Image Reconstruction

Parallel Imaging I

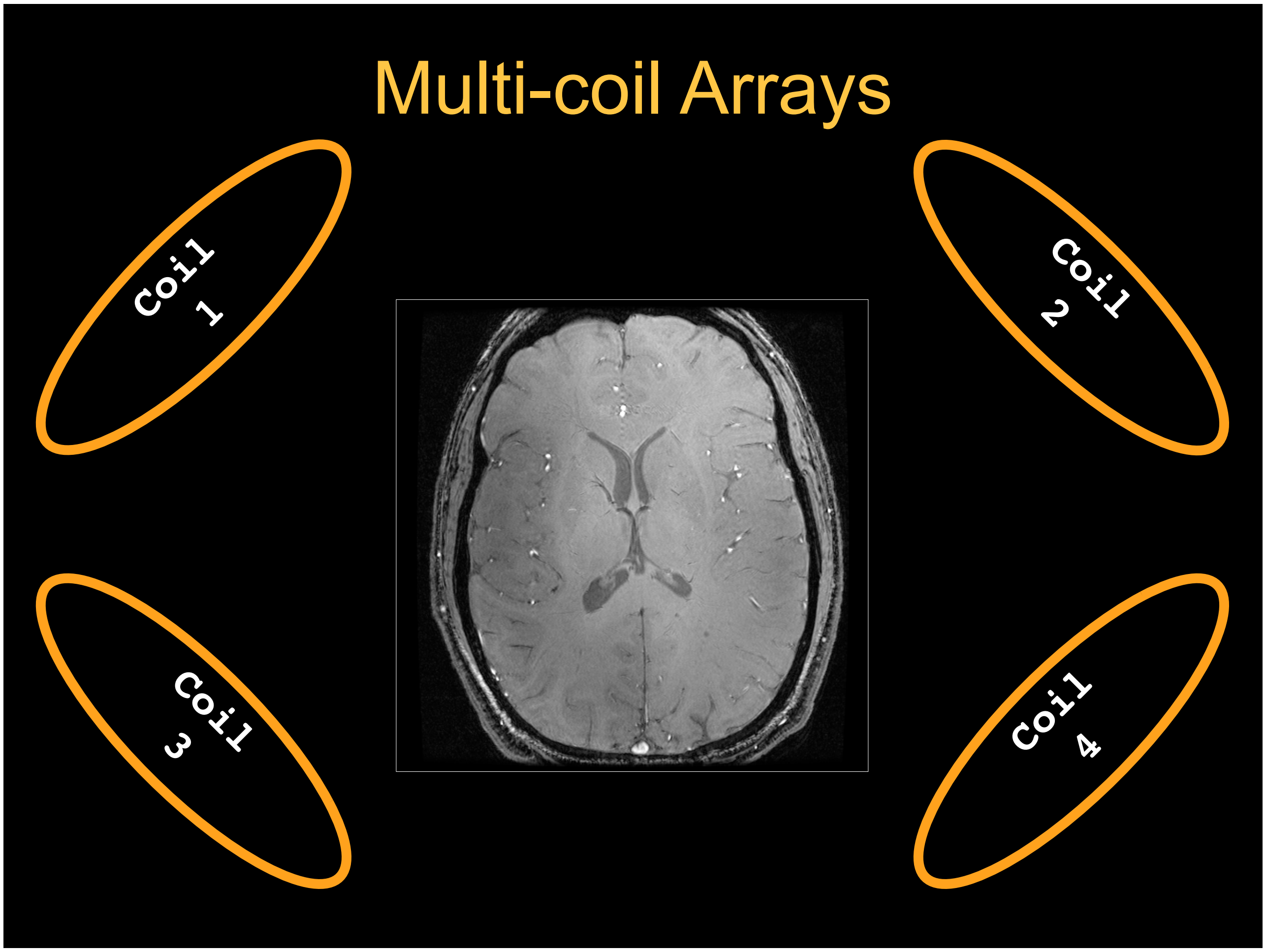
M229 Advanced Topics in MRI

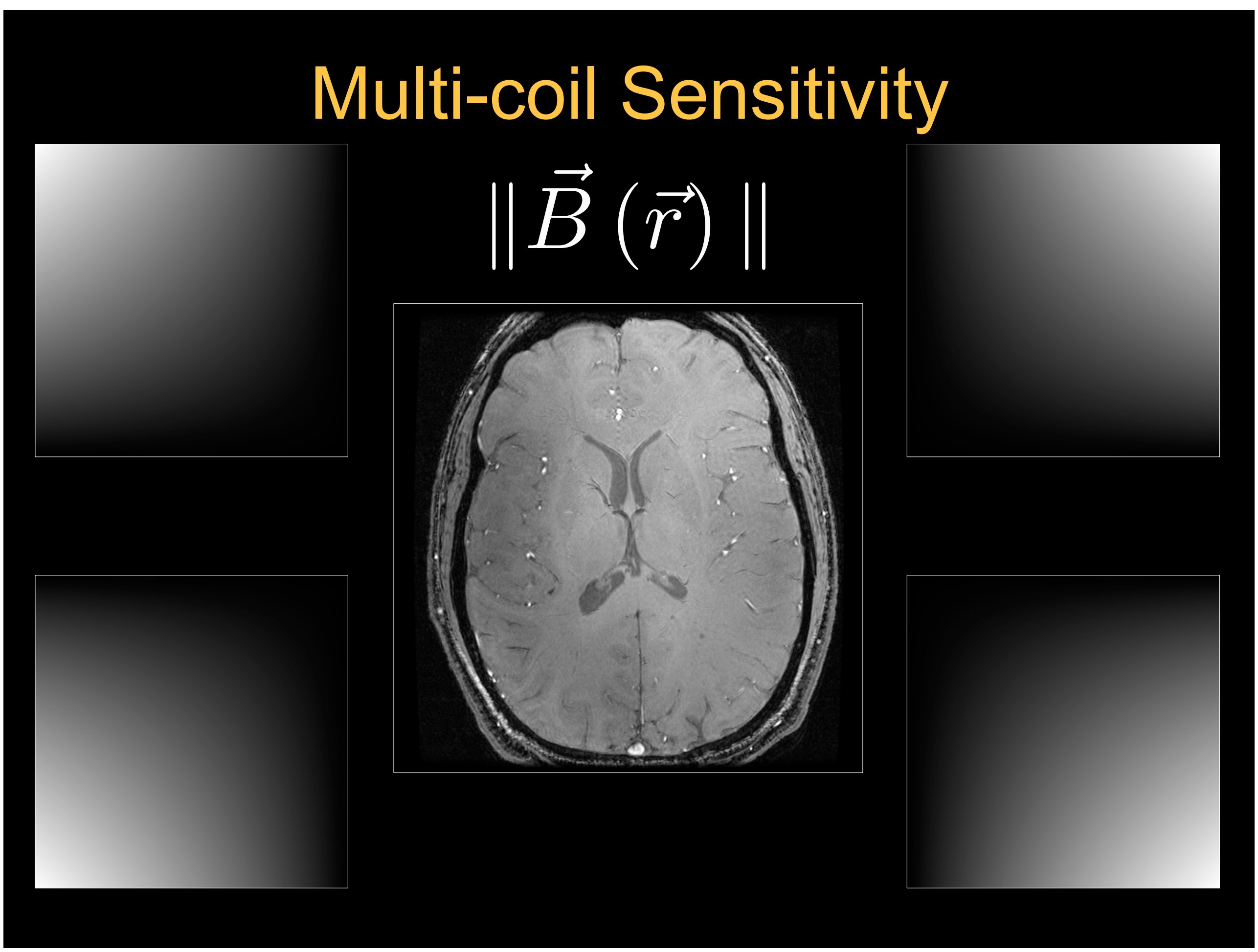
Kyung Sung, Ph.D.

2018.05.22

Today's Topics

- Multicoil reconstruction
- Parallel imaging
  - Image domain methods:
    - SENSE
  - k-space domain methods:
    - SMASH
    - GRAPPA (next time)


Multi-coil Arrays
Coil 1
Coil 2
Coil 3
Coil 4


Multi-coil Sensitivity
$\|\vec{B}(\vec{r})\|$

Multi-coil Reconstruction

- Each coil has a complete image of whole FOV and an amplitude and phase sensitivity

$$C_l(\vec{x}) \qquad l = 1,2,\ldots L$$

- Coils are coupled, so noise is correlated

$$E[n_i n_j] = \Psi$$

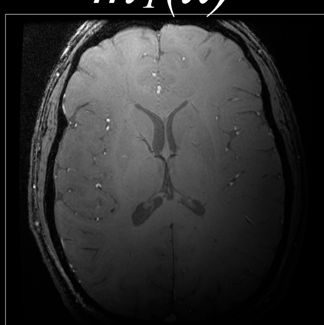
- Received data from coil l:

$$m_l(\vec{x}) = C_l(\vec{x}) m(\vec{x}) + n_l(\vec{x})$$

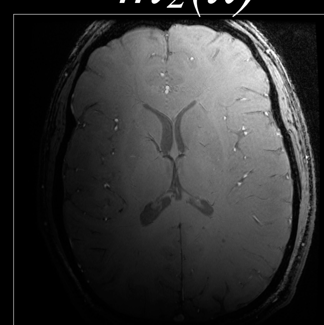
- Given $m_l(x)$, how do we reconstruct $m(x)$?

Multi-coil Images

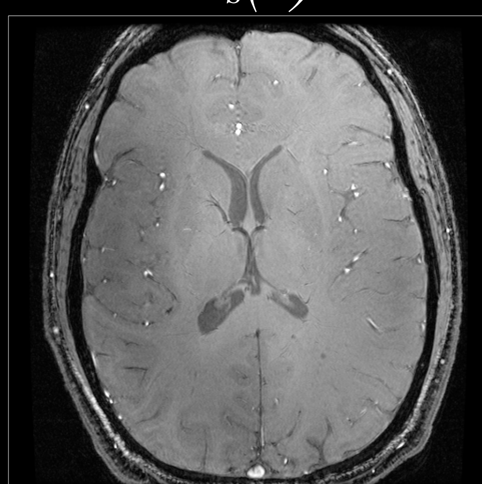
$m_1(x)$



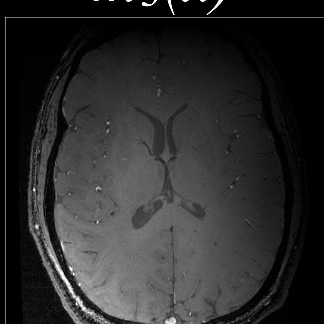
$m_2(x)$



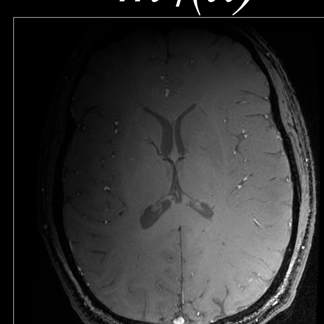
$m_s(x)$



$m_3(x)$



$m_4(x)$



Multi-coil Reconstruction

For a particular voxel x

$$\begin{pmatrix} m_1(\vec{x}) \\ m_2(\vec{x}) \\ \cdot \\ \cdot \\ \cdot \\ m_L(\vec{x}) \end{pmatrix} = \begin{pmatrix} C_1(\vec{x}) \\ C_2(\vec{x}) \\ \cdot \\ \cdot \\ \cdot \\ C_L(\vec{x}) \end{pmatrix} m(\vec{x}) + \begin{pmatrix} n_1(\vec{x}) \\ n_2(\vec{x}) \\ \cdot \\ \cdot \\ \cdot \\ n_L(\vec{x}) \end{pmatrix}$$

OR

$$\underbrace{m_s(\vec{x})}_{L \times 1} = \underbrace{C}_{L \times 1} m(\vec{x}) + \underbrace{n}_{L \times 1}$$

Minimum Variance Estimate

$$\hat{m}(\vec{x}) = \underbrace{(C^* \Psi^{-1} C)}_{1 \times 1}{}^{-1} \underbrace{C^* \Psi^{-1}}_{1 \times L} \underbrace{m_s(\vec{x})}_{L \times 1}$$

Covariance (variance)

$$COV(\hat{m}(\vec{x})) = C^* \Psi^{-1} C$$

What if Ψ is $\sigma^2 I$?

$$\hat{m}(\vec{x}) = \underbrace{(C^* C)}_{\text{Intensity Correction}}{}^{-1} \underbrace{C^*}_{\text{Phase Correction}} m_s(\vec{x})$$

Approximate Solution

- Often we don't know $C_l(x)$, but

$$m_l(\vec{x}) = C_l(\vec{x})m(\vec{x})$$

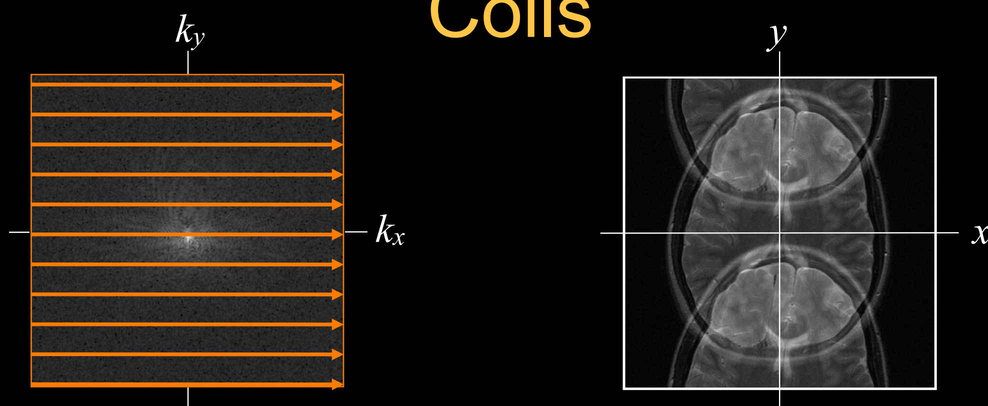
- Approximate solution:

$$\hat{m}_{SS}(\vec{x}) = \sqrt{\sum_l m_l^*(\vec{x})m_l(\vec{x})}$$

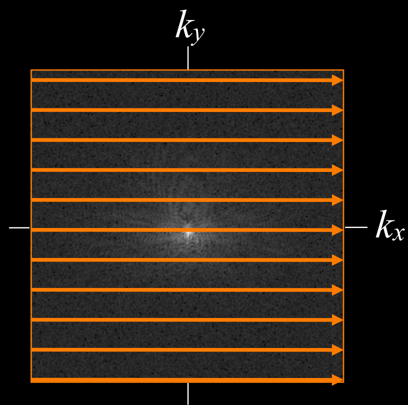
- For SNR > 20, within 10% of optimal solution

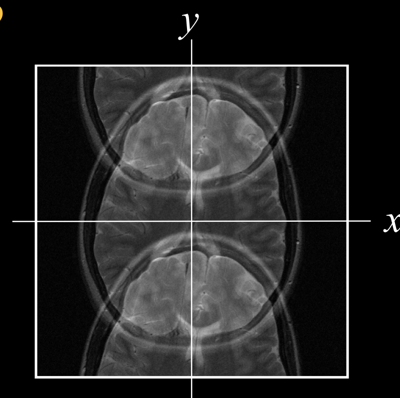
PB Roemer et al. MRM 1990

Accelerate Imaging with Array Coils



Accelerate Imaging with Array Coils





- Parallel Imaging
  - Coil elements provide some localization
  - Undersample in k-space, producing aliasing
  - Sort out in reconstruction

Parallel Imaging

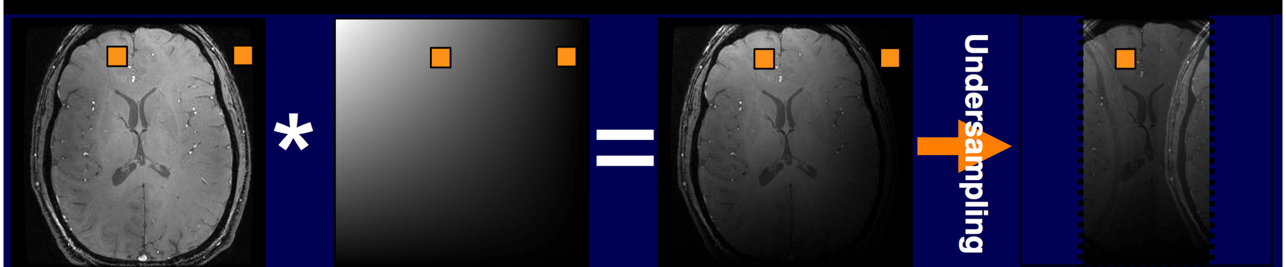
- Many approaches:
  - Image domain - SENSE
  - k-space domain - SMASH, GRAPPA
  - Hybrid - ARC

- We will focus on two:
  - SENSE: optimal if you know coil sensitivities
  - GRAPPA: autocalibrating / robust

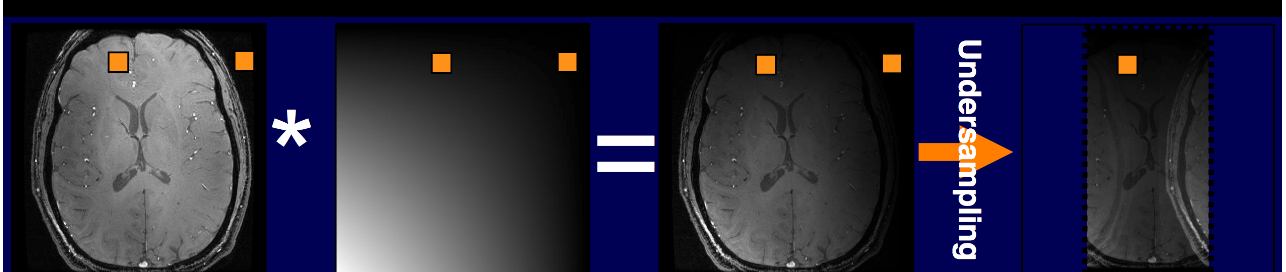
Parallel Imaging
(SENSE)

Cartesian SENSE

$$m_1(\vec{x_1}) = C_1(\vec{x_1})m(\vec{x_1}) + C_1(\vec{x_2})m(\vec{x_2})$$



$$m_2(\vec{x_1}) = C_2(\vec{x_1})m(\vec{x_1}) + C_2(\vec{x_2})m(\vec{x_2})$$



$$\begin{pmatrix} m_1(\vec{x_1}) \\ m_2(\vec{x_1}) \\ \cdot \\ \cdot \\ \cdot \\ m_L(\vec{x_1}) \end{pmatrix} = \begin{pmatrix} C_1(\vec{x_1}) & C_1(\vec{x_2}) \\ C_2(\vec{x_1}) & C_2(\vec{x_2}) \\ \cdot & \\ \cdot & \\ \cdot & \\ C_L(\vec{x_1}) & C_L(\vec{x_2}) \end{pmatrix} \begin{pmatrix} m(\vec{x_1}) \\ m(\vec{x_2}) \end{pmatrix} + \begin{pmatrix} n_1(\vec{x_1}) \\ n_2(\vec{x_1}) \\ \cdot \\ \cdot \\ \cdot \\ n_L(\vec{x_1}) \end{pmatrix}$$

Aliased Images — Sensitivity at Source Voxels — Source Voxels

OR

$$\underbrace{m_s}_{L \times 1} = \underbrace{C}_{L \times 2} \overbrace{m}^{2 \times 1} + \underbrace{n}_{L \times 1}$$

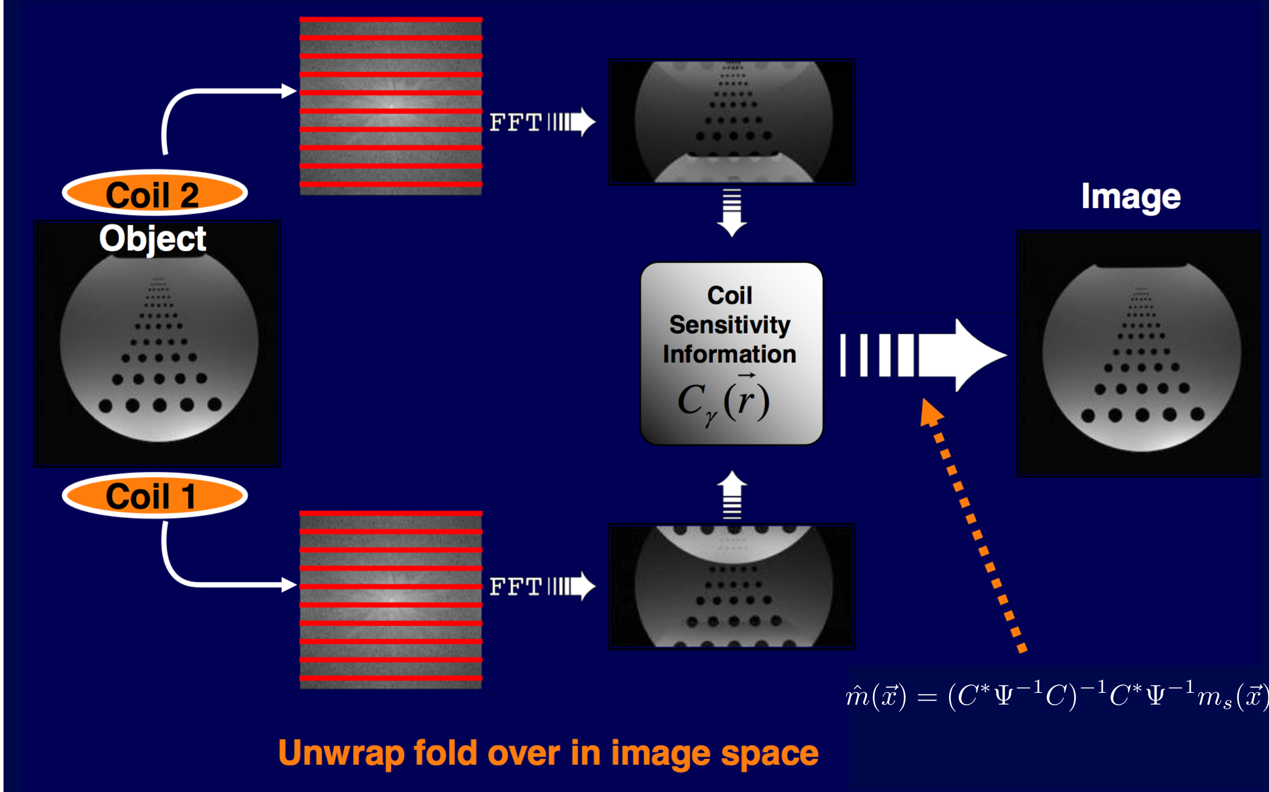
$$\hat{m}(\vec{x}) = \underbrace{(C^*\Psi^{-1}C)^{-1}}_{2 \times 2} \underbrace{C^*\Psi^{-1}}_{2 \times L} \underbrace{m_s(\vec{x})}_{L \times 1}$$

L aliased reconstruction resolves 2 image pixels

For an N x N image, we solve (N/2 x N)
2 x 2 inverse systems

For an acceleration factor R, we solve (N/R x N)
R x R inverse systems

SENSE Reconstruction



SNR Cost

- How large can R be?
- Two SNR loss mechanisms
  - Reduced scan time
  - Condition of the SENSE decomposition
- SNR Loss

$$SNR_{SENSE} = \frac{SNR}{g\sqrt{R}}$$

Geometry Factor (g) — Reduced Scan Time ($\sqrt{R}$)

Geometry Factor

- Covariance for a fully sampled image (variance of one voxel):

$$\chi_F = \frac{1}{n_F}(C_F^* \Psi^{-1} C_F)^{-1}$$

- Covariance for a reduced encoded image:

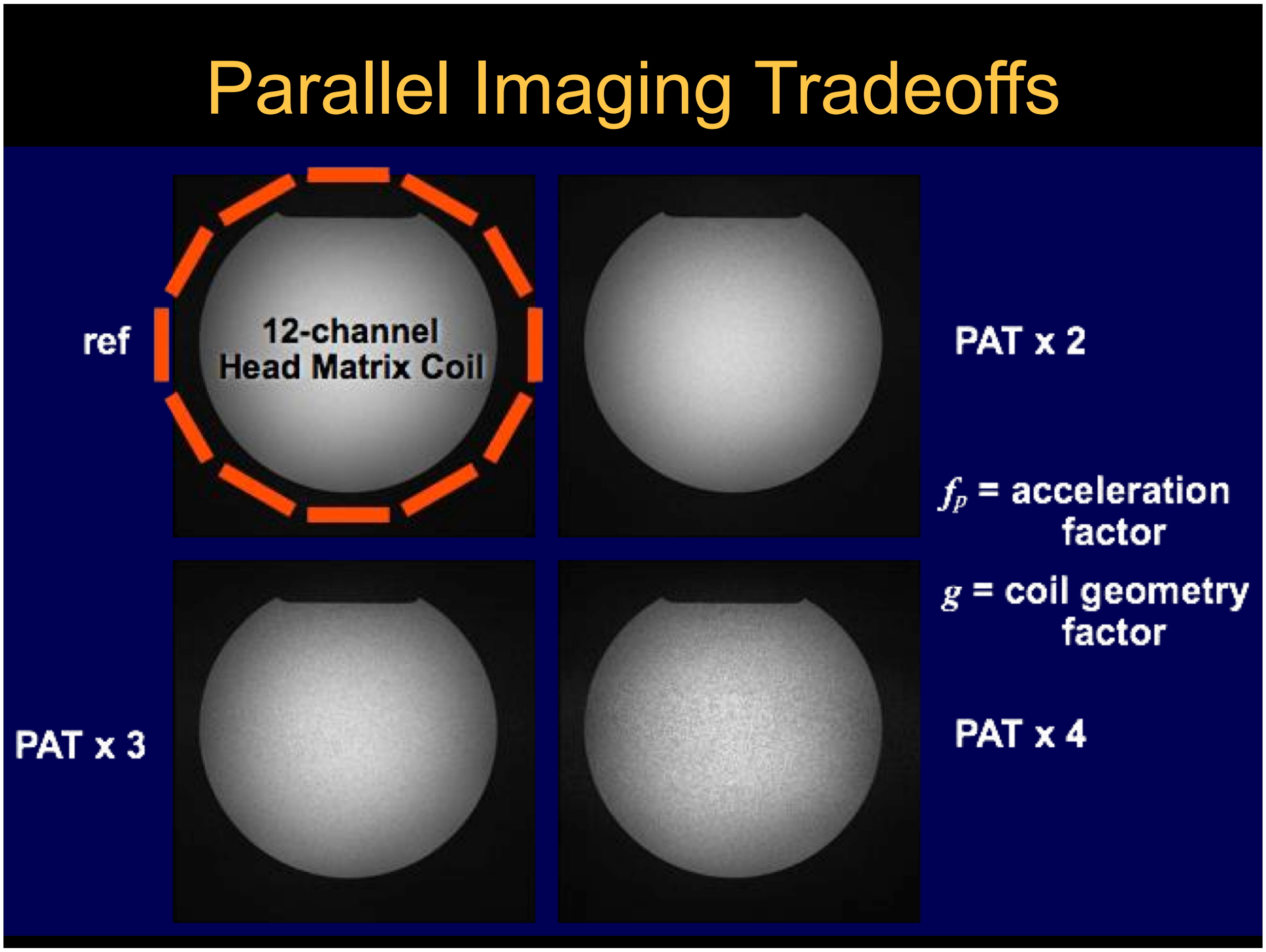
$$\chi_R = \frac{1}{n_R}(C_R^* \Psi^{-1} C_R)^{-1}$$

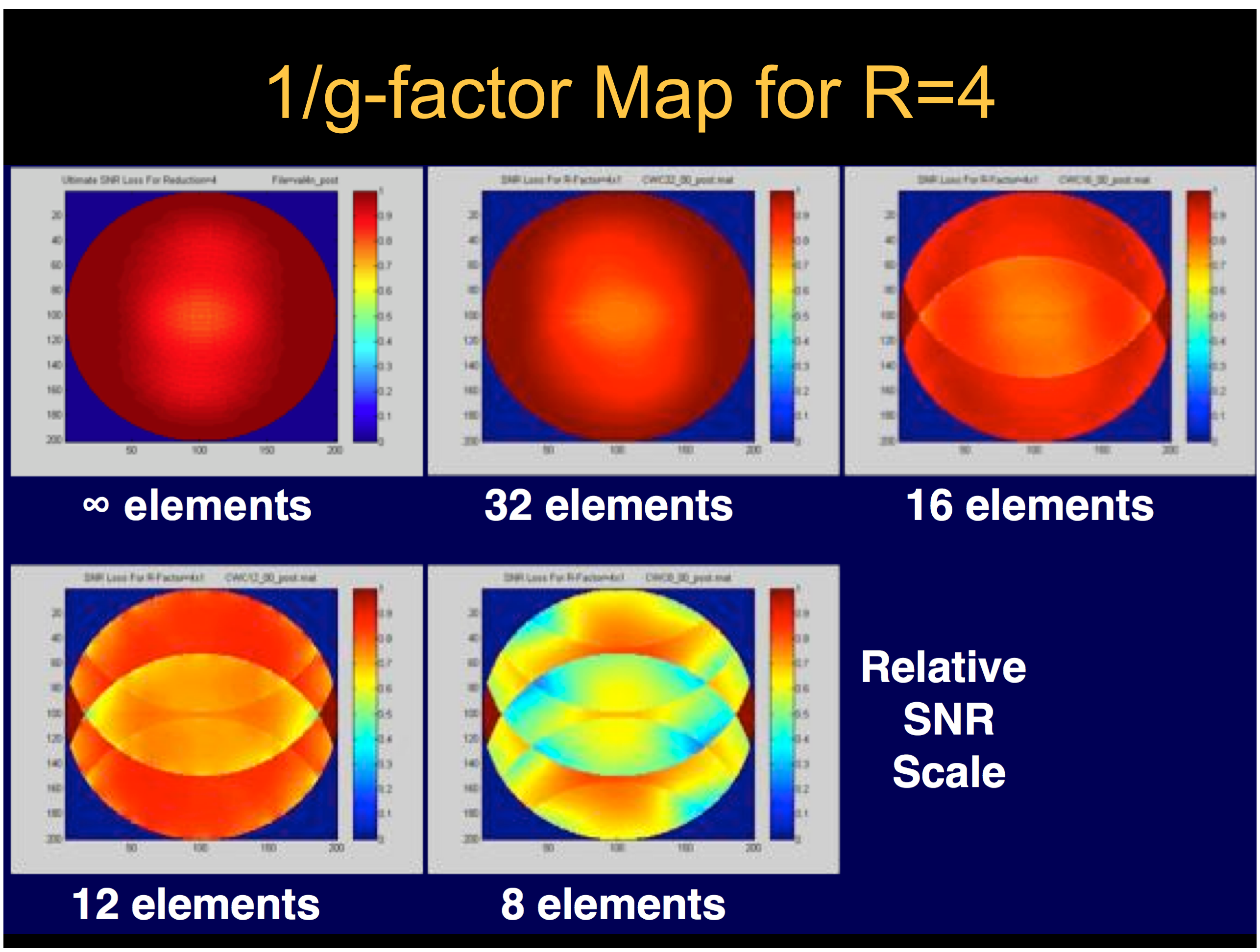
To the board ...

Geometry Factor

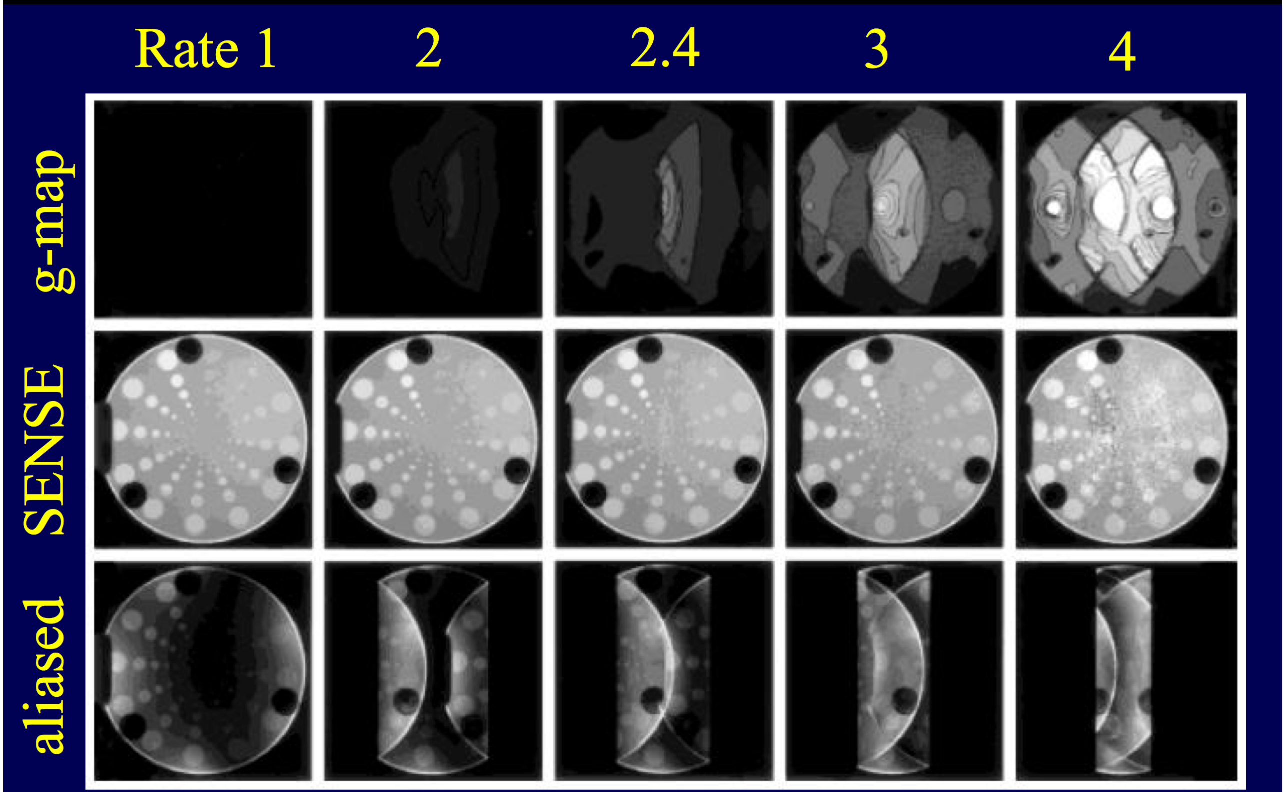
- g-factor is critical since it depends on:
  - Acceleration
  - Spatial position
  - Aliasing direction
  - Coil geometry
- Minimizing g-factor drives system design
- Sense coils are different from traditional array coils

To the board ...


Parallel Imaging Tradeoffs
ref
12-channel
Head Matrix Coil
PAT x 2
f_p = acceleration factor
g = coil geometry factor
PAT x 3
PAT x 4

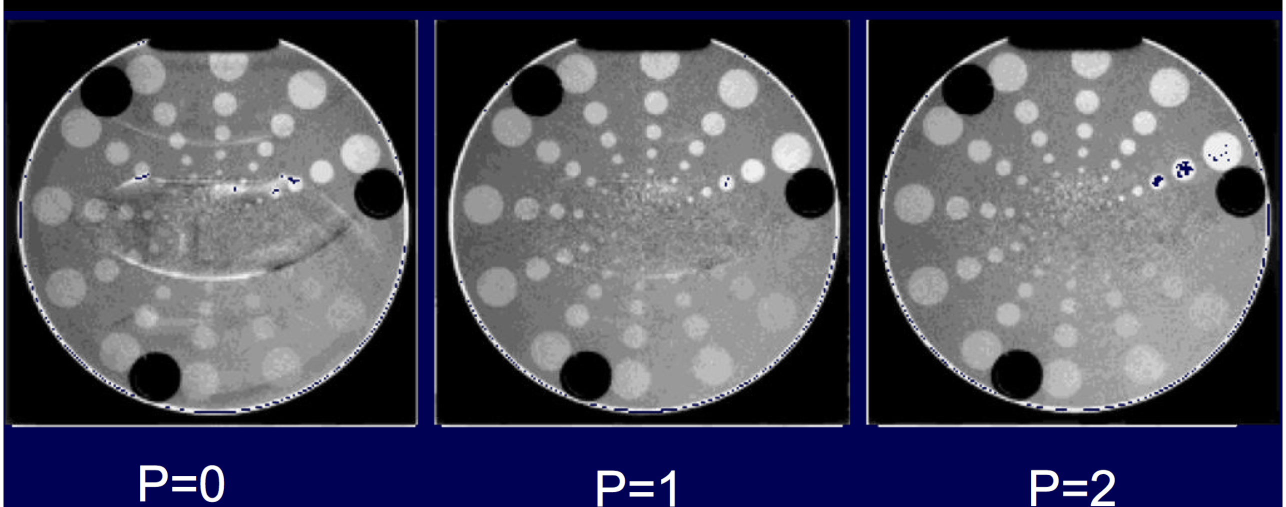

1/g-factor Map for R=4
∞ elements
32 elements
16 elements
12 elements
8 elements
Relative SNR Scale

g-factor and its impact on images



Dependence on Coil Sensitivity

- Images reconstructed using coil sensitivity maps with different order P of polynomial fitting



Pruessmann et al. MRM 1999

Parallel Imaging (SMASH)

SMASH

- Simultaneous Acquisition of Spatial Harmonics (SMASH) uses linear combinations of acquired k-space data from multiple coils to generate multiple data sets with offsets in k-space

Phase Encoding by Amplitude Modulation

- Signal Equation:

$$S(k_x, k_y) = \int\int C(x,y)\rho(x,y)e^{-ik_x x - ik_y y}dxdy$$

ρ(x,y) = spin density

C(x,y) = receiver coil sensitivity

Phase Encoding by Amplitude Modulation

$$S(k_x, k_y) = \int\int C(x,y)\rho(x,y)e^{-ik_x x - ik_y y}dxdy$$

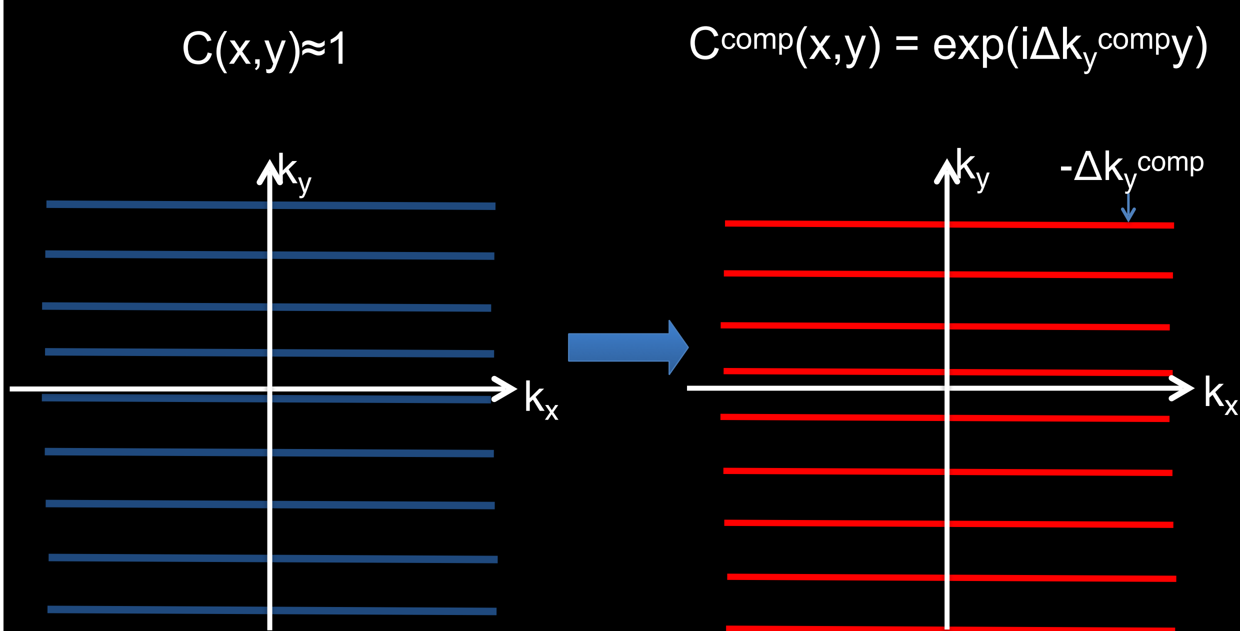
- If C(x,y) ≈ 1 (relatively homogeneous coil sensitivity), $S(k_x,k_y)$ = FT{ρ(x,y)}
- But coils often do not have uniform sensitivity, and usually there is a fall-off of sensitivity with distance from the coil

Phase Encoding by Amplitude Modulation

- Use the arrangement of coils to construct sinusoidal sensitivity profiles
  - Sensitivity profiles are combination of multiple coils, whose signals are combined to produce the desired sinusoidal sensitivity

$$C^{comp}(y) = \cos(\Delta k_y^{comp} y) + i \sin(\Delta k_y^{comp} y)$$
$$= e^{i \Delta k_y^{comp} y}$$

The wavelength could be $\lambda = 2\pi/\Delta k_y = FOV$



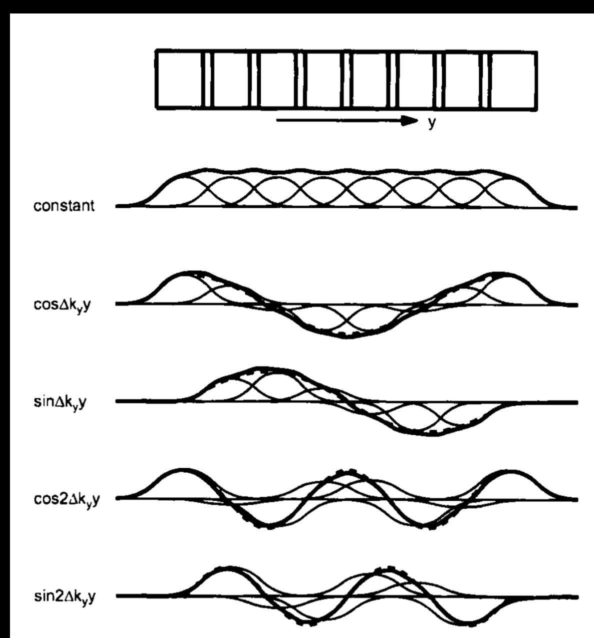
Spatial Harmonic Generation Using Coil Arrays

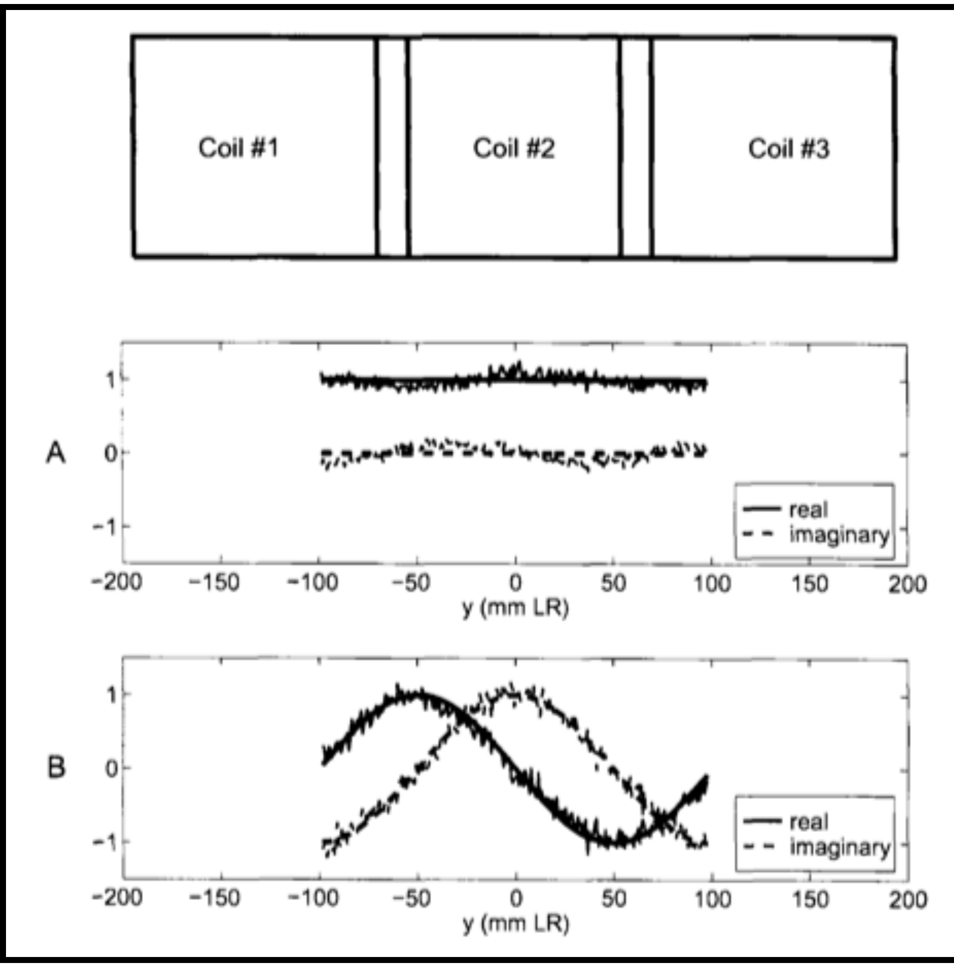
$$C_m^{comp}(y) = \sum_j a_{j,m} C_j(y) = e^{-i2\pi m \Delta k_y y}$$

- Linear surface coil array sensitivities C_j are combined with linear weights, $a_{j,m}$, to produce composite sinusoidal sensitivity
- Composite sensitivities are arranged to be spatial harmonics
- m is an integer, chosen to be a desired harmonic

Theory: Spatial Harmonics

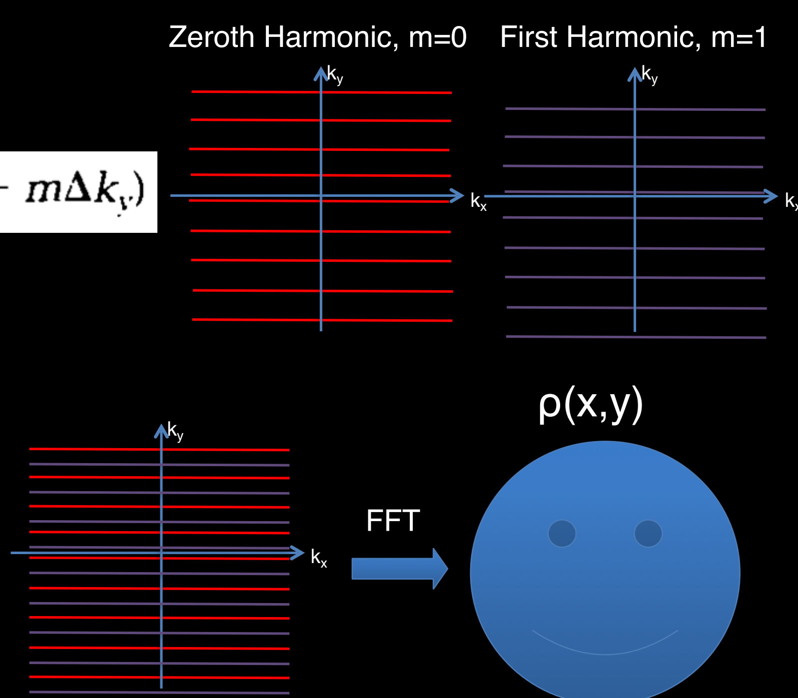
- 8 coil array
- Gaussian coil sensitivity distribution used
- m = 0, 1, -1, 2, -2
- Each spatial harmonic generated is shifted by $-m\Delta k_y$



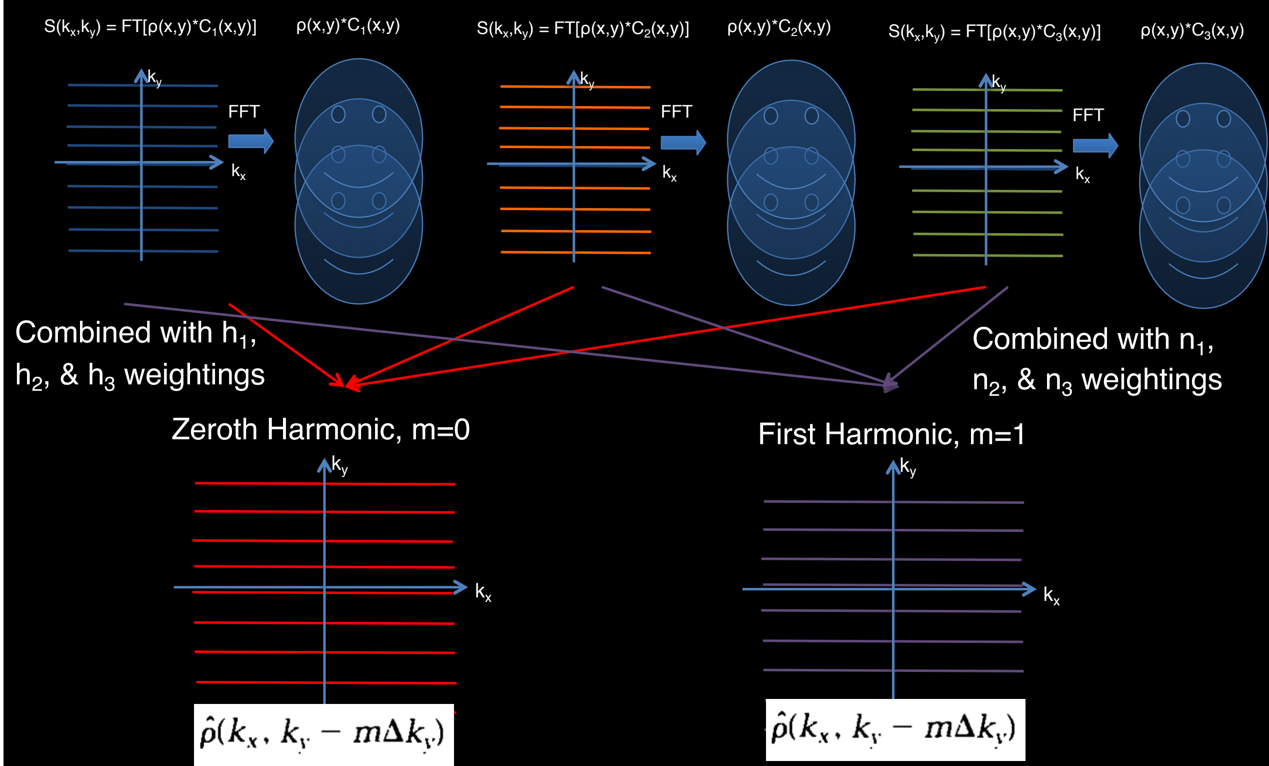


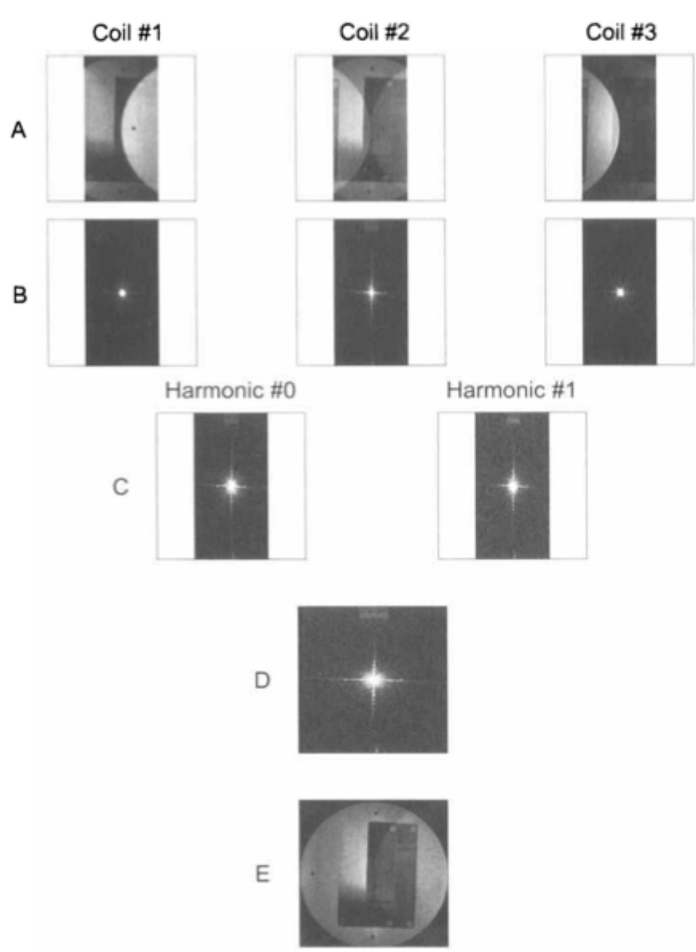
Interleave the Harmonics

$$\hat{\rho}(k_x, k_y - m\Delta k_y)$$



SMASH Reconstruction

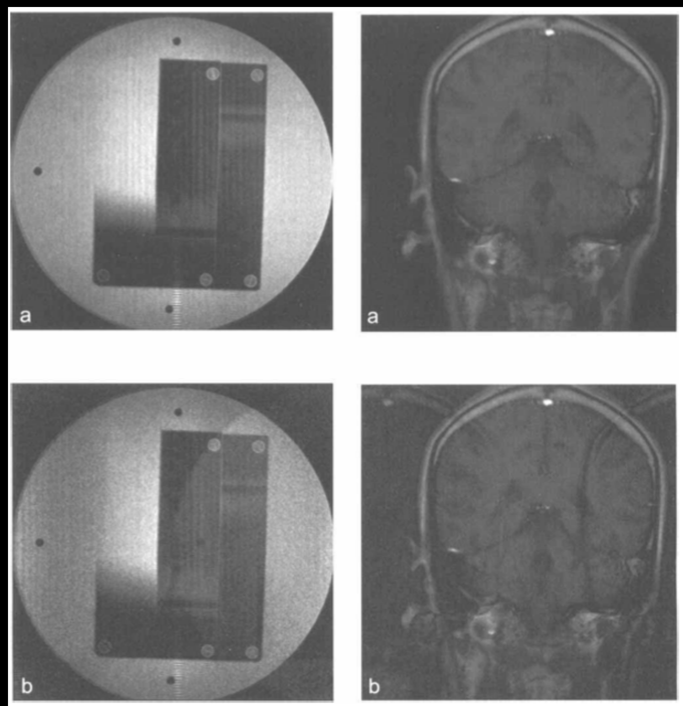




Three-Element Array

Reference images

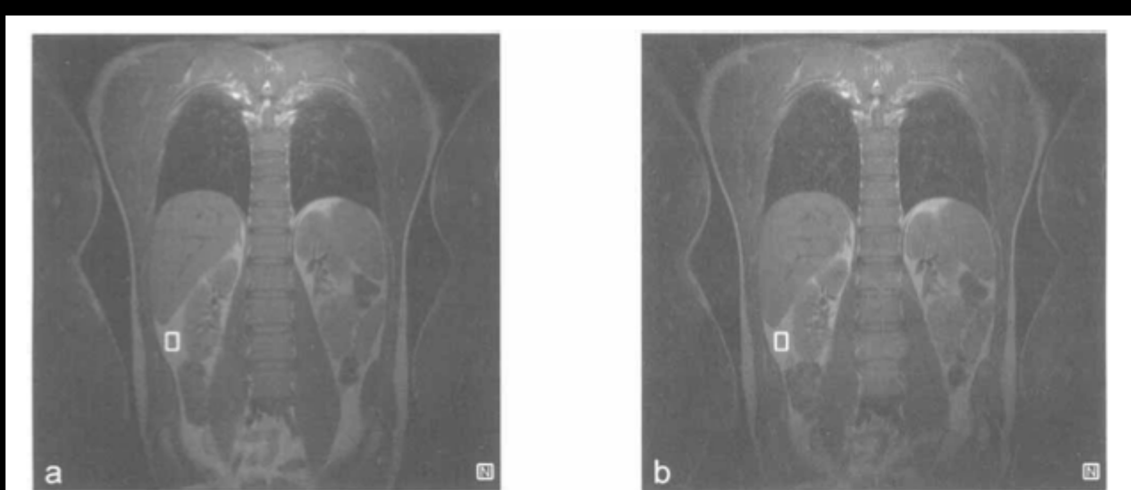
SMASH images



Four-Element Array

Reference images

SMASH images



Key Points of SMASH

- k-space lines are synthesized by combining signals from multiple coils such that it creates a partial replacement for a phase encoding gradient
- Decreases acquisition time by 1/N
  - N is the number of generated spatial Harmonics

$$\sum_j a_{j,m} C_j(y) = e^{-i2\pi\Delta k_y y}$$

Sodickson et al. MRM 1997

Summary

- Parallel imaging utilizes coil sensitivities to increase the speed of MRI
- Cases for parallel imaging
  - Higher patient throughput,
  - Real-time imaging/Interventional imaging
  - Motion suppression
- Cases against parallel imaging
  - SNR starving applications

Further Reading

- Multi-coil Reconstruction
  - http://onlinelibrary.wiley.com/doi/10.1002/mrm.1910160203/abstract
- SENSE
  - http://www.ncbi.nlm.nih.gov/pubmed/10542355
- SMASH
  - http://www.ncbi.nlm.nih.gov/pubmed/9324327
- Parallel Imaging Overview
  - http://www.ncbi.nlm.nih.gov/pubmed/17374908

Thanks!

Kyung Sung, PhD

ksung@mednet.ucla.edu

http://kyungs.bol.ucla.edu