

# Image Reconstruction

## *Partial k-space Reconstruction*

M229 Advanced Topics in MRI

Kyung Sung, Ph.D.

2019.05.21

## Class Business

- Homework 1 grading is done
- Project proposal comments will be out by this Friday
- Office hours
  - Instructors: Wed 3-5pm  
email beforehand would be helpful

# Today's Topics

- Fourier transform symmetries
  - Odd and Even functions
- Motivation for partial k-space recon
- Partial k-space recon methods
  - Direct method (Homodyne)
  - Iterative method (POCS)
- MATLAB code demo

## Even and Odd Functions

- function  $f$  is even (or symmetric) when
$$f(x) = f(-x)$$
- function  $f$  is odd (or antisymmetric) when
$$f(x) = -f(-x)$$

# Even and Odd Functions

- Any function can be written as a sum of even and odd functions

$$\begin{aligned}f(x) &= \frac{1}{2}[f(x) + f(-x) - f(-x) + f(x)] \\&= \frac{1}{2}[f(x) + f(-x)] + \frac{1}{2}[f(x) - f(-x)] \\&\quad \underline{\hspace{10em}} \qquad \underline{\hspace{10em}} \\&\quad f_e(x) \qquad \qquad \qquad f_o(x)\end{aligned}$$

# Even and Odd Functions

- The integral of the product of odd and even functions is zero

$$\begin{aligned}\int_{-\infty}^{\infty} f_e(x)f_o(x)dx \\&= \int_{-\infty}^0 f_e(x)f_o(x)dx + \int_0^{\infty} f_e(x)f_o(x)dx \\&= \int_0^{\infty} [f_e(-x)f_o(-x)dx + f_e(x)f_o(x)]dx\end{aligned}$$

# Fourier Transform Symmetry

$$F(f) = \int_{-\infty}^{\infty} f(x)e^{-j2\pi xf}dx$$

$$F(f) = \int_{-\infty}^{\infty} f(x) \cos(2\pi xf)dx - j \int_{-\infty}^{\infty} f(x) \sin(2\pi xf)dx$$

$$F(f) = \int_{-\infty}^{\infty} f_e(x) \cos(2\pi xf)dx + \int_{-\infty}^{\infty} f_o(x) \cos(2\pi xf)dx \xrightarrow{0}$$
$$-j \int_{-\infty}^{\infty} f_e(x) \sin(2\pi xf)dx - j \int_{-\infty}^{\infty} f_o(x) \sin(2\pi xf)dx \xrightarrow{0}$$

# Fourier Transform Symmetry

$$F(f) = \int_{-\infty}^{\infty} f_e(x) \cos(2\pi xf)dx - j \int_{-\infty}^{\infty} f_o(x) \sin(2\pi xf)dx$$

$$F(f) = F_e(f) + F_o(f)$$

real & even function?

real & odd function?

even function?

odd function?

# Fourier Transform Symmetry

- Fourier transform of even part (of a real function) is real

$$FT\{f_e(x)\} = Re\{F_e(f)\}$$

- Fourier transform of even part is even

$$FT\{f_e(x)\} = F_e(f) = F_e(-f)$$

# Fourier Transform Symmetry

- Fourier transform of odd part (of a real function) is imaginary

$$FT\{f_o(x)\} = Im\{F_o(f)\}$$

- Fourier transform of odd part is odd

$$FT\{f_o(x)\} = F_o(f) = -F_o(-f)$$

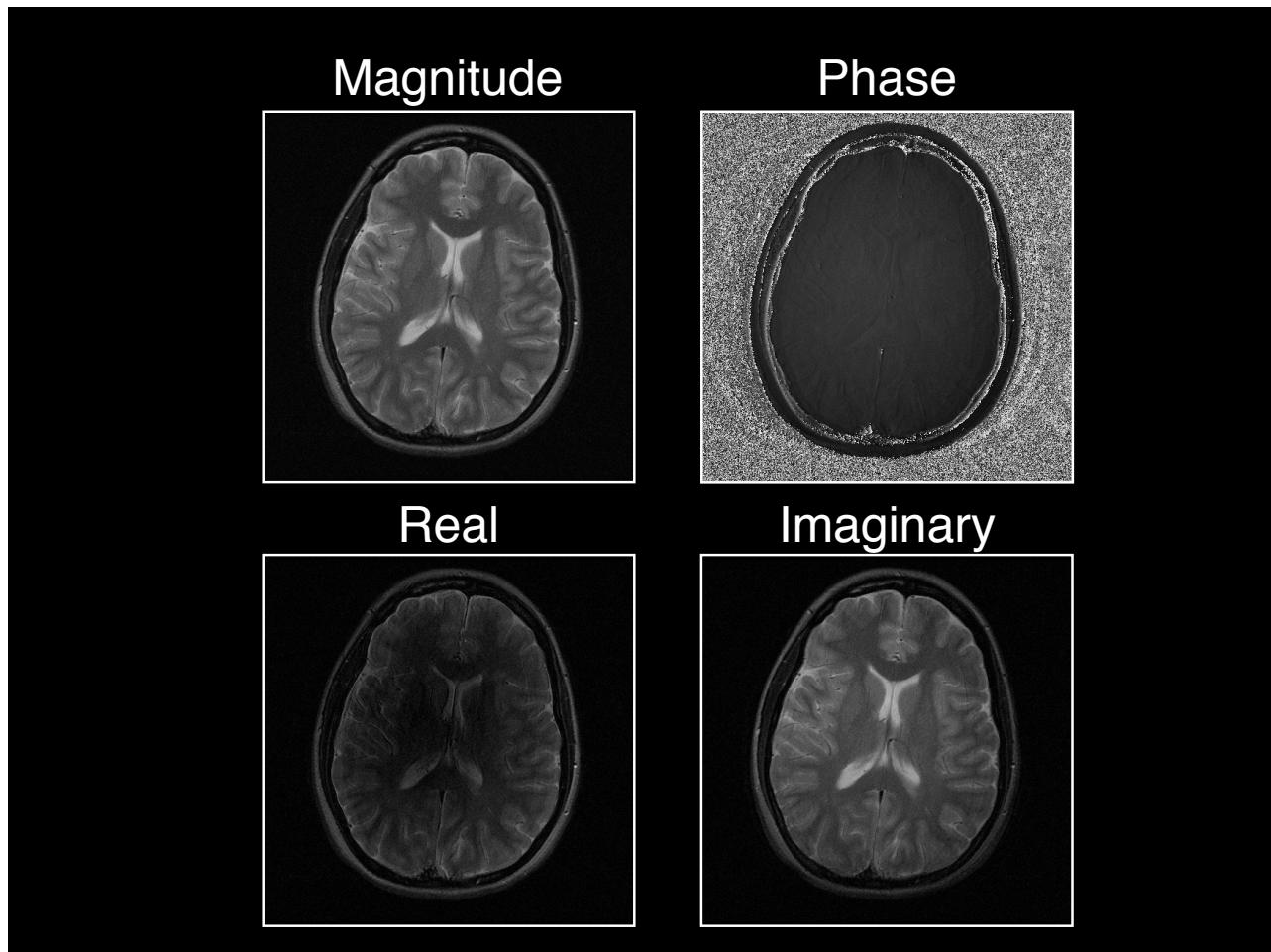
# Hermitian Symmetry

- We can summarize all four symmetries possessed by Fourier transform of a real function

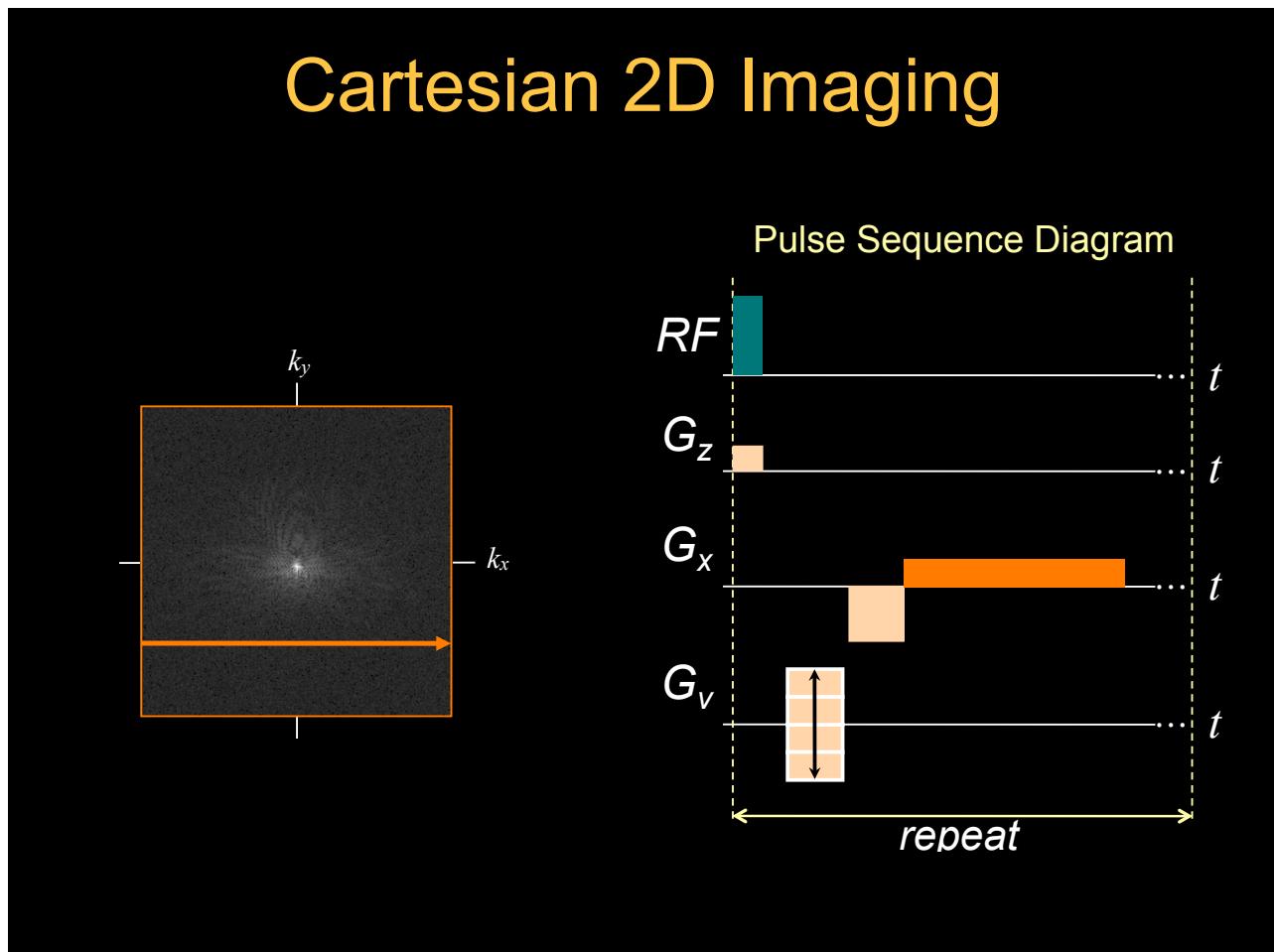
To the board ...

## Motivation

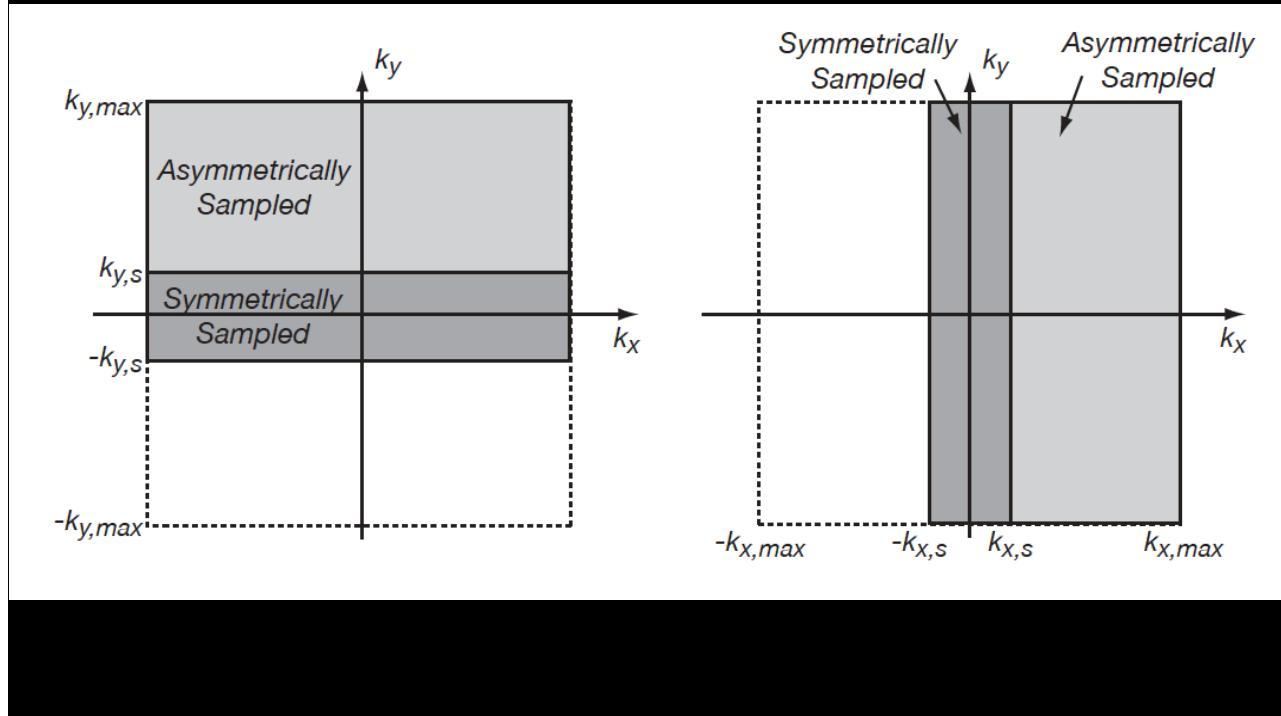
- MR images depict the spin density as a function of position
  - If this is true, only half of k-space data will need to be collected
  - Uncollected data could be synthesized by conjugate symmetry
- However, MR images are not real-valued!
  - Partial k-space reconstruction requires some type of phase correction



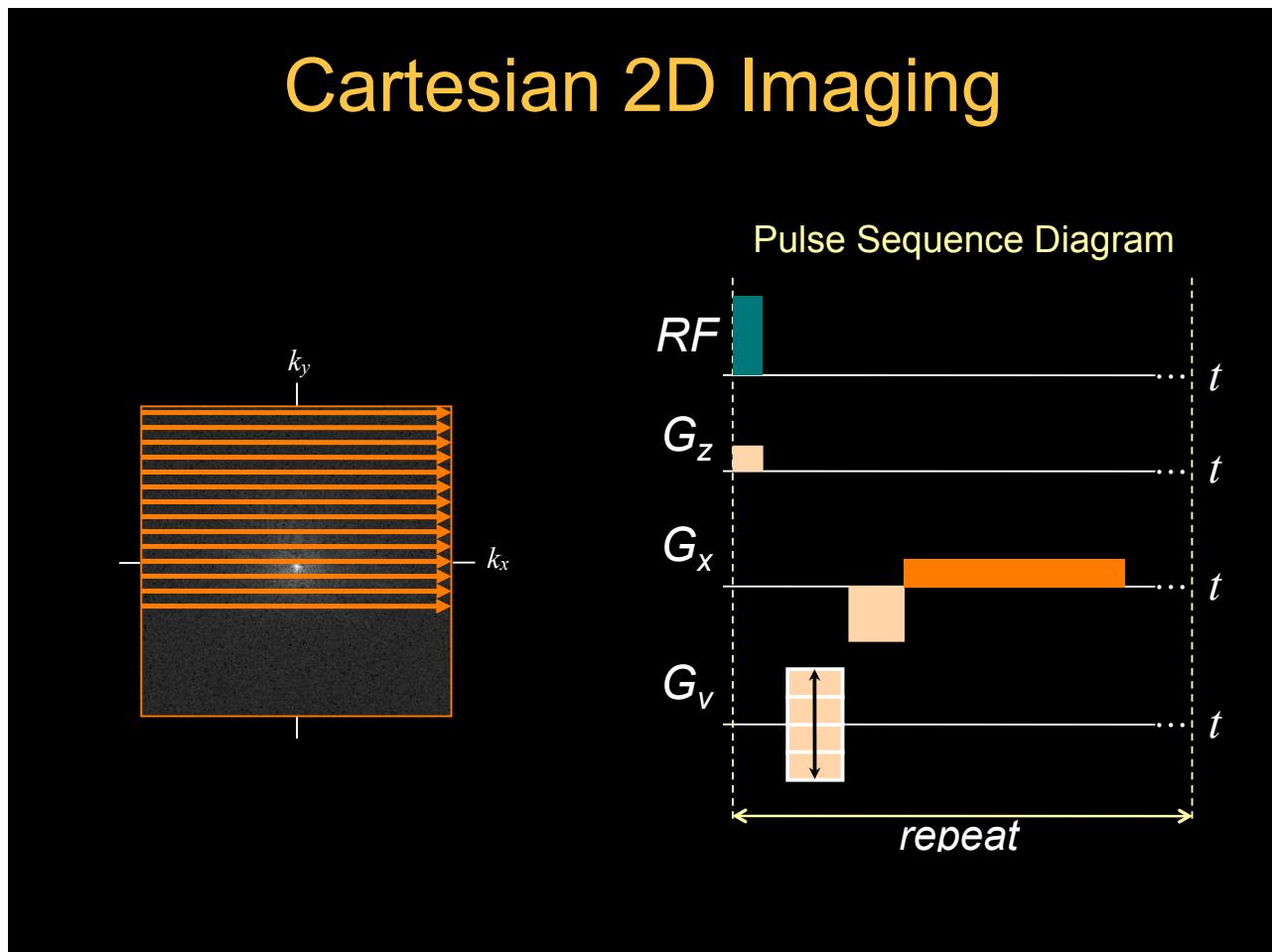
## Cartesian 2D Imaging



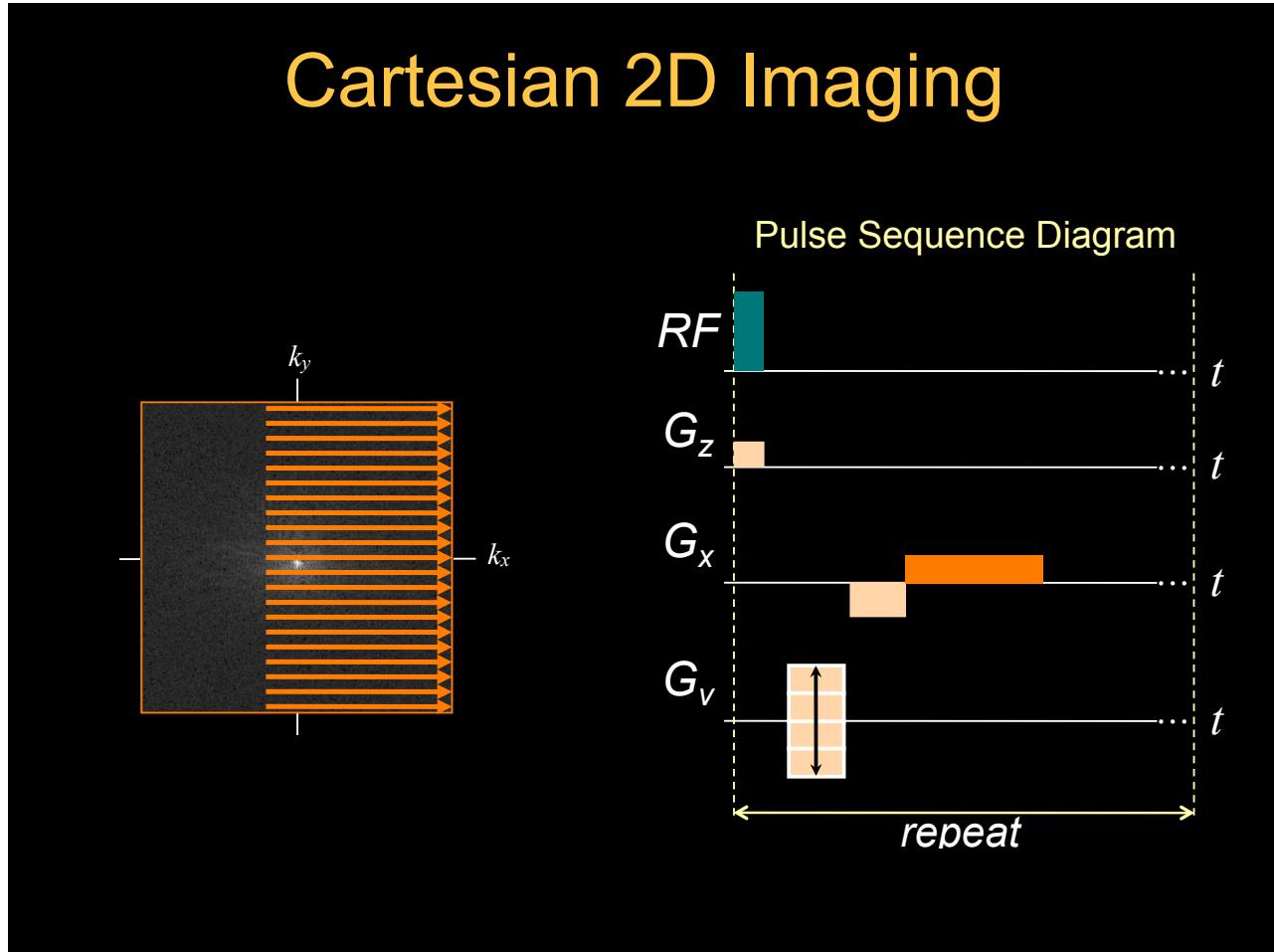
# Cartesian Sampling Application



# Cartesian 2D Imaging



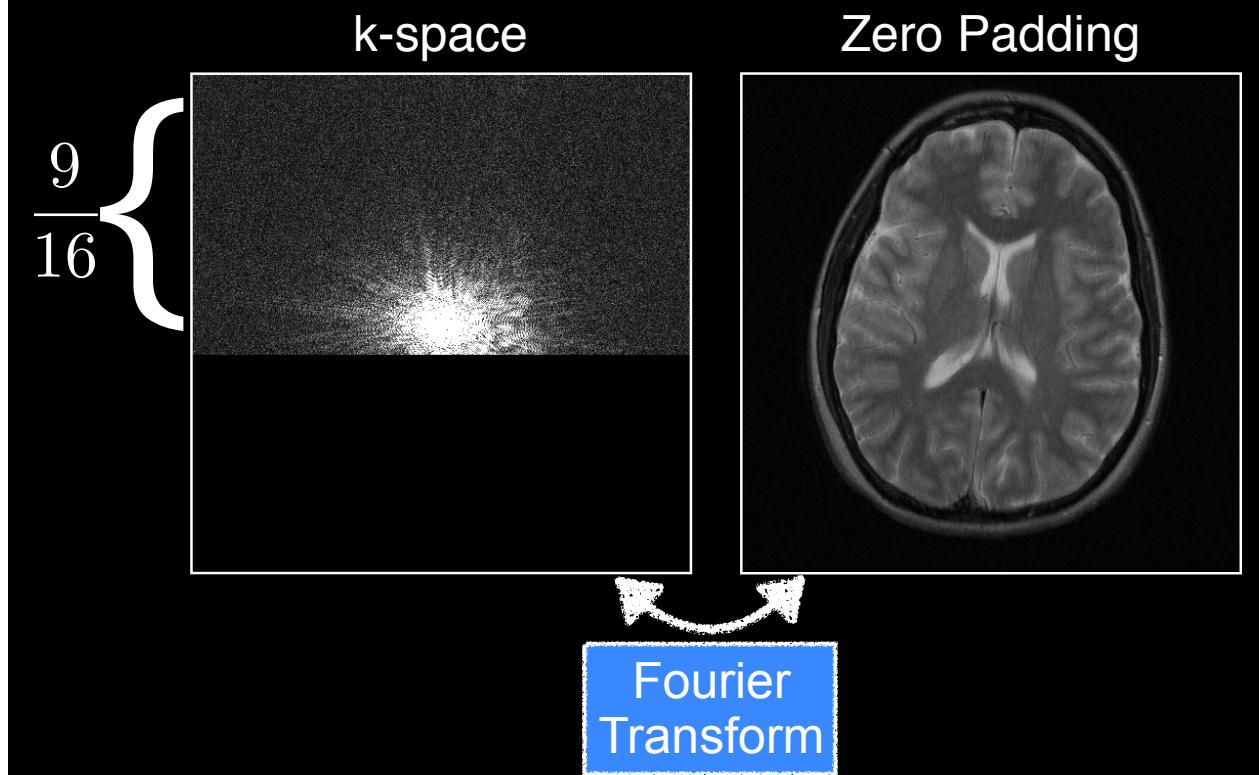
# Cartesian 2D Imaging



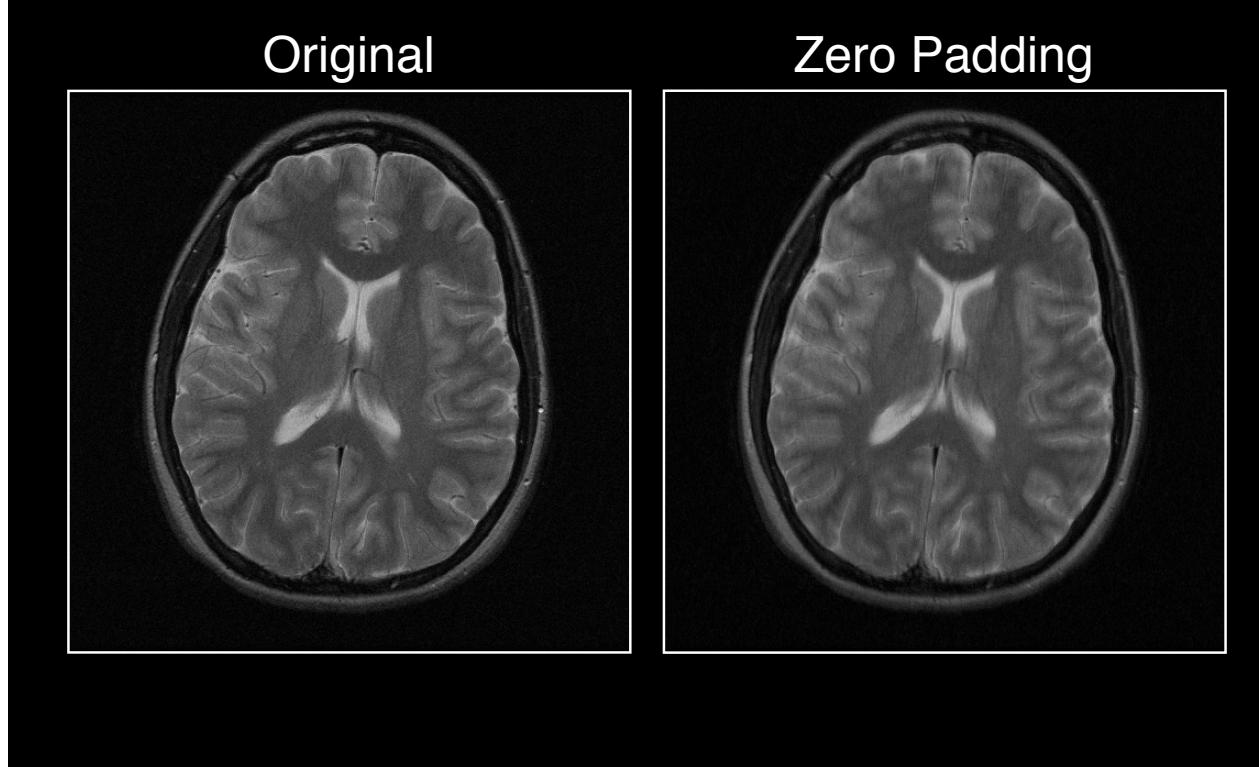
## Direct Reconstruction

- Zero padding
- Phase correction and conjugate synthesis
- Homodyne reconstruction

# Trivial Recon by Zero-Padding



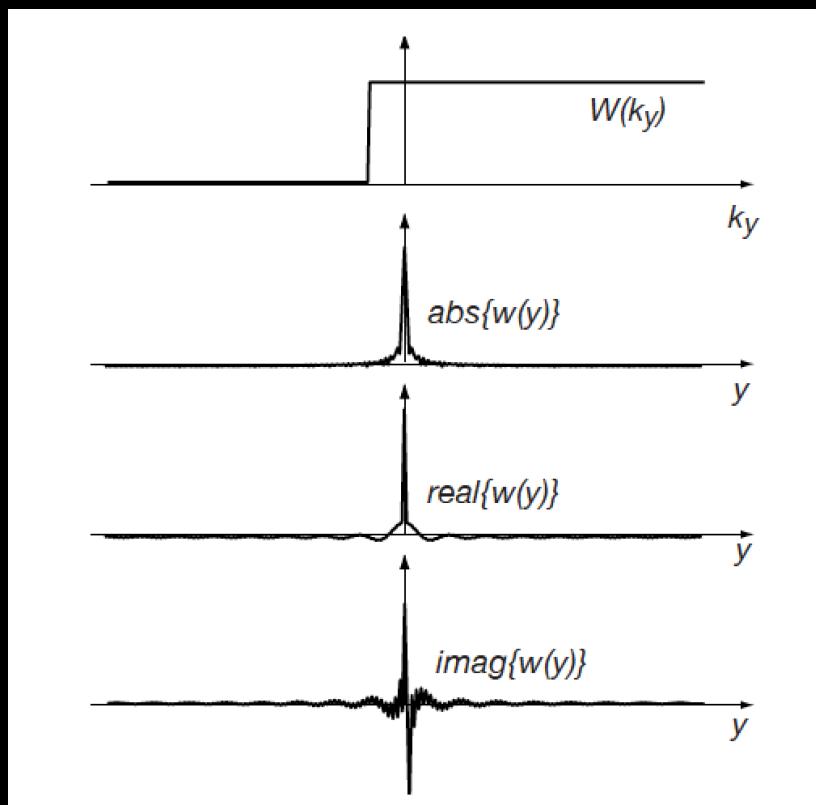
## Zero Padding



# Image Artifacts by Zero Padding

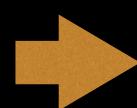
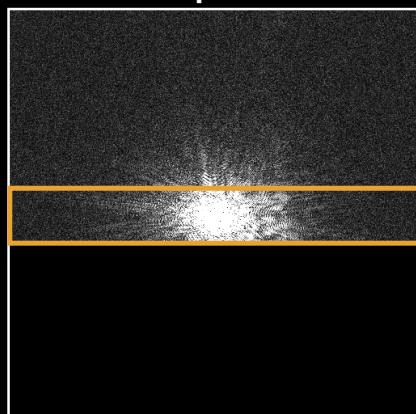
- Blurring can be identified by the product of a full k-space data set multiplied by a weighting function
- The inverse Fourier transform of this weighting function is the impulse response that produces the blurring

# Image Artifacts by Zero Padding



# Phase Correction and Conjugate Synthesis

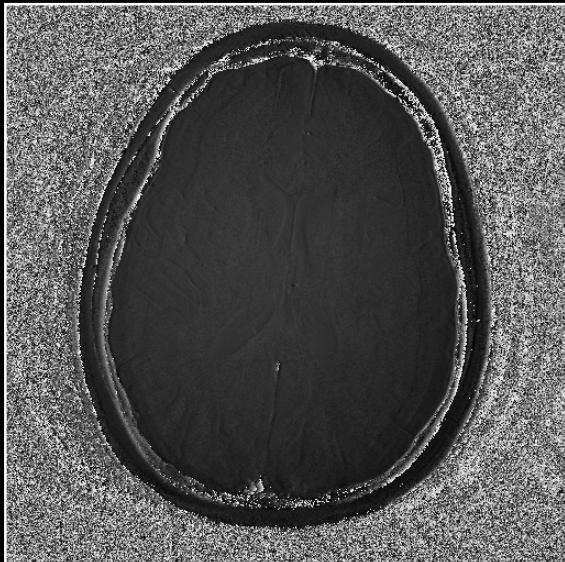
- Phase correction must be applied
    - Use the narrow strip of data for which we have symmetric coverage
- k-space



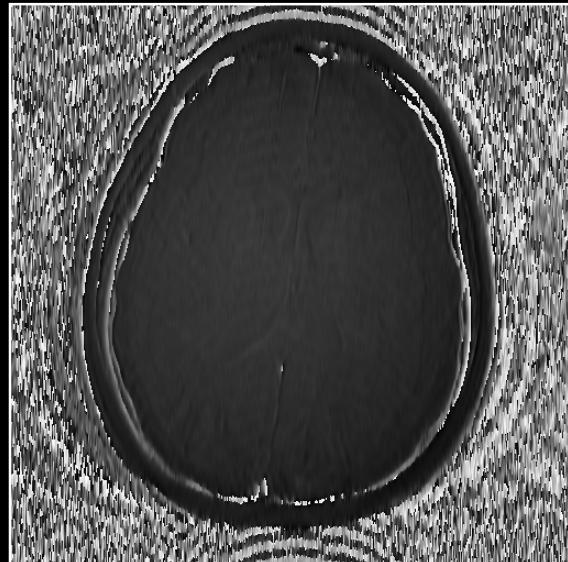
Phase  
Estimation  
 $p(x,y)$

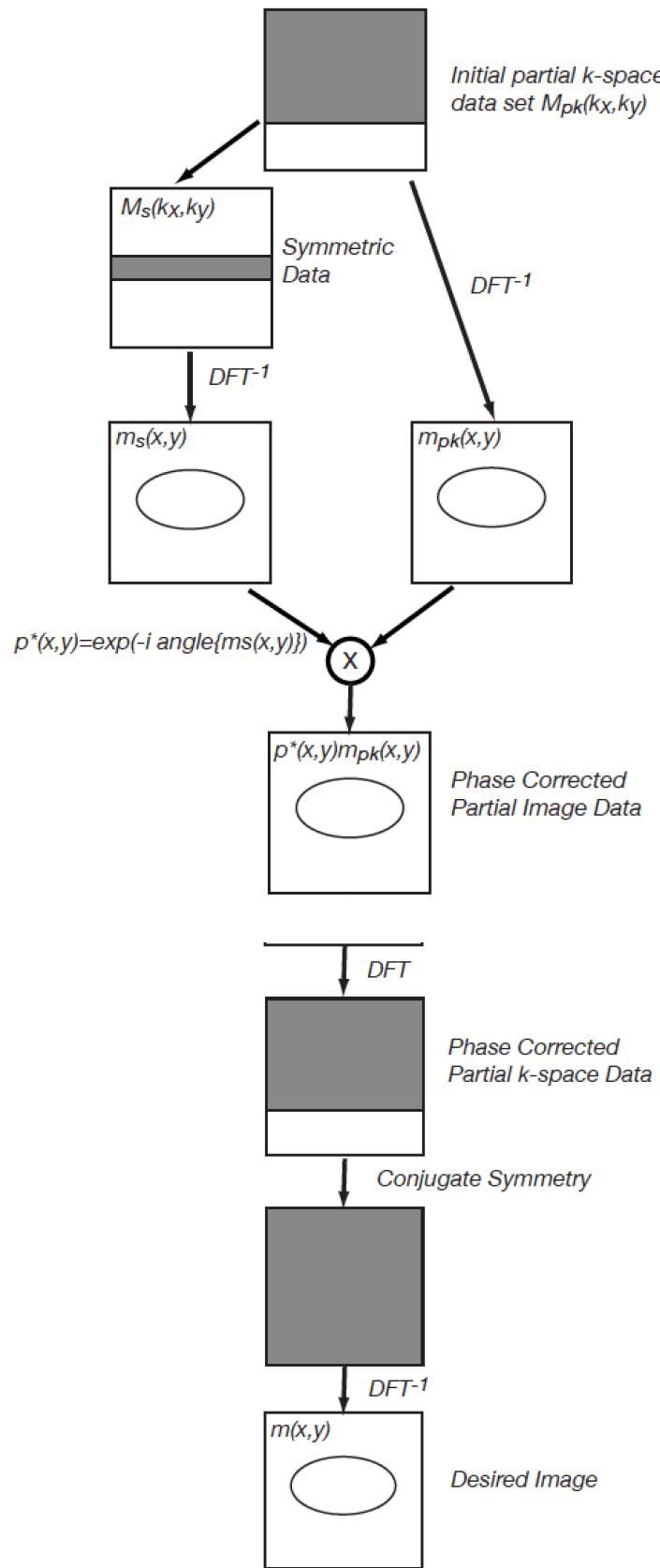
## Phase Estimation

Original Phase



Estimated Phase



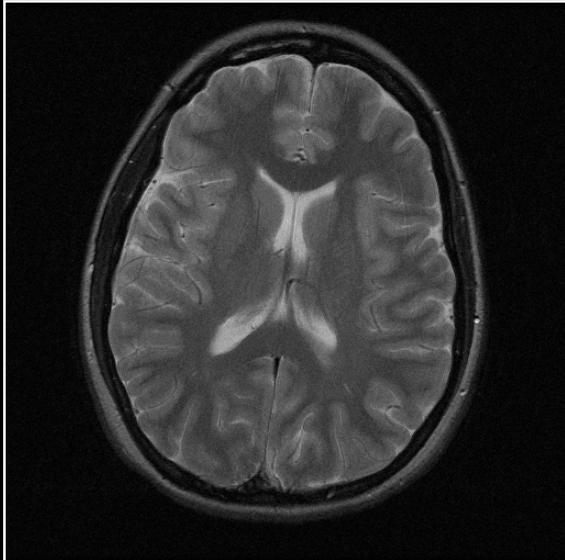


# MATLAB Code

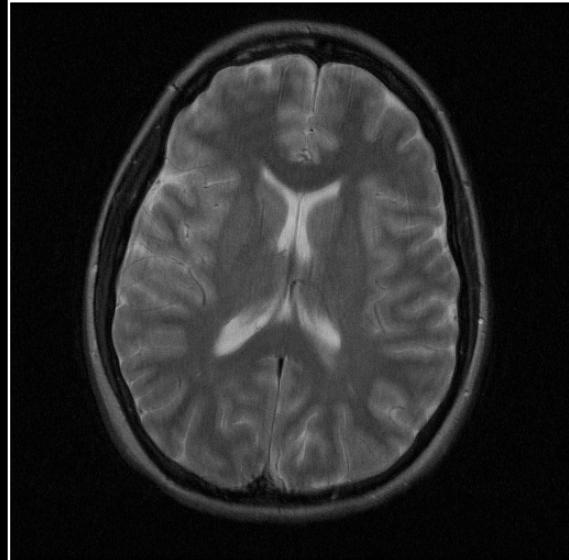
```
hncver = 224; % 7/16 sets to be zeros  
  
data_pk = data;  
data_pk(1+nx-hncver:end,:) = 0;  
  
im_zp = fftshift(ifftn(fftshift(data_pk)));  
  
data_center = data_pk;  
data_center(1:hncver,:) = 0;  
  
im_ph = fftshift(ifftn(fftshift(data_center)));  
  
im_pc = im_zp.*exp(-li*angle(im_ph));  
  
data_pc = fftshift(ifftn(fftshift(im_pc)));  
data_pc(1+nx-hncver:end,:) = 0;  
  
data_pc(1+nx-hncver:end,:) = rot90(data_pc(1:hncver,:),2);  
  
im_pc = fftshift(ifftn(fftshift(data_pc)));
```

## Phase Correction and Conjugate Synthesis

Original

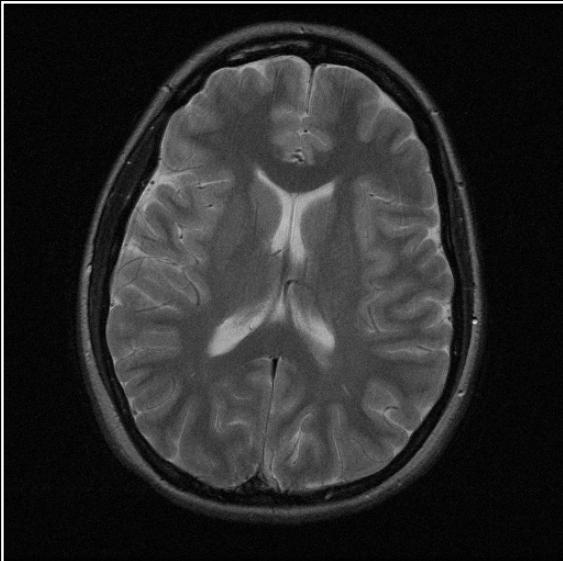


Zero Padding

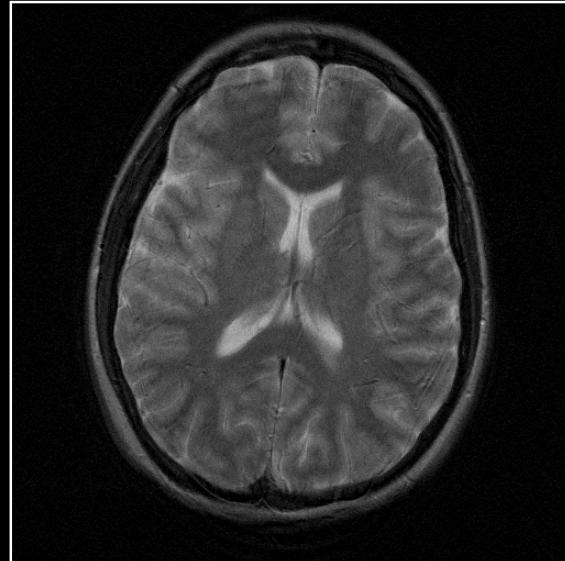


# Phase Correction and Conjugate Synthesis

Original

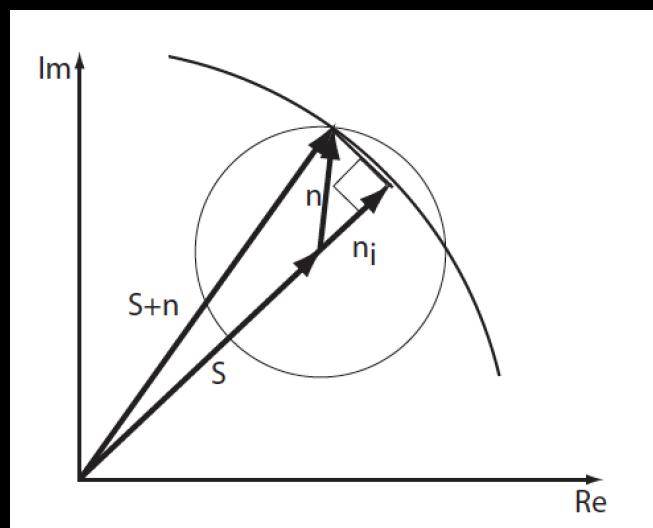


Phase Correction



## Noise Consideration

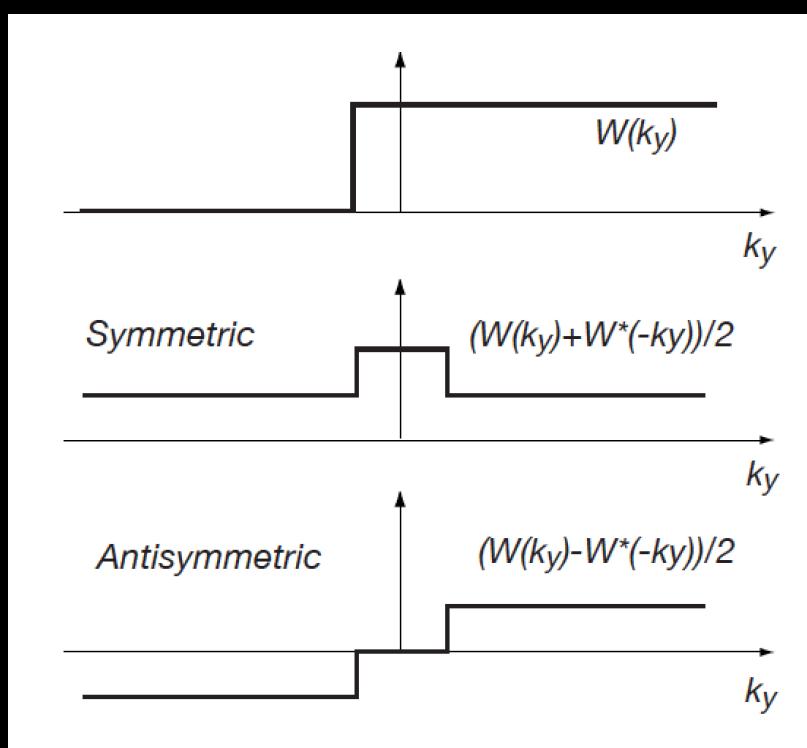
- Background in the phase corrected image has lower noise because one component of the complex noise has been suppressed



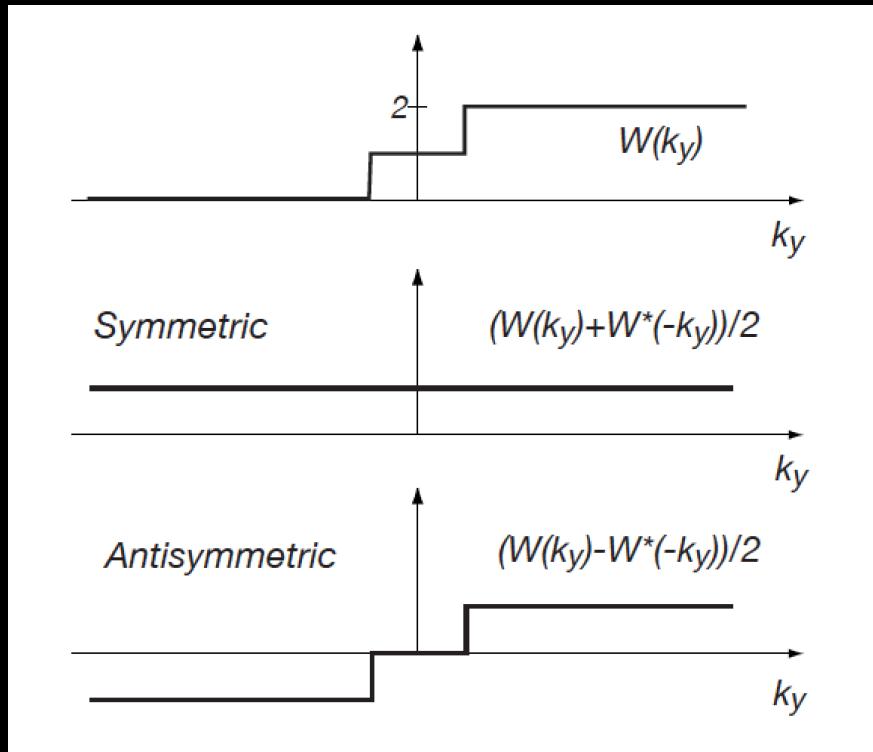
# Homodyne Reconstruction

- *Real part* of an image corresponds to the conjugate symmetric component of the transform
- *Imaginary part* of an image corresponds to the conjugate anti-symmetric component of the transform

## Symmetric and Antisymmetric Components



# Symmetric and Antisymmetric Components

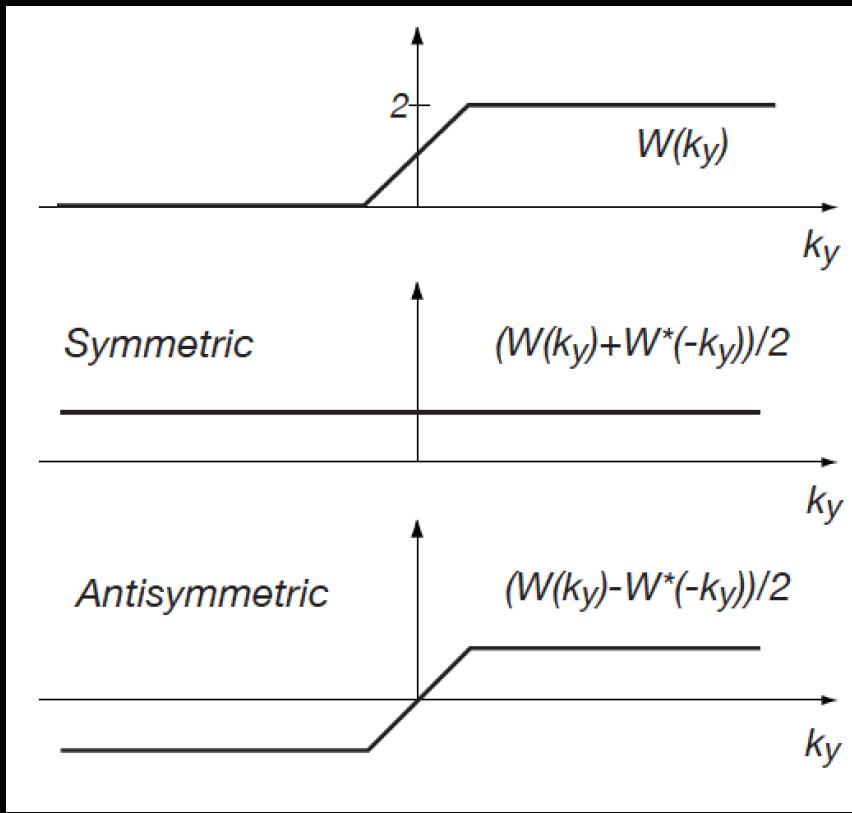


## Weighting Function

$$m(x, y) = \text{Re}\{p^*(x, y)(m(x, y) * w(x, y))\}$$

- The phase correction in image space corresponds to a convolution in k-space
- The weighting sharp discontinuities of the weighting function can produce image artifacts

# Preferred Weighting Function

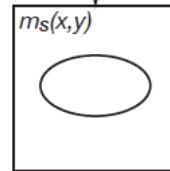


Initial partial  $k$ -space data set  $M_{pk}(k_x, k_y)$

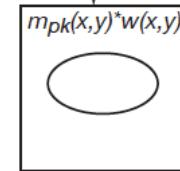
Pre-Weighting Function  $W(k_y)$

Symmetric Data

$DFT^{-1}$



$DFT^{-1}$



$$p^*(x, y) = \exp(-i \angle\{m_s(x, y)\})$$

$\times$

$m_s(x, y)$

Desired Image

$p^*(x, y) = \exp(-i \angle\{m_{pk}(x, y)^*w(x, y)\})$

$\times$

$m_{pk}(x, y)^*w(x, y)$

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

Desired Image

$\times$

$m_s(x, y)$

Desired Image

$\times$

$m_{pk}(x, y)^*w(x, y)$

# MATLAB Code

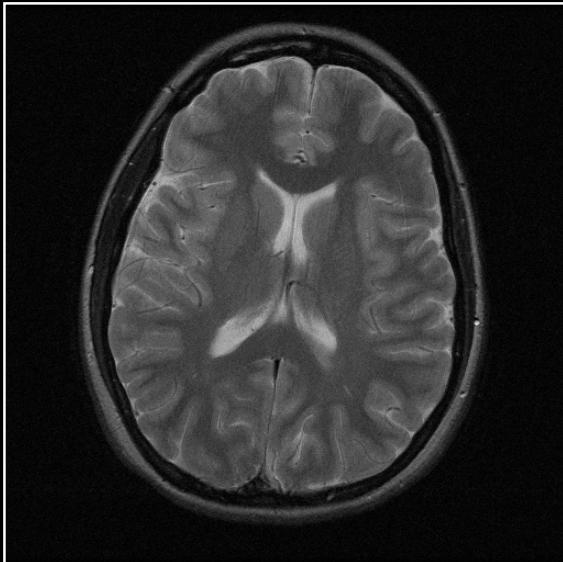
```
% Generate pre-weighting function W(ky)
Wld = zeros(nx,1);
Wld(1:hover) = 2;
Wld(hover+1:nx-hover) = 2*(nx-2*hover-1:-1:0)/(nx-2*hover);
Wky = repmat(Wld,[1 nx]);

data_pw = data_pk.*Wky;
im_pw = fftshift(ifftn(fftshift(data_pw)));

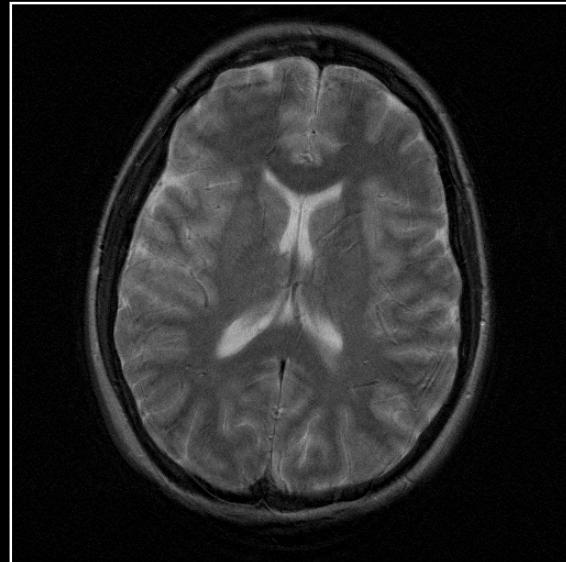
im_homodyne = im_pw.*exp(-1i*angle(im_ph));
```

## Homodyne Reconstruction

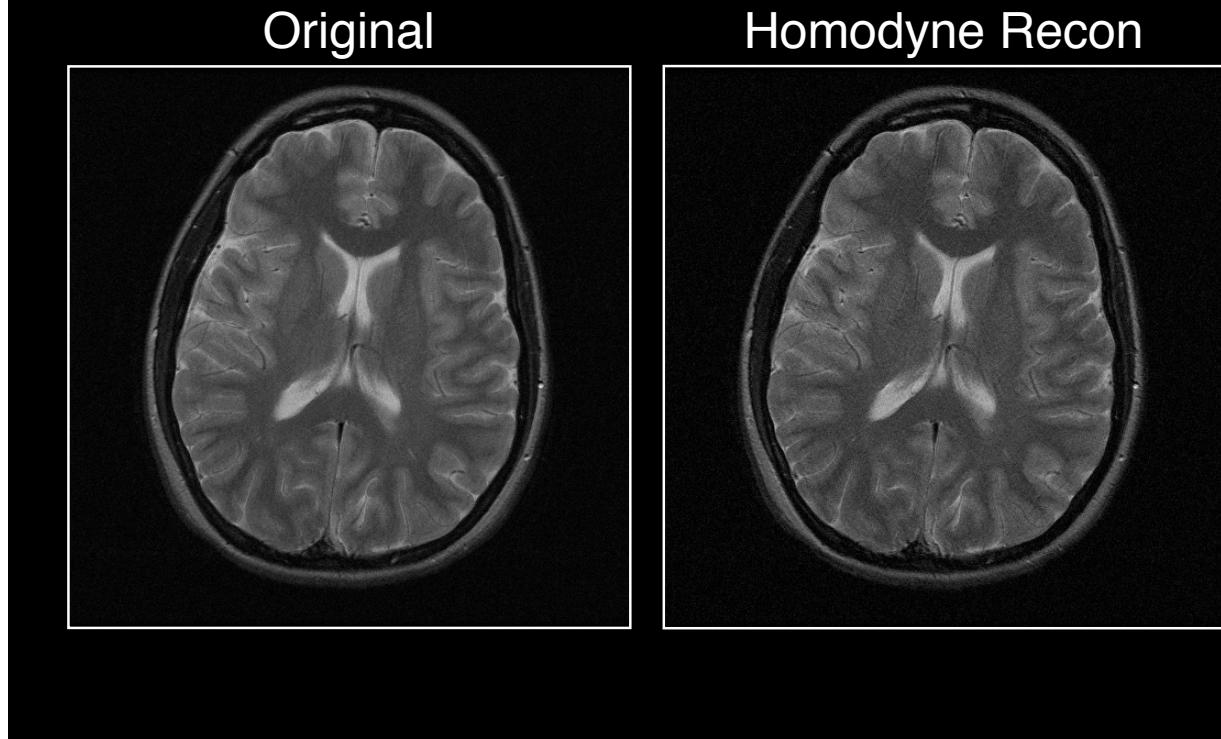
Original



Phase Correction



# Homodyne Reconstruction



## Summary of Direct Methods

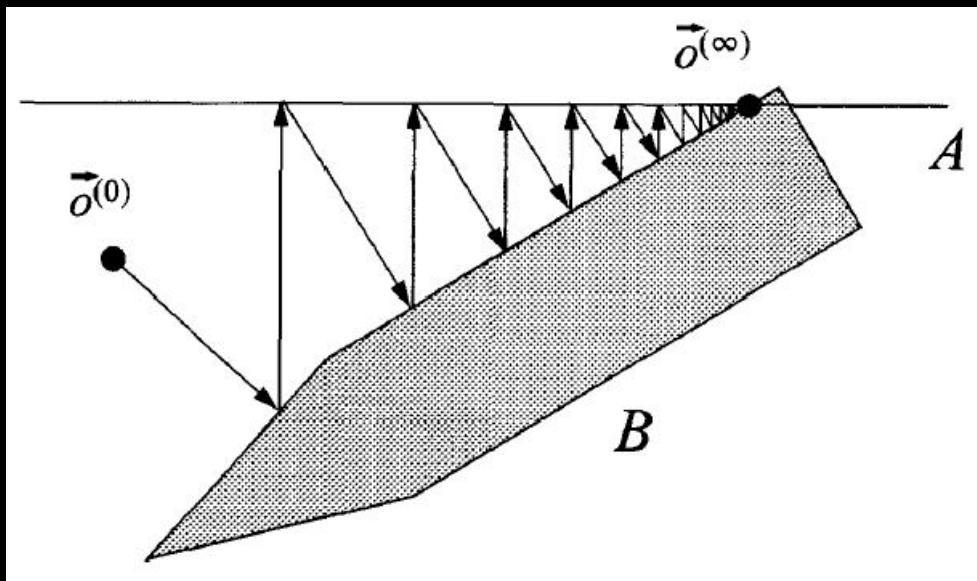
- Both homodyne and phase corrected conjugate synthesis approaches work well if image phase does not vary rapidly
- Problems with homodyne approach are the result of performing phase correction after conjugate synthesis.
- Problems with phase corrected conjugate synthesis approach are due to performing the conjugate synthesis after the phase correction

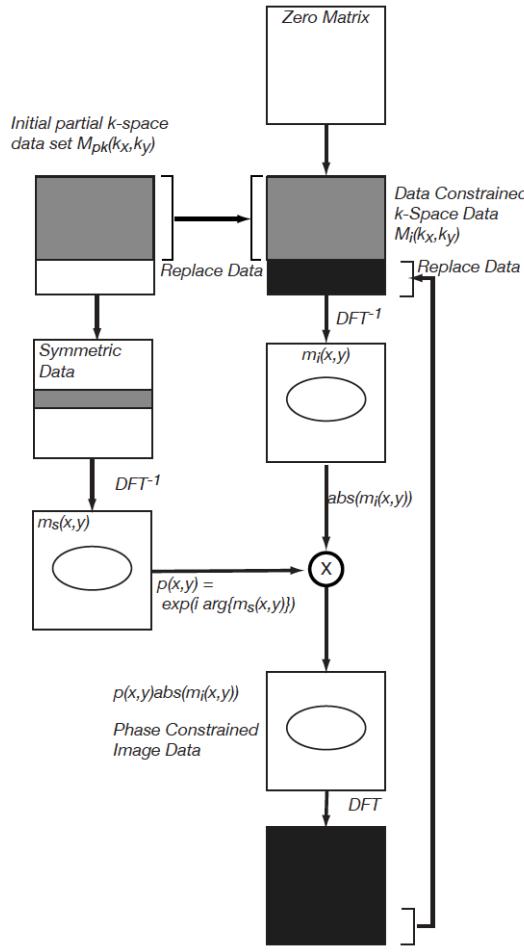
# Iterative Reconstruction

$$m_i(x, y) = |m_i(x, y)|p(x, y)$$

- Estimate the missing k-space data by iteratively applying phase correction and conjugate synthesis
- In the image domain, the image phase is constrained to be that of the low resolution estimate
- In the frequency domain, the k-space data is constrained to match the acquired data when available

## Projection Onto Convex Set (POCS)





## MATLAB Code

```

threshold_pocs = 0.001;

% Zero padding for initial guess
im_init = fftshift(ifftn(fftshift(data_pk))); % Inverse DFT
% Take only magnitude term & Apply phase term
im_init = abs(im_init).*exp(li*angle(im_ph));

% FFT
tmp_k = fftshift(fftshift(im_init));
diff_im = threshold_pocs + 1;

while (abs(diff_im) > threshold_pocs)
    tmp_k(1:nx-hnover,:) = data_pk(1:nx-hnover,:);
    tmp_im = fftshift(ifftn(fftshift(tmp_k))); % Inverse DFT

    % Take only magnitude term & Apply phase term
    tmp_im = abs(tmp_im).*exp(li*angle(im_ph));
    tmp_k = fftshift(fftshift(tmp_im));

    % Compare the reconstructed image
    diff_im = abs(tmp_im - im_init);
    diff_im = sum(diff_im(:).^2);
    fprintf('Difference is %f\n',diff_im);

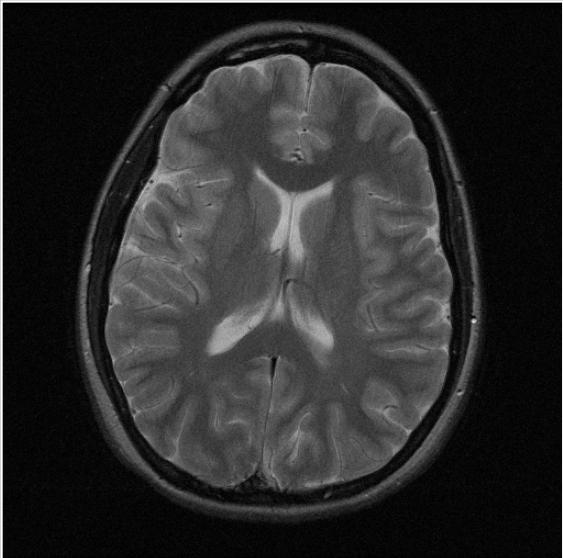
    im_init = tmp_im;
end

im_pocs = tmp_im;

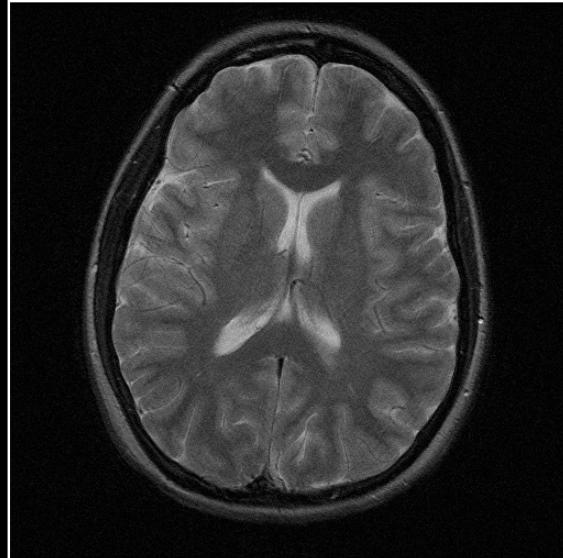
```

# POCS Reconstruction

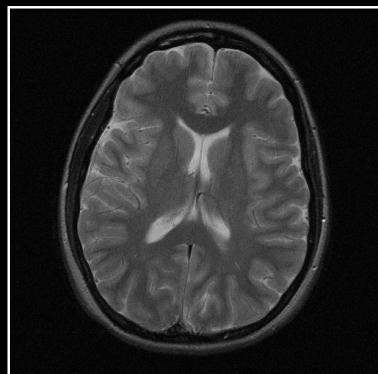
Original



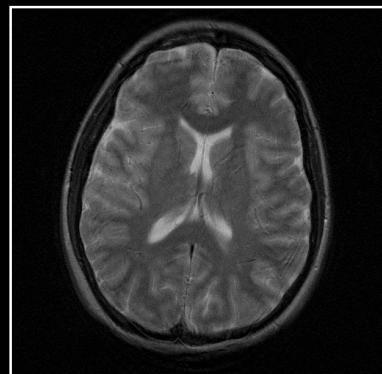
POCS Recon



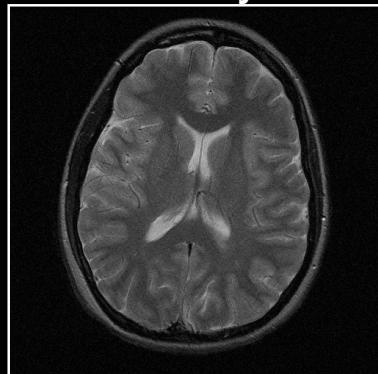
Original



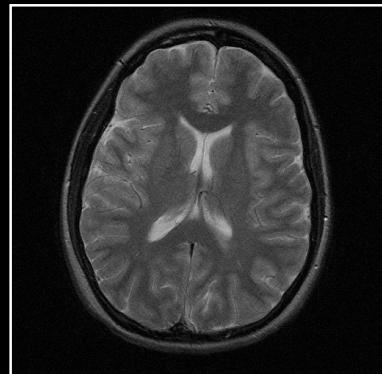
Phase Correction



Homodyne



POCS



# Conclusions

- All of these algorithms work well when the image phase variations are smooth
- When the image phase changes rapidly, the homodyne algorithm produces ghosting
- POCS algorithm performs somewhat better as the k-space fraction decreases

Thanks!

- Next time:
  - Parallel Imaging
  - Read “Parallel Imaging Reconstruction”  
p522-544

Kyung Sung, PhD

[ksung@mednet.ucla.edu](mailto:ksung@mednet.ucla.edu)

<http://kyungs.bol.ucla.edu>