

Nuts & Bolts of Advanced Imaging

Image Reconstruction – Parallel Imaging

Michael S. Hansen, PhD

Magnetic Resonance Technology Program

National Institutes of Health, NHLBI



Declaration of Financial Interests or Relationships

Speaker Name: Michael S. Hansen

I have no financial interests or relationships to disclose with regard to the subject matter of this presentation.

Outline

- Noise correlation
- SNR scaled reconstruction
 - Obtaining images in SNR units
- Pseudo Replica Method
 - Determining the SNR (and g-map) for any parallel imaging reconstruction
- Iterative methods
 - Non-Cartesian Parallel Imaging
- Regularization in Iterative Methods

Noise in Parallel Imaging

Idealized Experiment:

$$\mathbf{s} = \mathbf{E}\boldsymbol{\rho}$$

In practice, we are affected by noise

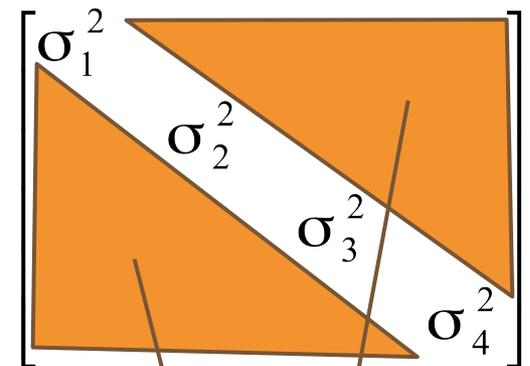
$$\mathbf{s} = \mathbf{E}\boldsymbol{\rho} + \boldsymbol{\eta}$$

We can measure this noise covariance:

```
% Matlab  
% eta:[Ncoils, Nsamples]  
Psi = (1/(Nsamples-1))*(eta * eta');
```

Noise covariance matrix

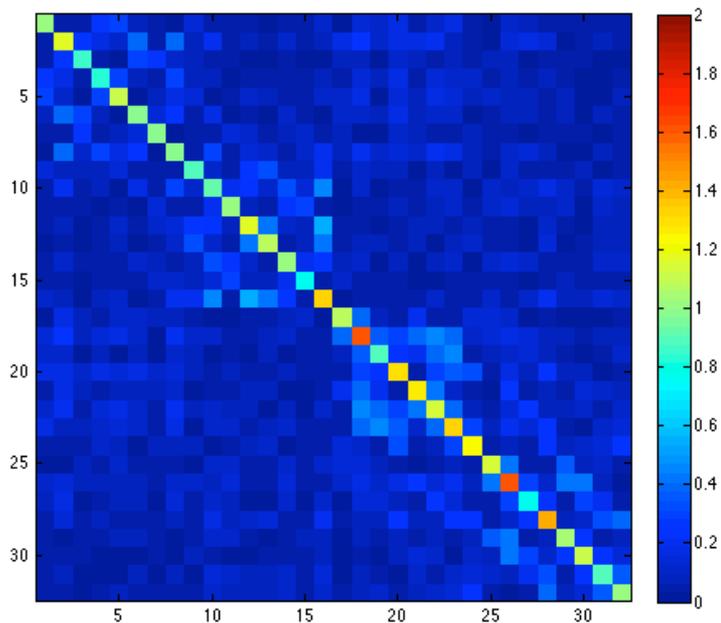
$$\Psi_{\gamma, \gamma'} = \langle \eta_{\gamma}, \eta_{\gamma'} \rangle$$



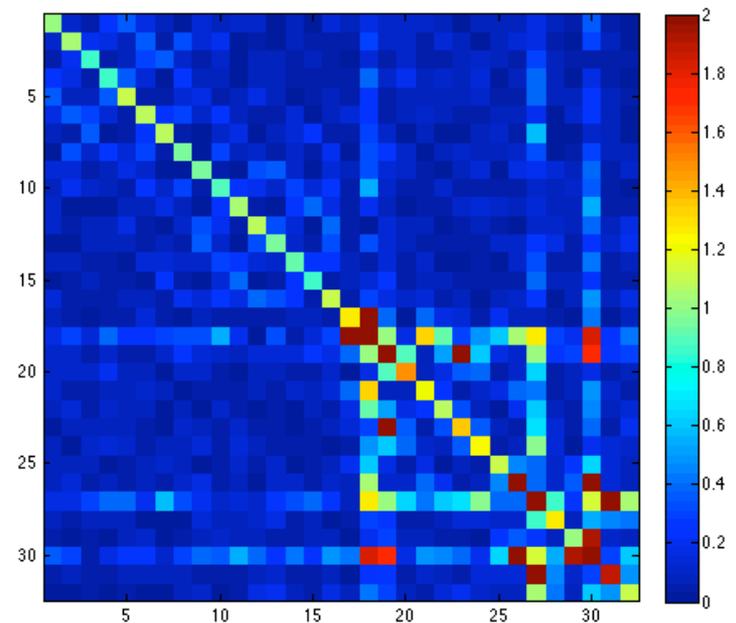
Noise correlation

Psi Examples – 32 Channel Coil

“Normal Coil”



“Broken Coil”



Examination of the noise covariance matrix is an important QA tool. Reveals broken elements, faulty pre-amps, etc.

Noise Pre-Whitening

Solving Linear Equations:

$$\mathbf{Ax} + \boldsymbol{\eta} = \mathbf{b} = \begin{bmatrix} c_1 & c_2 \\ c_3 & c_4 \\ c_5 & c_6 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} X_1 \\ X_2 \\ X_3 \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix}$$

X_i : Random value with zero mean ($\mu = 0$) and variance σ_i^2

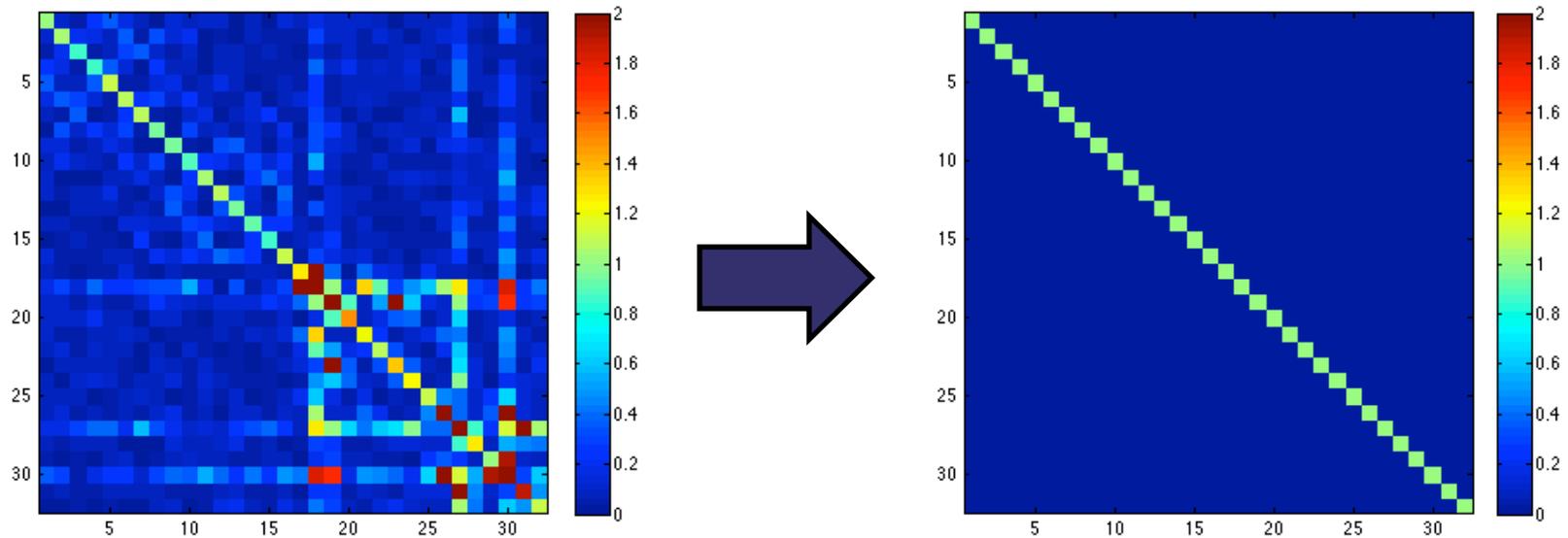
Suppose you know that:

$$\sigma_3^2 = 5\sigma_1^2 = 5\sigma_2^2$$

Put less weight on this equation

Noise Pre-Whitening

We would like to apply an operation such that we have unit variance in all channels:



Noise Pre-Whitening

More generally, we want to weight the equations with the “inverse square root” of the noise covariance, if

$$\Psi = \mathbf{L}\mathbf{L}^H$$

We will solve:

$$\mathbf{L}^{-1}\mathbf{A}\mathbf{x} = \mathbf{L}^{-1}\mathbf{b}$$

Or:

$$\mathbf{x} = \left(\mathbf{A}^H\Psi^{-1}\mathbf{A}\right)^{-1}\mathbf{A}^H\Psi^{-1}\mathbf{b}$$

In practice, we simply generate “pre-whitened” input data before recon

Noise Pre-Whitening

Matlab:

```
%eta [Ncoils,Nsamples]
%psi [Ncoils,Ncoils]
%data [Ncoils,Nsamples]
%csm : Coil sensitivity map

psi = (1/(Nsamples-1))*(eta * eta');

L = chol(psi,'lower');
L_inv = inv(L);

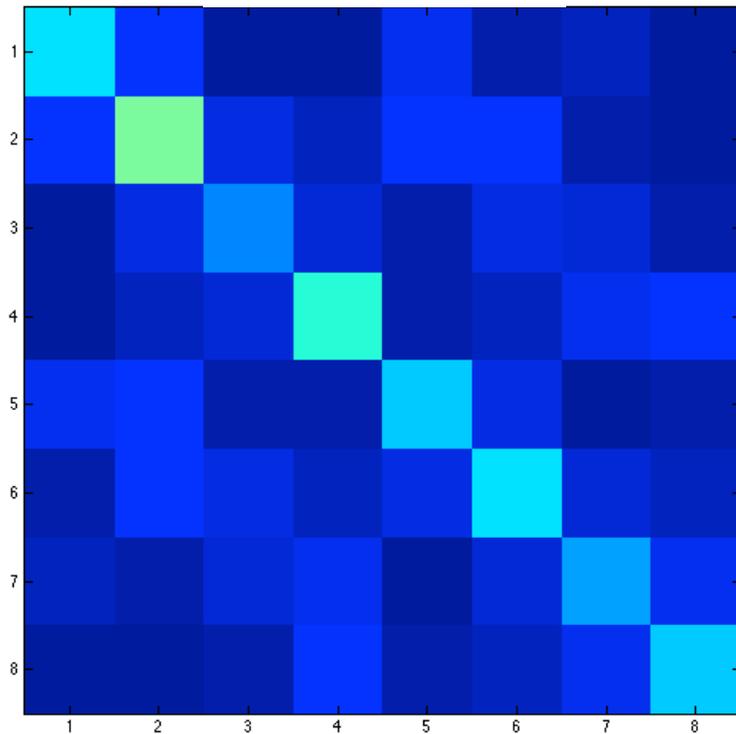
data = L_inv * data;
csm = L_inv * csm;

%Now noise is "white"
%Reshape data and do recon
```

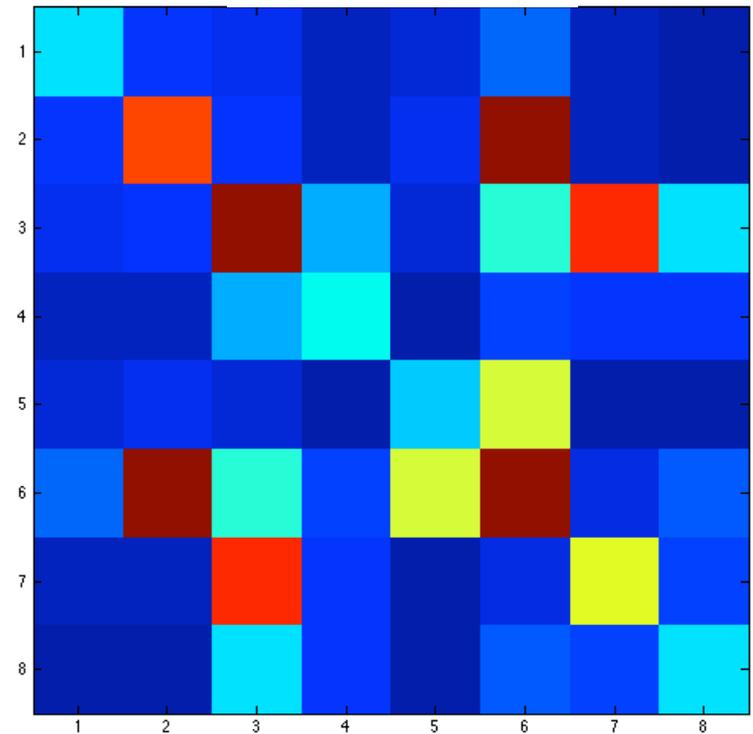
Noise covariance matrix

Example with test dataset

“Normal Coil”

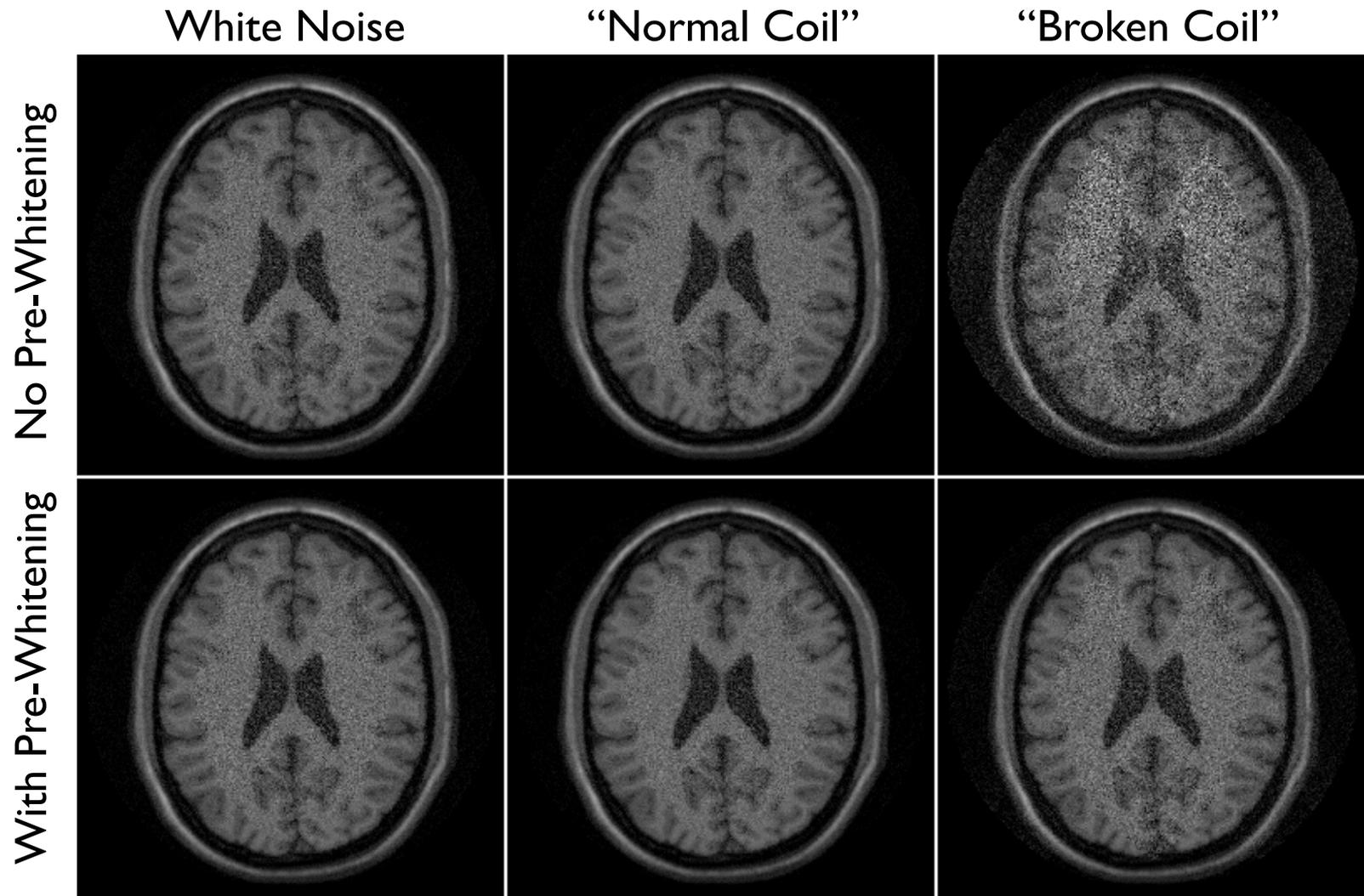


“Broken Coil”



At least two broken pre-amps

Noise Pre-Whitening – SENSE Example

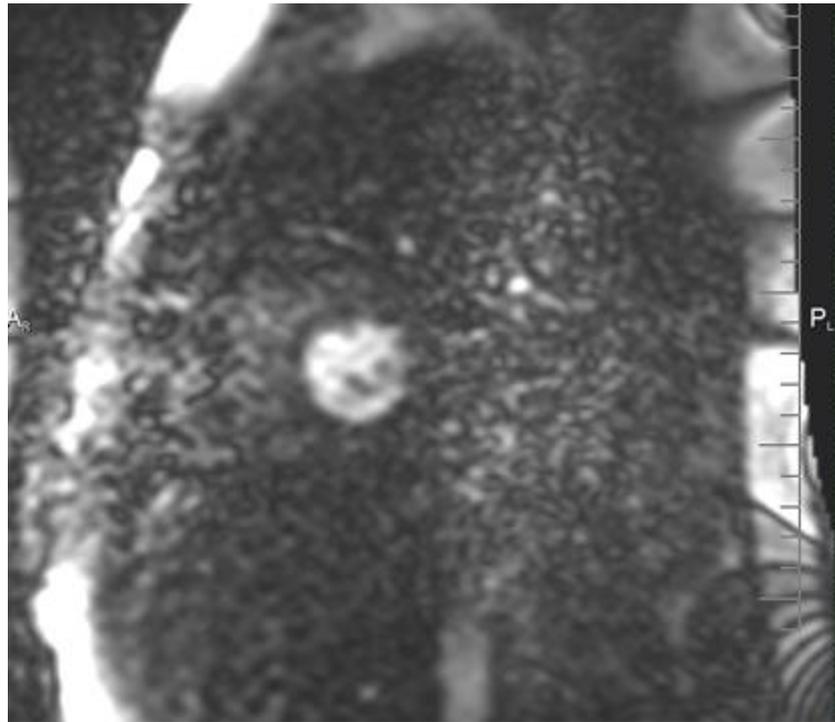


ismrm_demo_noise_decorrelation.m

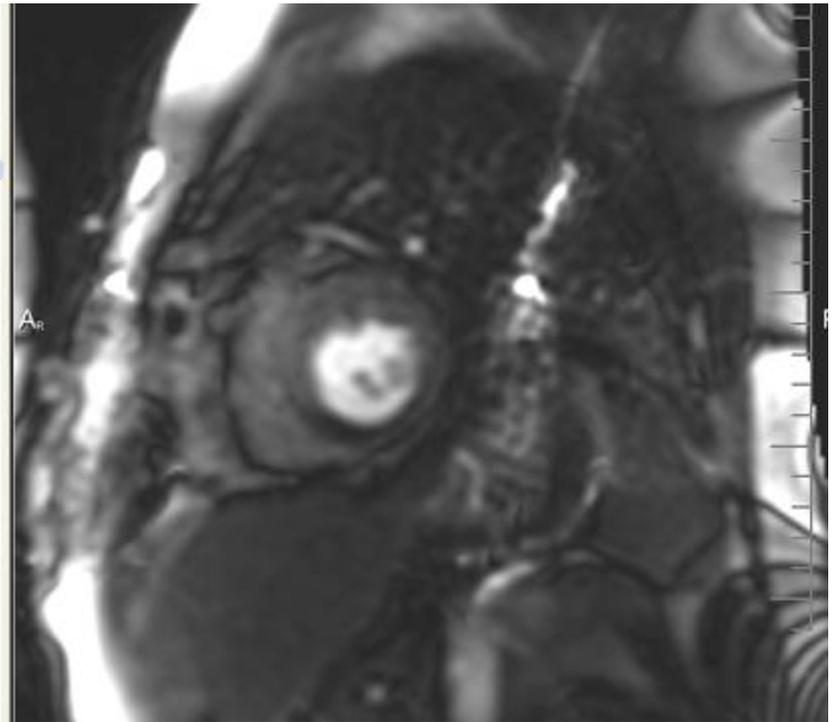
Noise Pre-Whitening – In vivo example

In vivo stress perfusion case where broken coil element resulted in non-diagnostic images.

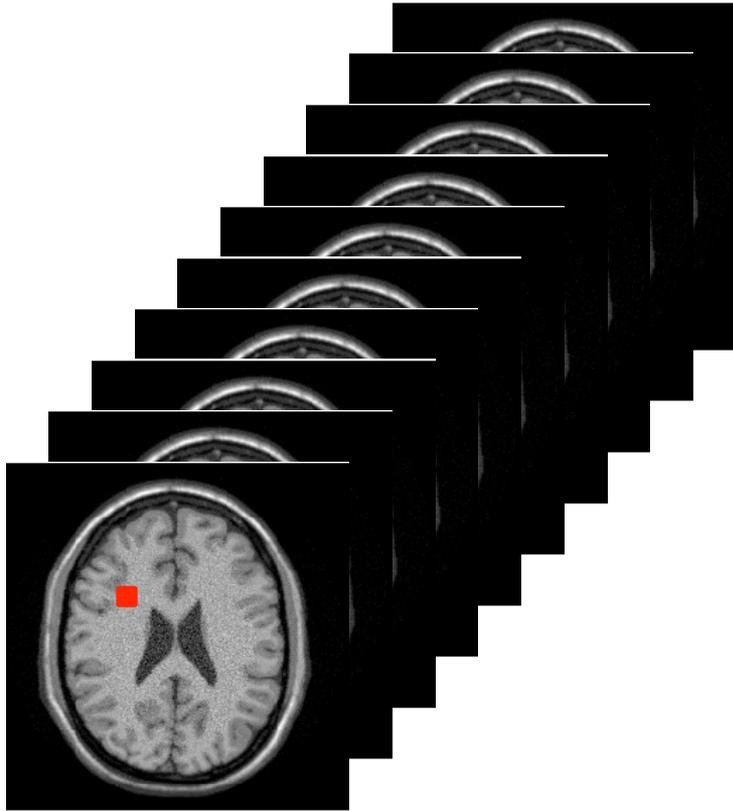
Without pre-whitening



With pre-whitening



Signal to Noise Ratio (Definitions)



Intuitively, SNR is measured by repeating the experiment.

Signal level is the mean signal over multiple experiments.

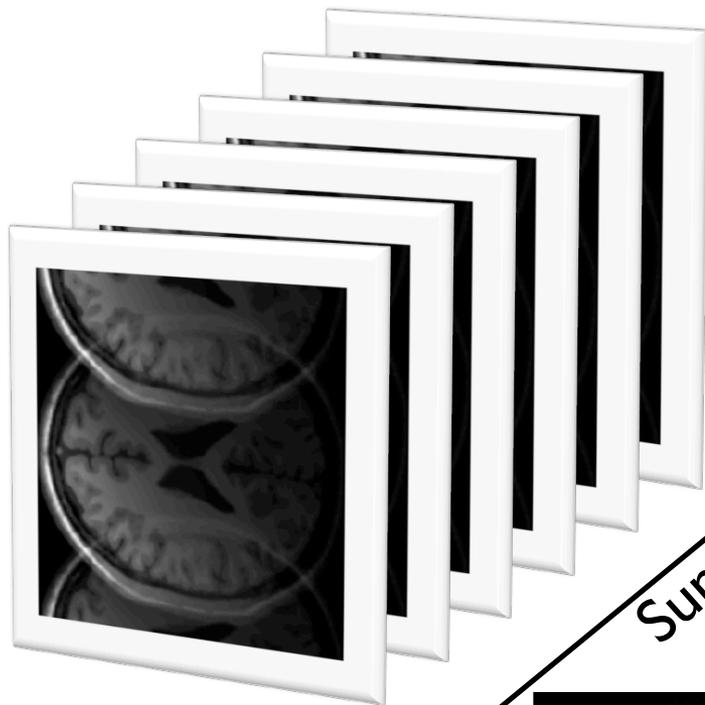
Noise level is the standard deviation over multiple experiments

Such experiments are hard to perform in practice.

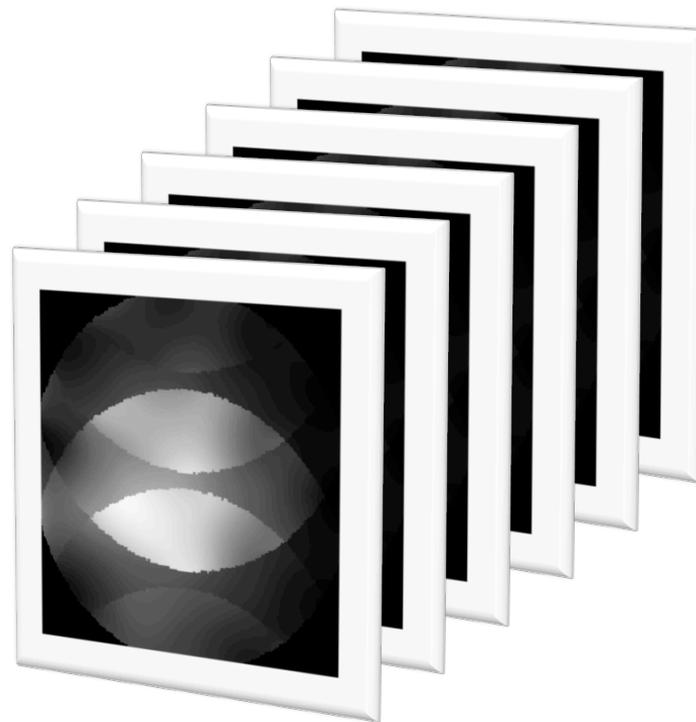
$$SNR(x, y) = \frac{S(x, y)}{\sigma(x, y)}$$

SENSE – Image Synthesis with Unmixing Coefficients

Aliased coil images

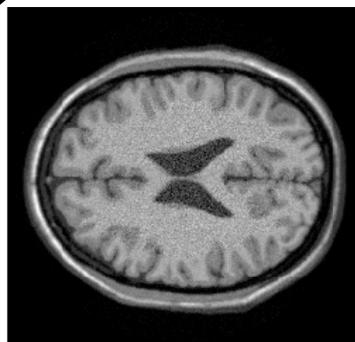


Unmixing Coefficients



\cdot $*$

Sum

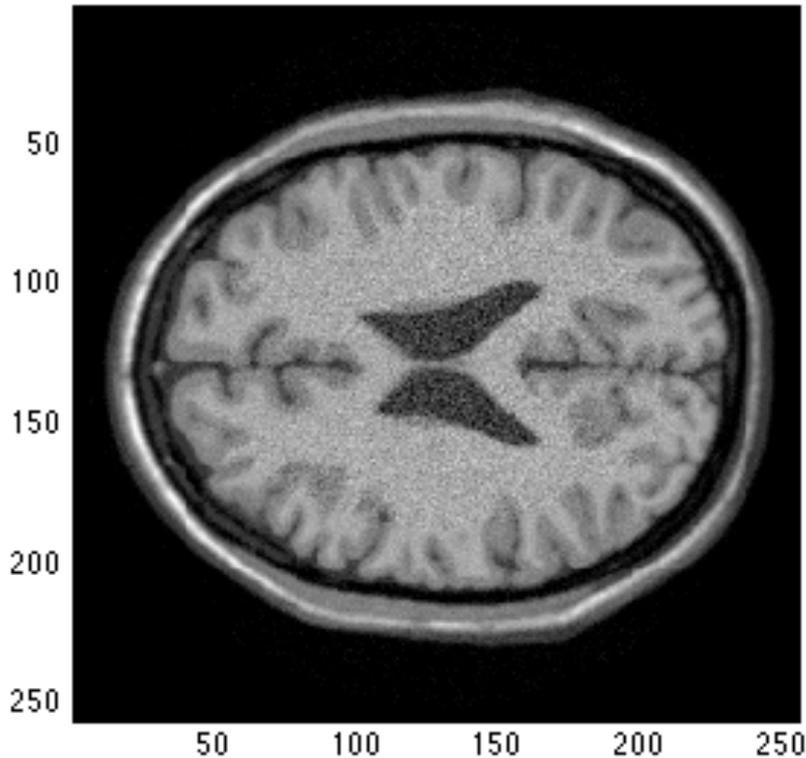


SENSE – Simple Rate 4 Example

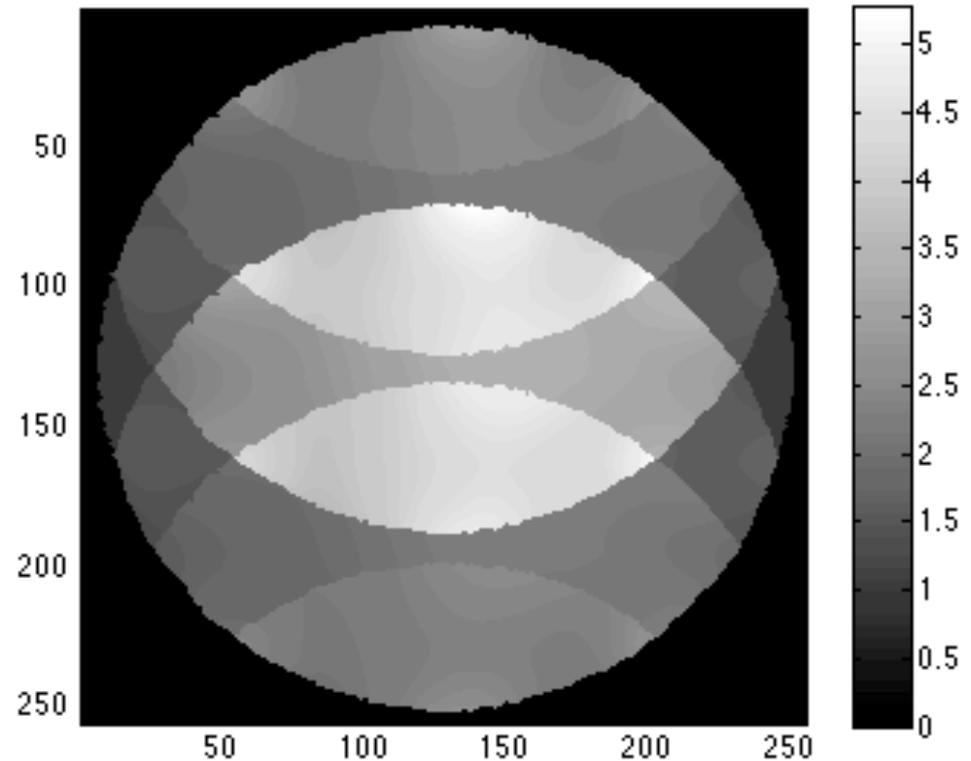
$$\tilde{\rho}(x_1) = \sum_{i=0}^{N_c} u_i a_i$$

$$g(x_1) = \sqrt{\sum_{i=0}^{N_c} |u_i|^2} \sqrt{\sum_{i=0}^{N_c} |S_i|^2}$$

SENSE

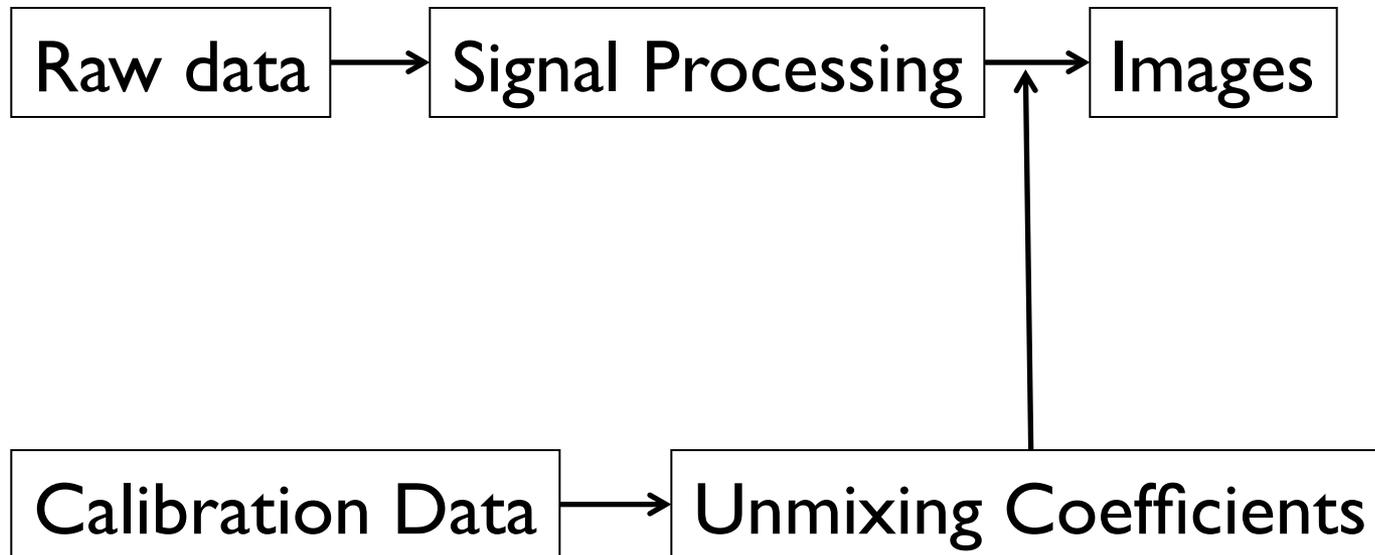


SENSE g-factor



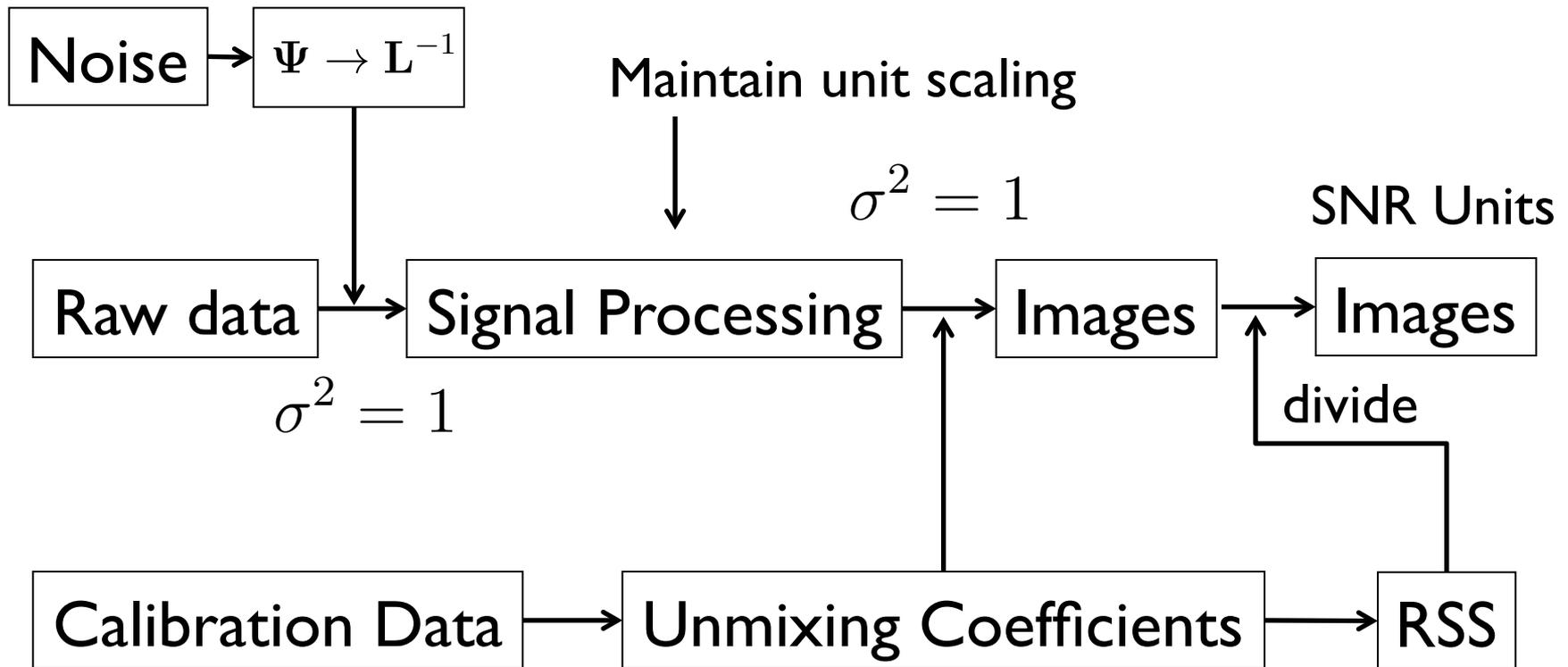
Reconstruction in SNR Units

Reconstruction Pipeline



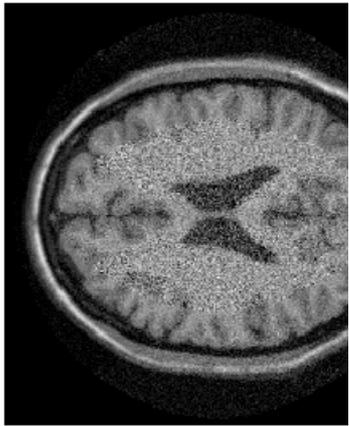
Reconstruction in SNR Units

Reconstruction Pipeline

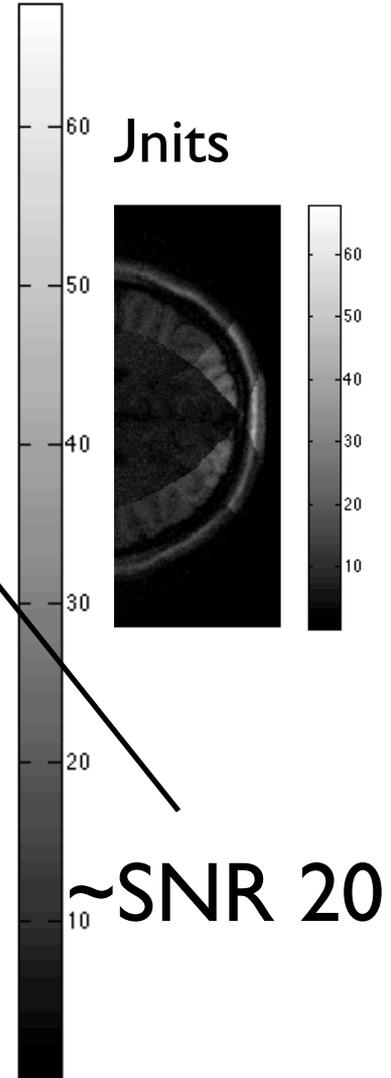
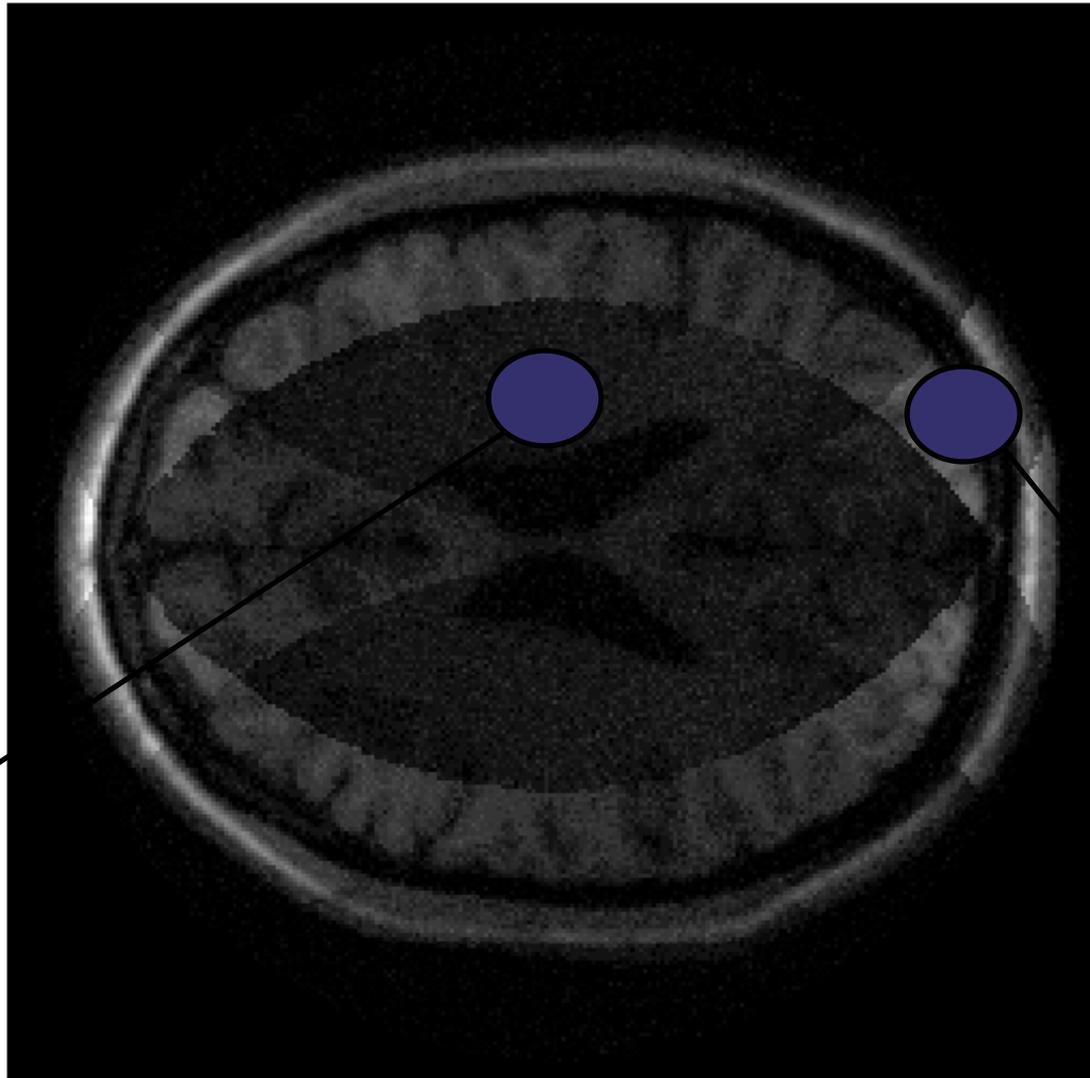


Reconstruction in SNR Units

Reconstruct



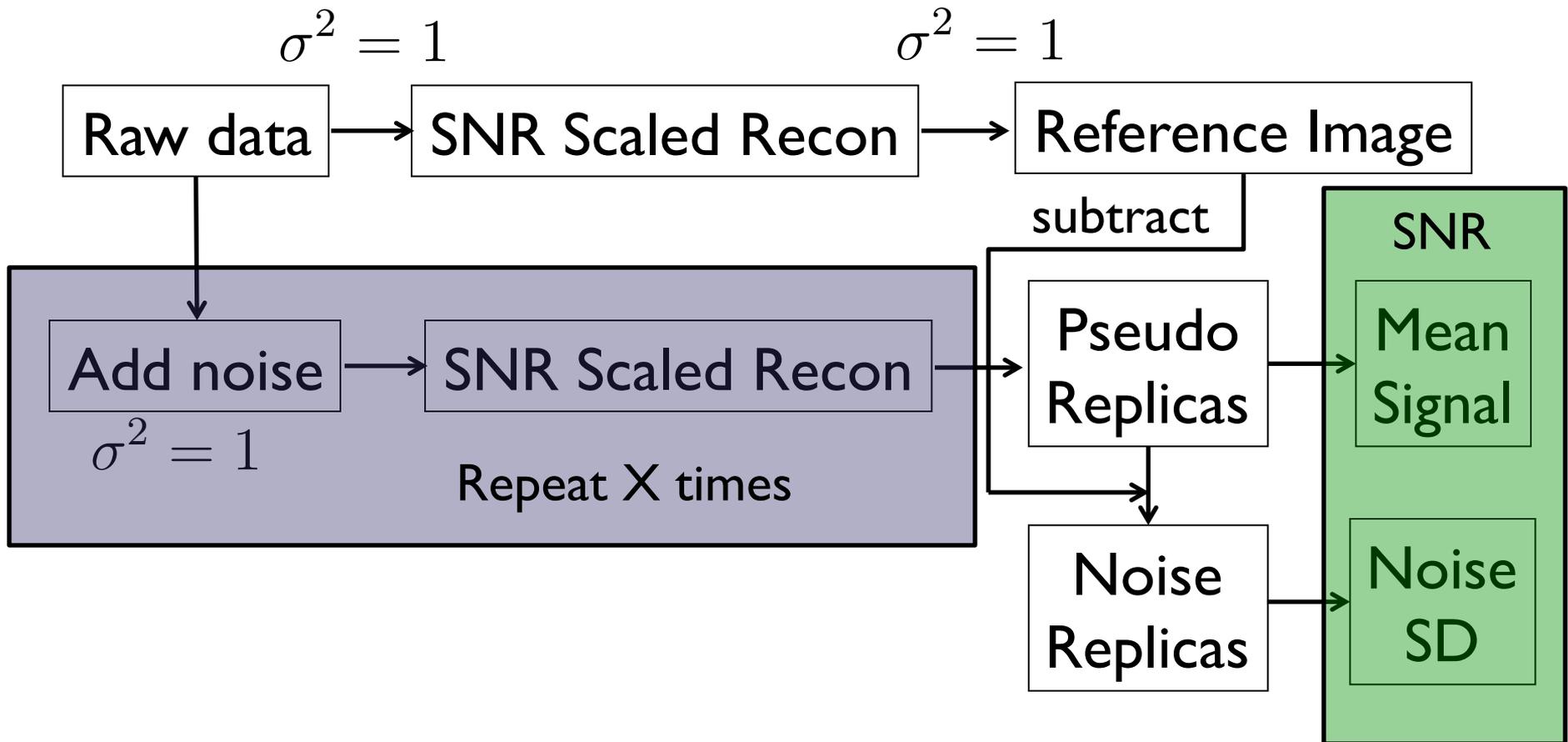
~SNR 8



~SNR 20

Pseudo-Replica Method

What if unmixing coefficients are never explicitly formed:



`ismrm_pseudo_replica.m`

Pseudo-Replica Method – Example 256 trials

SENSE R4

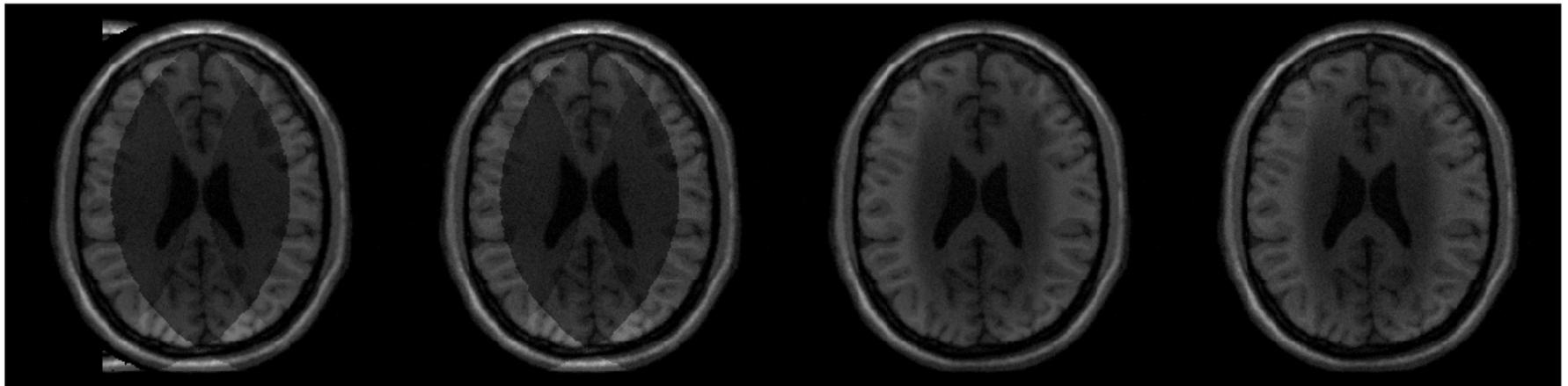
GRAPPA R4

SNR UNMIX

SNR PSEUDO

SNR UNMIX

SNR PSEUDO

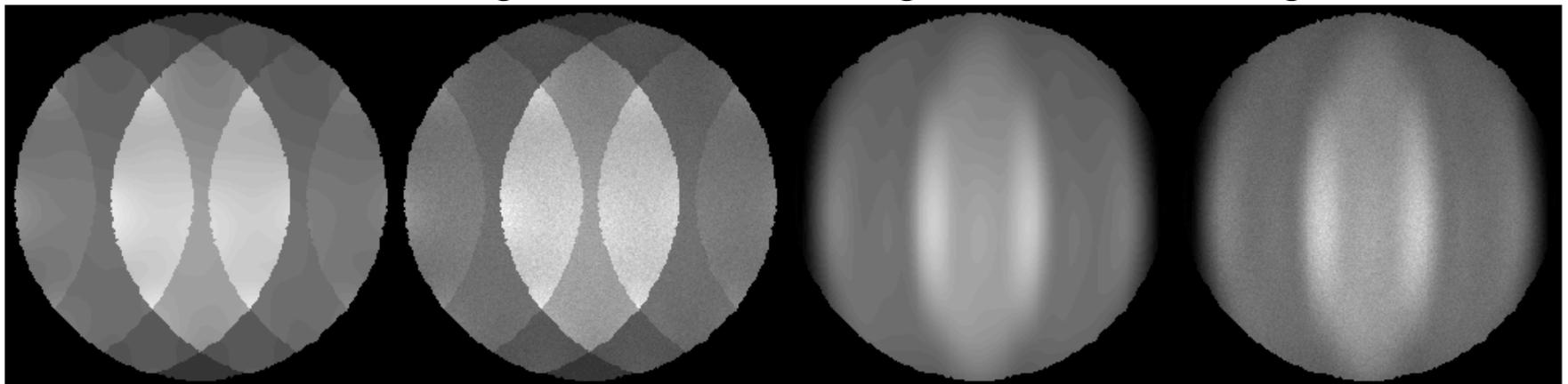


g UNMIX

g PSEUDO

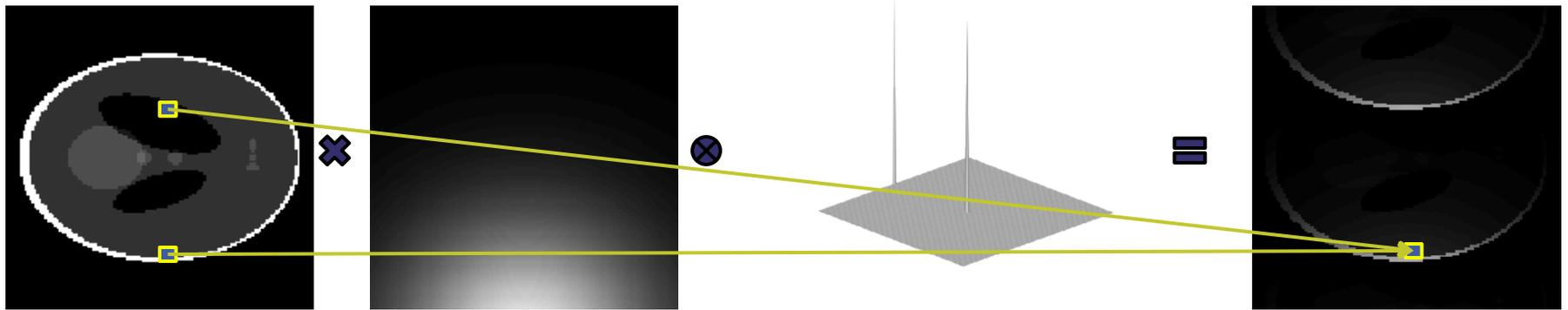
g UNMIX

g PSEUDO

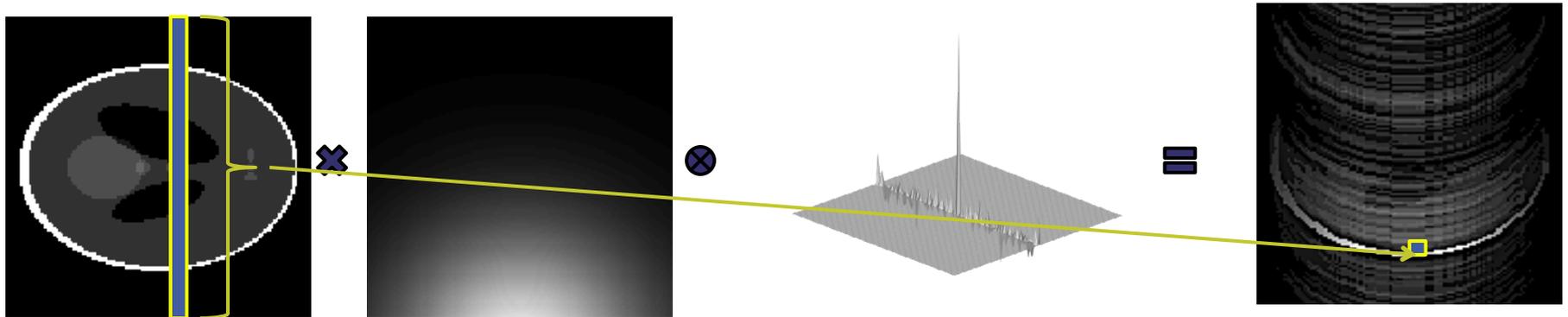


Advantage of Cartesian Undersampling

Cartesian Undersampling



“Random” Undersampling



Non-Cartesian Parallel MRI

To solve the general non-Cartesian case, we return to the original problem:

$$\mathbf{s} = \mathbf{E}\boldsymbol{\rho} \quad \tilde{\boldsymbol{\rho}} = \arg \min_{\boldsymbol{\rho}} \{ \|\mathbf{E}\boldsymbol{\rho} - \mathbf{s}\|_2 \}$$

It is not practical to solve with direct inversion in general.

But we can use a number of different iterative solvers to arrive at the solution

- Conjugate Gradients
- LSQR (Matlab)

```
>> help lsqr
lsqr  lsqr Method.
  X = lsqr(A,B) attempts to solve the system of linear equations A*X=B
  for X if A is consistent, otherwise it attempts to solve the least
  squares solution X that minimizes norm(B-A*X)...

  X = lsqr(AFUN,B) accepts a function handle AFUN instead of the matrix A.
  AFUN(X,'notransp') accepts a vector input X and returns the
  matrix-vector product A*X while AFUN(X,'transp') returns A'*X. In all
  of the following syntaxes, you can replace A by AFUN...
```

Iterative SENSE – First Cartesian

To use LSQR (or Conjugate Gradients), we “just” need to be able to write a function that does the multiplication with E and E^H :

Let’s first look at a simple Cartesian case

Multiplication with E^H

```
rho = zeros(size(csm)); %csm: coil sensitivities
%sampling_mask: 1 where sampled, zero where not
rho(repmat(sampling_mask,[1 1 size(csm,3)]) == 1) = s(:);
rho = ismrm_transform_kspace_to_image(rho,[1,2]);
rho = sum(conj(csm) .* rho,3);
```

Multiplication with E

```
s = repmat(reshape(rho,size(csm,1),size(csm,2)), [1 1 size(csm,3)]) .* csm;
s = ismrm_transform_image_to_kspace(s, [1,2]);
s= s(repmat(sampling_mask,[1 1 size(csm,3)]) == 1);
```

Iterative SENSE

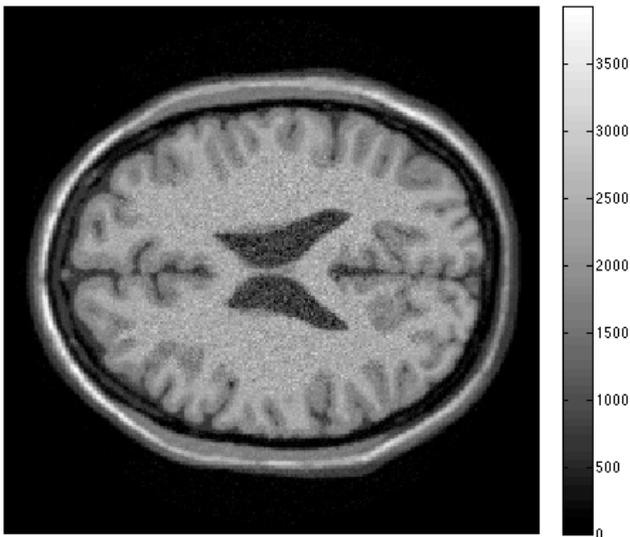
If we have the multiplication with E and E^H implemented as a Matlab function:

```
function o = e_cartesian_SENSE(inp, csm, sp, transpose_indicator)
% sp: sampling pattern
% csm: coil sensitivities
```

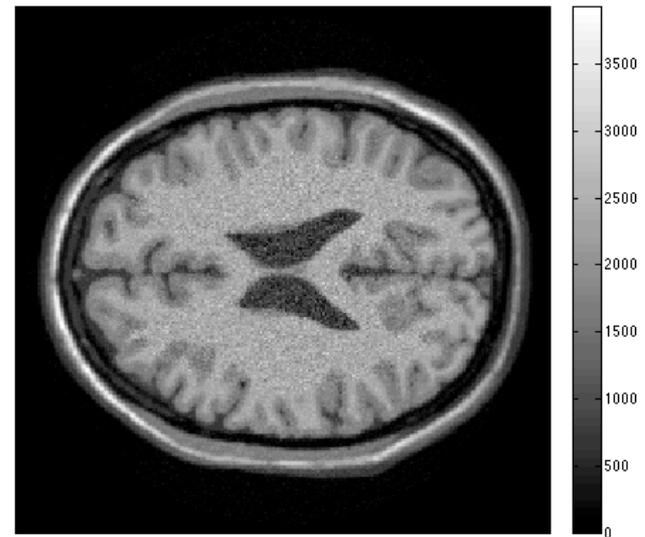
Iterative SENSE could be implemented as:

```
% s: vector of acquired data
E = @(x,tr) e_cartesian_SENSE(x,csm,(sp > 0),tr);
img = lsqr(E, s, 1e-5,50);
img = reshape(img,size(csm,1),size(csm,2));
```

Cartesian SENSE



Iterative SENSE



Quick note on the non-uniform FFT

To implement multiplication with E and E^H in the non-Cartesian case, we need to do the non-uniform Fourier transform^{1,2}.

In this course, we will use Jeff Fessler's “nufft” package. We recommend you download the latest version from:

<http://web.eecs.umich.edu/~fessler/irt/fessler.tgz>

```
%k: k-space coordinates [Nsamples, 2], range -pi:pi
%w: Density compensation weights
%s: Data

%Prepare NUFFT
N = [256 256]; %Matrix size
J = [5 5];    %Kernel size
K = N*2;     %Oversampled Matrix size
nufft_st = nufft_init(k,N,J,K,N/2,'minmax:kb');

recon = nufft_adj(s .* repmat(w,[1 size(s,2)]),nufft_st);
```

¹Keiner, J., Kunis, S., and Potts, D. Using NUFFT 3 - a software library for various nonequispaced fast Fourier transforms. ACM Trans. Math. Software, 2009

²Fessler J and Sutton B. Nonuniform fast Fourier transforms using min-max interpolation. IEEE TSP 2003

Iterative SENSE – non-Cartesian

To use LSQR (or Conjugate Gradients), we “just” need to be able to write a function that does the multiplication with E and E^H :

Now we have the tools for the non-Cartesian case:

Multiplication with E^H

```
samples = size(nufft_st.om,1); coils = numel(s)/samples;
s = reshape(s,samples,coils);
rho = nufft_adj(s .* repmat(sqrt(w),[1 coils]),nufft_st)./sqrt(prod(nufft_st.Kd));
rho = sum(conj(csm) .* rho,3);
rho = rho(:);
```

Ensure operators are adjoint

Multiplication with E

```
s = repmat(reshape(rho,size(csm,1),size(csm,2)),[1 1 size(csm,3)]) .* csm;
s = nufft(s,nufft_st)./sqrt(prod(nufft_st.Kd));
s = s .* repmat(sqrt(w),[1 size(s,2)]);
s = s(:);
```

From nufft_init

Iterative SENSE – non-Cartesian

If we have the multiplication with E and E^H implemented as a Matlab function:

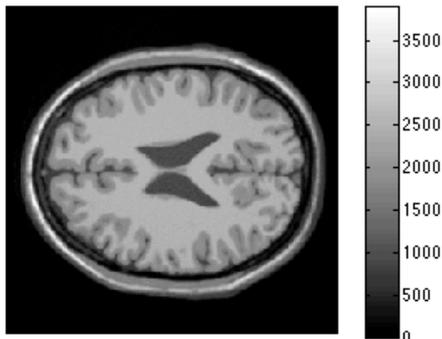
```
function o = e_non_cartesian_SENSE(inp, csm, nufft_st, w, transpose_indicator)
% nufft_st: From nufft_init
% csm: coil sensitivities, w: density compensation
```

Non-Cartesian SENSE could be implemented as:

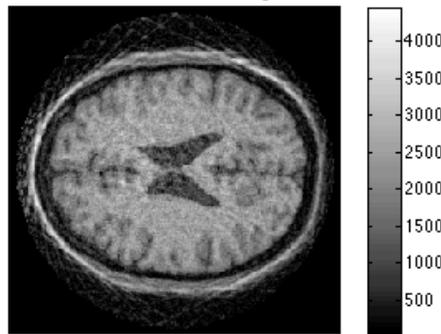
```
% s: vector of acquired data
E = @(x,tr) e_non_cartesian_SENSE(x, csm, nufft_st, w, tr);
img = lsqr(E, s .* repmat(sqrt(w),[size(csm,3),1]), 1e-3,30);
img = reshape(img,size(csm,1),size(csm,2));
```

Due to definition of E

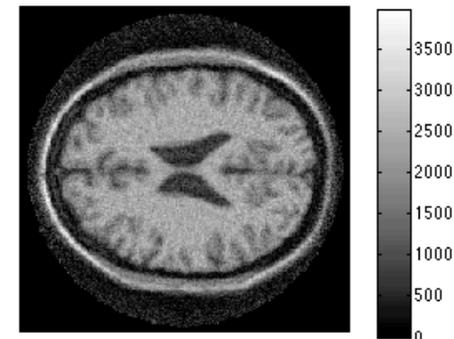
Fully sampled



24 projections
nufft only



24 projections
SENSE



Regularization – Iterative Methods

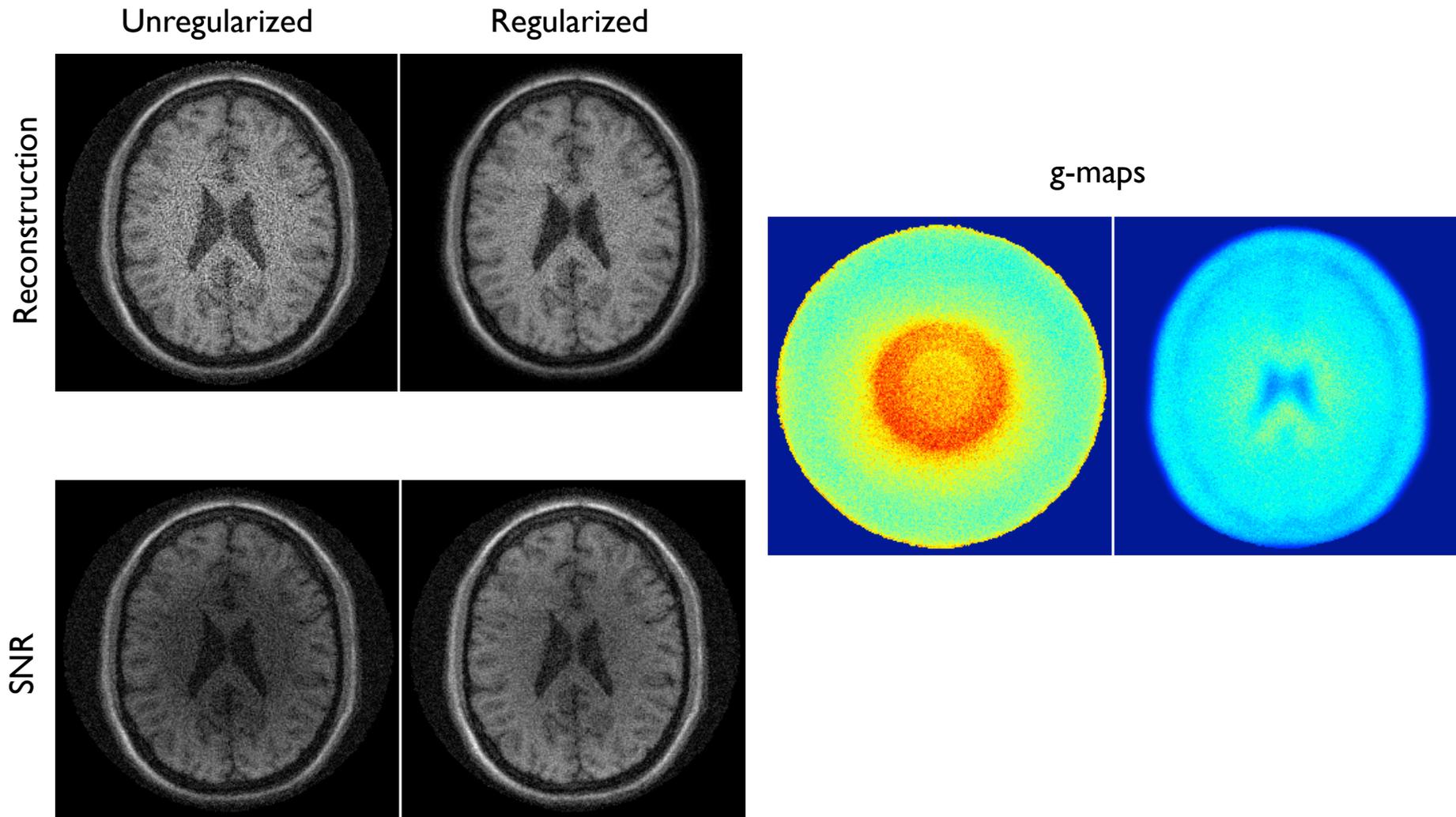
$$\tilde{\boldsymbol{\rho}} = \arg \min_{\boldsymbol{\rho}} \{ \|\mathbf{E}\boldsymbol{\rho} - \mathbf{s}\|_2 + \lambda \|\mathbf{L}\boldsymbol{\rho}\|_2 \}$$

Equivalent to solving:

$$\begin{array}{l} \text{Measured data} \longrightarrow \\ \text{Vector of zeros} \longrightarrow \end{array} \begin{bmatrix} \mathbf{S} \\ \mathbf{0} \end{bmatrix} = \begin{bmatrix} \mathbf{E} \\ \mathbf{L} \end{bmatrix} \boldsymbol{\rho}$$

`ismrm_demo_regularization_iterative_sense.m`

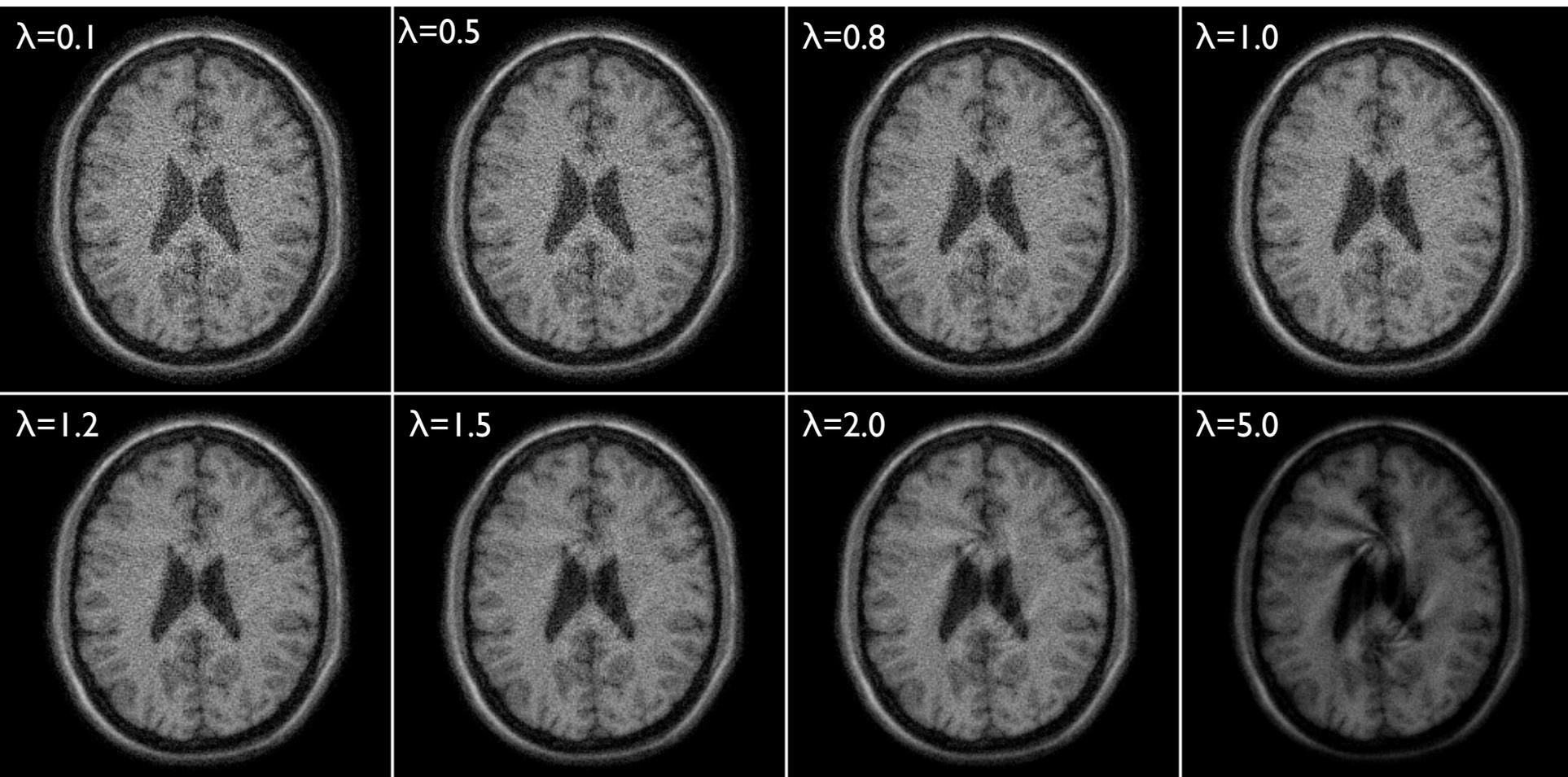
Regularization – Iterative Methods



ismrm_demo_regularization_iterative_sense.m

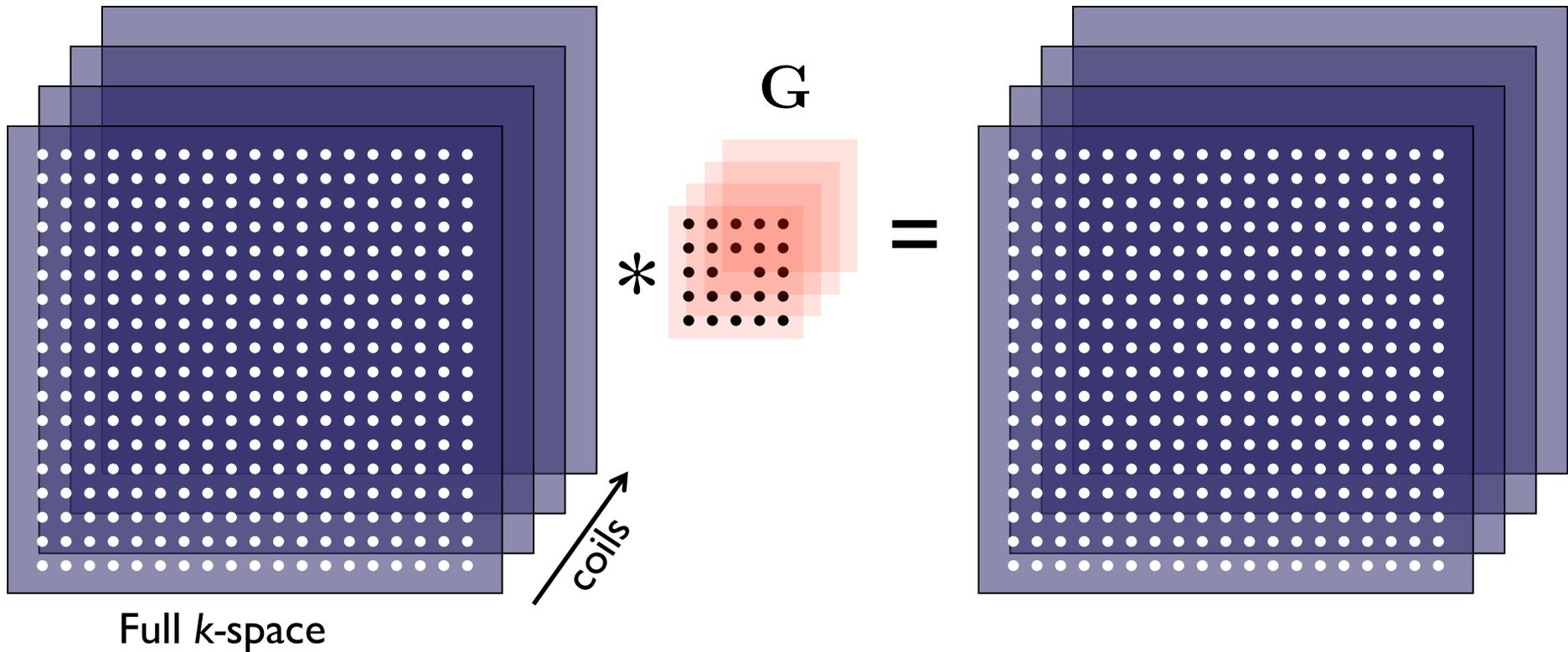
Regularization – Iterative Methods

$$\tilde{\rho} = \arg \min_{\rho} \{ \|\mathbf{E}\rho - \mathbf{s}\|_2 + \lambda \|\mathbf{L}\rho\|_2 \}$$



SPIRiT Approach

k -space points can be synthesized from neighbors



$$Gd = d$$

SPIRiT Approach

We can formulate the reconstruction problem in k -space as:

$$\tilde{\mathbf{x}} = \arg \min_{\mathbf{x}} \{ \|\mathbf{D}\mathbf{x} - \mathbf{y}\|_2 + \lambda \|\mathbf{G}\mathbf{x} - \mathbf{x}\|_2 \}$$

\mathbf{x} : Cartesian k -space solution.

\mathbf{D} : Sampling operator (e.g. onto non-Cartesian k -space)

\mathbf{y} : Sampled data

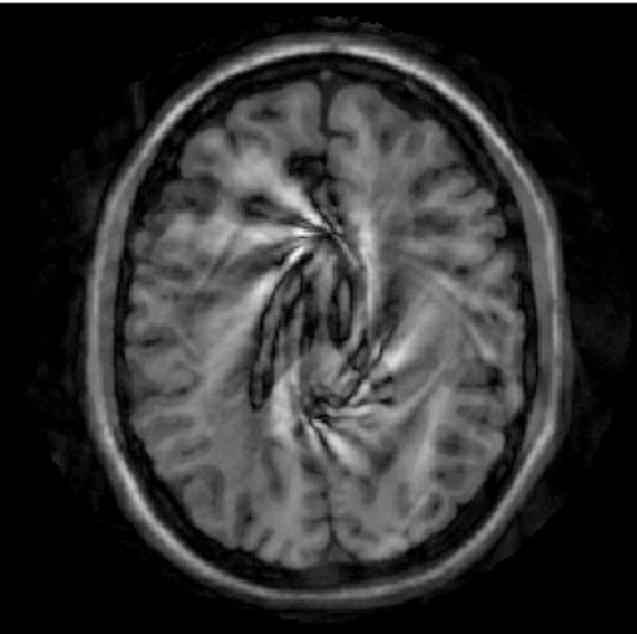
\mathbf{G} : SPIRiT convolution operator

Can be applied as multiplication in image space

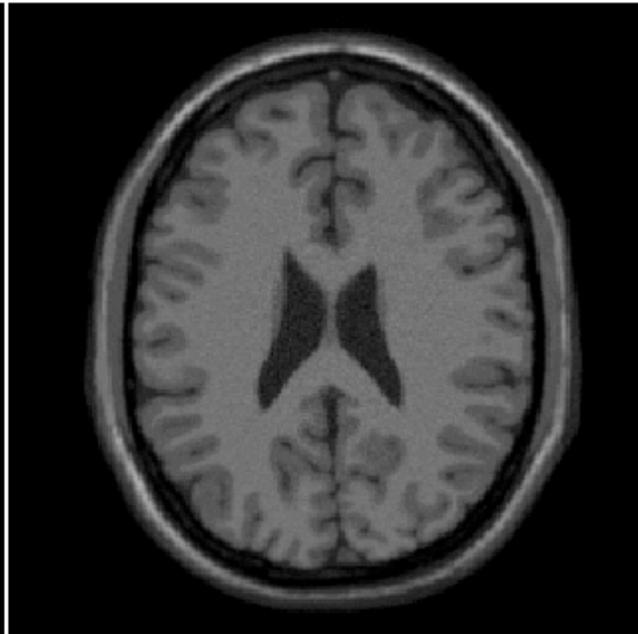
Could also be sampling operator from image to k -space

Spiral Imaging Example

Gridding



SENSE



SPIRiT



`ismrm_demo_non_cartesian.m`

Summary

- Noise decorrelation is used to reduce the impact of varying noise levels in receive channels.
- SNR scaled reconstruction are a way to evaluate reconstructions directly on the images.
- Pseudo Replica Method allows the formation of SNR scaled images in methods where unmixing coefficients are not explicitly obtained
- Iterative methods can be used for both Cartesian and non-Cartesian methods
- Regularization can be added to iterative methods in a straightforward fashion

Acknowledgements

- Jeff Fessler

- <http://web.eecs.umich.edu/~fessler/code/>

- Brian Hargreaves

- <http://mrsrl.stanford.edu/~brian/mritools.html>

- Miki Lustig

- <http://www.eecs.berkeley.edu/~mlustig/Software.html>

Download code, examples:

<http://gadgetron.sf.net/sunrise>

<http://gadgetron.sourceforge.net/sunrise/>

ISMRM Sunrise Course on

Teachers

Michael S. Hansen - michael.hansen@nih.gov
Philip Beatty - philip.beatty@sri.utoronto.ca

Slides

- [Hansen Slides](#)

Source Code and Examples

Download [ismrm_sunrise_parallel.zip](#) with source code and

Exercises

- [Beatty Practical Session](#)
- [Hansen Practical Session](#)

ISMRM Sunrise Practical Session

This document contains the second set of practical exercises for the ISMRM course on parallel imaging.

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- [Pseudo Replica Method](#)
- [Iterative Non-Cartesian SENSE](#)
- [Additional Demos](#)

Exercise Data

All the data used in this set of exercises can be found in the file `hansen_exercises.mat`. We will start by clearing the workspace and load

```
close all; clear all;  
load hansen_exercises.mat  
whos
```

Name	Size	Bytes	Class	Attributes
data	256x256x8	8388608	double	complex
data_spiral	18176x8	2326528	double	complex
k_spiral	18176x2	290816	double	
noise_color	256x256x8	8388608	double	complex
noise_spiral	18176x8	2326528	double	complex
reg_img	256x256	524288	double	
smaps	256x256x8	8388608	double	complex
sp	256x256	524288	double	
w_spiral	18176x1	145408	double	

Noise Pre-Whitening

Hands-on Cheat Sheet