1} + k_y^1 \cdot y_{M-1})} \\ \vdots & \vdots & \dots & \vdots \\ e^{-j\pi(k_x^{L-1} \cdot x_0 + k_y^{L-1} \cdot y_0)} & e^{-j\pi(k_x^{L-1} \cdot x_0 + k_y^{L-1} \cdot y_1)} & \dots & e^{-j\pi(k_x^{L-1} \cdot x_{N-1} + k_y^{L-1} \cdot y_{M-1})} \end{bmatrix}_{L \times N \cdot M} \cdot \begin{bmatrix} \alpha_{0,0} \\ \alpha_{0,1} \\ \vdots \\ \alpha_{N-1, M-1} \end{bmatrix}_{N \cdot M \times 1}
 \end{aligned}$$



Idea

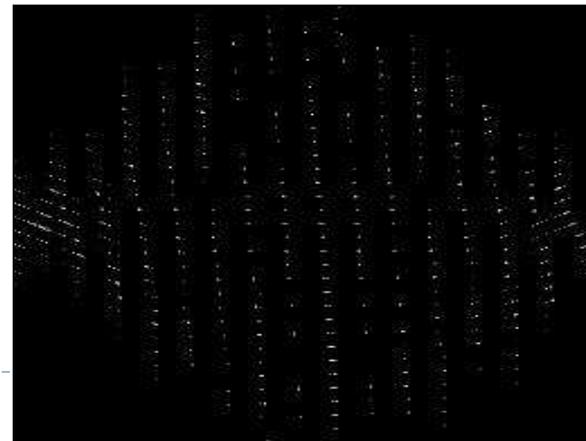
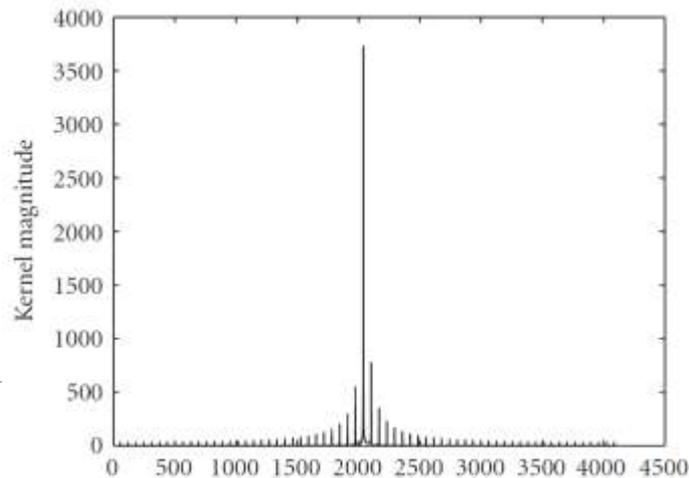
- ▶ Problem: A matrix is dense and computational complexity of solution is prohibitive
- ▶ Solution Strategy: Try to make the A matrix sparse by seeking a compact representation of rows in terms of suitable basis functions
- ▶ Observation: applying a 1-D Fourier transformation to the rows of A matrix results in energy concentration in only a few elements



Methods

- ▶ Multiply the rows of the system matrix by the $N \times M$ -point discrete Fourier transform matrix H in the following form:

$$H = \frac{1}{\sqrt{NM}} \times \begin{bmatrix} 1 & 1 & \dots & 1 \\ 1 & e^{-j2\pi/NM} & \dots & e^{-j2\pi(NM-1)/NM} \\ \vdots & \vdots & \dots & \vdots \\ 1 & e^{-j2\pi(NM-1)/NM} & \dots & e^{-j2\pi(NM-1)^2/NM} \end{bmatrix}_{N \cdot M \times N \cdot M}$$



Methods

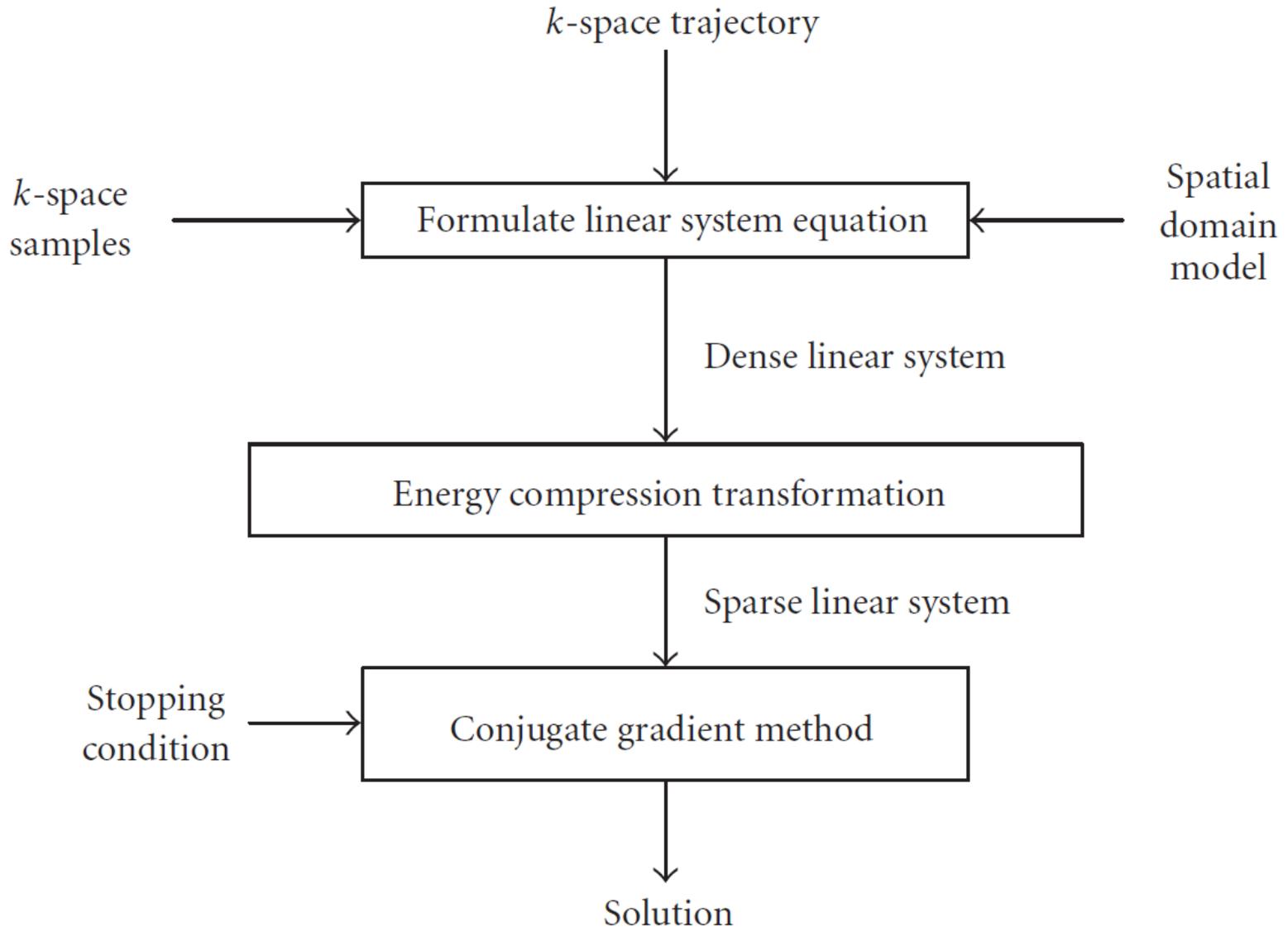
- ▶ How to multiply \mathbf{H} without changing the linear system?
 - ▶ Row energy compacting transformation converts the system into a sparse linear system as follows:

$$\vec{b} = \mathbf{A}\vec{v} = \mathbf{A} \cdot \mathbf{H}^H \cdot \mathbf{H} \cdot \vec{v} = (\mathbf{H} \cdot \mathbf{A}^H)^H \cdot \vec{V} = \mathbf{M} \cdot \vec{V},$$

- ▶ To convert to sparse form, only a percentage η of kernel energy in each row is retained
 - ▶ The only parameter in the new method
 - ▶ Correlates directly to both image quality and computational complexity
- ▶ Sparse matrix techniques are used to store and manipulate the new linear system
 - ▶ Since the linear system is sparse, iterative methods such as conjugate gradient can be used to solve the system with very low complexity



Methods



Results

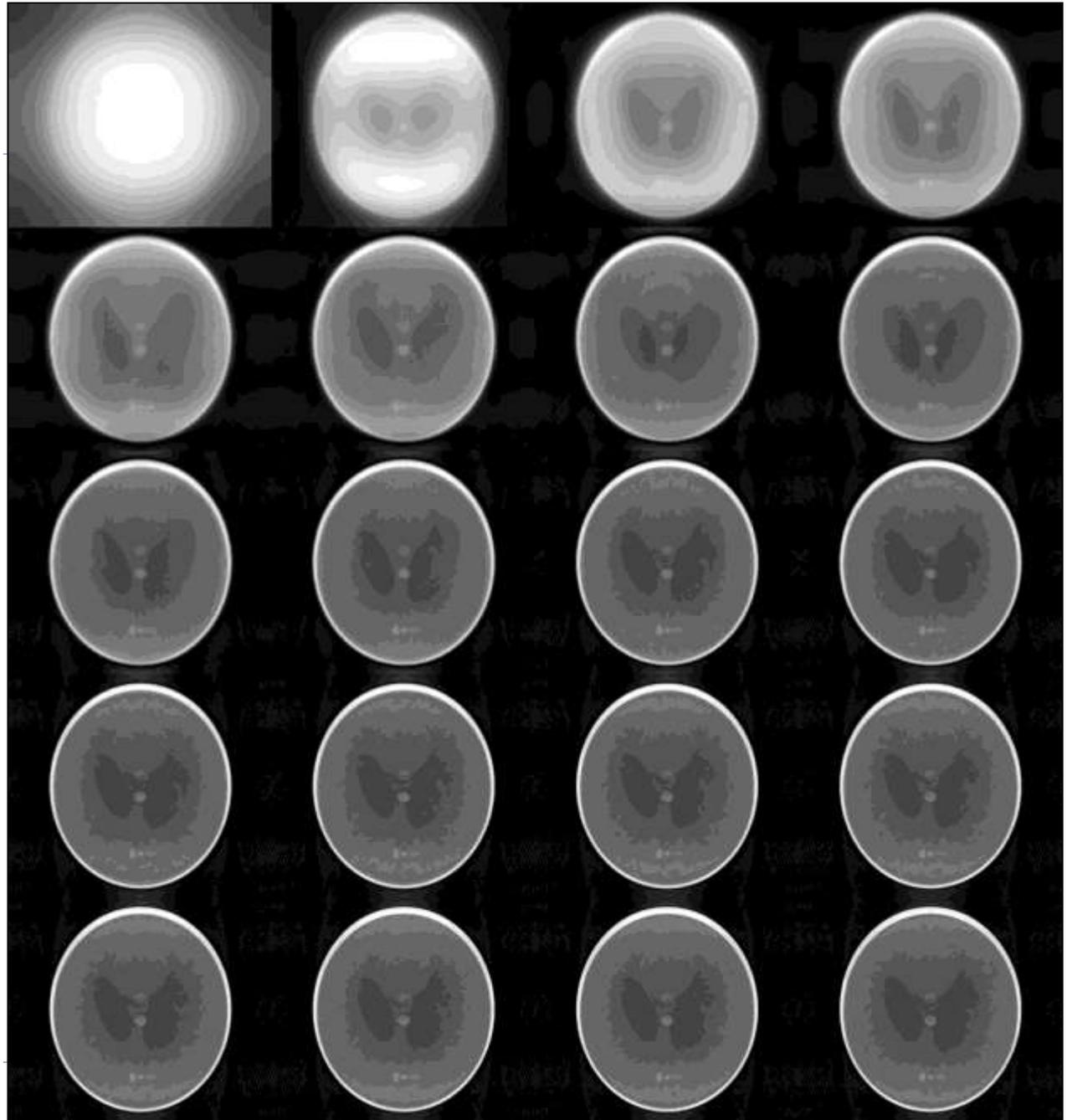
▶ 256x256

Analytical

Shepp-Logan

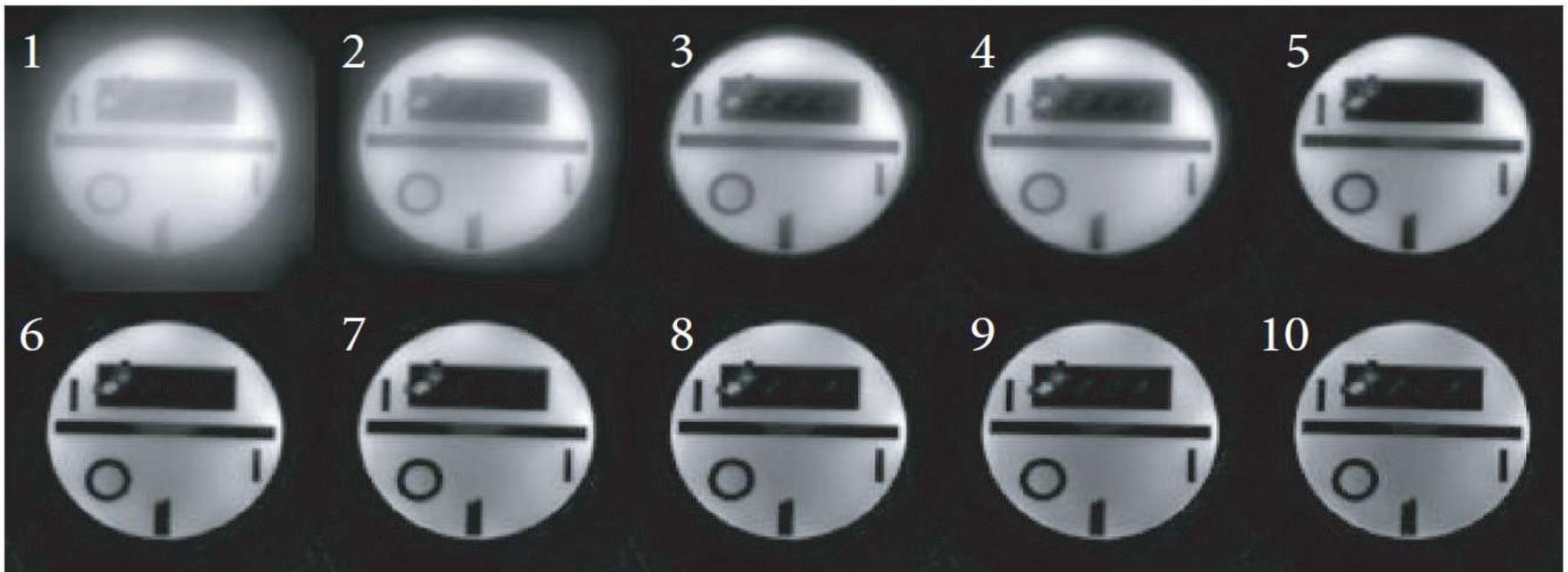
Phantom

(Radial sampling)

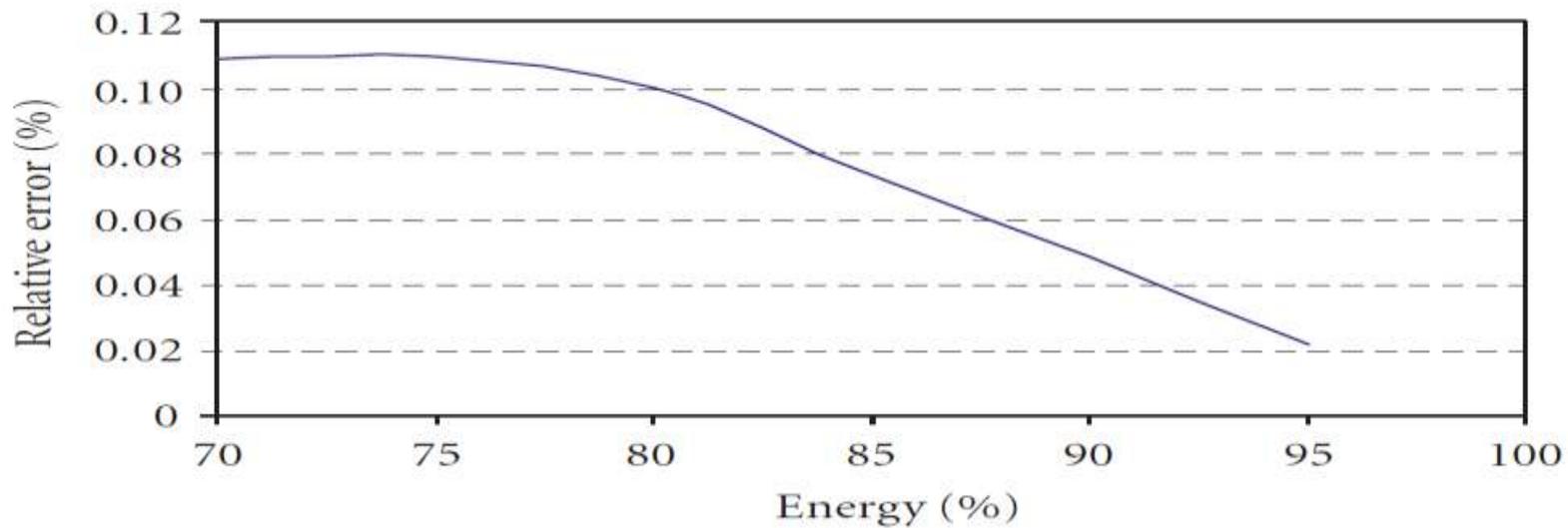
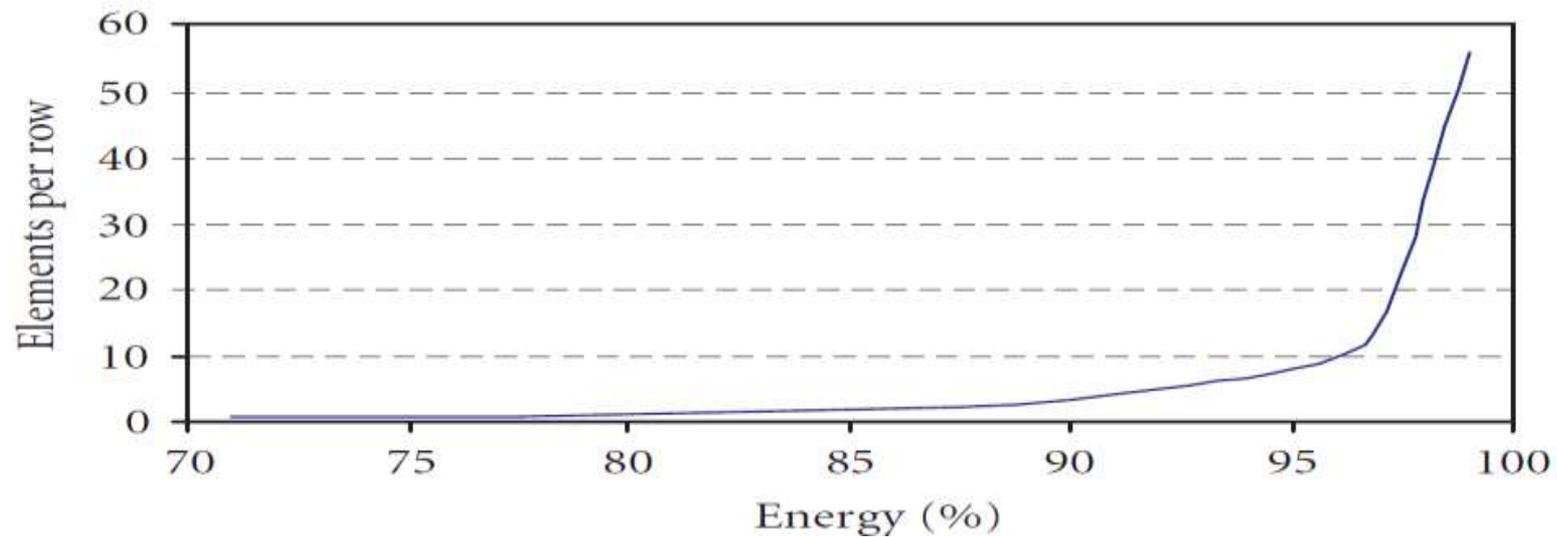


Results

- ▶ 256x256 Real data from a resolution phantom at 3T from a Siemens Magnetom Trio system using a spiral trajectory



Results



Discussion

- ▶ Full control over the accuracy versus complexity trade-off through η selection
- ▶ Computational complexity is comparable to conventional gridding with small kernel
 - ▶ $\mathcal{O}(g(\eta) \cdot L)$ per CGM step, where $g(\eta)$ is the average # of elements/row, $L = \#$ of acquired k-space samples
 - ▶ Average 4.9 elements/row to retain 92% of energy
- ▶ Progressive reconstruction is possible
 - ▶ Add more iterations to process
 - ▶ Use a different reconstruction table with higher η



Exercise

- ▶ Verify the energy compactness transformation and generate Figure 2 (c) for any trajectory you prefer. [1 Point]
- ▶ Assuming that we have a rectilinear sampling instead of the nonuniform sampling in this paper, how do you expect the linear system to look like? [1 Points]
- ▶ Assume that we are constructing an $N \times N$ image, compute the exact number of computation (not an order or computation) detailing the list of computations in each step in the implementation. [1 Point]

