



# Improving sub-Nyquist MRI reconstruction performance

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BASP Frontiers Workshop (September 4-9, 2011)

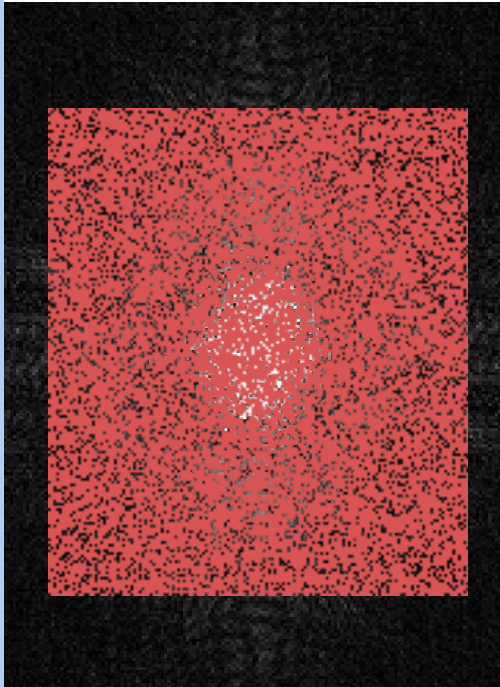
Authors: Jan Aelterman, Hiệp Luong, Bart Goossens, Aleksandra Pižurica, Wilfried Philips

# Fourier Acquisition in MRI

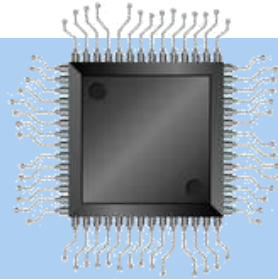


SIGNAL ACQUISITION

K-Space

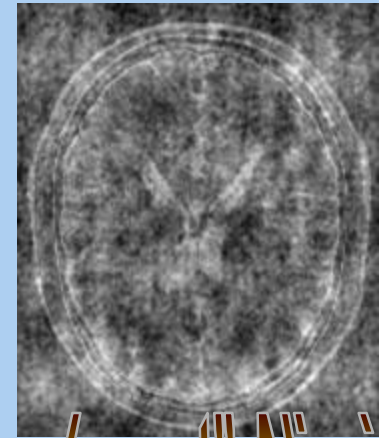


Randomly Subsampled

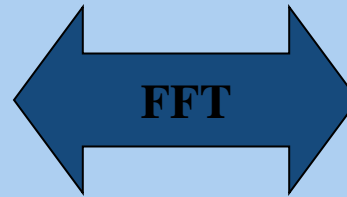


SIGNAL PROCESSING

Image Space



*"incoherent" Aliasing*



# Problem Formulation

$$\hat{\vec{x}} = \arg \min_{\vec{x}} \|\vec{S}\vec{x}\| \quad \text{s.t.} \quad \|\vec{y} - \vec{F}\vec{x}\| = 0$$



FFT/CG/Gauss-Seidel

STEP 1.1.1

$$\vec{x}_{j+1} = \arg \min_{\vec{x}} \frac{\lambda_{df}}{2} \|\vec{y}_i - \vec{F}\vec{x}\|^2 + \frac{\lambda_b}{2} \|\vec{d}_j - \vec{S}\vec{x} - \vec{b}_l\|^2$$

STEP 1.1.2

$$\vec{d}_{j+1} = \arg \min_{\vec{d}} |d| + \frac{\lambda_b}{2} \|\vec{d}_j - \vec{S}\vec{x}_{j+1} - \vec{b}_l\|^2$$

Soft Thresholding

STEP 1.2

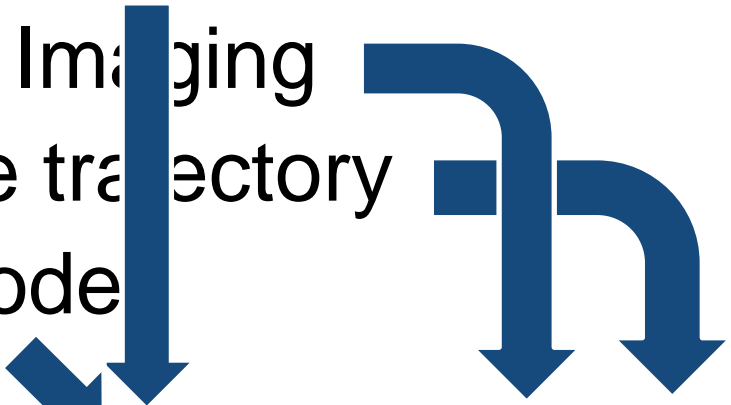
$$\vec{b}_{l+1} = \vec{b}_l + \vec{S}\vec{x}_{j+1} - \vec{d}_{j+1}$$

STEP 2

$$\vec{y}_{i+1} = \vec{y}_i + \vec{y} - \vec{F}\vec{x}_{j+1}$$



- A number of improvement ideas:
  - Image representation
  - Parallel Imaging
  - K-space trajectory
  - Prior models

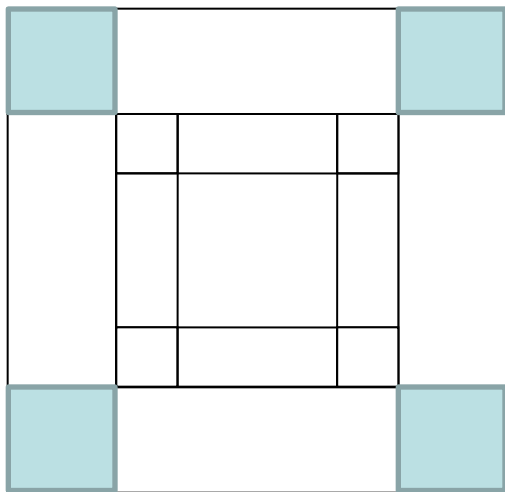


$$\hat{\vec{x}} = \arg \min_{\vec{x}} |\vec{S}\vec{x}| \quad \text{s.t.} \quad \left\| \vec{y} - \vec{F}\vec{x} \right\| = 0$$

- A number of improvement ideas:
  - **Image representation**
  - Parallel Imaging
  - K-space trajectory
  - Prior model

# Improvement 1: the discrete shearlet transform

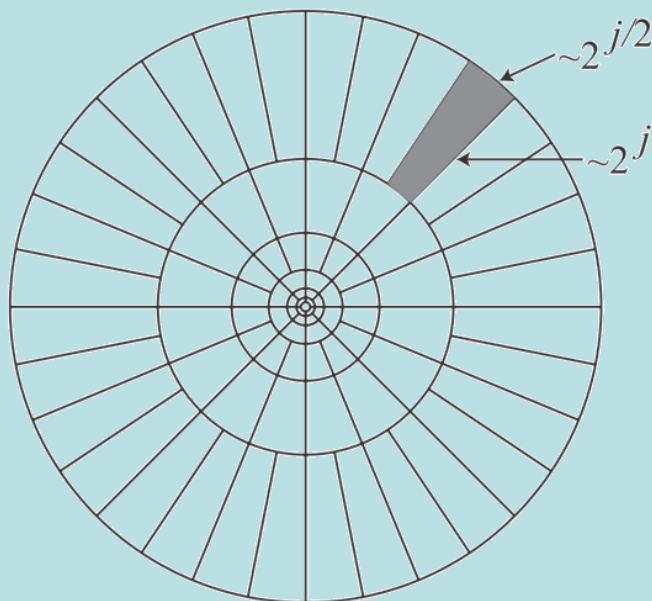
Real DWT



Approximation error:

$$\epsilon_M \leq CM^{-1}$$

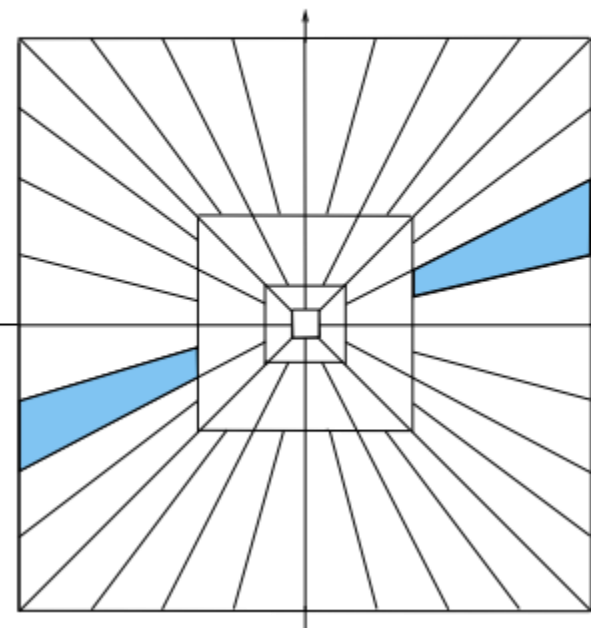
curvelet



Approximation error:

$$\epsilon_M \leq C(\log M)^3 M^{-2}$$

shearlet



Approximation error:

$$\epsilon_M \leq C(\log M)^3 M^{-2}$$

optimal for piecewise  
C<sup>2</sup> images

[Candès et al.; *Multiscale mod.* 2006]

[Guo et al.; *SIAM Mat. An.* 2007][Easley et al; *Appl. Comput.*

# Improvement 1: the discrete shearlet transform

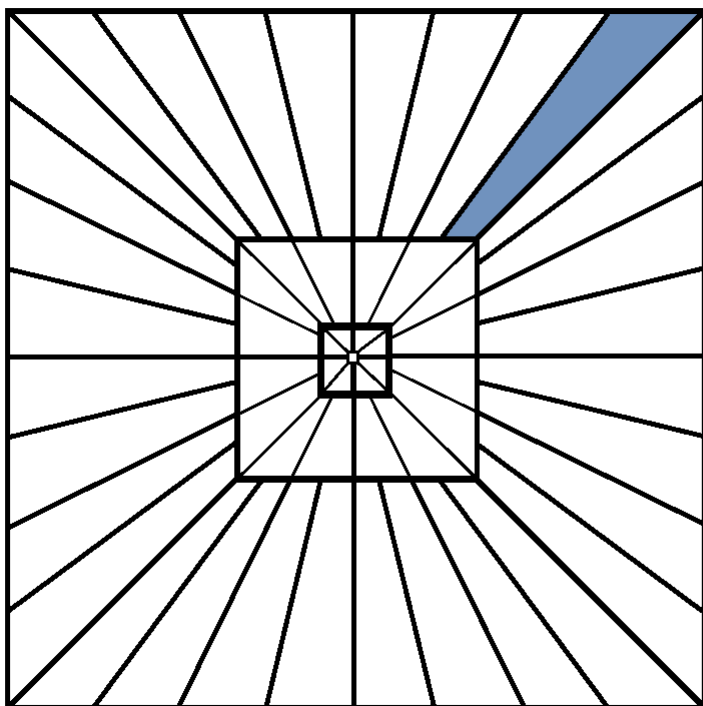
25% Fourier acquisition  
+ reconstruction with resolution increase of 50%



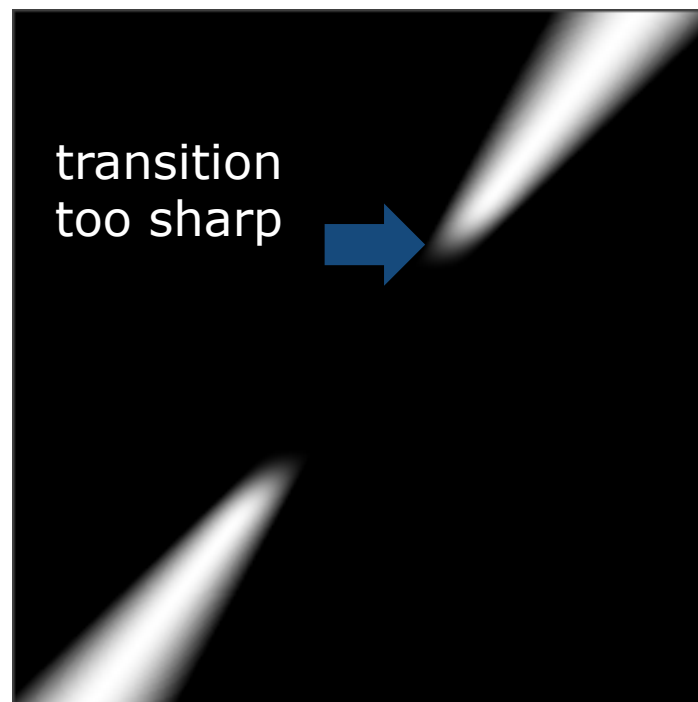
Shearlet

# Improvement 1: the discrete shearlet transform

Ideal spectral support  
of 1 upperscale shearlet



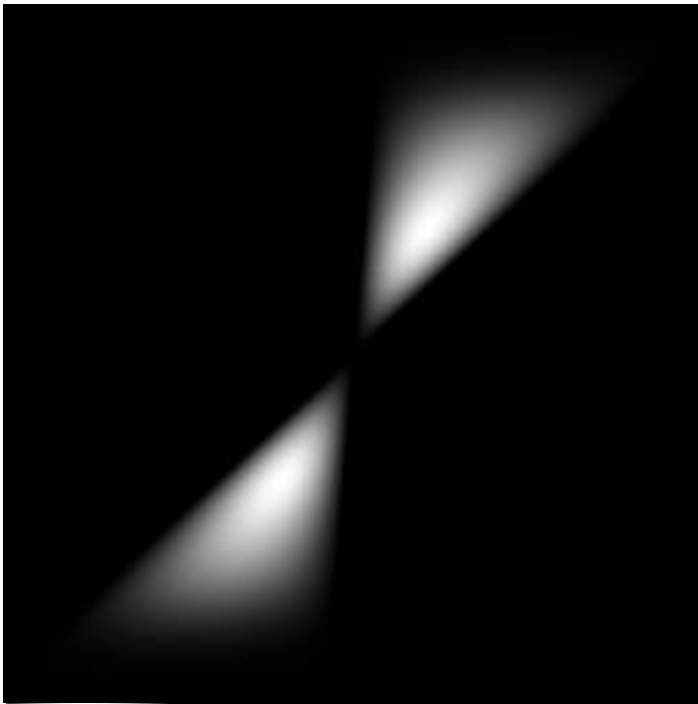
Power Spectral Density  
of the corresponding shearlet filter



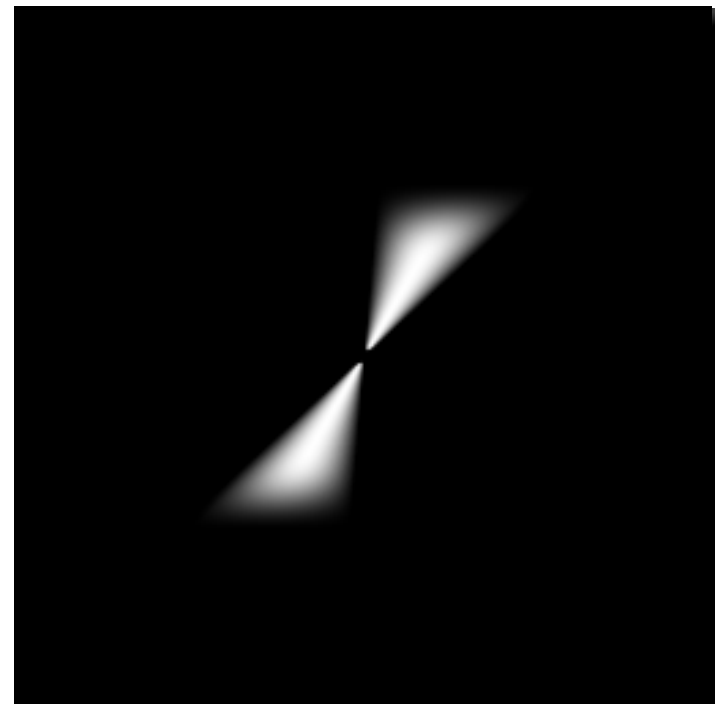


# Improvement 1: the discrete shearlet transform

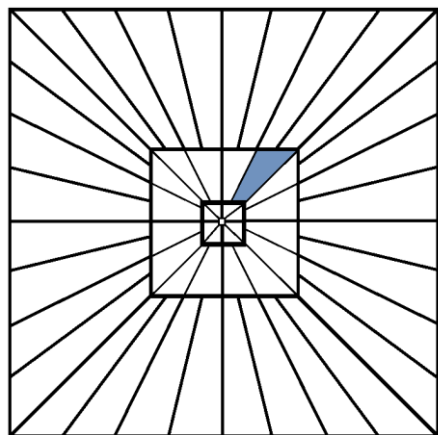
Power Spectral Density  
of the smooth filter



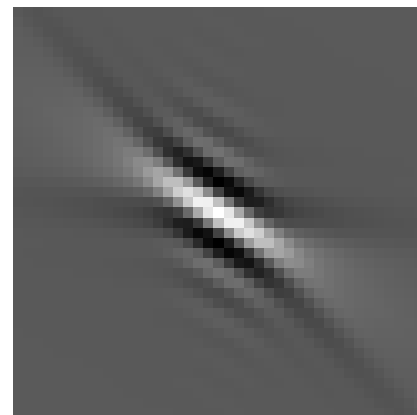
Power Spectral Density  
of the original shearlet filter



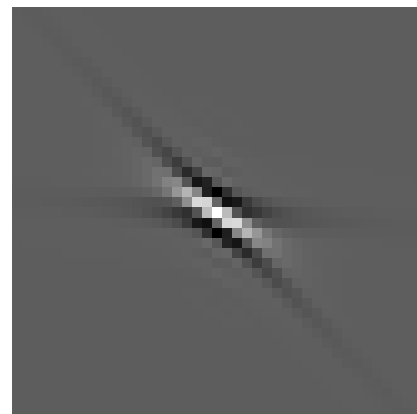
# Improvement 1: the discrete shearlet transform



'sharp'  
shearlet  
transform

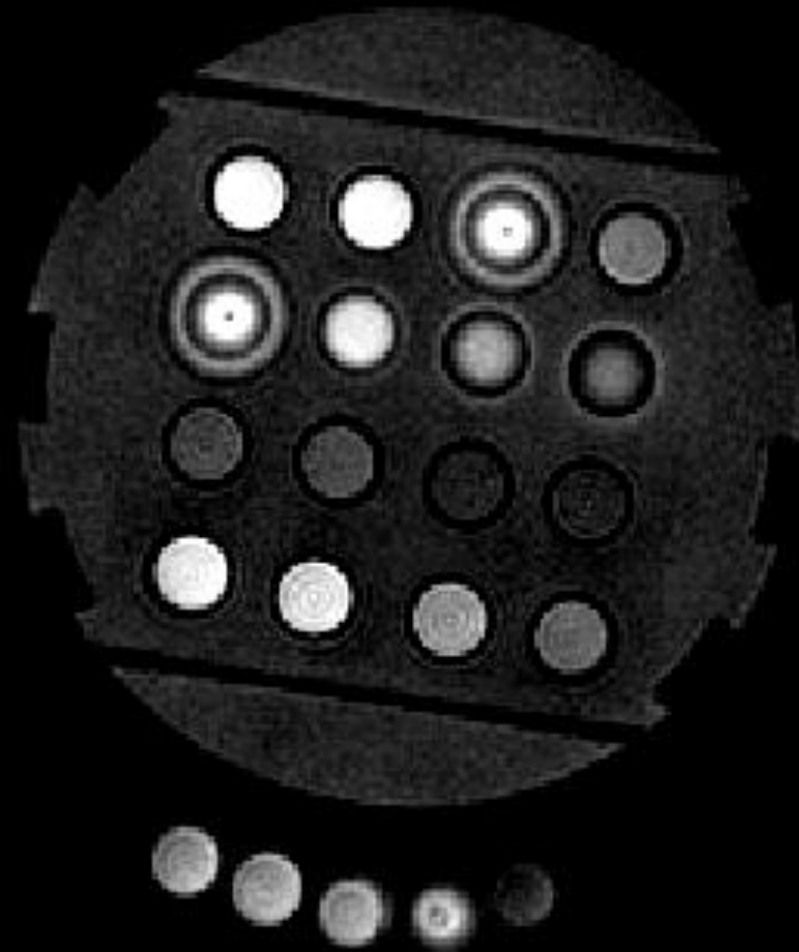


'smooth'  
shearlet  
transform

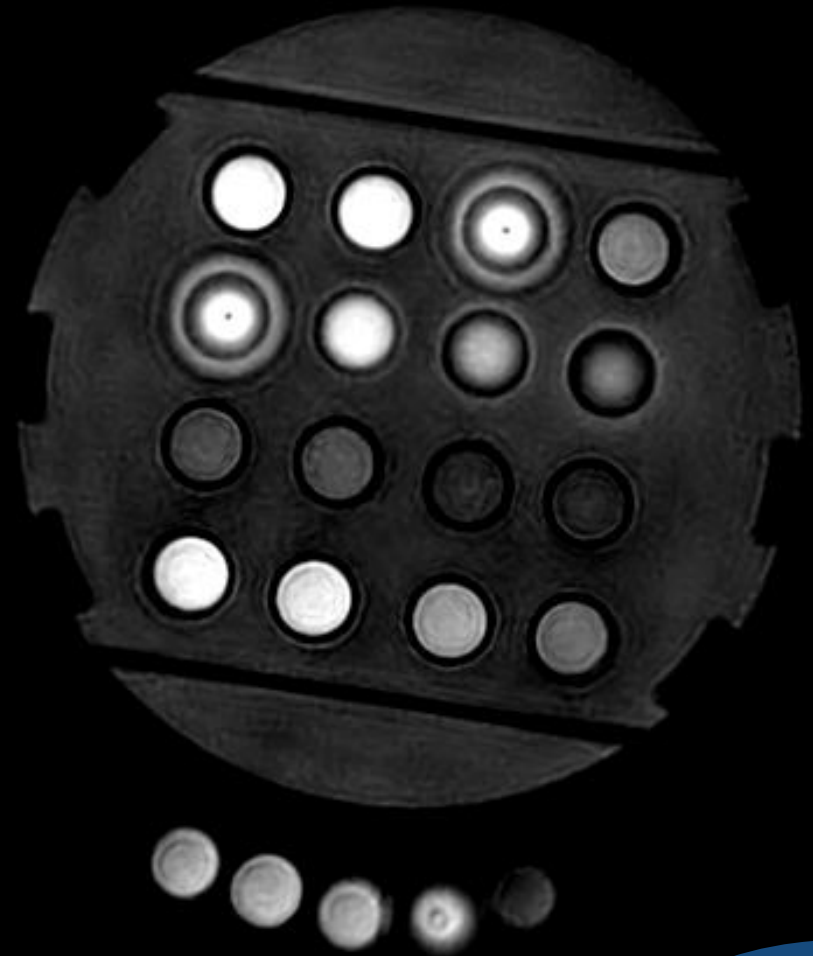


# Spirally Acquired Data

Naive reconstruction



'sharp' shearlets



Anatomical Data

Only TV  
35.6dB

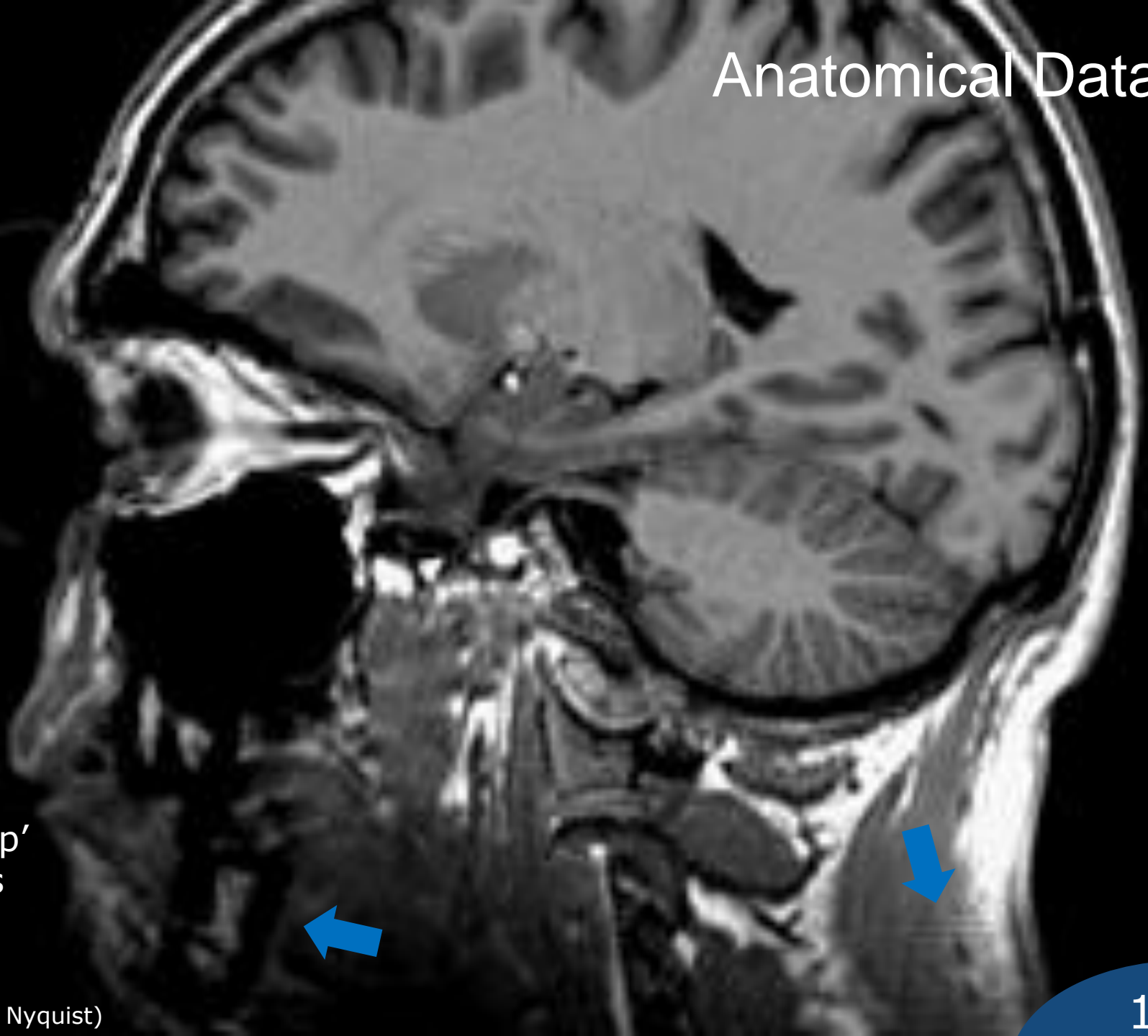


(spiral, 25% of Nyquist)

# Anatomical Data

Only 'sharp'  
shearlets  
36.5dB

(spiral, 25% of Nyquist)



# Anatomical Data

Only 'smooth'  
shearlets  
36.6dB

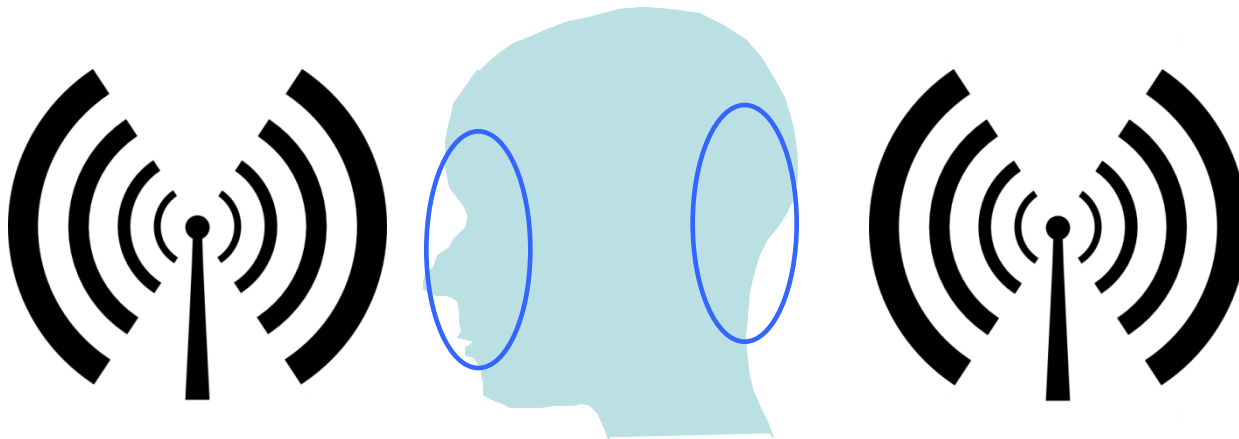


(spiral, 25% of Nyquist)

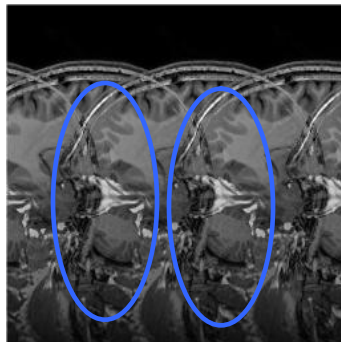
- A number of improvement ideas:
  - Image representation
  - **Parallel Imaging**
  - K-space trajectory
  - Prior model

# Improvement 2: Parallel Imaging

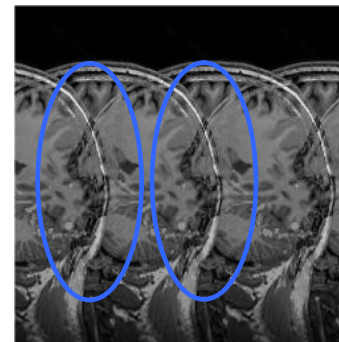
- Subsampled MRI with multiple receiver antennas (e.g. SPIR-iT [Lustig et al.; *MRM* 2009]):



Clear  
aliases of  
the front of  
the head



Clear  
aliases of  
the back of  
the head





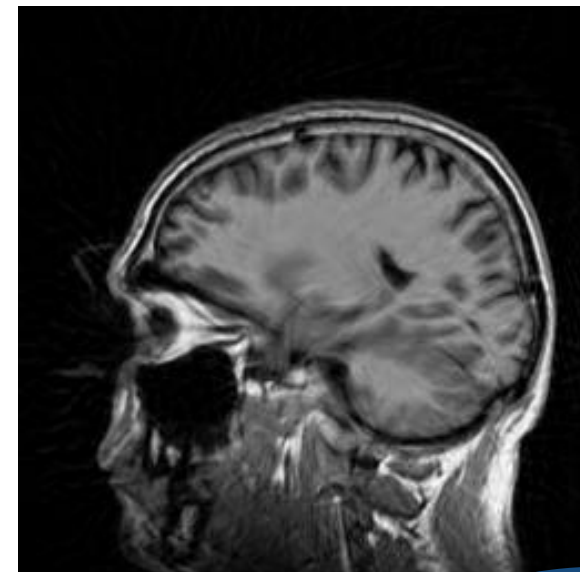
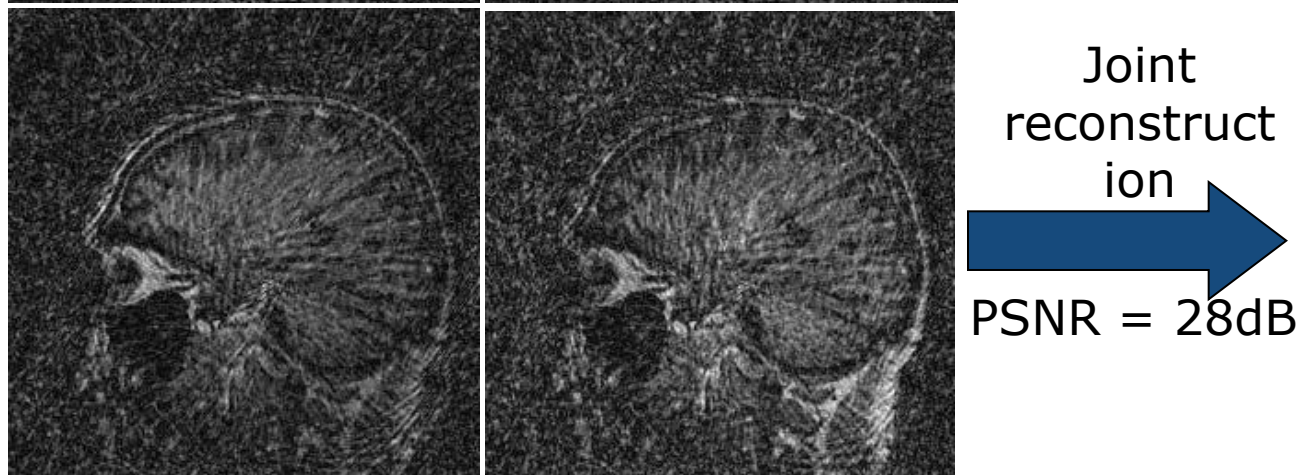
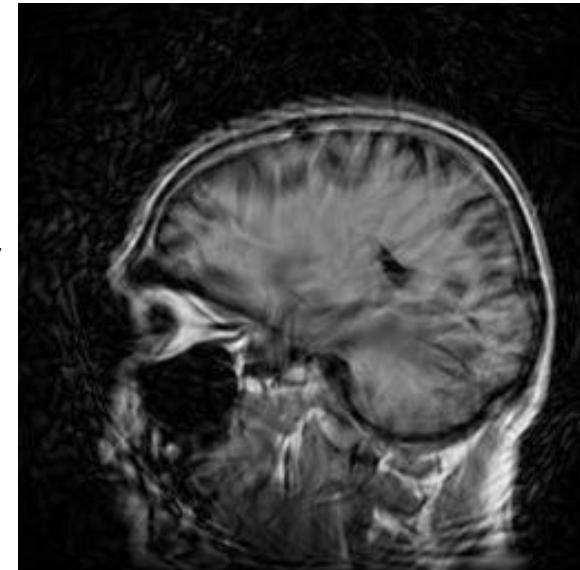
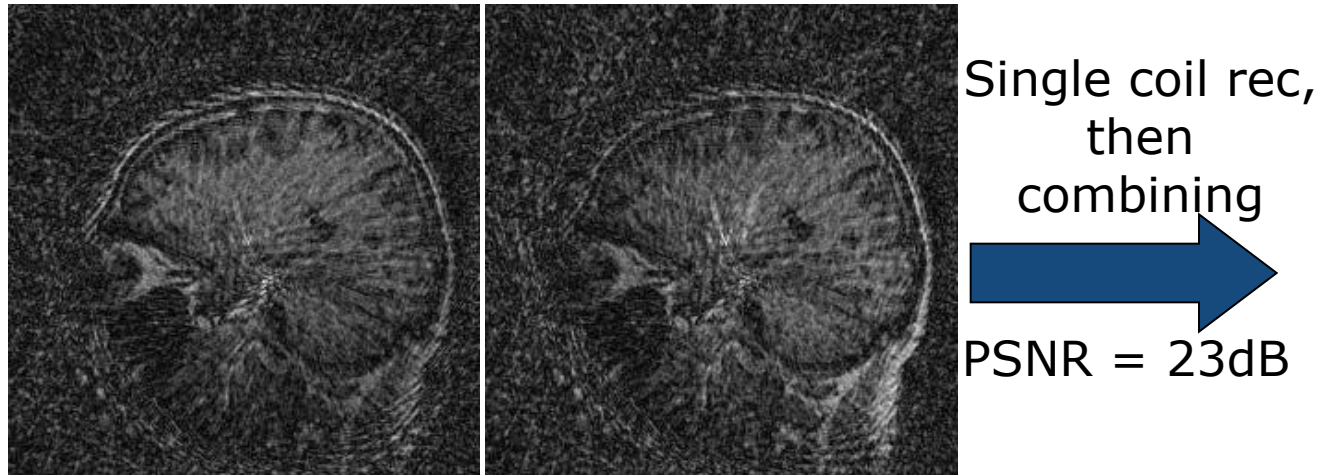
# Improvement 2: Parallel Imaging

- Compressive Sensing:
  - Sub-Nyquist MRI data
  - Regularized reconstruction exploiting sparsity
  - Estimation of missing K-space data
- Parallel Imaging:
  - Sub-Nyquist MRI data
  - well-posed reconstruction through large number of different coil sensitivities
  - “Calculation” of missing K-space data

Complementary techniques

# Experiment: joint vs. Separate CS-pMRI

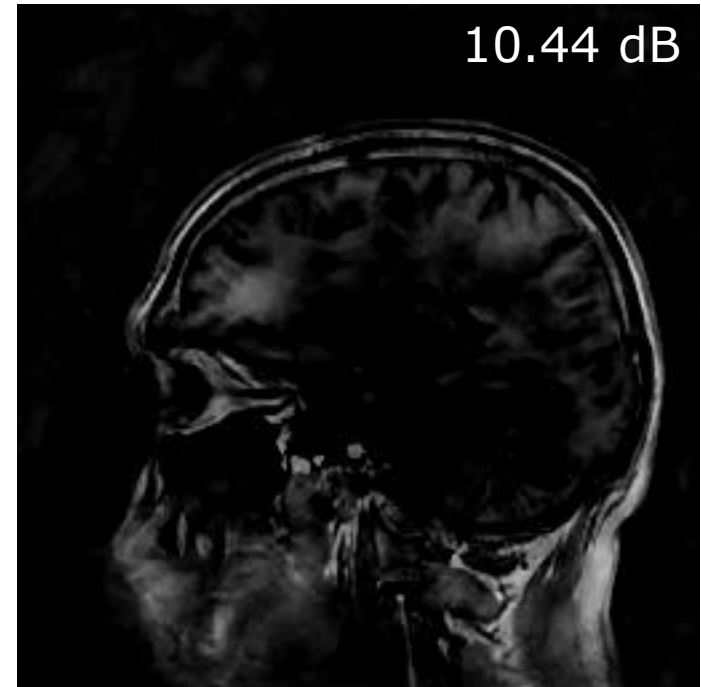
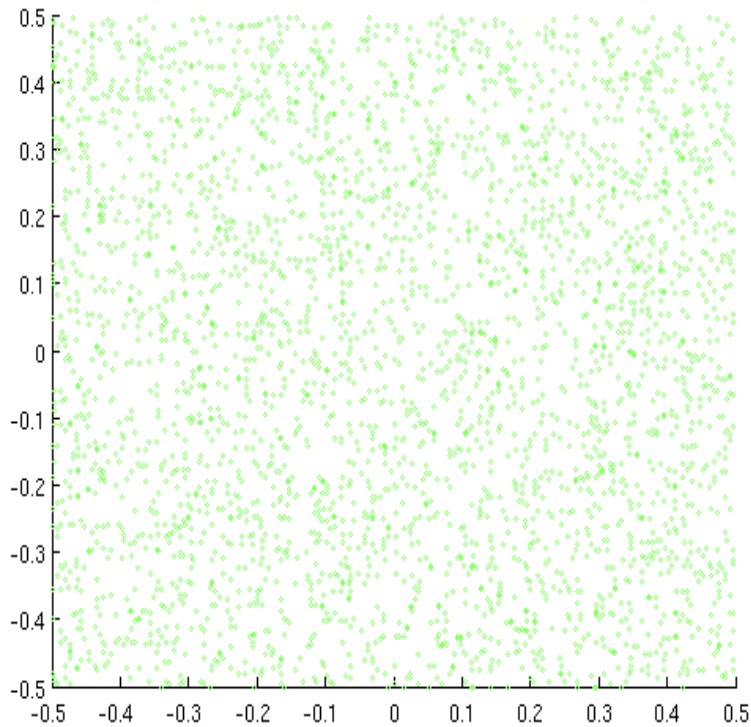
- 4 coils, 3% sub-Nyquist sampled



- A number of improvement ideas:
  - Image representation
  - Parallel Imaging
  - **K-space trajectory**
  - Prior model

# Improvement 3: Improved Trajectory

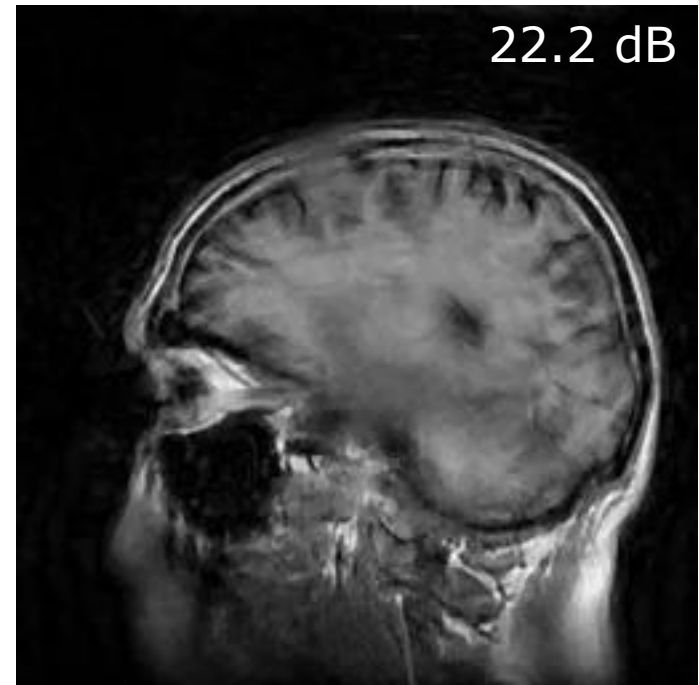
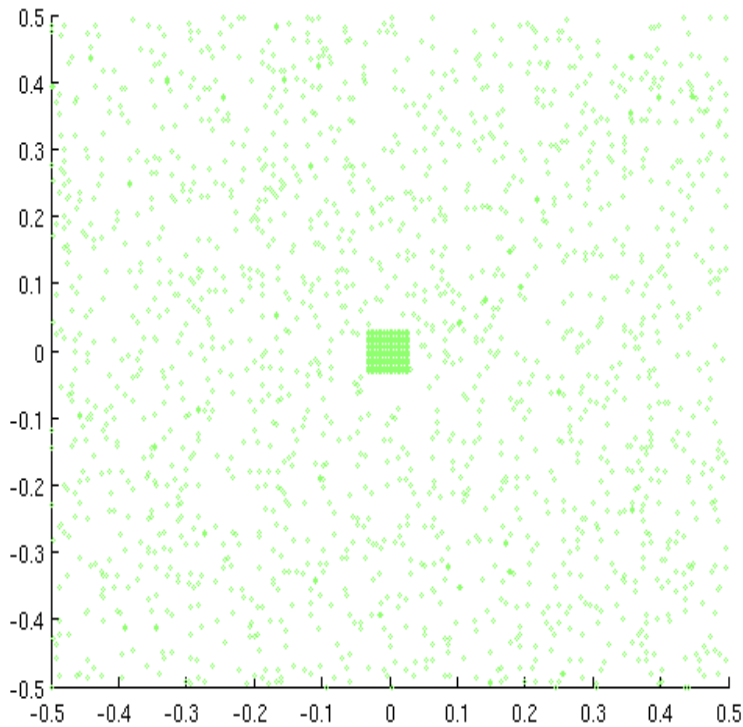
- At first:



(10% of Nyquist)

# Improvement 3: Improved Trajectory

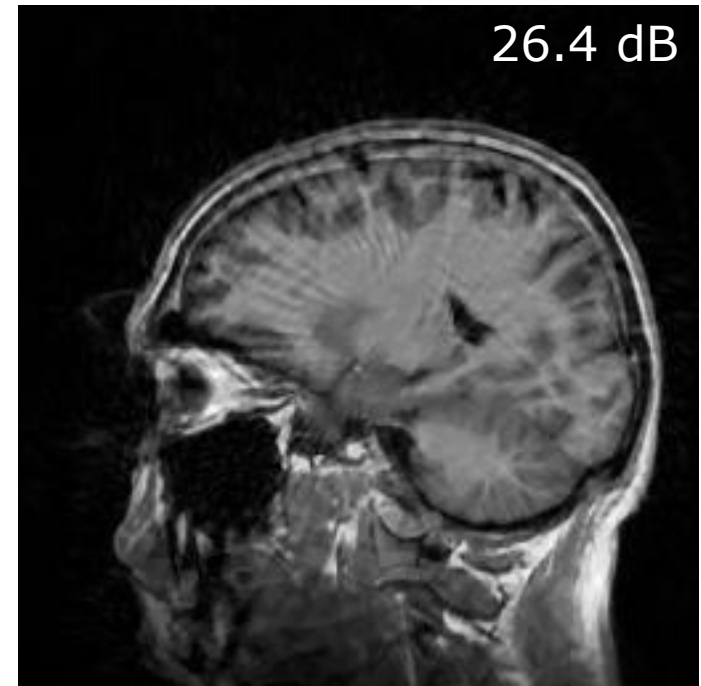
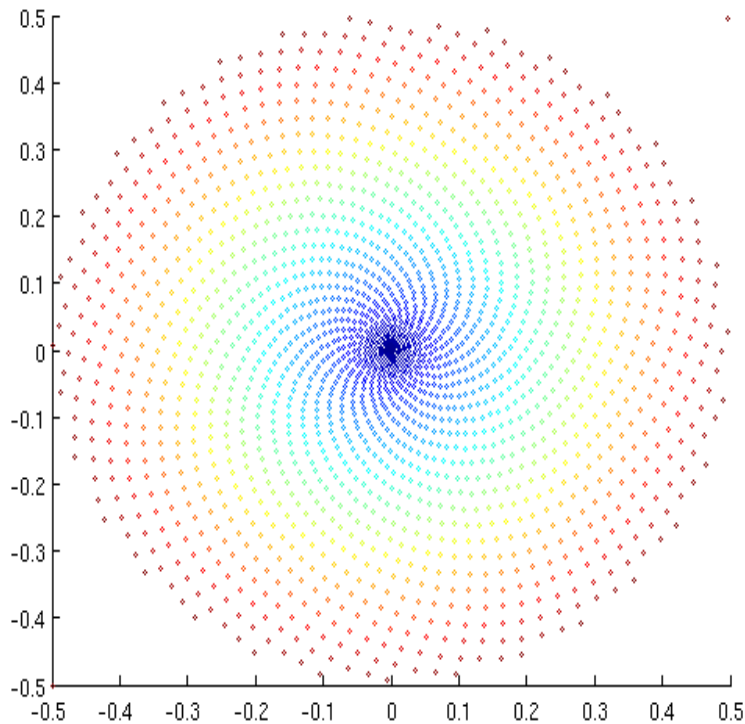
- But better is:



(10% of Nyquist)

# Improvement 3: Improved Trajectory

- Or:

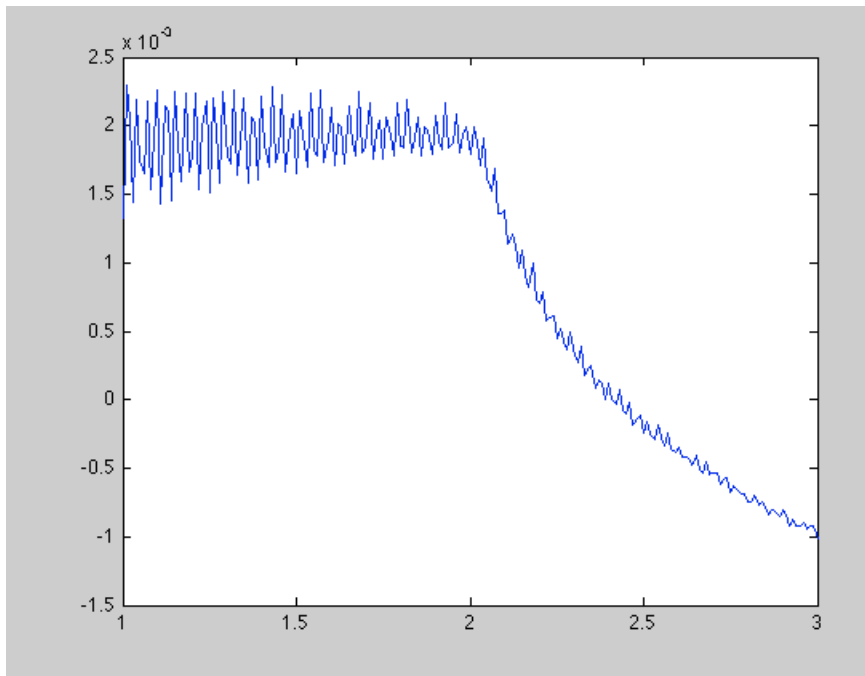


(10% of Nyquist)

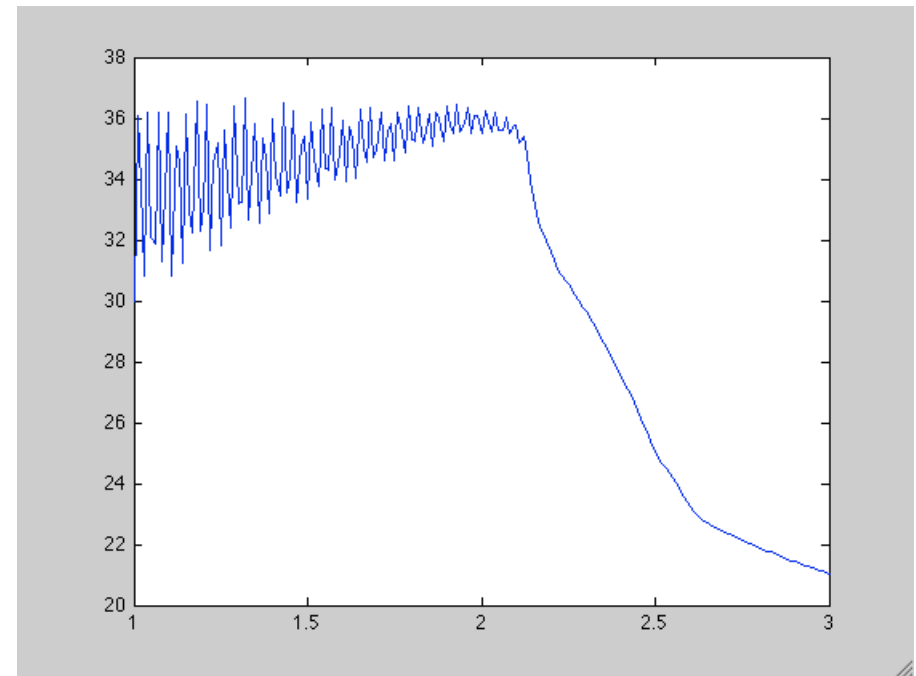
Need  
Regridding!

# Improvement 3: Improved Trajectory

- Archimedean spirals with varying radii:



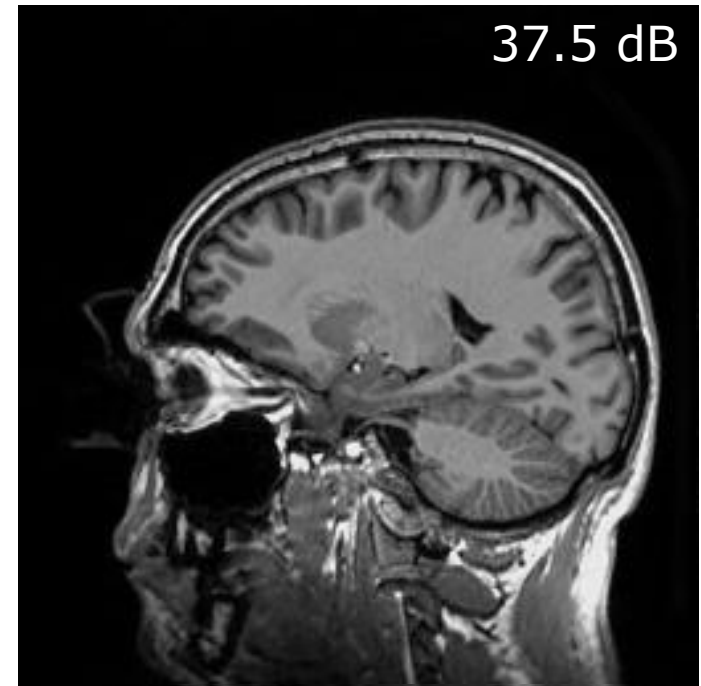
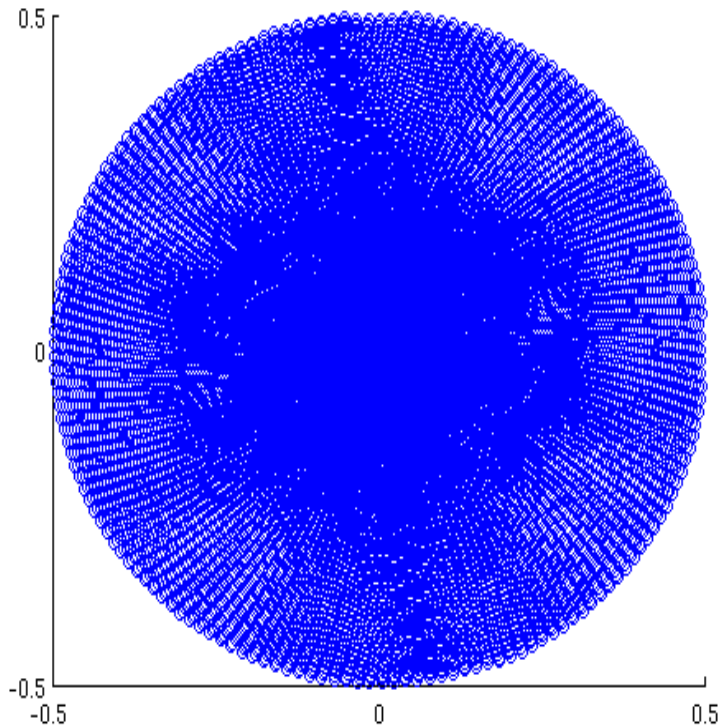
prediction



ground truth

# Improvement 3: Improved Trajectory

- For a more moderate speedup:

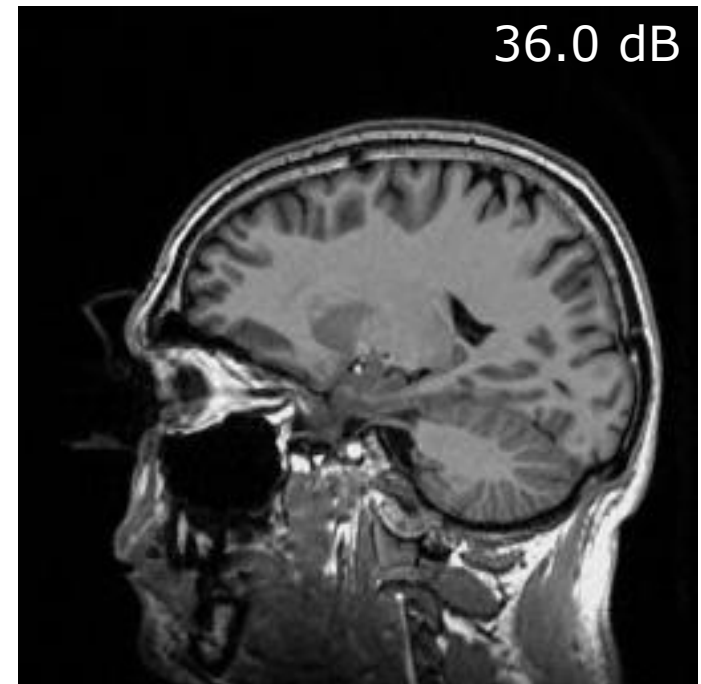
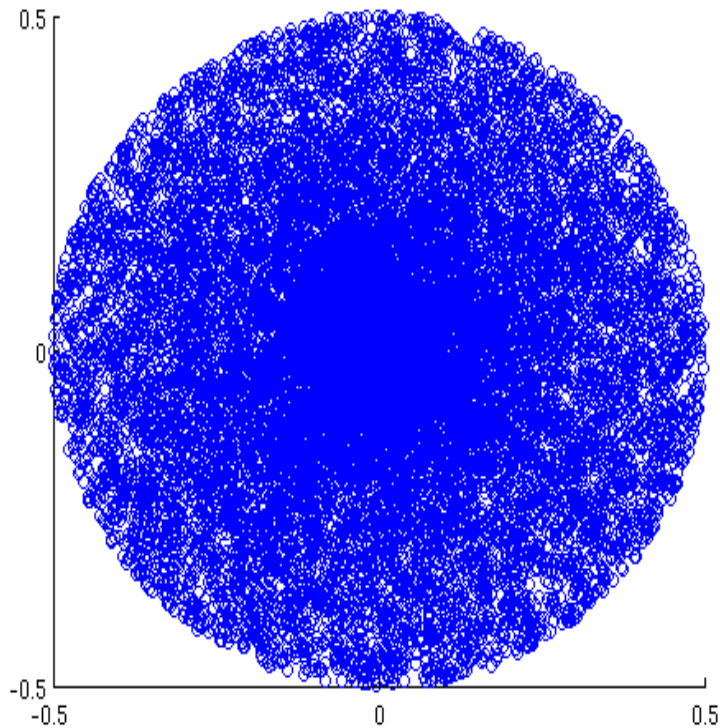


(25% of Nyquist)



# Improvement 3: Improved Trajectory

- Curiously:



(25% of Nyquist)

# Improvement 3: Improved Trajectory

The MRI Imaging equation:

$$\nu(\mathbf{k}) = \int_{\mathbb{R}^2} \rho(\mathbf{x}) e^{i\pi w |\mathbf{x}|^2} e^{-2i\pi \mathbf{k} \cdot \mathbf{x}} d^2 \mathbf{x}$$

Phase Scrambling

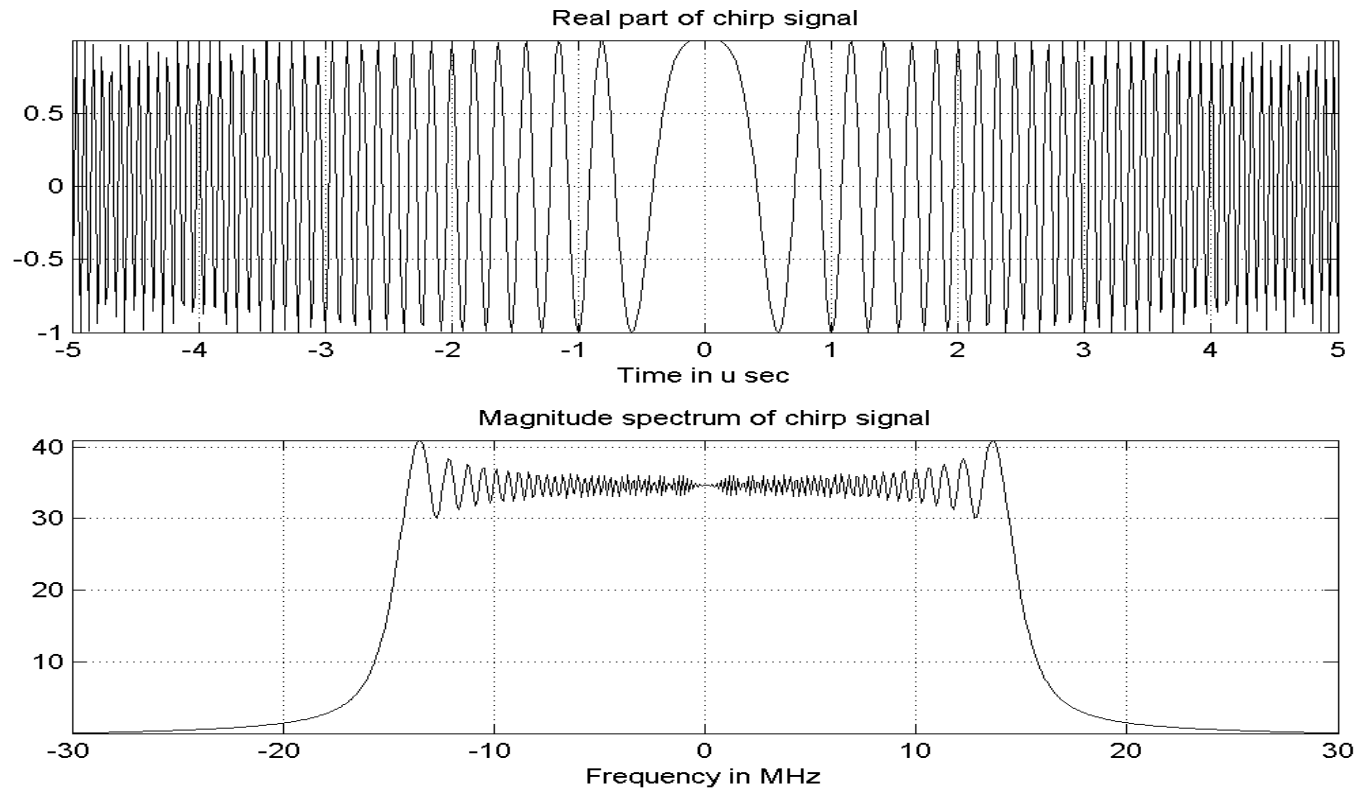
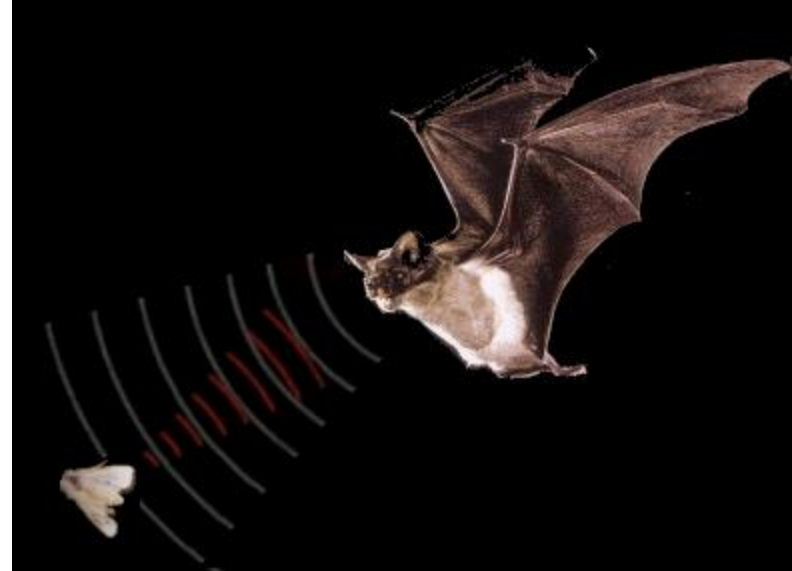
- well-known in MRI (high Dynamic, reduce aliasing)
- obtained through dedicated coils or RF pulses

[Puy et al.; *ISMRM 2011*]

Increases signal  
bandwidth

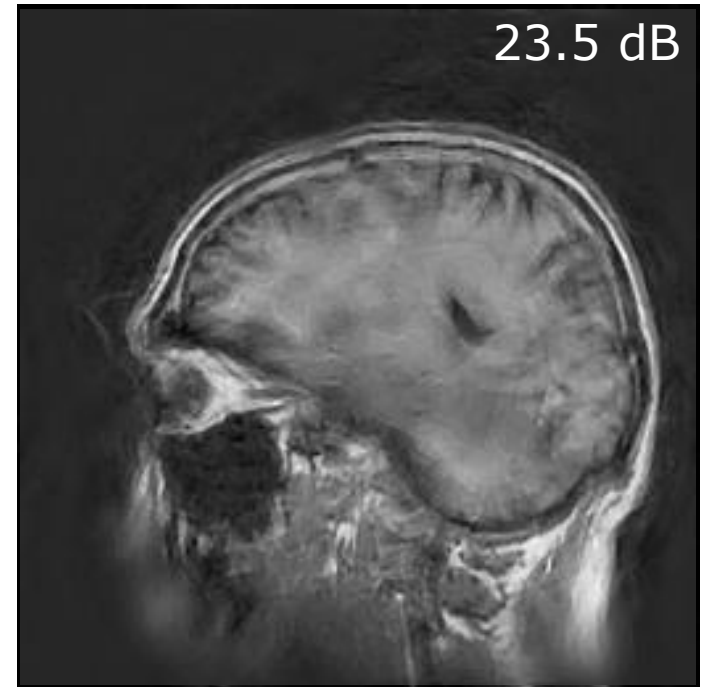
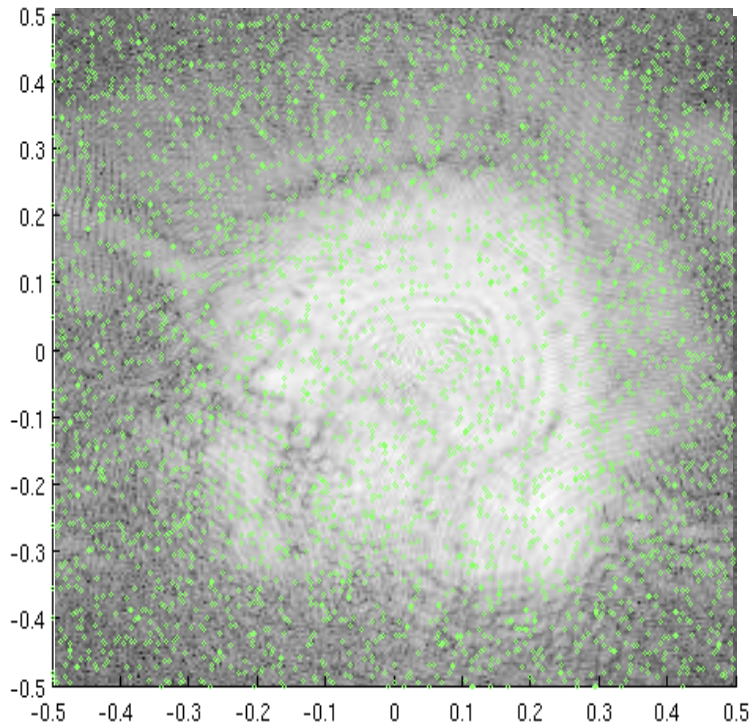
# Some Biology

- Distance Estimation through correlating with received echos
- Spatially compact autocorrelation function: Broadband signal
- Sweep over all frequencies: A Chirp!



# Improvement 3: Improved Trajectory

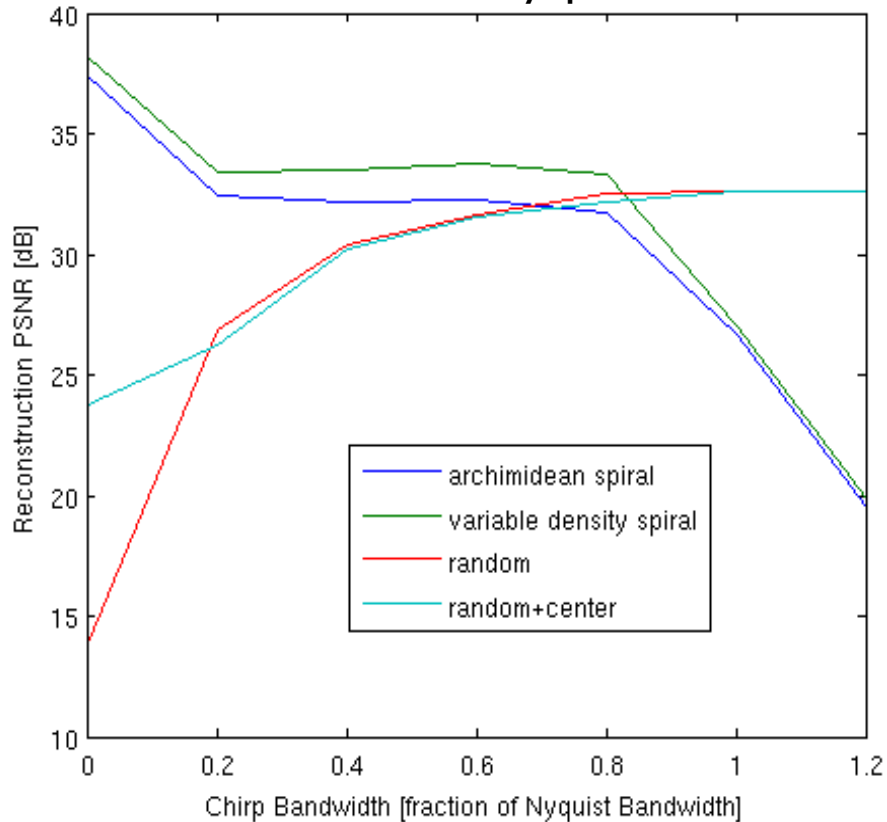
- Great effect!



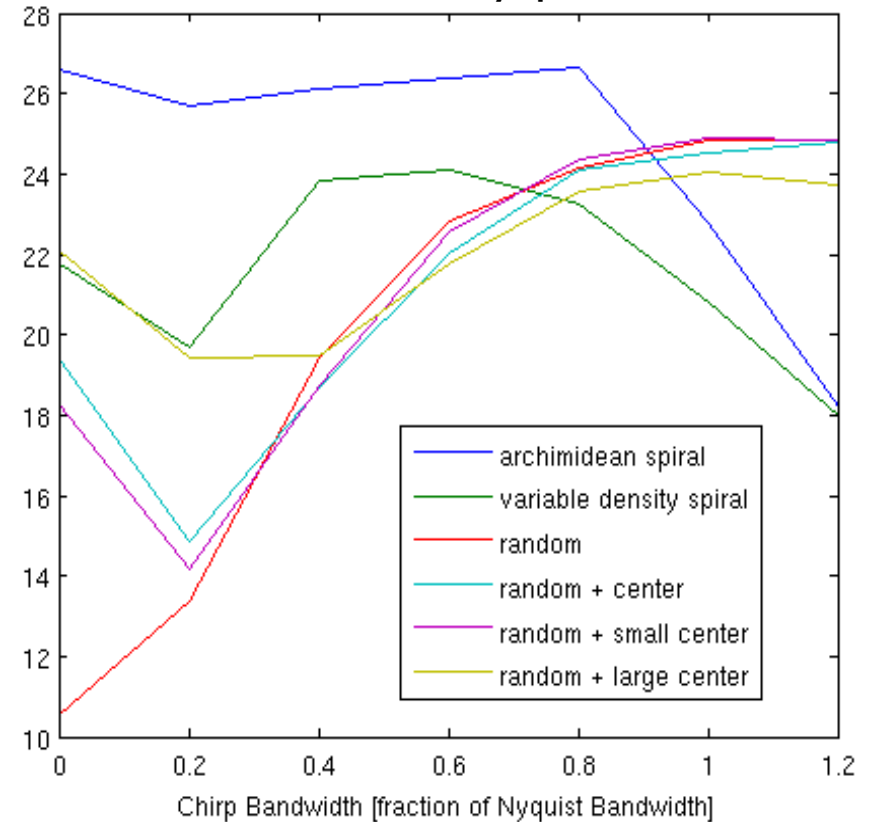
(10% of Nyquist)

# Improvement 3: Improved Trajectory

## 25% of Nyquist



## 10% of Nyquist



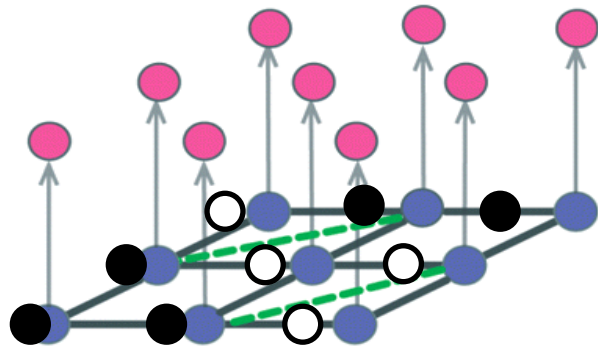
- A number of improvement ideas:
  - Image representation
  - Parallel Imaging
  - K-space trajectory
  - **Prior model**

# Improvement 4: Prior Model

- Using structure in addition to sparsity. Many recent developments include:
  - **Group sparsity, Group Lasso, Block sparsity, Tree sparsity, Graph sparsity** [Huang et al, *ICML'09*], **Model based sparsity** [Baraniuk et al, *IEEE Trans IT* 2010]
- We encode spatial structure using **Markov Random Field**. Closely related work (not reported on MRI):
  - **LaMP** – Lattice Matching Pursuit [Cevher et al; *Sig Proc Mag* 2010]

# Improvement 4: Prior Model

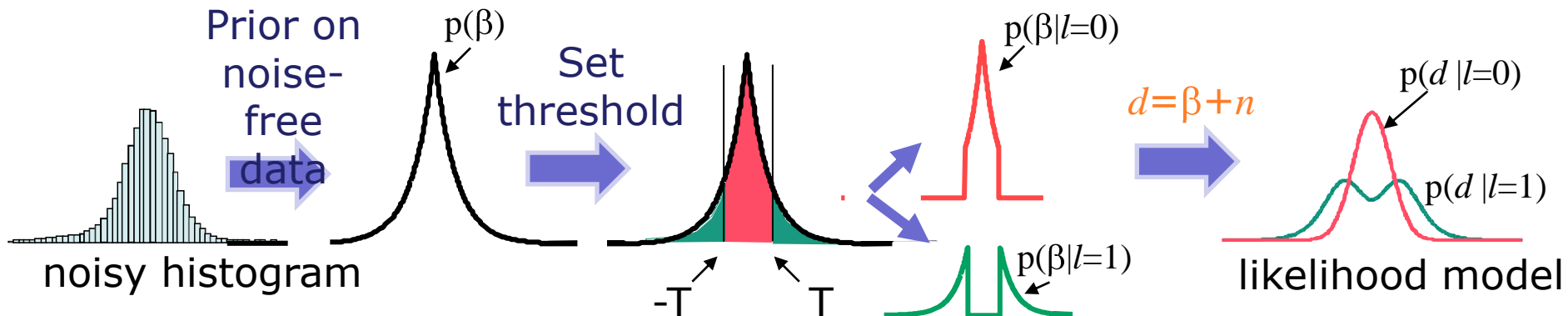
Observable random field  $d = \{d_1, d_2 \dots d_N\}$



- $l=0$
- $l=1$

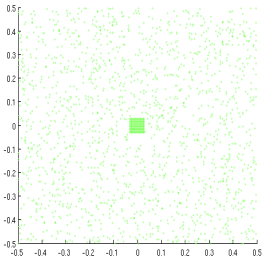
$$V_C(l_i, l_j) = \begin{cases} -\gamma, & l_i = l_j \\ \gamma, & l_i \neq l_j \end{cases}, \quad \gamma > 0$$

Hidden random field  $l = \{l_1, l_2 \dots l_N\}$

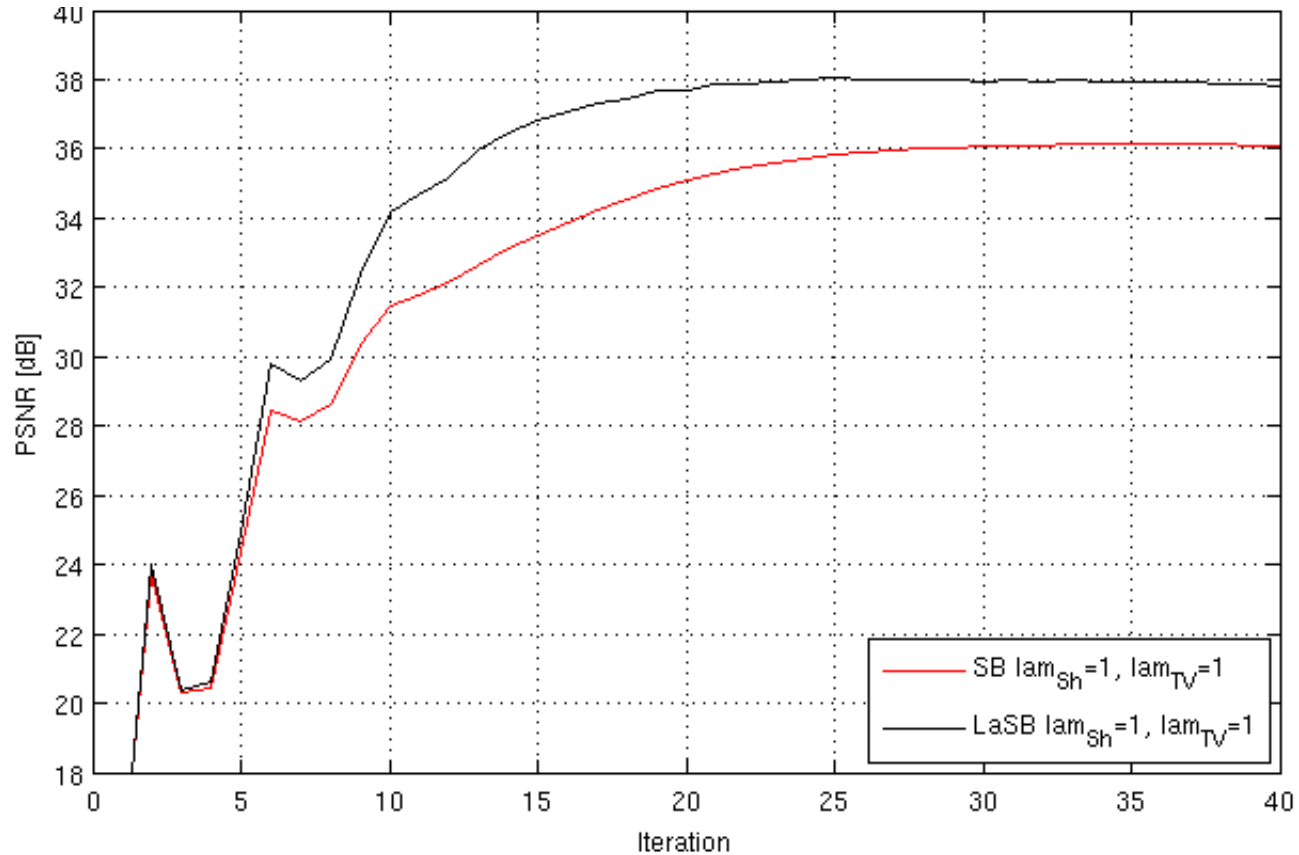




# Improvement 4: Prior Model

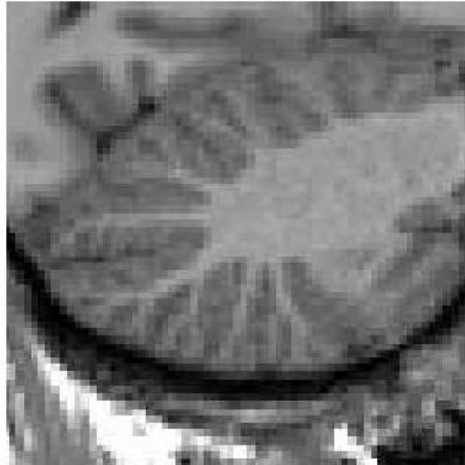


Random subsampling with center low pass, 50%

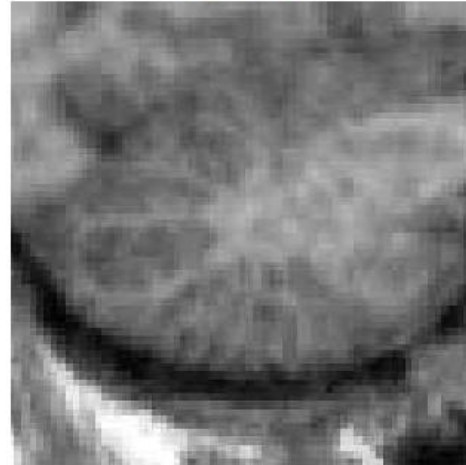


# Improvement 4: Prior Model

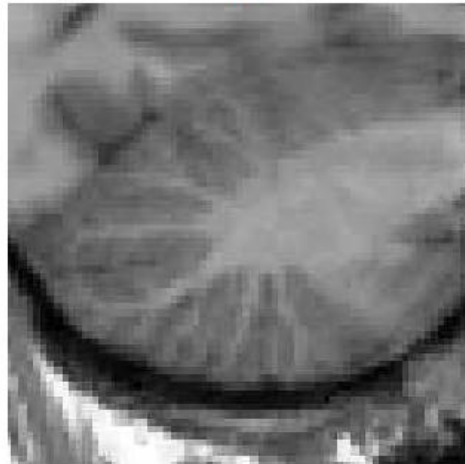
ground truth



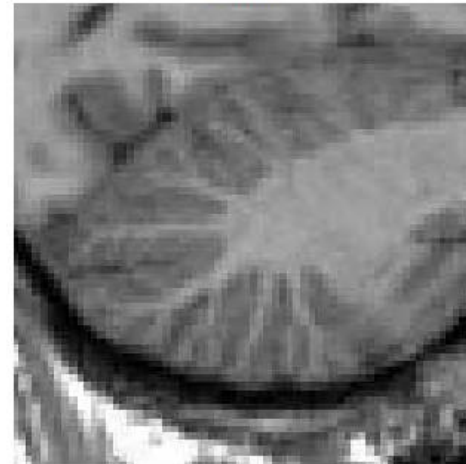
zero-fill



SB

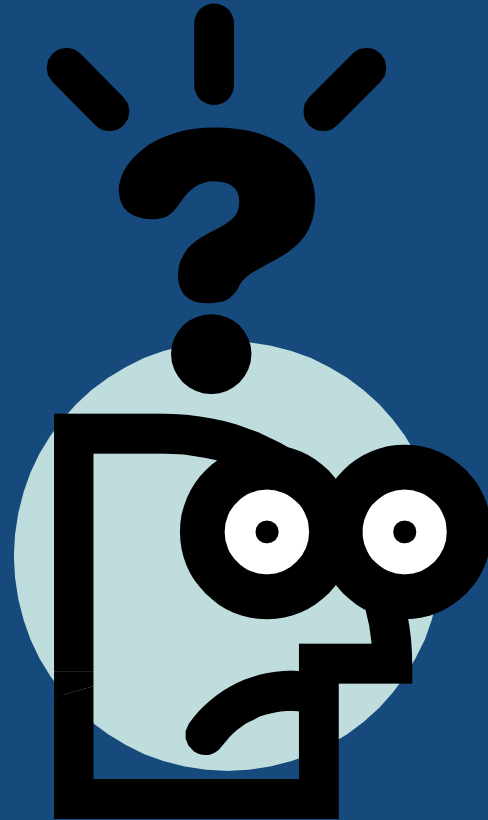


LaSB



- In conclusion:
  - In order to maximize reconstruction performance, a combination of optimal image representation, parallel imaging, a well designed trajectory (!) and properly handling spatial structure in the regularization are needed.

Any questions?



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GENT

Thank you for your attention.

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