

# Image Reconstruction – Parallel Imaging Part I

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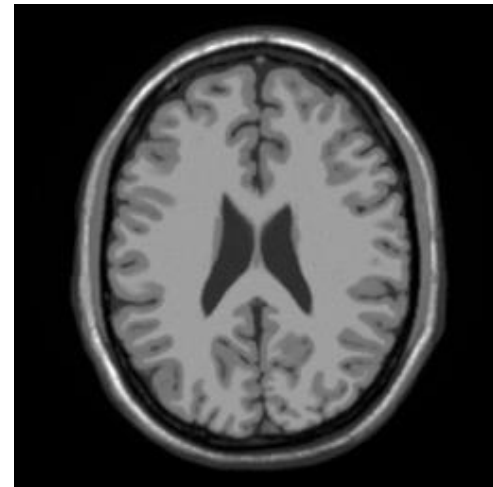
No conflicts of interest to disclose

# Image Reconstruction Goal

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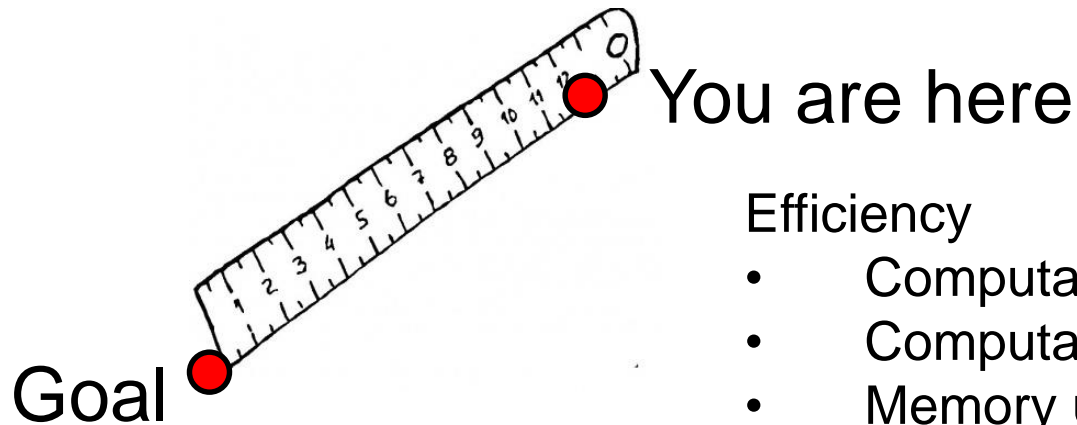
- Instantaneous results
- Perfect signal fidelity with no artifacts
- No noise

```
load im1.mat
```



# How far away are we?

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## Efficiency

- Computation operations
- Computation time
- Memory usage

## Artifacts

- Image shading
- Aliasing energy

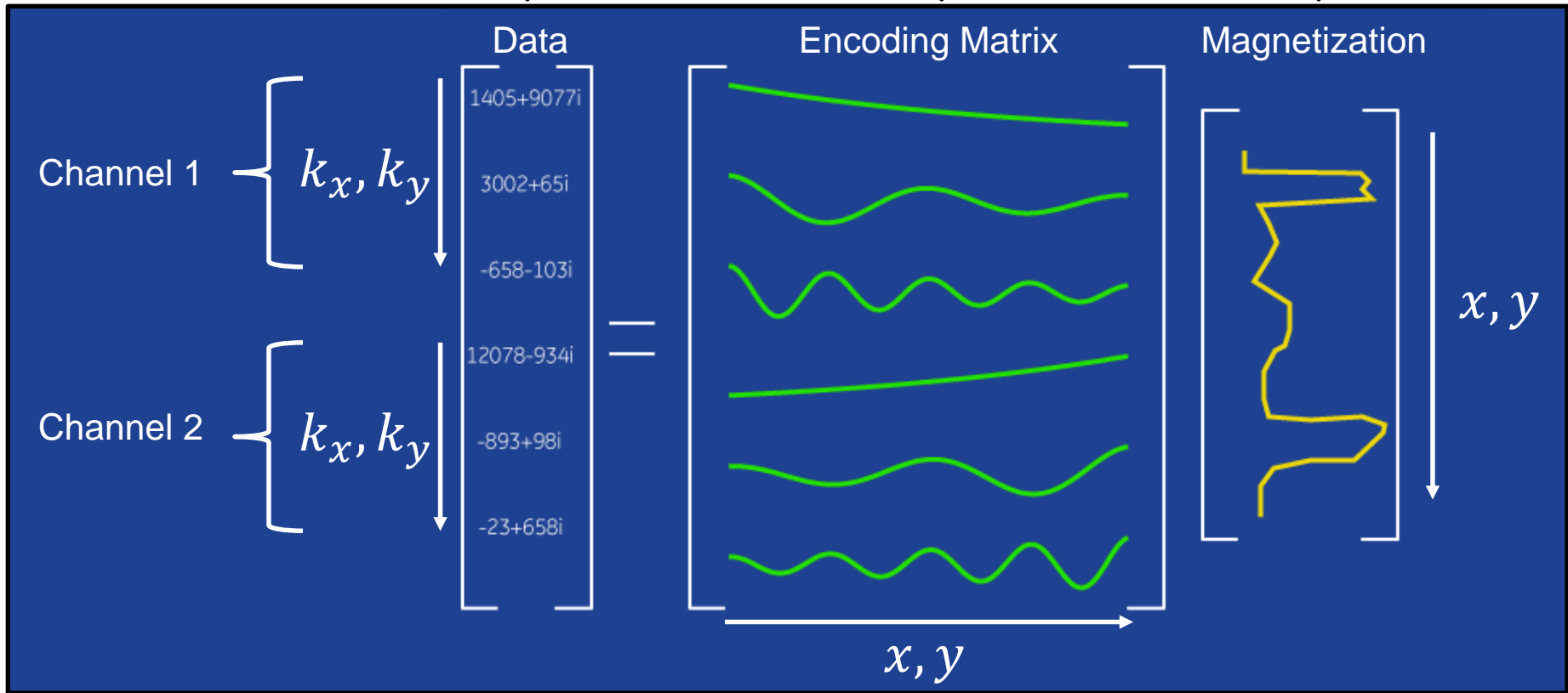
## Noise

- G-factor maps
- Noise amplification maps
- SNR-scaled reconstruction

# Concept of Sensitivity Encoding

# Encoding Model

$$\underbrace{d_j(k_x, k_y)} = \iiint \underbrace{s_j(x, y) e^{i2\pi(k_x x + k_y y)}} \underbrace{m(x, y)} dx dy$$

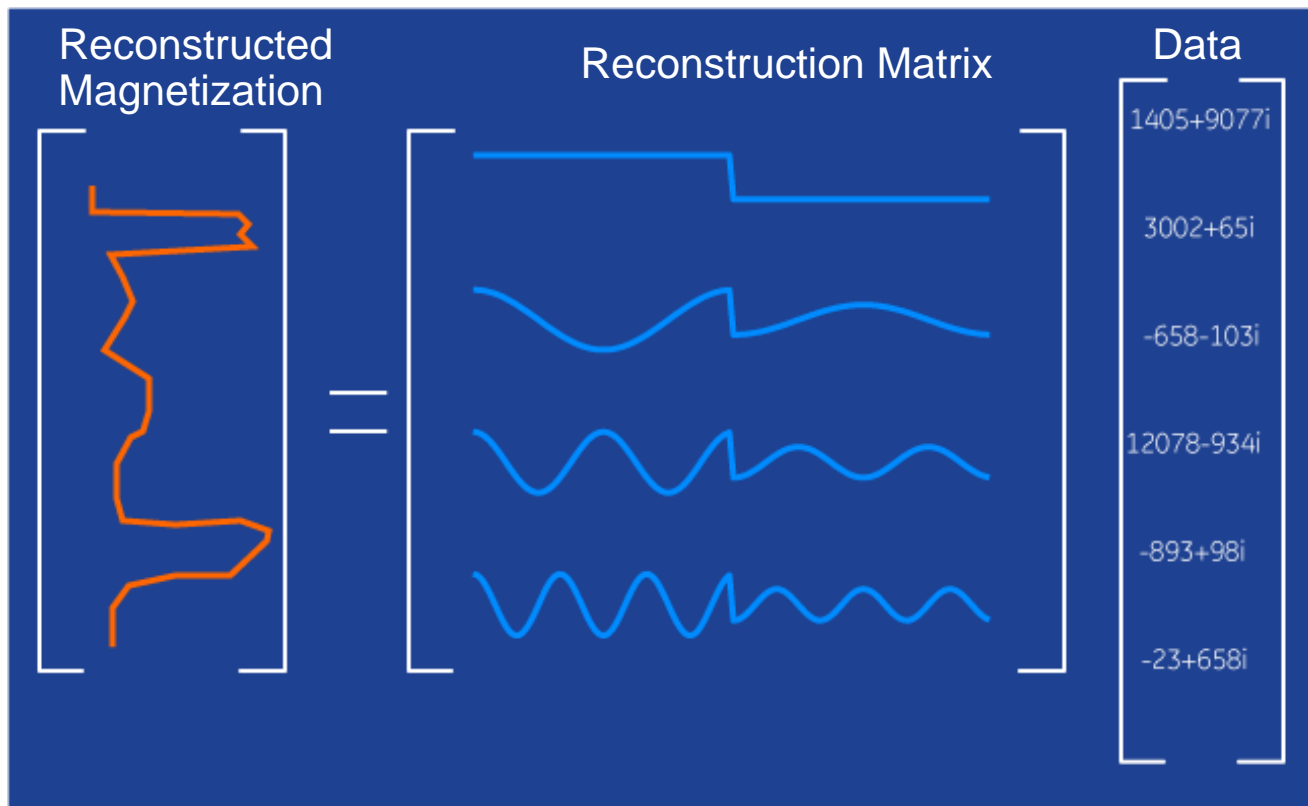


$$d = Em + \text{noise}$$

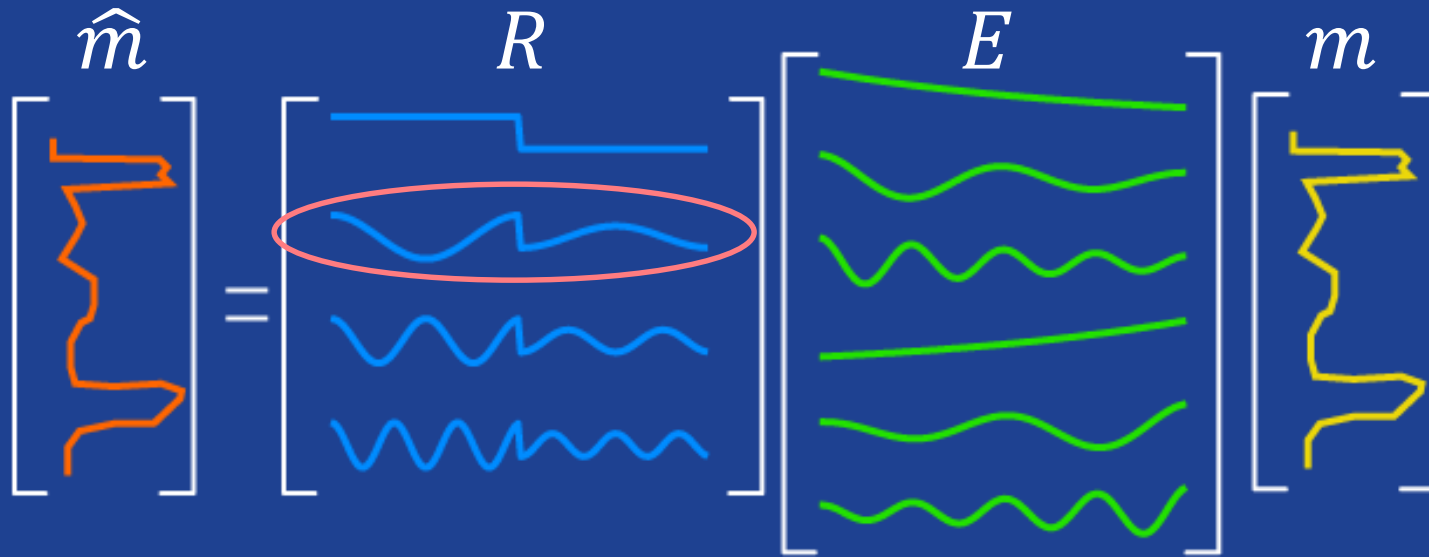
# Reconstruction

$$\hat{m} = (E^H E)^{-1} E^H d$$

$$\hat{m} = R d$$



# Reconstruction Matrix Design



Linear combination of acquired encoding functions to give desired encoding function





# Reconstruction Components

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## 1. Estimate $E$

- $s_j(x, y)$  Estimate coil sensitivities

## 2. Generate $R$

- One possibility:  $R = \text{pinv}(E)$

## 3. Apply $R$

- $\hat{m} = Rd$

# Reconstruction Components

## 1. Estimate $E$

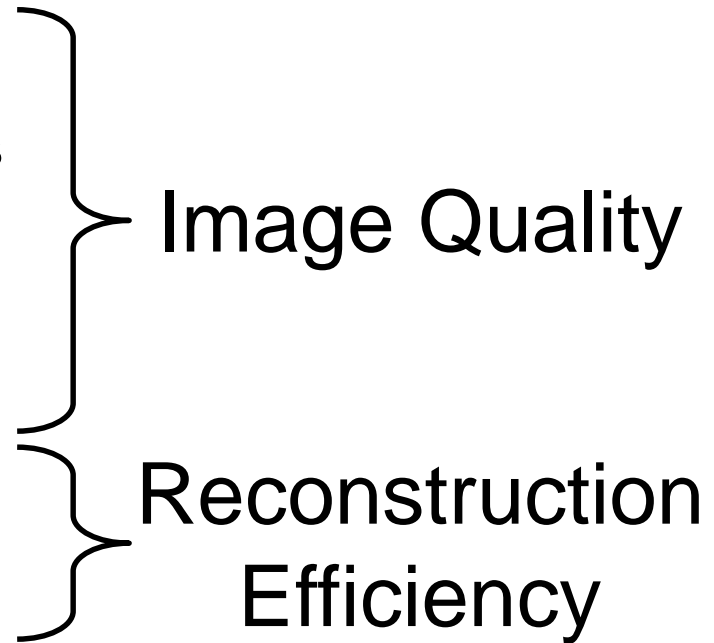
- $s_j(x, y)$  Estimate coil sensitivities

## 2. Generate $R$

- One possibility:  $R = \text{pinv}(E)$

## 3. Apply $R$

- $\hat{m} = Rd$



# Reconstruction Components: Noniterative Methods

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## 1. Estimate $E$

- $s_j(x, y)$  Estimate coil sensitivities

## 2. Generate $R$

- One possibility:  $R = \text{pinv}(E)$

## 3. Apply $R$

- $\hat{m} = Rd$

} Calibration

# Reconstruction Components: Iterative Methods

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## 1. Estimate $E$

- $s_j(x, y)$  Estimate coil sensitivities

} Calibration

## 2. Generate $R$

- One possibility:  $R = \text{pinv}(E)$

## 3. Apply $R$

- $\hat{m} = Rd$

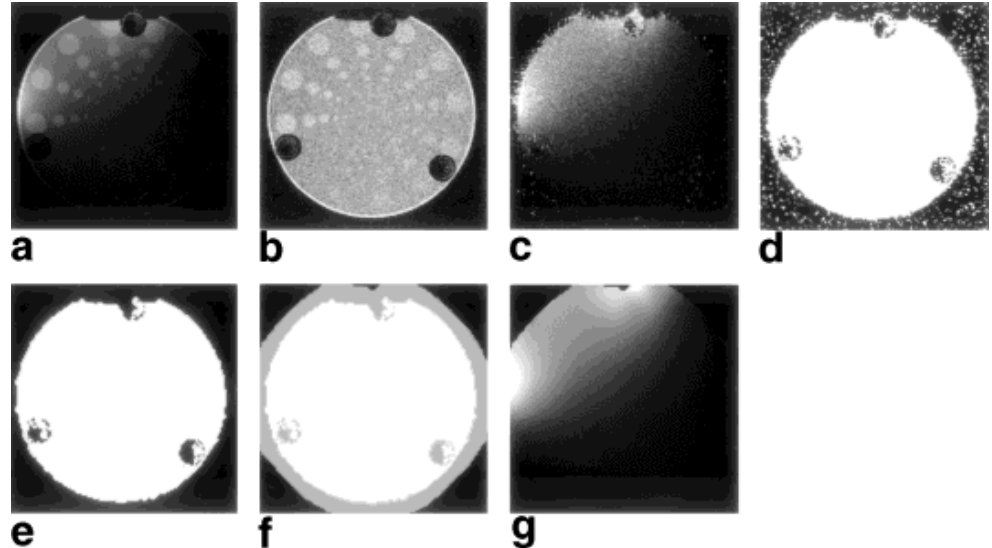
} Fused in  
iterative loop

# SENSE: Sensitivity Encoding for Fast MRI

Klaas P. Pruessmann, Markus Weiger, Markus B. Scheidegger, and Peter Boesiger\*

## 1. Estimate $E$

- $s_j(x, y)$  Estimate coil sensitivities



## 2. Generate $R$

- One possibility:  $R = \text{pinv}(E)$

“unfolding matrix”

$$U = (S^H \Psi^{-1} S)^{-1} S^H \Psi^{-1},$$

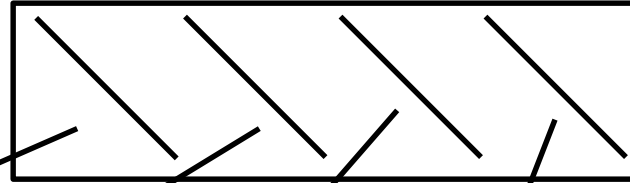
# SENSE: Sensitivity Encoding for Fast MRI

Klaas P. Pruessmann, Markus Weiger, Markus B. Scheidegger, and Peter Boesiger\*

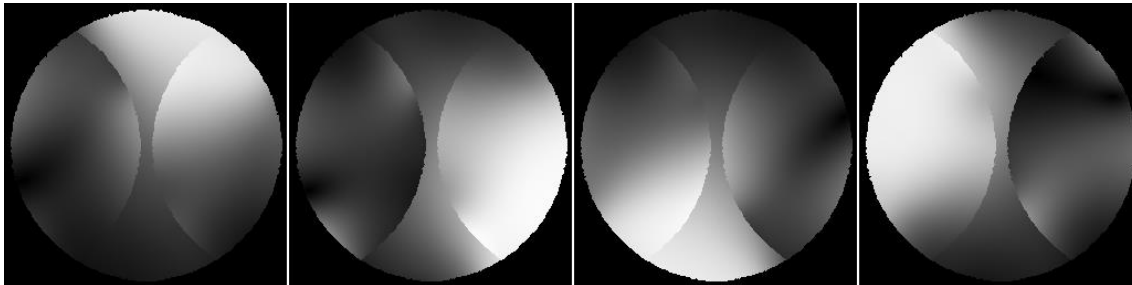
## 3. Apply $R$

- $\hat{m} = Rd$

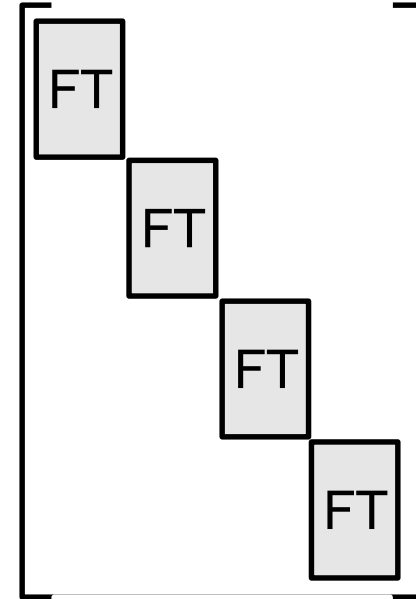
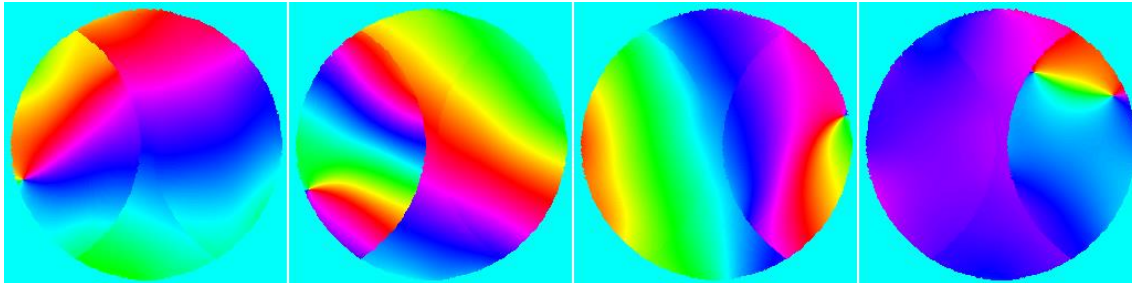
$$R =$$



mag



phase



“unmixing  
images”

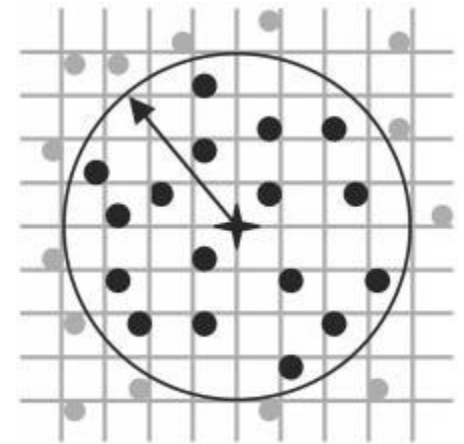
$N_c$  Fourier Transforms +  $N_c$  multiplications per voxel

# Local k-Space Kernels

- Enable non-iterative reconstruction of non-uniform sampling patterns.

SMASH

PARS



AUTO-SMASH

VD-AUTO-SMASH

GRAPPA

...and more

# Composite Channel Local k-Space Kernels

SMASH, AUTO-SMASH, VD-AUTO-SMASH,...

$$R = \left[ \begin{array}{c} \boxed{\text{FT}} \end{array} \right] \left[ \begin{array}{cccc} \diagdown & \diagdown & \diagdown & \diagdown \end{array} \right]$$

↑  
Apply kernels

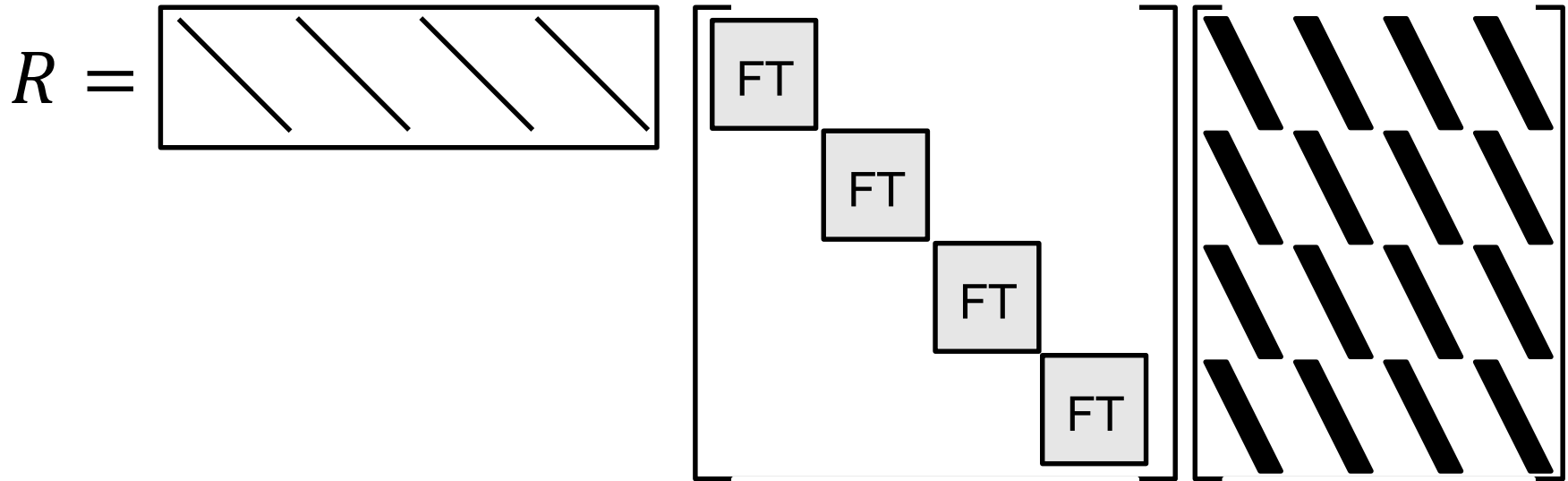
1 Fourier Transform +

$N_c \times N_{\text{kernel}}$  multiplications per missing sample



# Channel-by-channel k-Space Kernels

## GRAPPA, PARS...



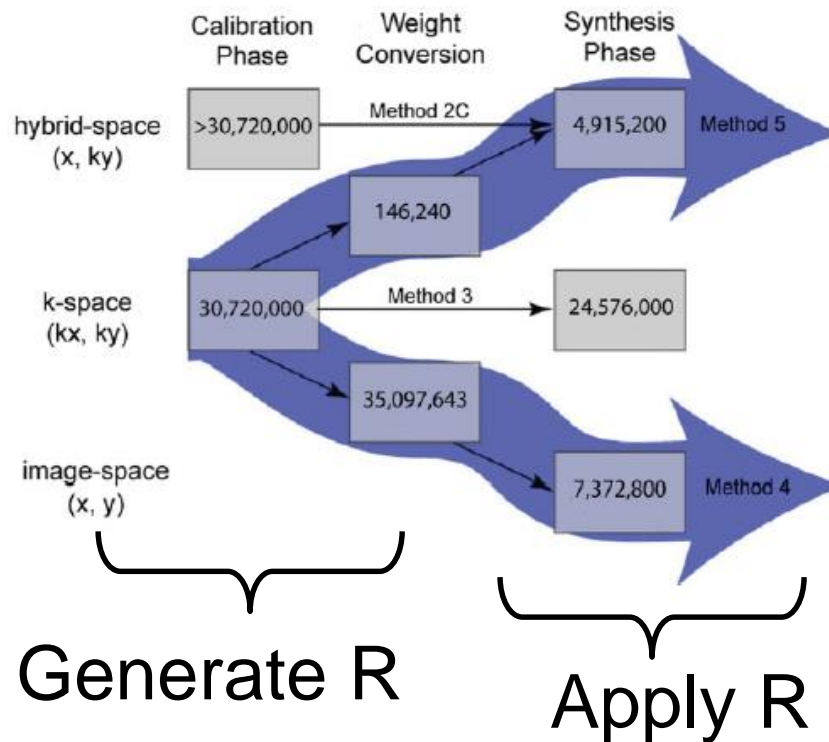
$N_{\text{kernel}} N_c^2$  multiplications per missing sample +  
 $N_c$  Fourier Transforms +  
 $N_c$  multiplications per voxel

# Mixing Reconstruction Components

Magnetic Resonance in Medicine 59:382–395 (2008)

## Comparison of Reconstruction Accuracy and Efficiency Among Autocalibrating Data-Driven Parallel Imaging Methods

Anja C.S. Brau,<sup>1\*</sup> Philip J. Beatty,<sup>1</sup> Stefan Skare,<sup>2</sup> and Roland Bammer<sup>2</sup>



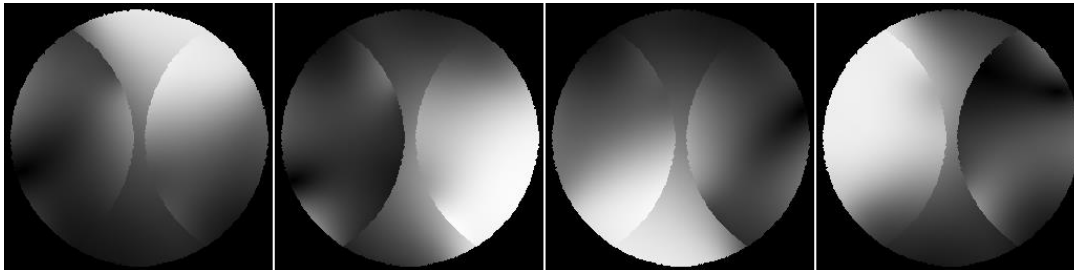
# MRI Toolbox

## ■ Uniform sampling with image space synthesis

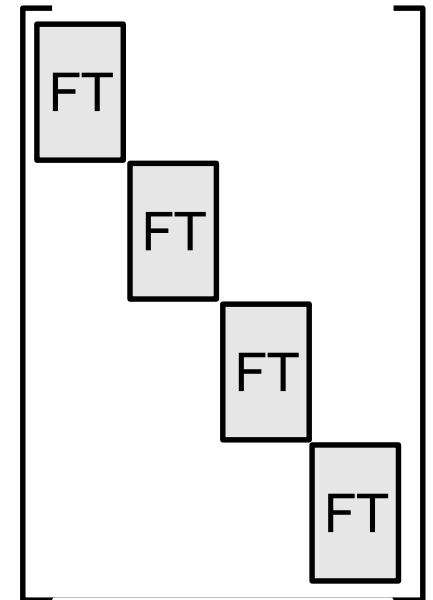
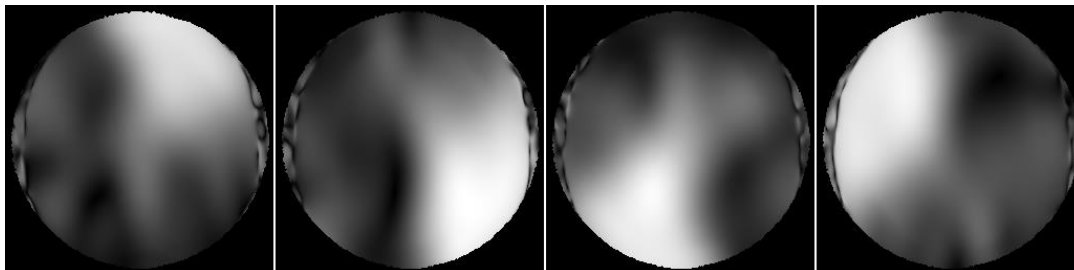
- `calculate_sense_unmixing(...)`
- `calculate_grappa_unmixing(...)`
- `calculate_jer_unmixing(...)`

$$R = \begin{bmatrix} \diagdown & & & \\ & \diagdown & & \\ & & \diagdown & \\ & & & \diagdown \end{bmatrix}$$

SENSE  
unmixing



GRAPPA  
unmixing

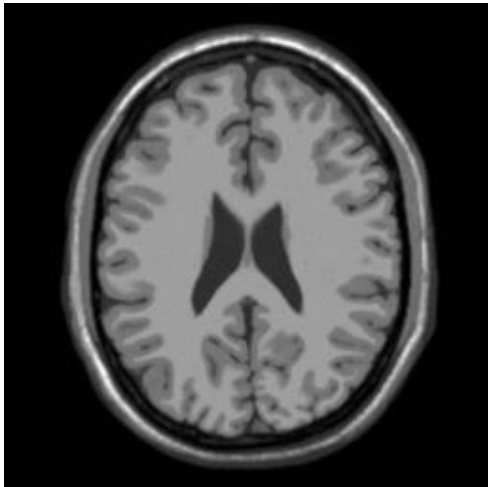


# Application of local k-space kernels

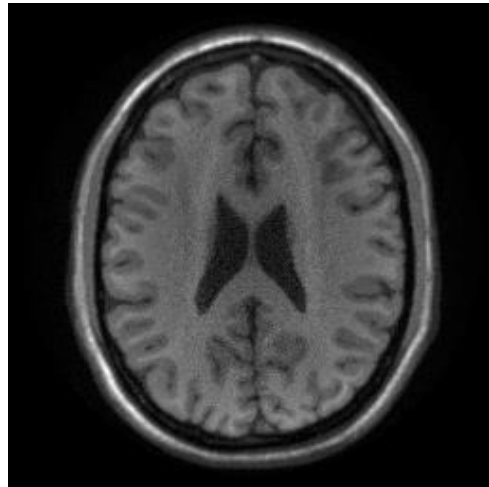
Property	k-space	(x, ky, kz)-space	image space
Merge with channel combination	Hard	Hard	Easy
Non-uniform Cartesian sampling	Yes	Yes	No
Apply during data acquisition	Yes	Yes	No
Cost to transform kernels	None	Minimal	Moderate
Memory needed to store coefficients	$W_x W_y W_z N_c N_c$ 120KB*	$N_x W_y W_z N_c N_c$ 6MB*	$N_x N_y N_z N_c$ 1GB*
Application computation	$W_x W_y W_z N_c N_c$ per missing sample	$W_y W_z N_c N_c$ per missing sample	$N_c$ per voxel

\* Example based on 5x7x7 kernel for 256x256x256 image with 8 channels

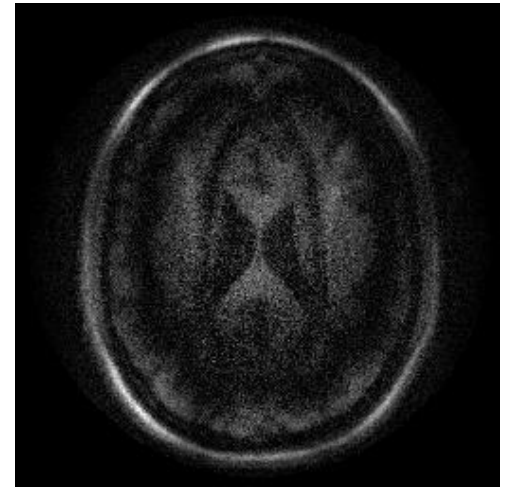
# Image Quality



-



=

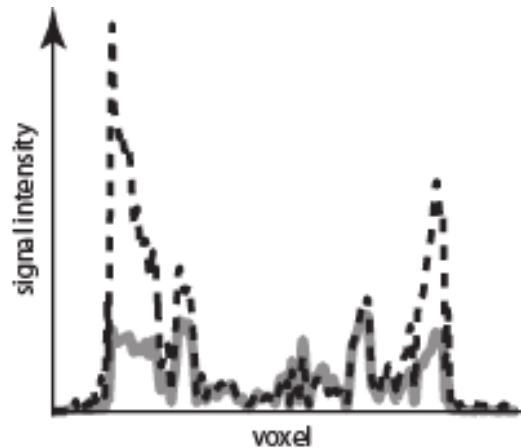
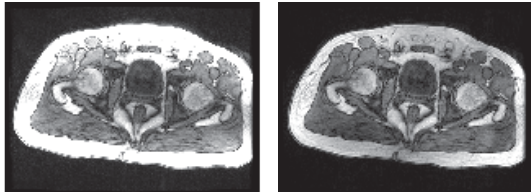


Shading?

Aliasing?

Noise?

# Image Shading



- Affects all multi-channel imaging (accelerated or not)
- Correction requires an absolute sensitivity reference to convert from *relative* coil sensitivities to *absolute* coil sensitivities.
  - e.g. calibration with uniformly sensitive reference coil or using uniform signal phantom/sequence.

# Common Shading for Relative Coil Sensitivities

- Compare reconstruction methods without absolute reference

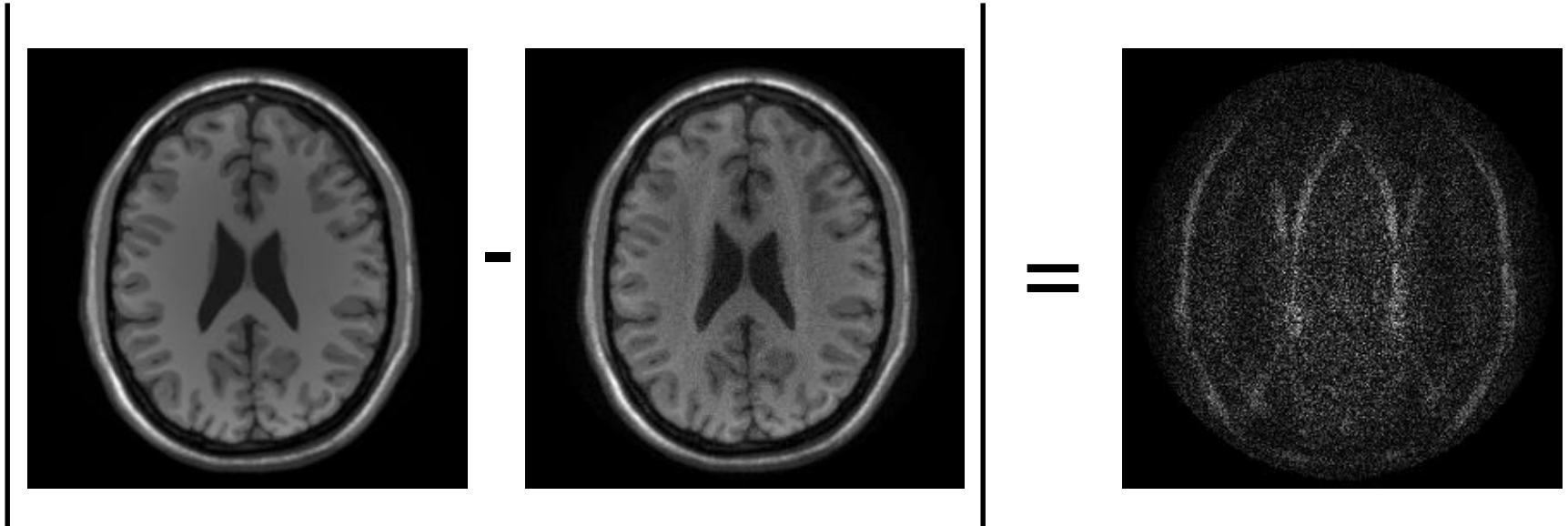
- Target profile:  $\sqrt{\sum_{j=1}^{N_c} |s_j(x, y)|^2}$

- Same shading profile as a square-root sum-of-squares reconstruction.

- Take any relative channel combination maps,  $c_j(x, y)$  and apply the following correction:

$$\hat{c}_j(x, y) = \frac{c_j(x, y)}{\sqrt{\sum_{j'=1}^{N_c} |c_{j'}(x, y)|^2}}$$

# Image Quality



~~Shading?~~

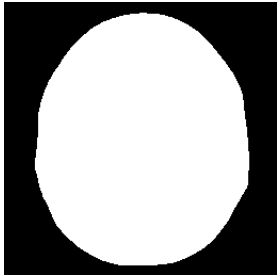
Aliasing?

Noise?



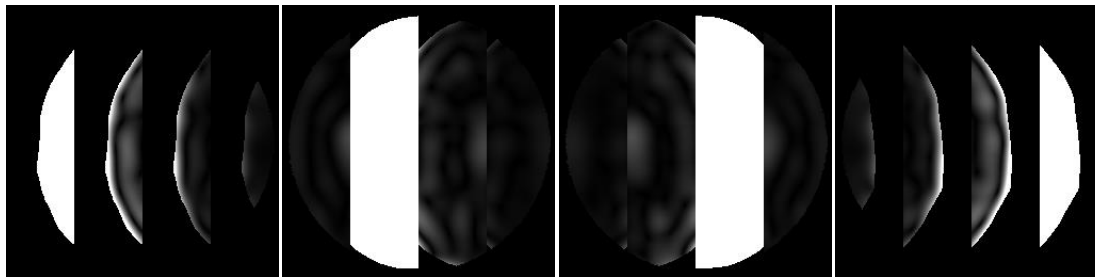
# Aliasing Energy

pixel mask



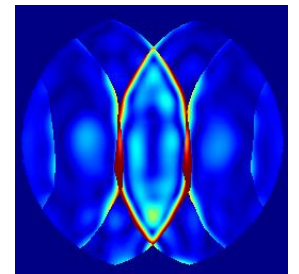
acceleration = 4

test signals



Signal spread

$\sqrt{\text{aliasing energy}}$



# Coil Sensitivity Estimation

Magnetic Resonance in Medicine 43:682–690 (2000)

## **Adaptive Reconstruction of Phased Array MR Imagery**

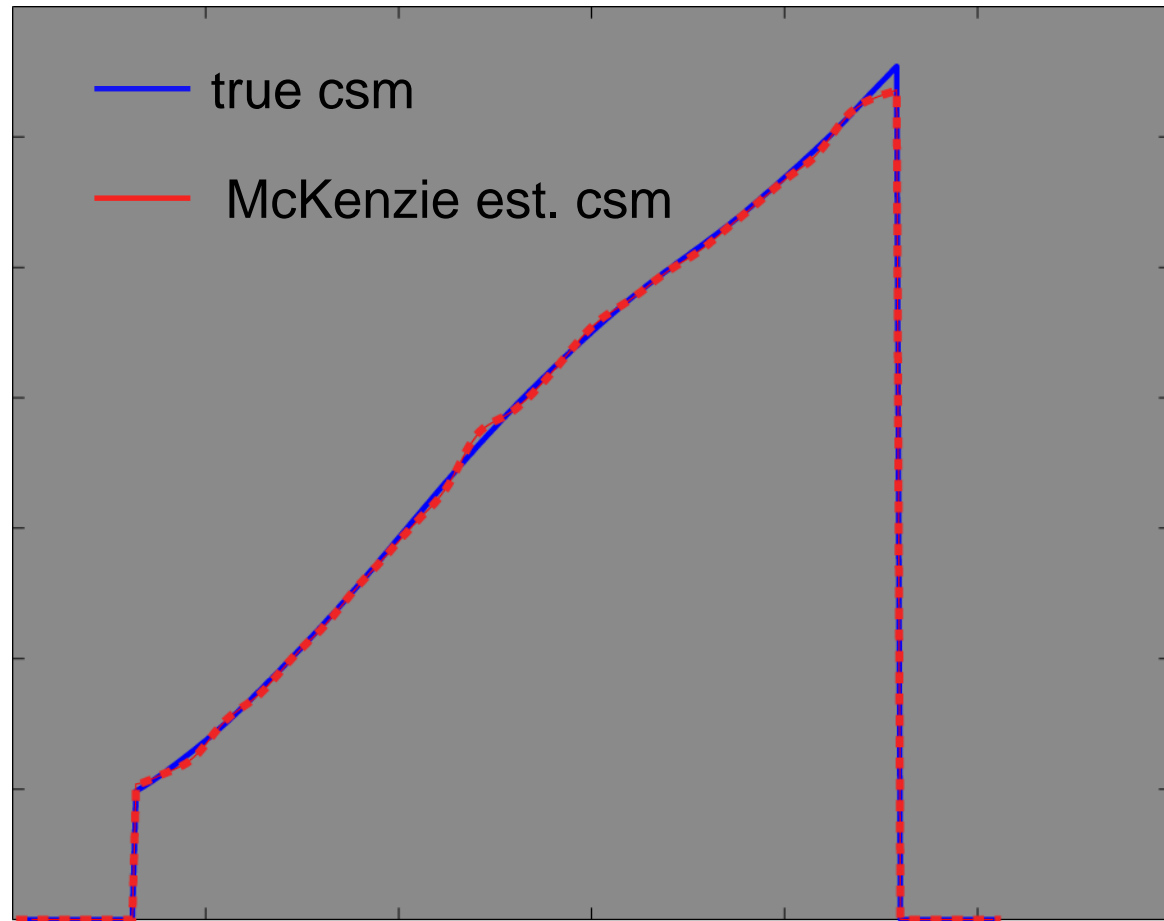
David O. Walsh,<sup>1</sup> Arthur F. Gmitro,<sup>2\*</sup> and Michael W. Marcellin<sup>3</sup>

Magnetic Resonance in Medicine 47:529–538 (2002)  
DOI 10.1002/mrm.10087

## **Self-Calibrating Parallel Imaging With Automatic Coil Sensitivity Extraction**

Charles A. McKenzie,<sup>1\*</sup> Ernest N. Yeh,<sup>2</sup> Michael A. Ohliger,<sup>2</sup>  
Mark D. Price,<sup>2</sup> and Daniel K. Sodickson<sup>1,2</sup>

# Coil Sensitivity Estimation



# Local Kernel Calibration

Magnetic Resonance in Medicine 47:1202–1210 (2002)

## Generalized Autocalibrating Partially Parallel Acquisitions (GRAPPA)

Mark A. Griswold,<sup>1\*</sup> Peter M. Jakob,<sup>1</sup> Robin M. Heidemann,<sup>1</sup> Mathias Nittka,<sup>2</sup> Vladimir Jellus,<sup>2</sup> Jianmin Wang,<sup>2</sup> Berthold Kiefer,<sup>2</sup> and Axel Haase<sup>1</sup>

$$\text{“Data Driven” } w = (D_S^H D_S)^{-1} D_S^H d_t$$

Magnetic Resonance in Medicine 53:1383–1392 (2005)

## 3Parallel Magnetic Resonance Imaging with Adaptive Radius in $k$ -Space (PARS): Constrained Image Reconstruction using $k$ -Space Locality in Radiofrequency Coil Encoded Data

Ernest N. Yeh,<sup>1,2</sup> Charles A. McKenzie,<sup>2</sup> Michael A. Ohliger,<sup>1,2</sup> and Daniel K. Sodickson<sup>1,2,3\*</sup>

$$\text{“Model Driven” } w = (E_S^H E_S)^{-1} E_S^H e_t$$

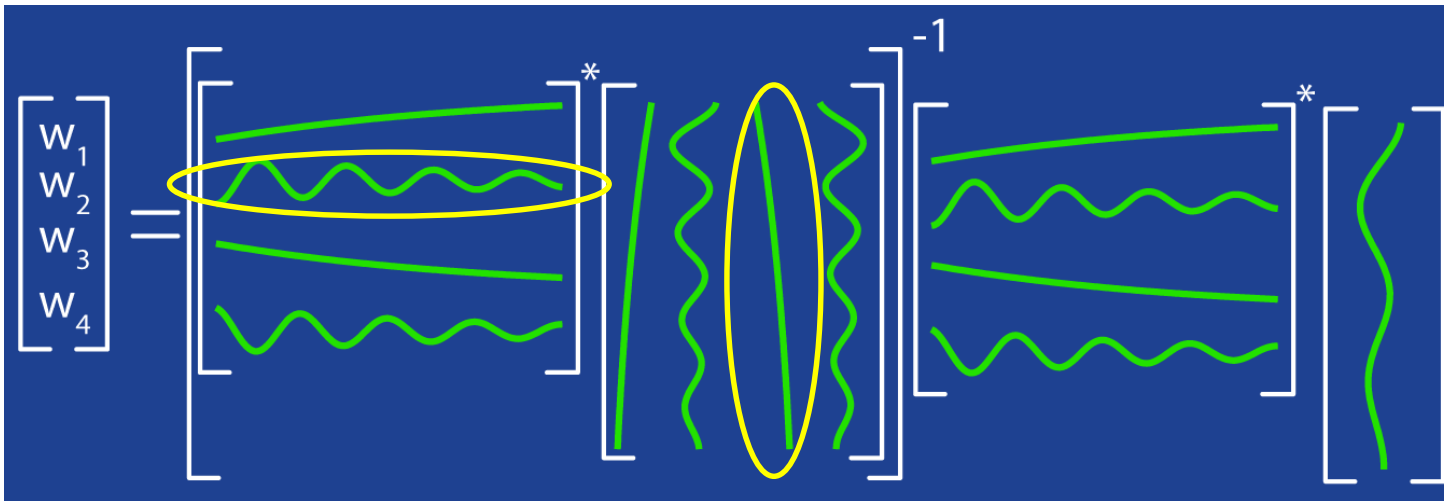
# Joint Encoding Relations

A Method for Autocalibrating 2-D Accelerated Volumetric Parallel Imaging with Clinically Practical Reconstruction Times

P. J. Beatty<sup>1</sup>, A. C. Brau<sup>1</sup>, S. Chang<sup>2</sup>, S. M. Joshi<sup>2</sup>, C. R. Michelich<sup>2</sup>, E. Bayram<sup>2</sup>, T. E. Nelson<sup>3</sup>, R. J. Herfkens<sup>3</sup>, and J. H. Brittain<sup>4</sup>

Proc. Intl. Soc. Mag. Reson. Med. 15 (2007)

1749



$\langle e_1, e_2 \rangle$

# Joint Encoding Relations – Lookup Table

Encoding  
location

$j, k_x, k_y$



Encoding location  $j, k_x, k_y$

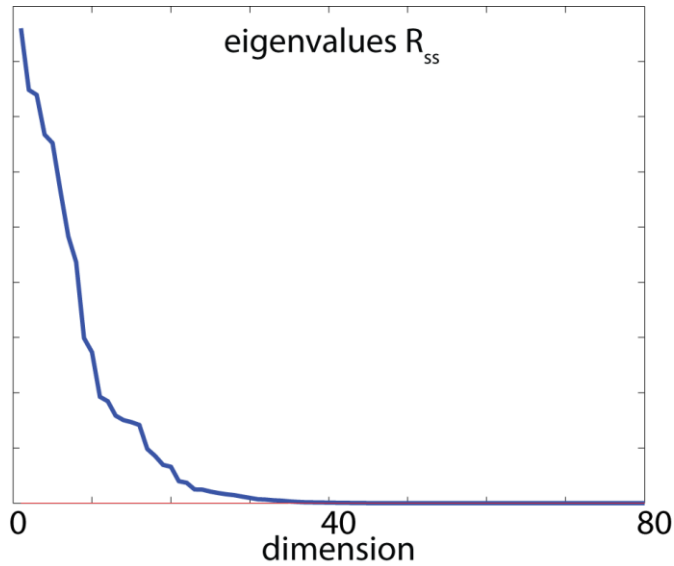


# Joint Encoding Relations & Toolbox

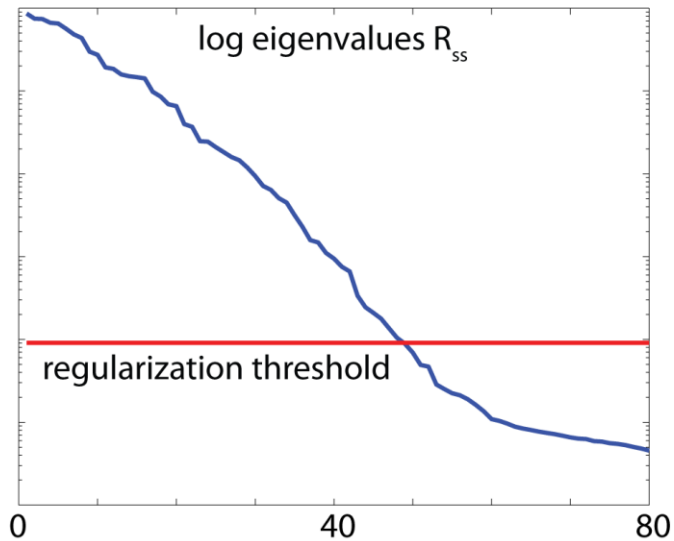
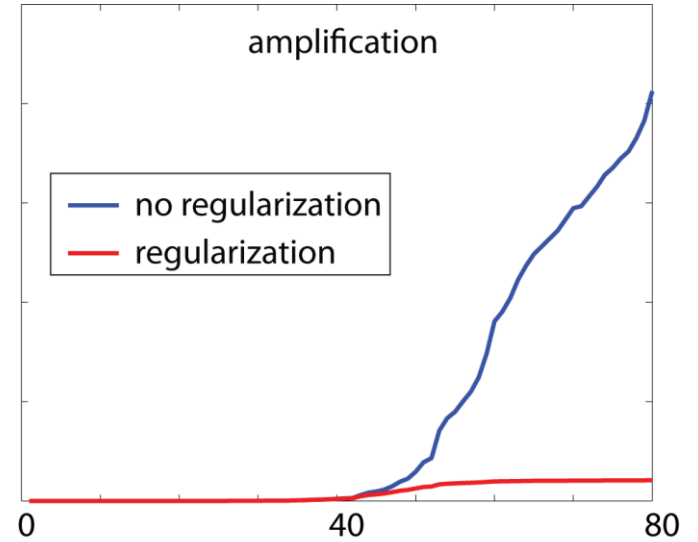
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- Image space GRAPPA
  - `ismrm_compute_jer_data_driven(...)`
  - `ismrm_calculate_jer_unmixing(...)`
- Image space PARS
  - `ismrm_compute_jer_model_driven(...)`
  - `ismrm_calculate_jer_unmixing(...)`

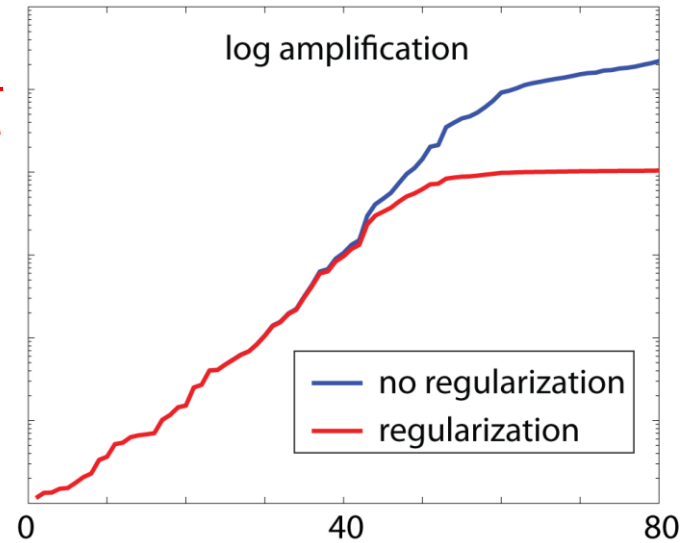
# Tychonov Regularization



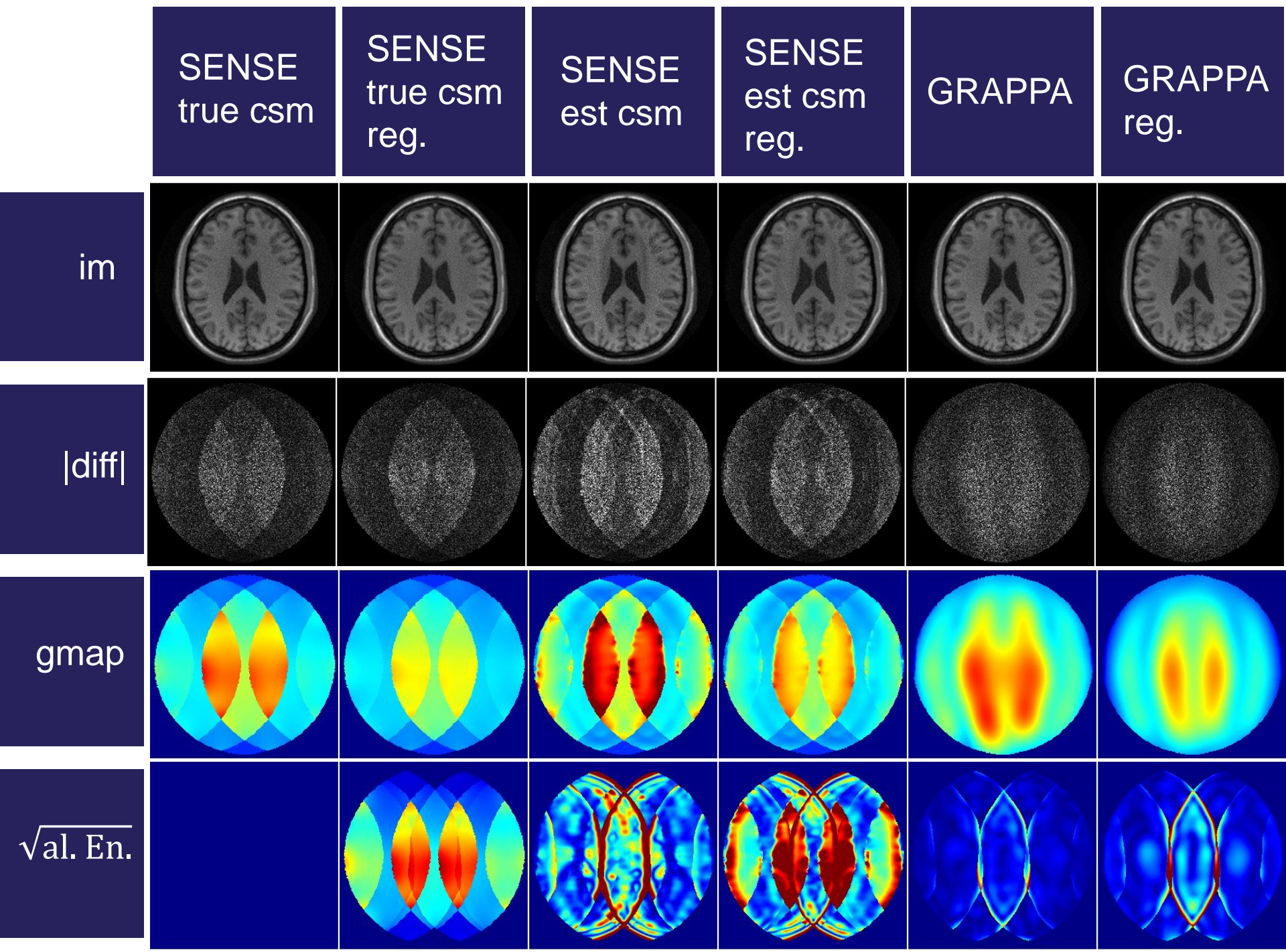
$\frac{1}{\text{eigenvalue}}$



$\frac{1}{\lambda + \text{eigenvalue}}$





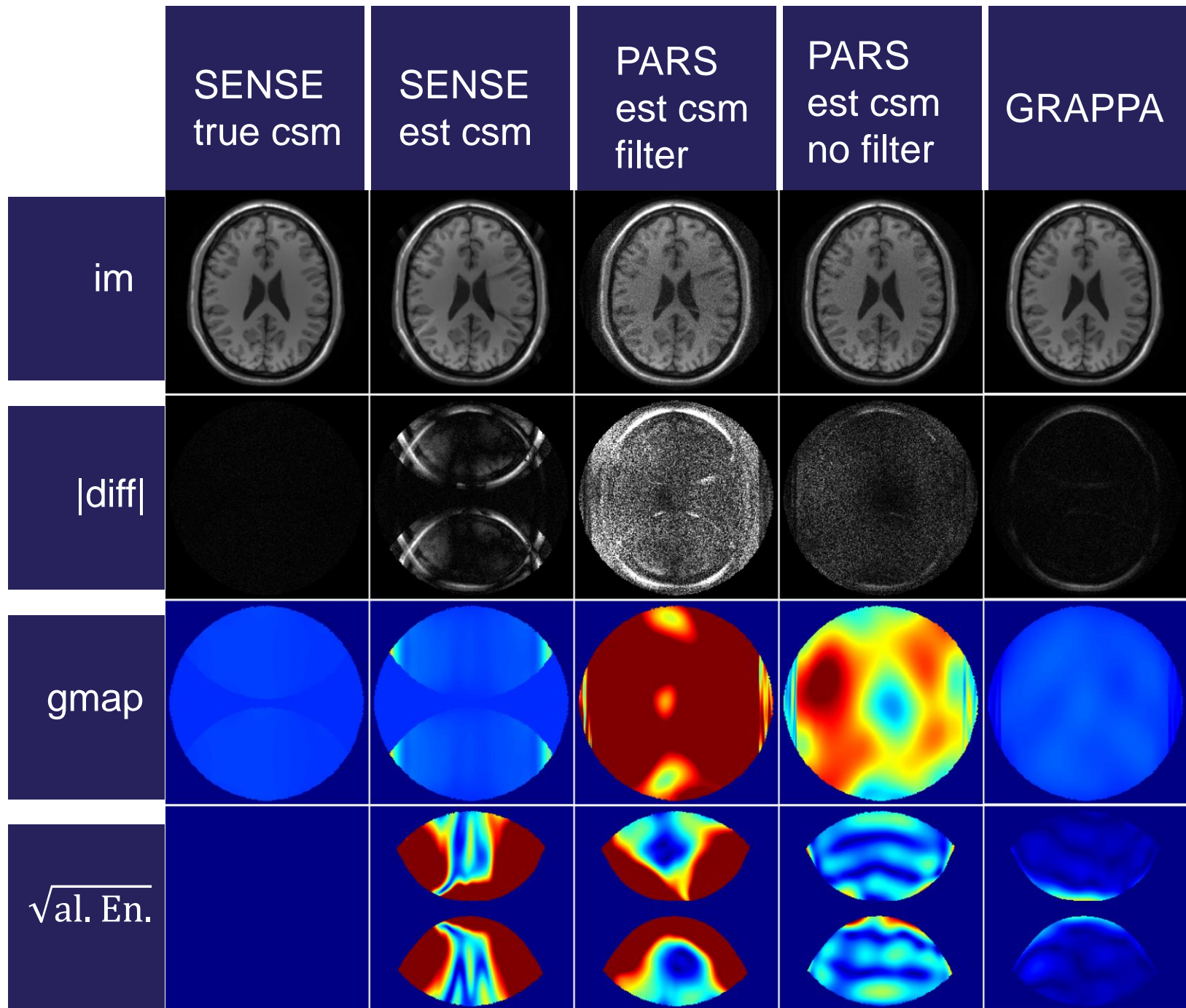


# Minimal Calibration Data

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- In some cases, collecting 32(+) lines of k-space for calibration is not feasible, or drastically reduces net acceleration. e.g. PROPELLER
- Challenging to estimate sensitivity maps:
  - Cal data is a low resolution image of the magnetization-weighted sensitivities:  $[m(r)s_j(r)] * \text{psf}(r)$
  - Even if sensitivities are low resolution, separating the sensitivity function is an approximation that can lead to aliasing artifacts.

$$[m(r) * \text{psf}(r)]s_j(r)$$





# Reduced FOV case

Magnetic Resonance in Medicine 52:1118–1126 (2004)

## Field-of-View Limitations in Parallel Imaging

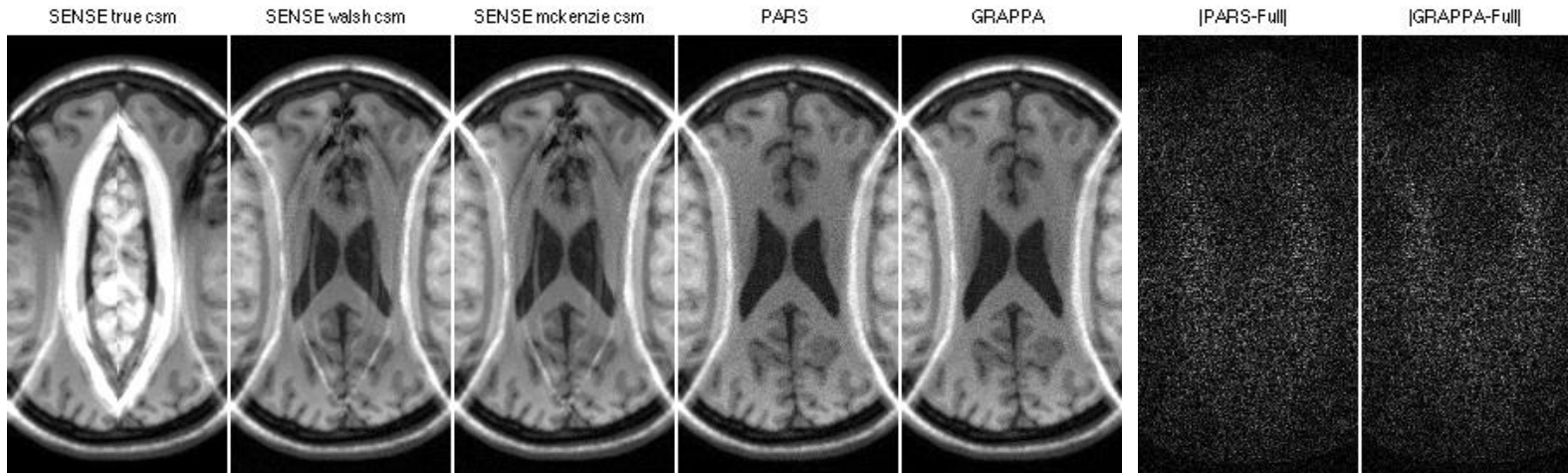
Mark A. Griswold,<sup>1\*</sup> Stephan Kannengiesser,<sup>2</sup> Robin M. Heidemann,<sup>1</sup> Jianmin Wang,<sup>2</sup> and Peter M. Jakob<sup>1</sup>

## Understanding the GRAPPA Paradox

P. J. Beatty<sup>1,2</sup>, A. C. Brau<sup>1</sup>

Proc. Intl. Soc. Mag. Reson. Med. 14 (2006)

2467



- ismrm\_demo\_rFOV.m
- Low resolution unaliasing kernels; coil sensitivities with discontinuities
- Calibration approach impacts image quality

# Summary

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- Divide reconstruction components into separate components
  - Calibration approach impacts image quality
  - Data synthesis approach impacts reconstruction efficiency
  - Mix and match components to get desired behavior
- Tradeoffs between efficiency, artifacts and noise
  - Match operating point to target application
- Use tools to help separate shading, aliasing and noise degradation