An Introduction to Image Reconstruction, Processing, and their Effects in FMRI

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Working Group on Image Reconstruction and Processing
Thursdays 2 pm ET

Outline

Introduction

FMRI and fcMRI have been utilized with amazing precision.

Image Reconstruction

Voxels are not directly measured (k-space). Reconstructed!

Image Processing

Images are processed for enhancement & artifact reduction.

Implications

Effects of image reconstruction & processing? Mean, Var, Corr?

Discussion

We need to be careful and know what is done to our data

Introduction

Words of Wisdom:
Ideally we should model and analyze the original data that we measure, not a processed version of our data.

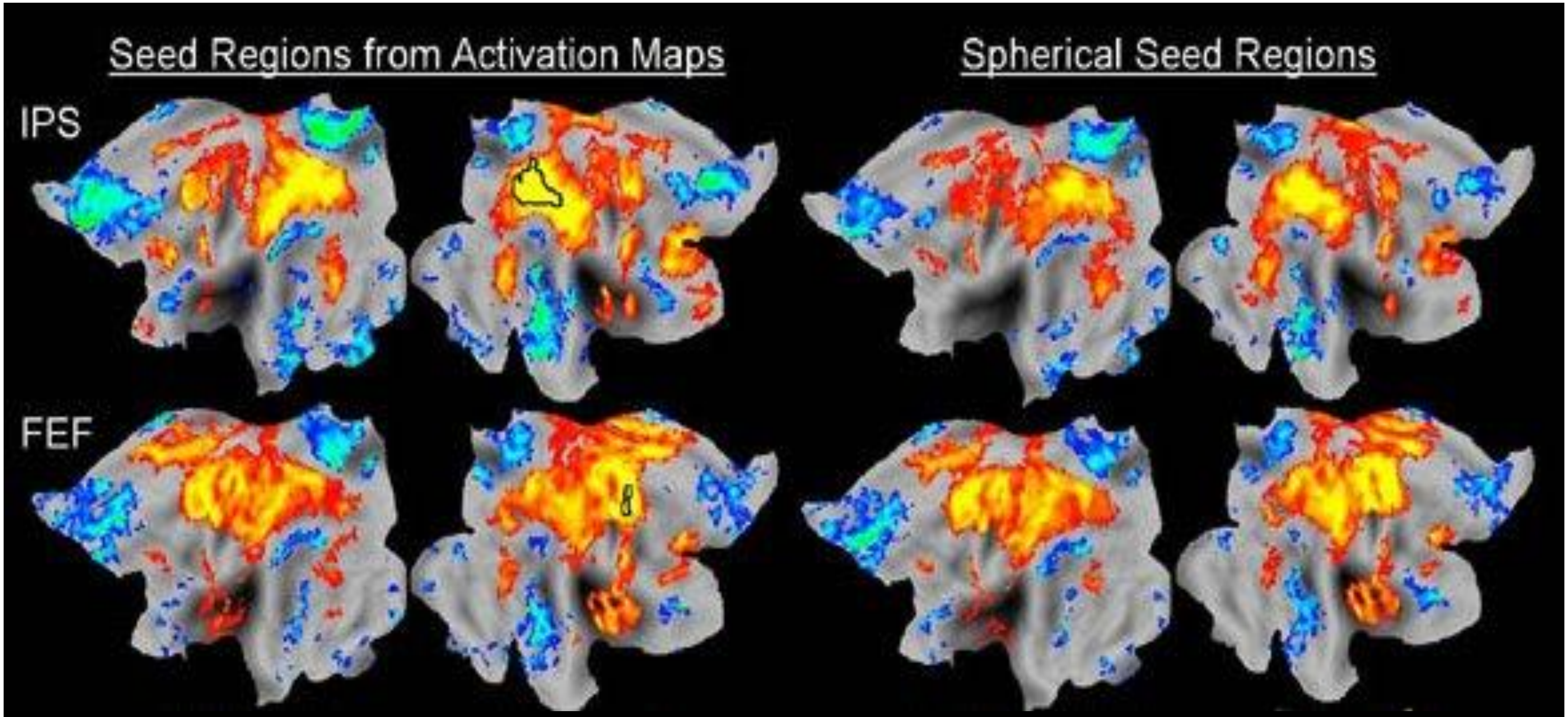
Don't change the data to fit the model,
change the model to fit the data.

We should statistically analyze all of our data and not delete half of it for convenience.

Favorite Phrase:
Analyzed "raw preprocessed data."

Introduction

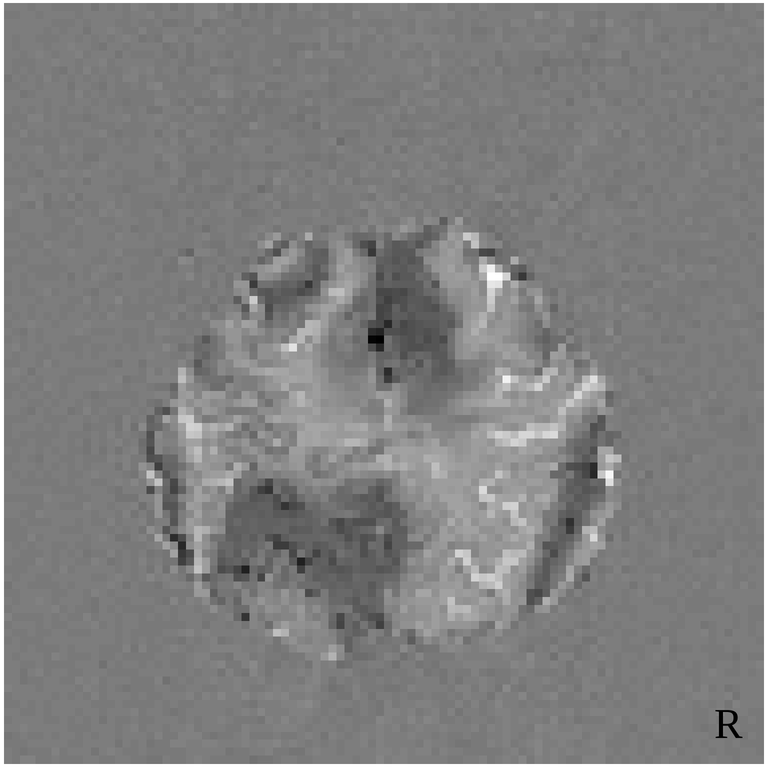
In fMRI and fcMRI, there has been an amazing amount of advanced analysis and interpretations presented, but little attention has been paid to what the data truly are.

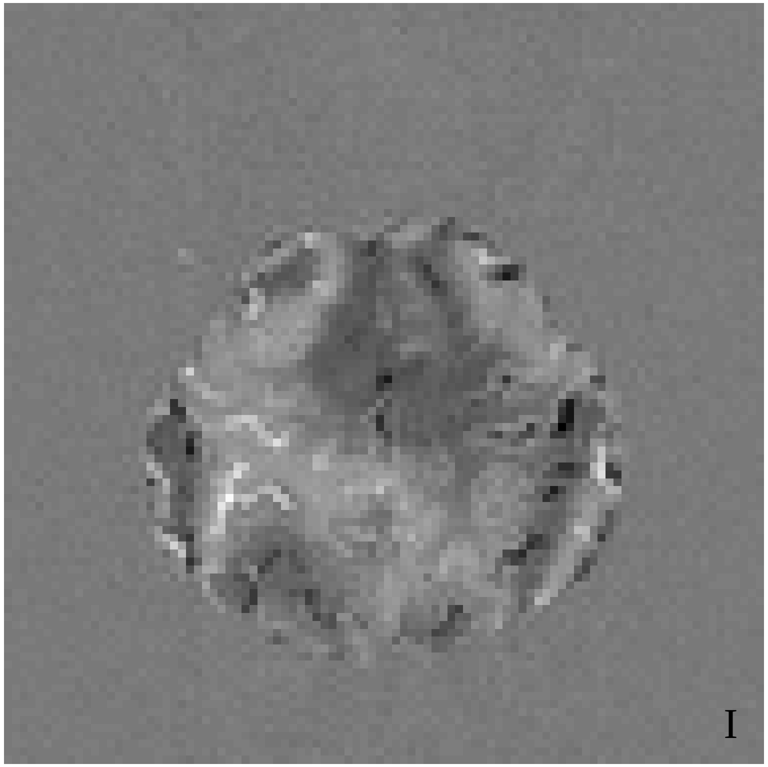


Fox et al, PNAS, 2006.

Introduction

In general, reconstructed GRE EPI images look like below.
How do we get from the below to the previous activation?
And the below isn't even our original measurements.





96×96
19.2cm FOV
2mm×2mm
In-Plane

Are we ahead of the data with our analyses and interpretations?

Image Reconstruction

In fMRI and MRI, the measurements taken by the machine are an array of complex-valued spatial frequencies.

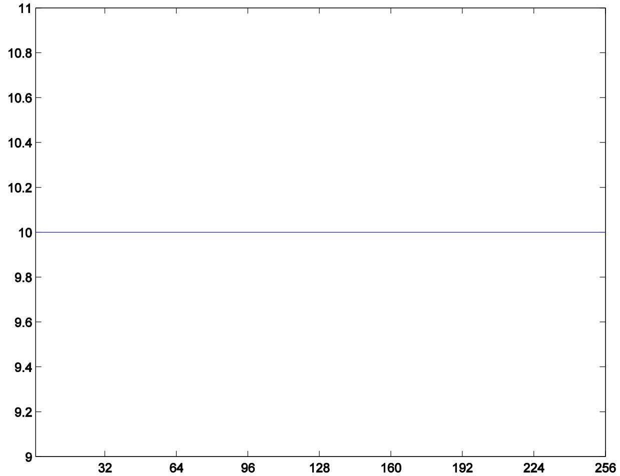
This array of complex-valued spatial frequencies need to be reconstructed into an image for us to see, analyze, and interpret.

The array of complex-valued spatial frequencies are reconstructed into an image via the inverse Fourier transform.

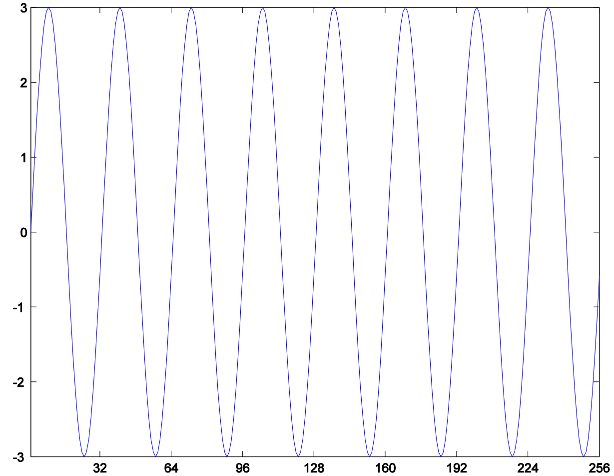
So lets briefly remind ourselves what the FT and IFT are.

Image Reconstruction

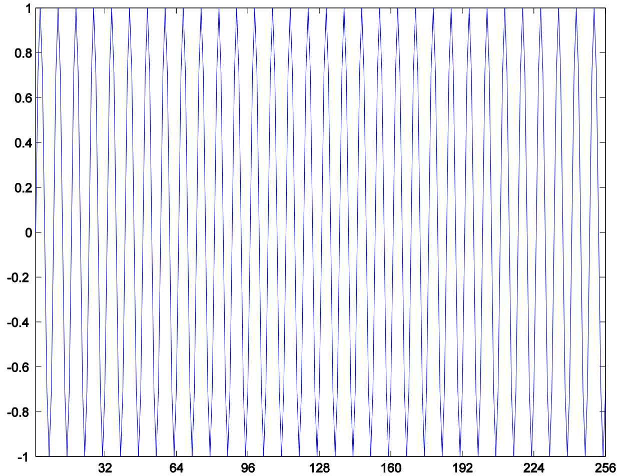
(n=256, Δt=2 s)



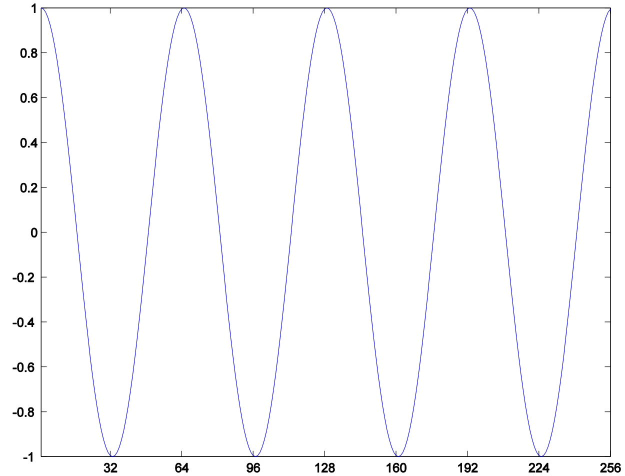
$10\cos(2\pi 0/512t)$



$3\sin(2\pi 8/512t)$



$1\cos(2\pi 32/512t)$

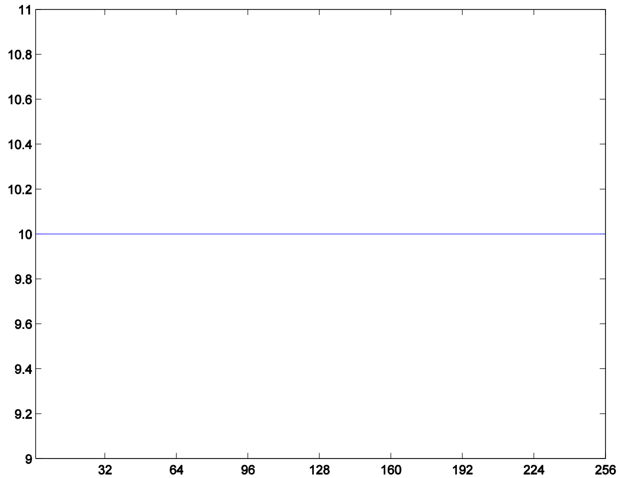


$1\sin(2\pi 4/512t)$

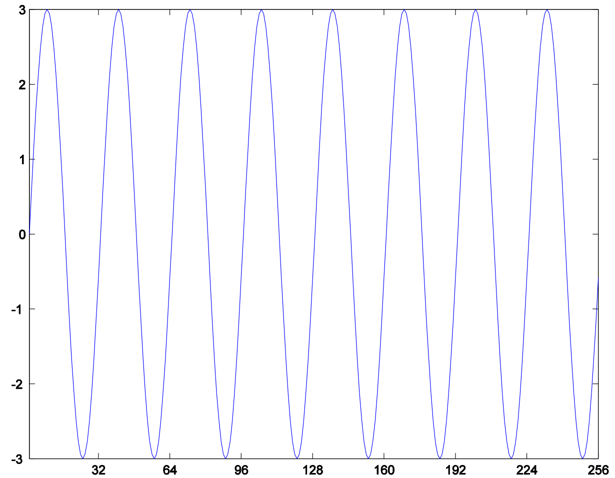
$A\cos(2\pi\nu t)$
$A\sin(2\pi\nu t)$

Image Reconstruction

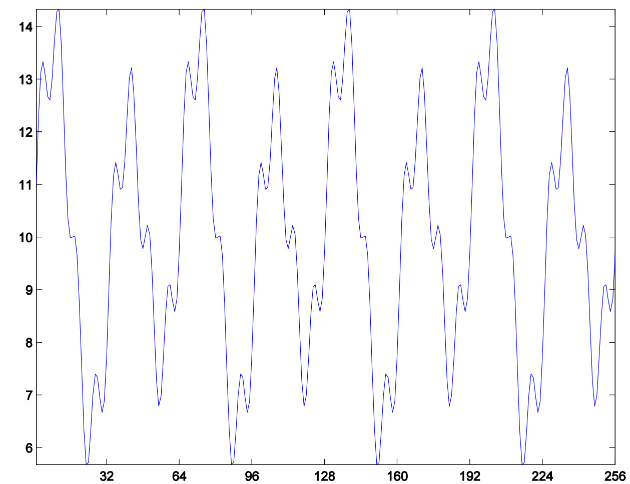
(n=256, Δt=2 s)



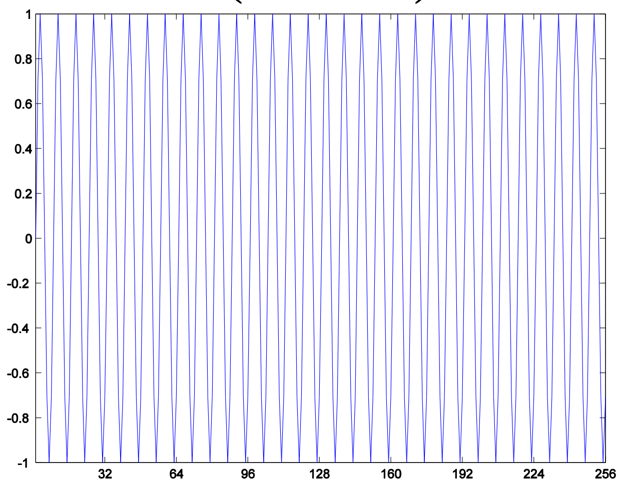
$10\cos(2\pi 0/512t)$



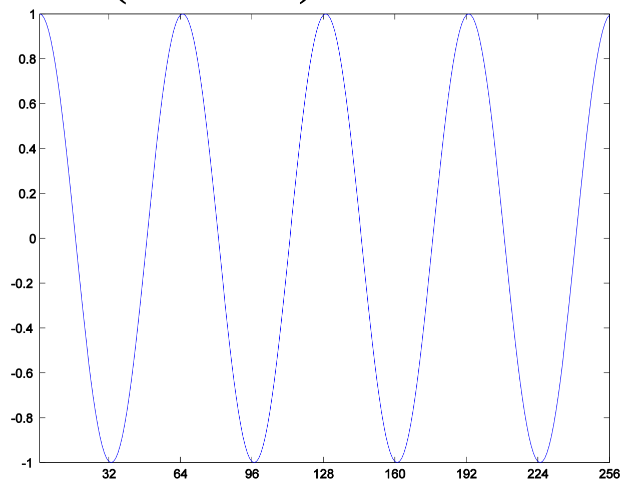
$3\sin(2\pi 8/512t)$



sum



$1\cos(2\pi 32/512t)$

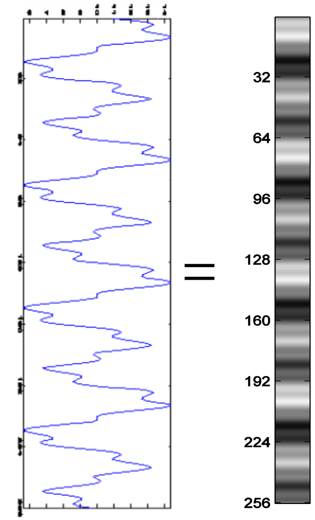


$1\sin(2\pi 4/512t)$

$A\cos(2\pi \nu t)$
$A\sin(2\pi \nu t)$

Image Reconstruction

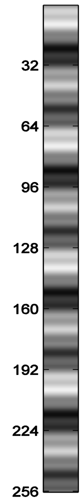
represent



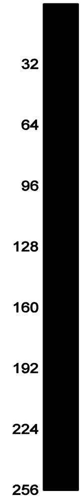
sum

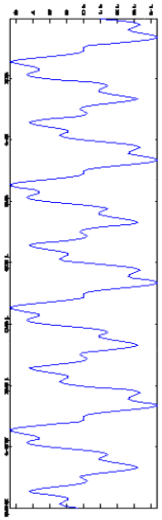
Image Reconstruction

represent



$+i$





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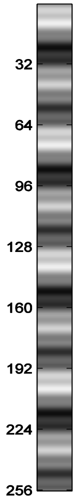
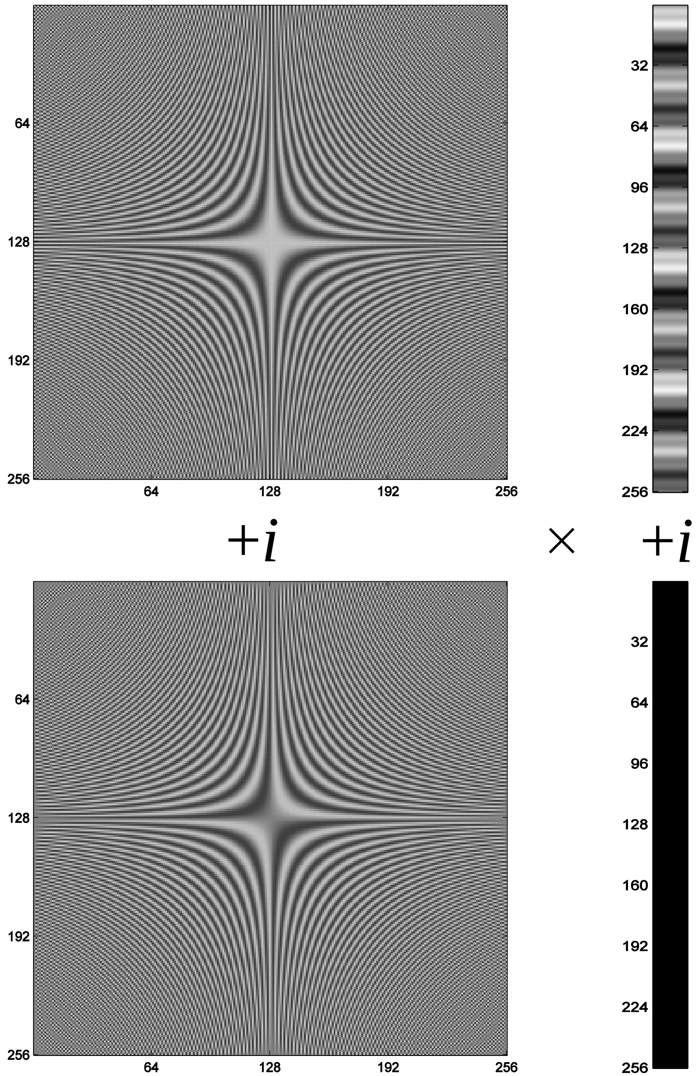
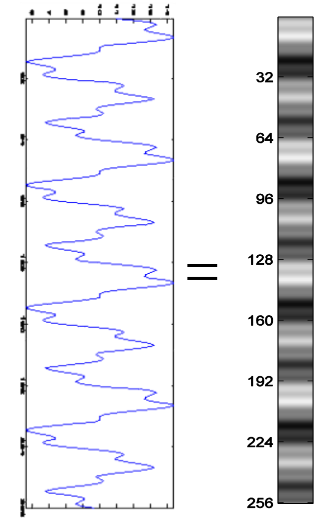


sum

Image Reconstruction

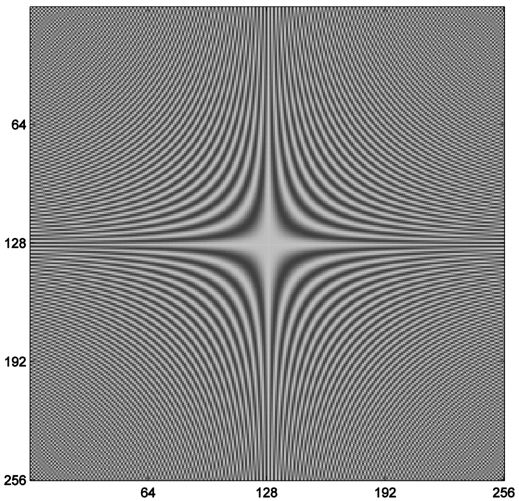


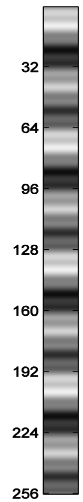
represent

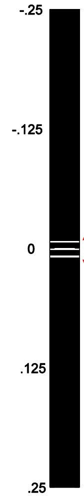


sum

Image Reconstruction





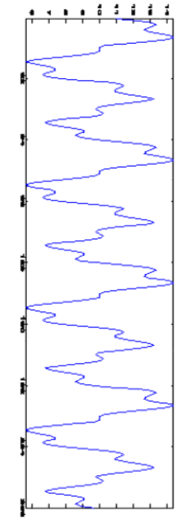


$1\cos(2\pi 32/512t)$

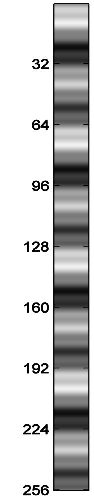
$10\cos(2\pi 0/512t)$

$1\cos(2\pi 32/512t)$

represent

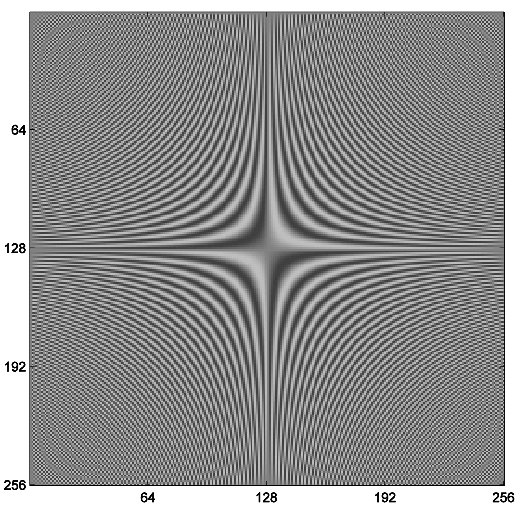


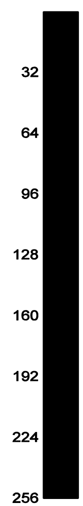
$=$

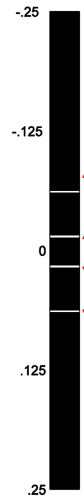


sum

$+i \qquad \times \qquad +i \qquad = \qquad +i$







$3\sin(2\pi 8/512t)$

$1\sin(2\pi 4/512t)$

$1\sin(2\pi 4/512t)$

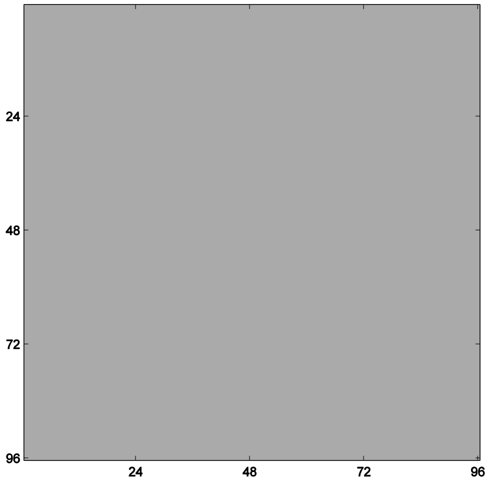
$3\sin(2\pi 8/512t)$

Freq Lines
R = cos freqs
I = sine freq
Intensity = amps

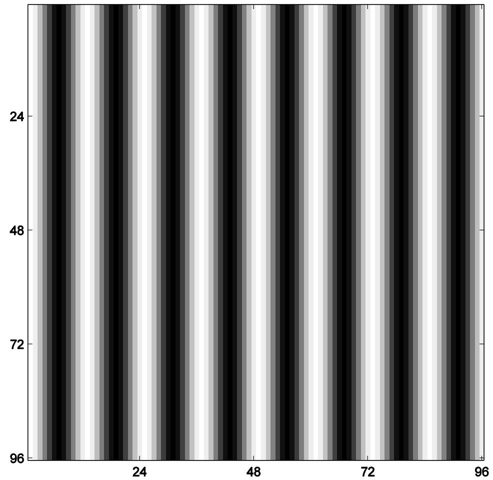
(FOV=192 mm)

(n_x=n_y=96, Δx=Δy=2 mm)

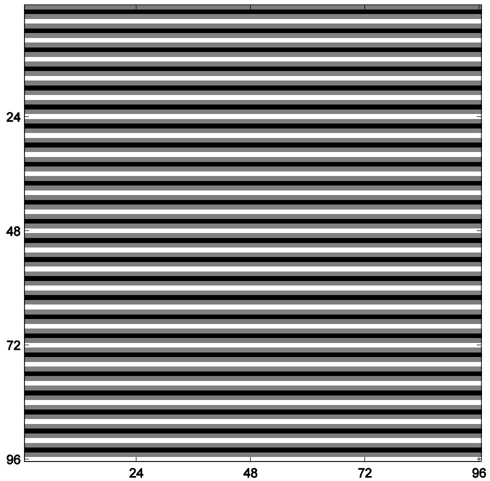
Image Reconstruction



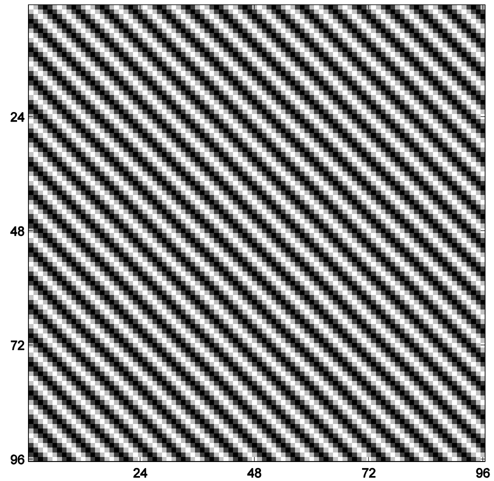
$10\cos(2\pi 0/96x)$



$1.5\cos(2\pi 8/96x)$



$\sin(2\pi 24/96y)$

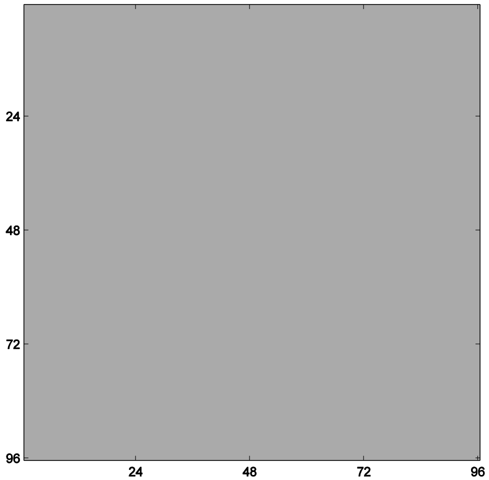


$\cos(2\pi 4/96x+2\pi 4/96y)$

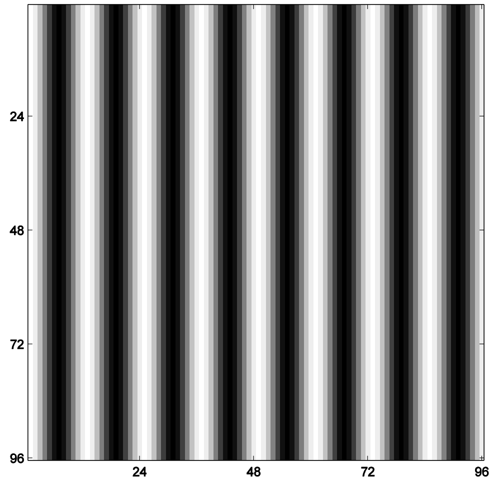
(FOV=192 mm)

$(n_x=n_y=96, \Delta x=\Delta y=2 \text{ mm})$

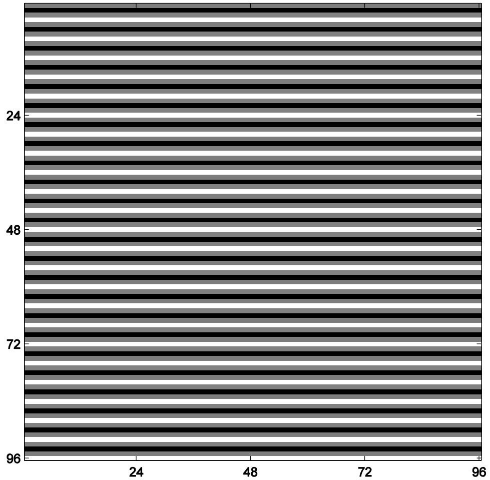
Image Reconstruction



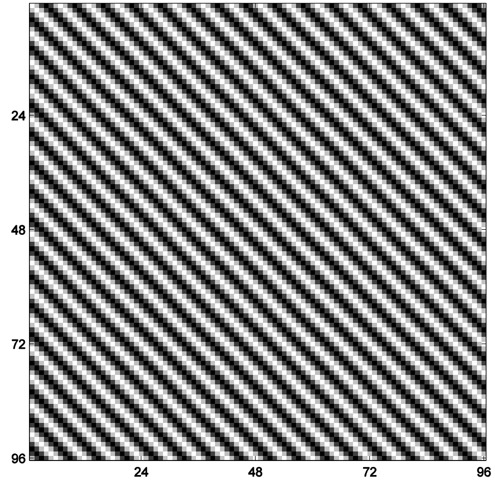
$10\cos(2\pi 0/96x)$



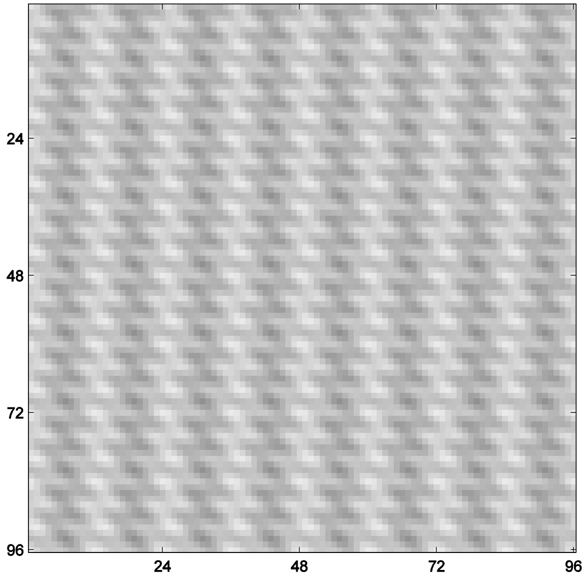
$1.5\cos(2\pi 8/96x)$



$\sin(2\pi 24/96y)$



$\cos(2\pi 4/96x+2\pi 4/96y)$



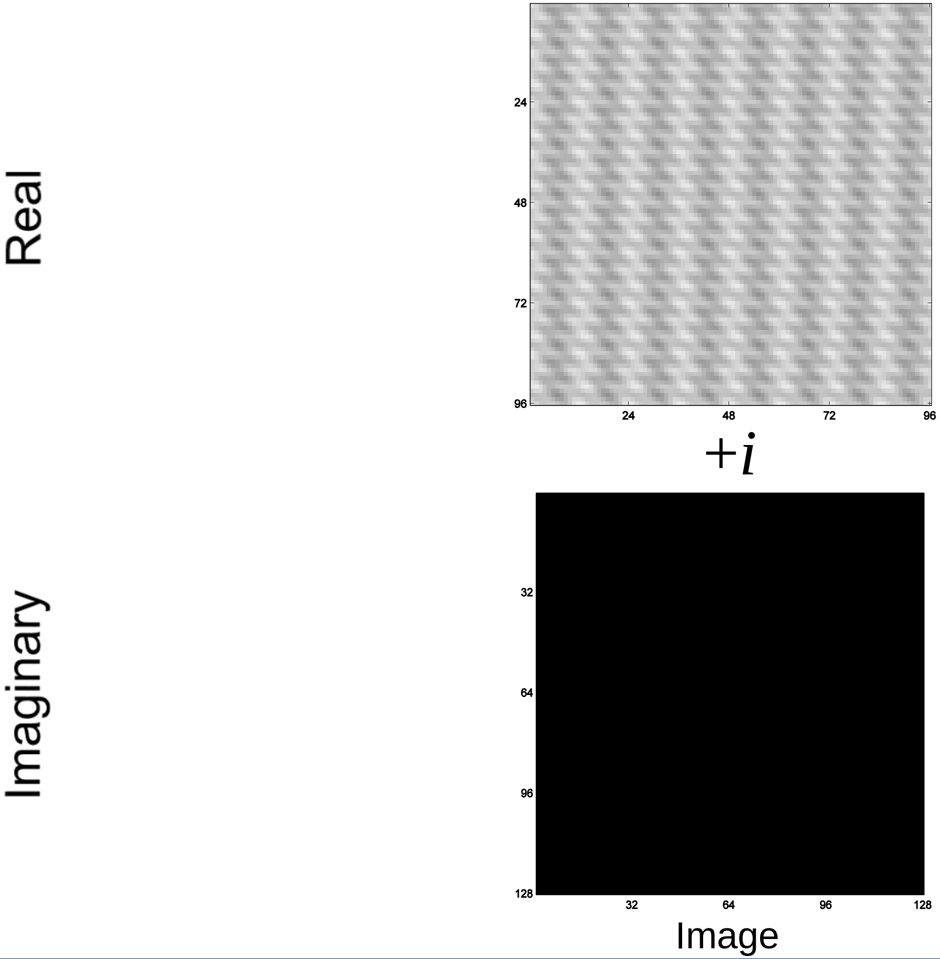
sum

(FOV=192 mm)

Image Reconstruction

(n_x=n_y=96, Δx=Δy=2 mm)

The machine Fourier encodes the image. Measure spatial freq.

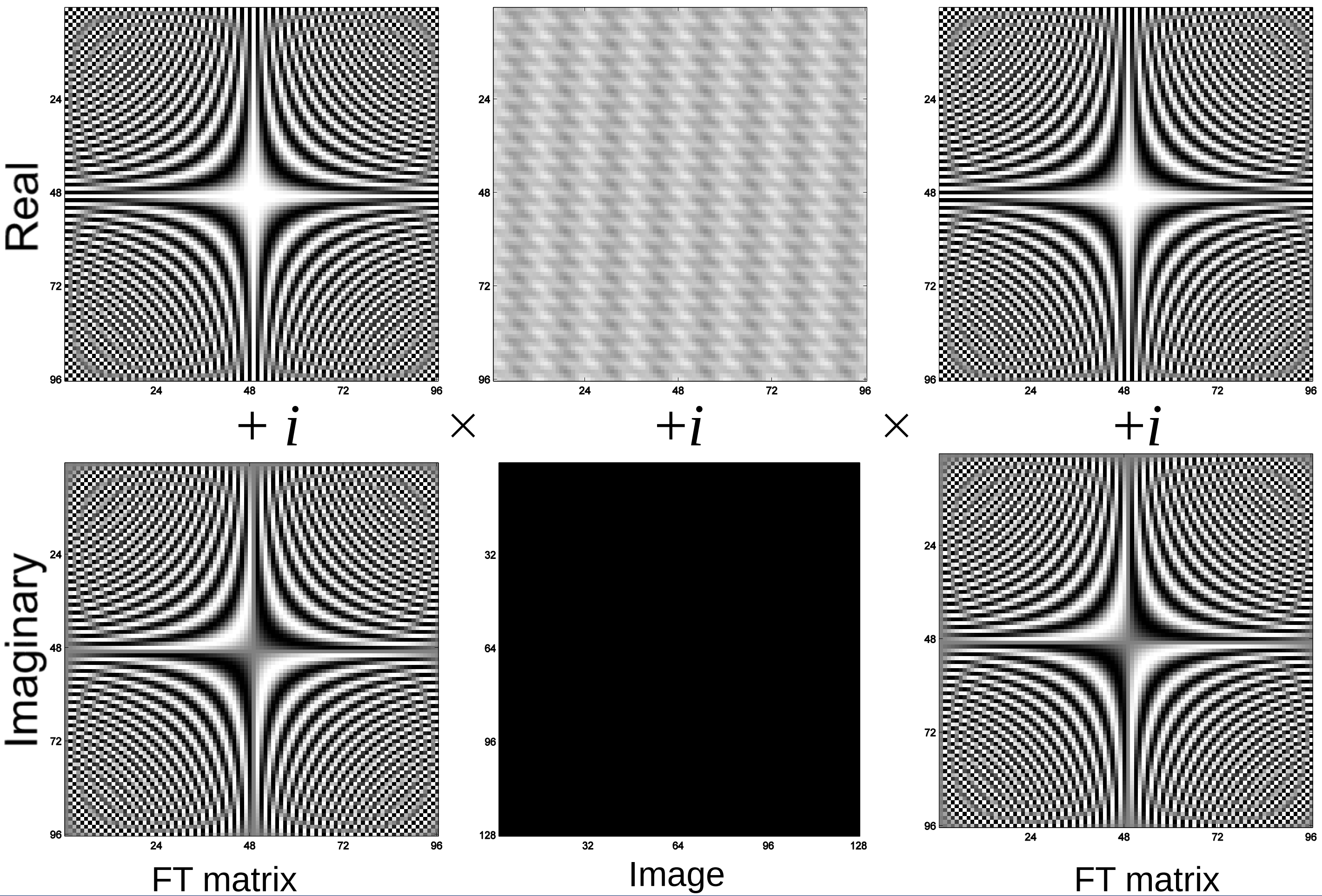


(FOV=192 mm)

$(n_x=n_y=96,\ \Delta x=\Delta y=2\text{ mm})$

Image Reconstruction

The machine Fourier encodes the image. Measure spatial freq.

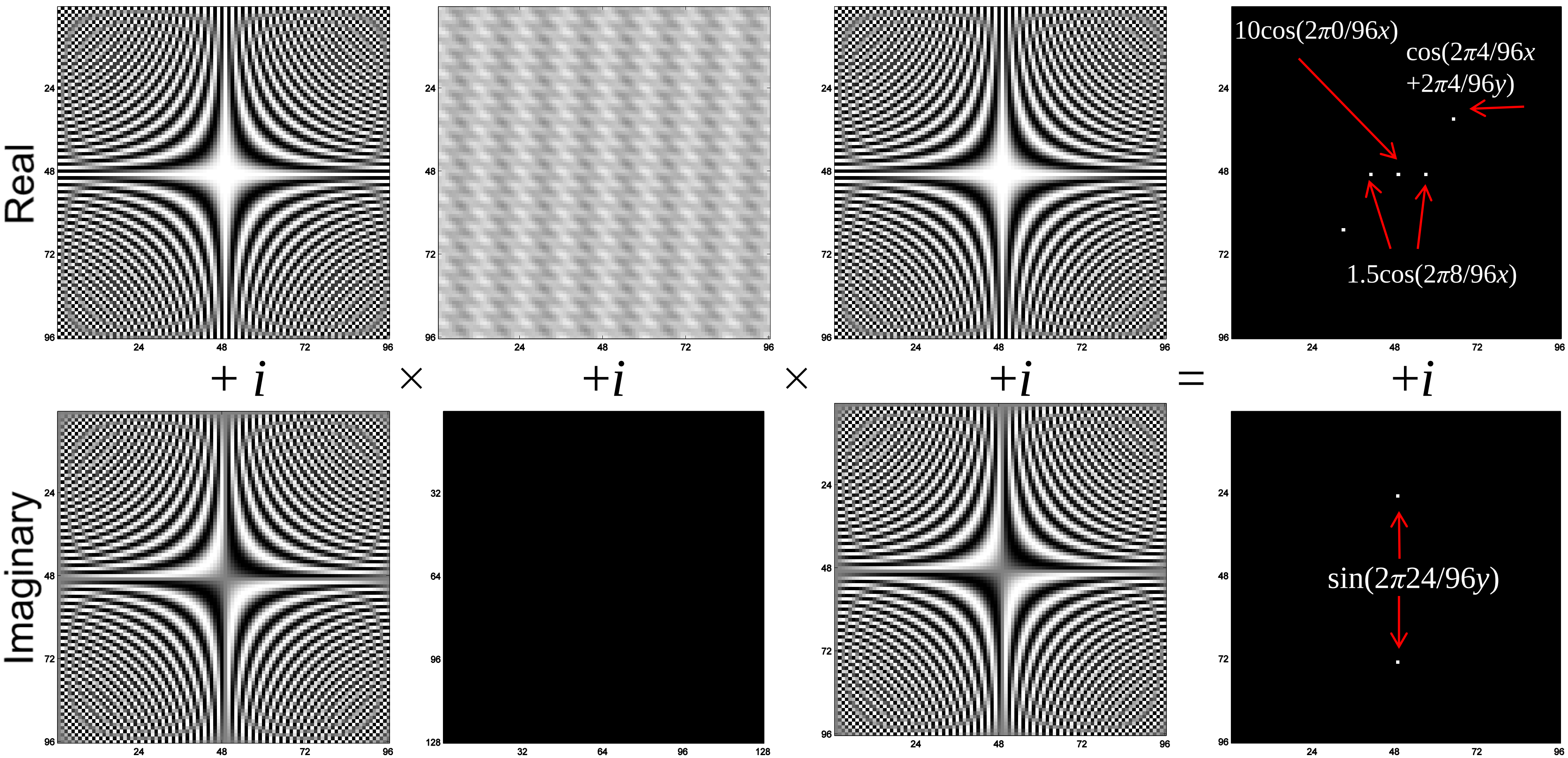


(FOV=192 mm)

($n_x = n_y = 96$, $\Delta x = \Delta y = 2$ mm)

Image Reconstruction

The machine Fourier encodes the image. Measure spatial freq.



FT matrix | image | FT matrix | spatial frequencies

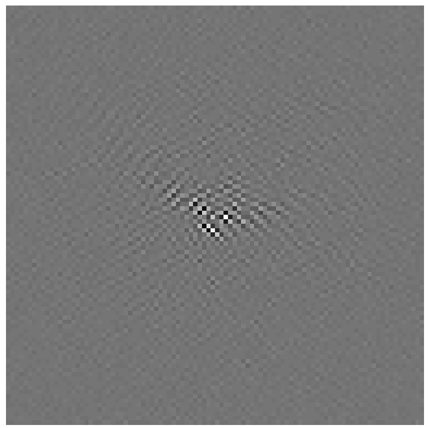
(FOV=192 mm)

Image Reconstruction

($n_x=n_y=96$, $\Delta x=\Delta y=2$ mm)

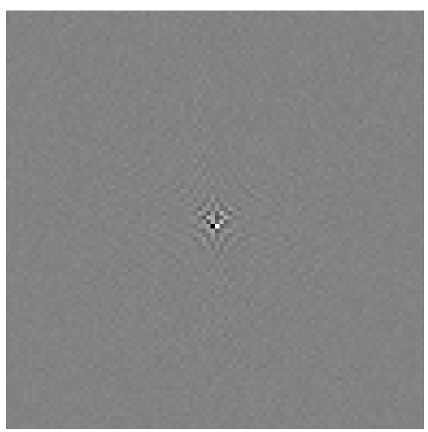
We inverse Fourier transform spatial freqs to generate image.

Real



$+i$

Imaginary



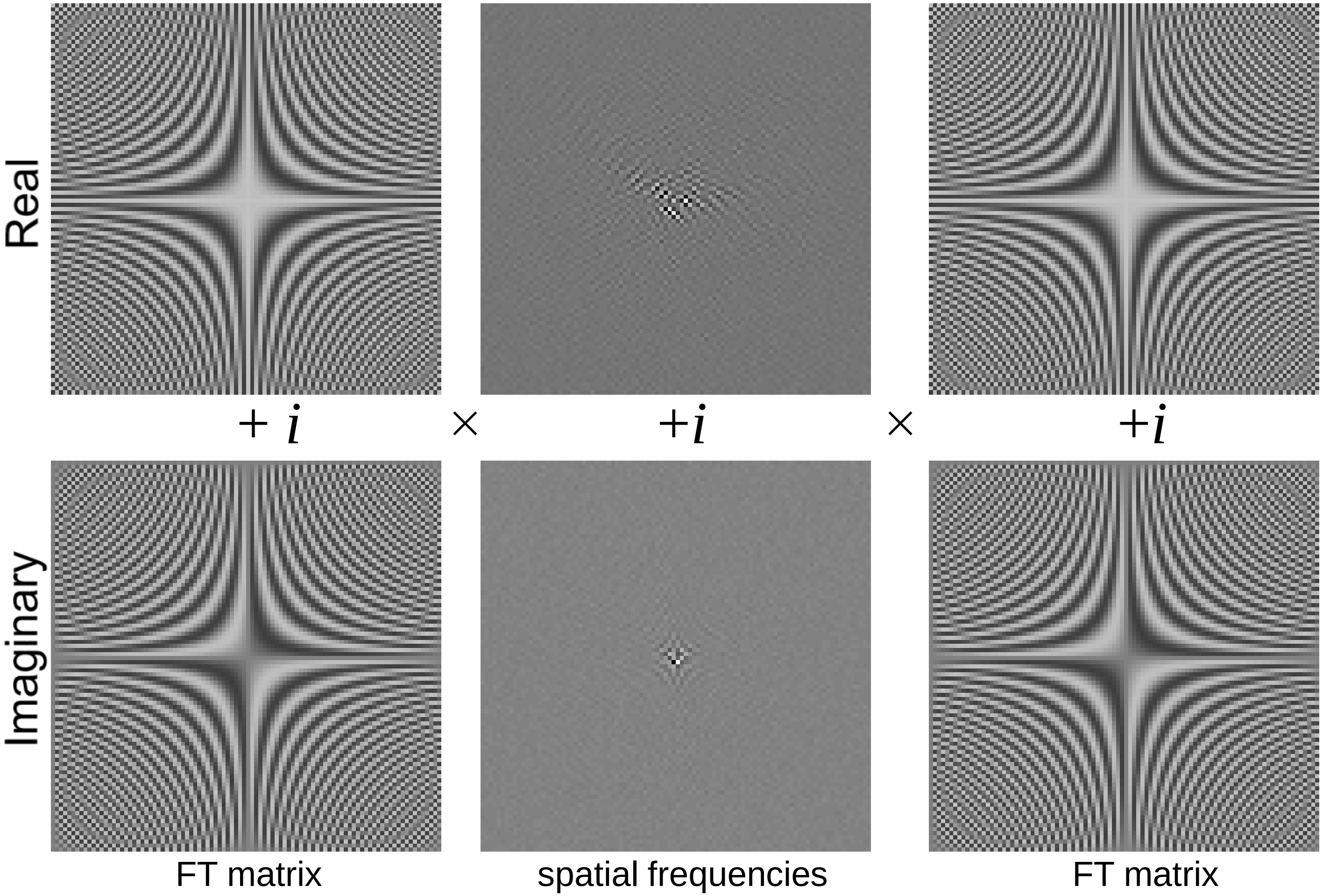
spatial frequencies

(FOV=192 mm)

Image Reconstruction

(n_x=n_y=96, Δx=Δy=2 mm)

We inverse Fourier transform spatial freqs to generate image.

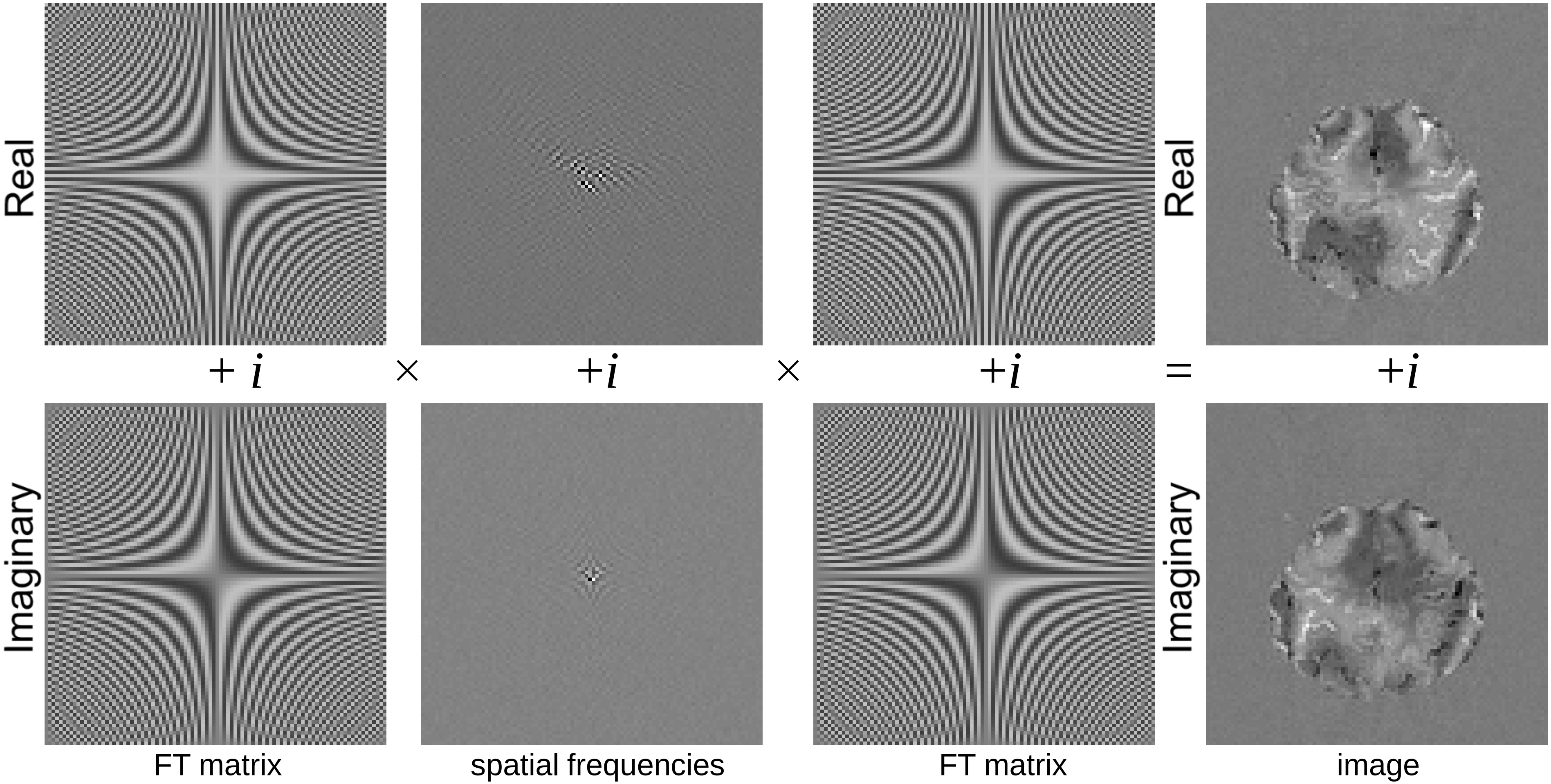


(FOV=192 mm)

(n_x=n_y=96, Δx=Δy=2 mm)

Image Reconstruction

We inverse Fourier transform spatial freqs to generate image.

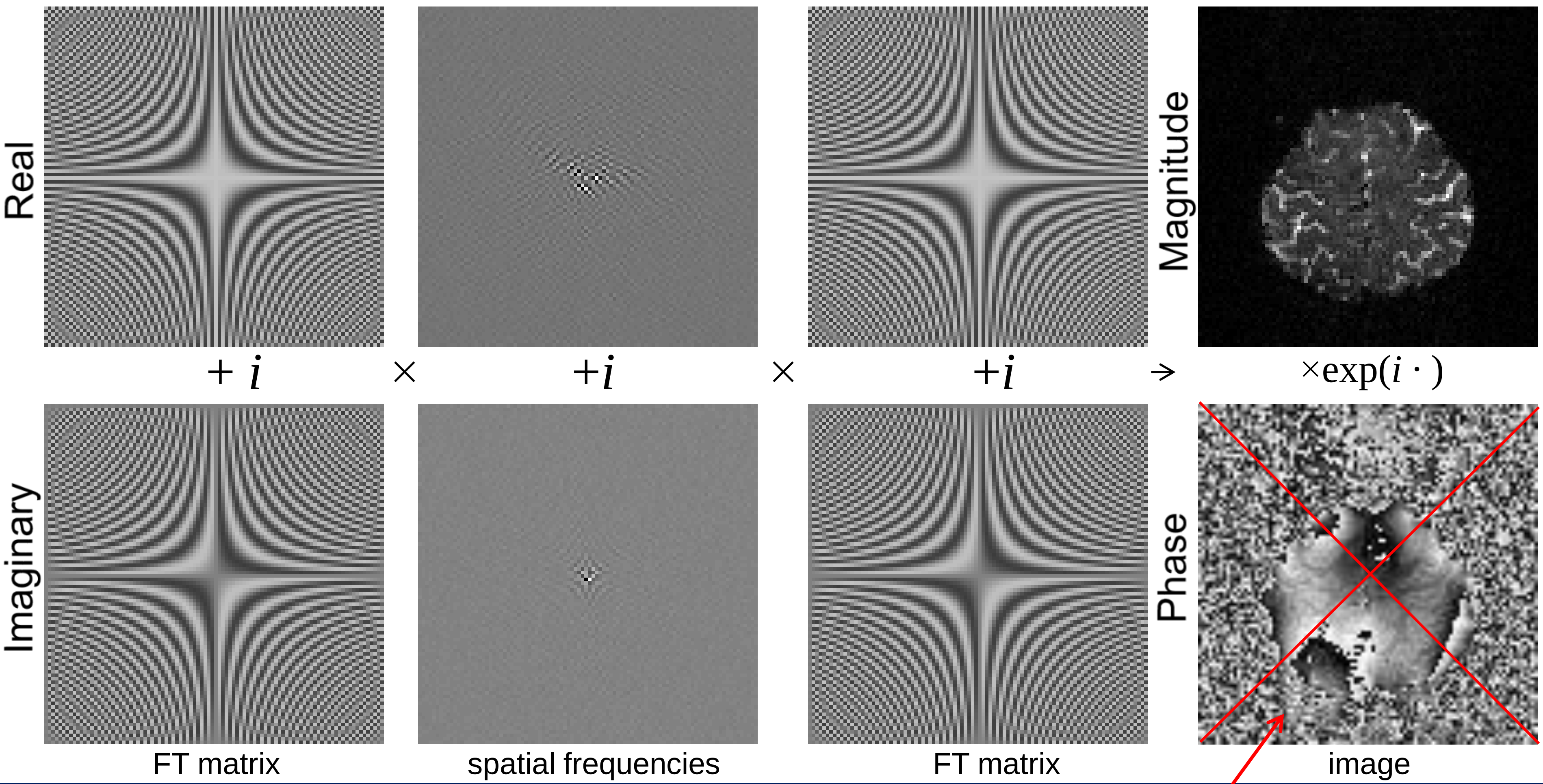


(FOV=192 mm)

Image Reconstruction

($n_x = n_y = 96$, $\Delta x = \Delta y = 2$ mm)

We inverse Fourier transform spatial freqs to generate image.



Phase discarded. Ask for the other ½ of YOUR data.

(FOV=192 mm)

($n_x=n_y=96$, $\Delta x=\Delta y=2$ mm)

Image Reconstruction

We inverse Fourier transform spatial freqs to generate image.

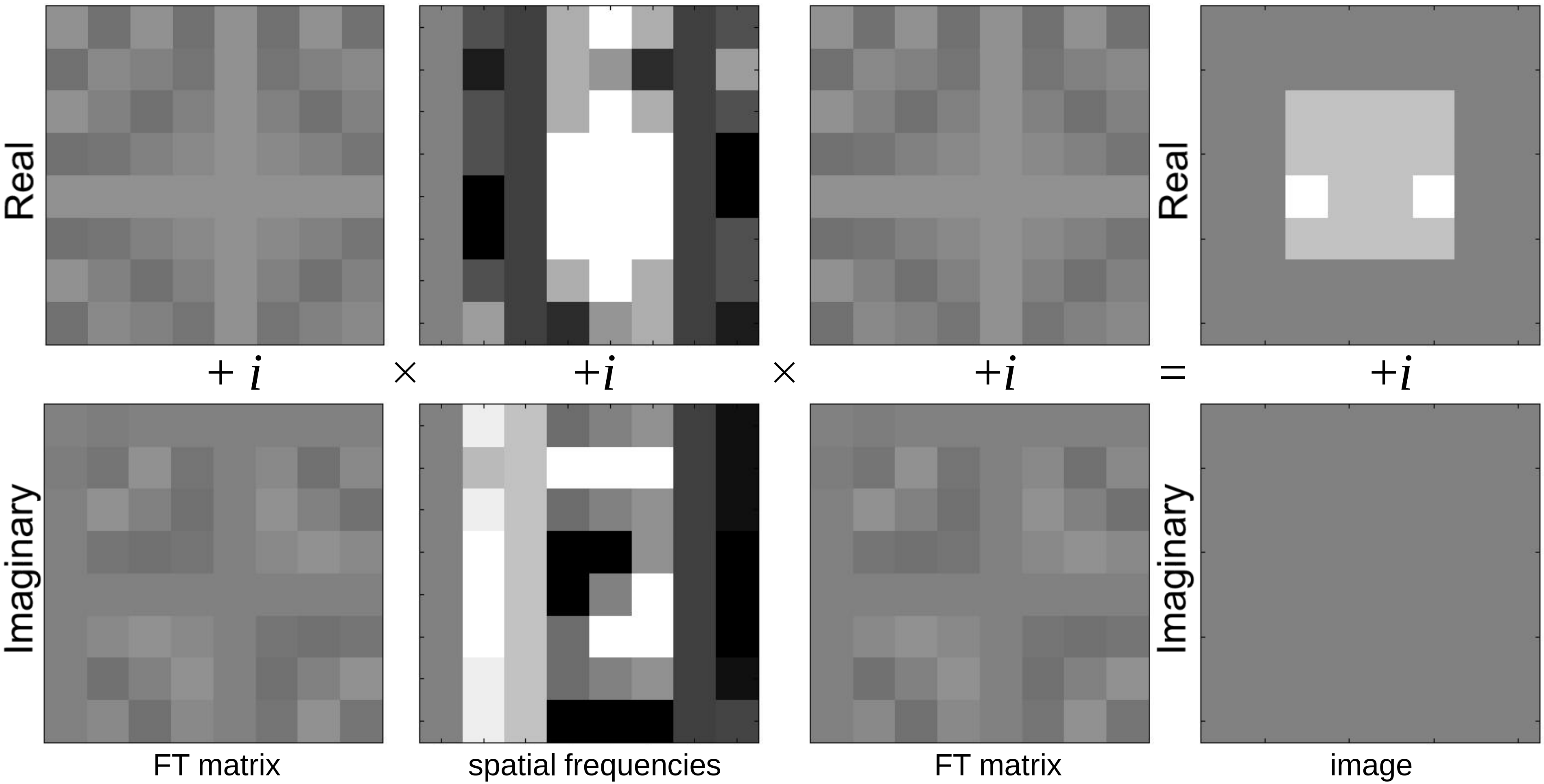
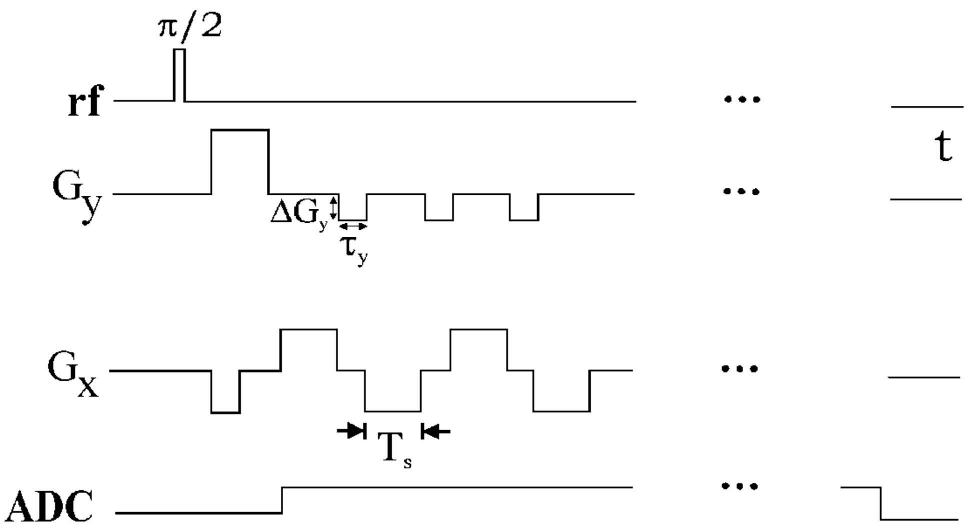
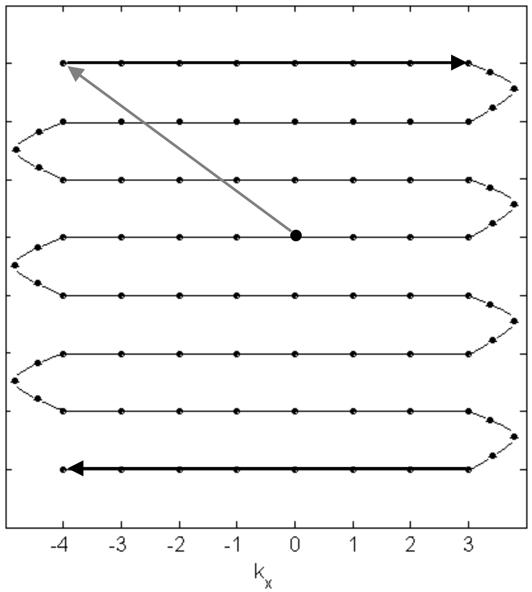


Image Reconstruction

We get *k*-space measurements by changing gradients



Adapted from Haacke et al., 1999



R-I Points

taking complex-valued measurements over time.

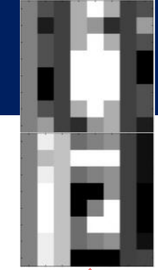
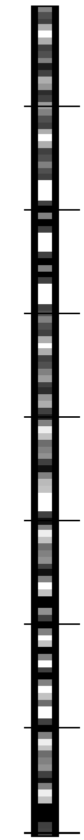


Image Reconstruction

We can stack freq. rows of reals over rows of imaginaries,



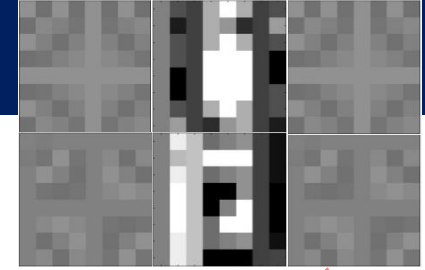
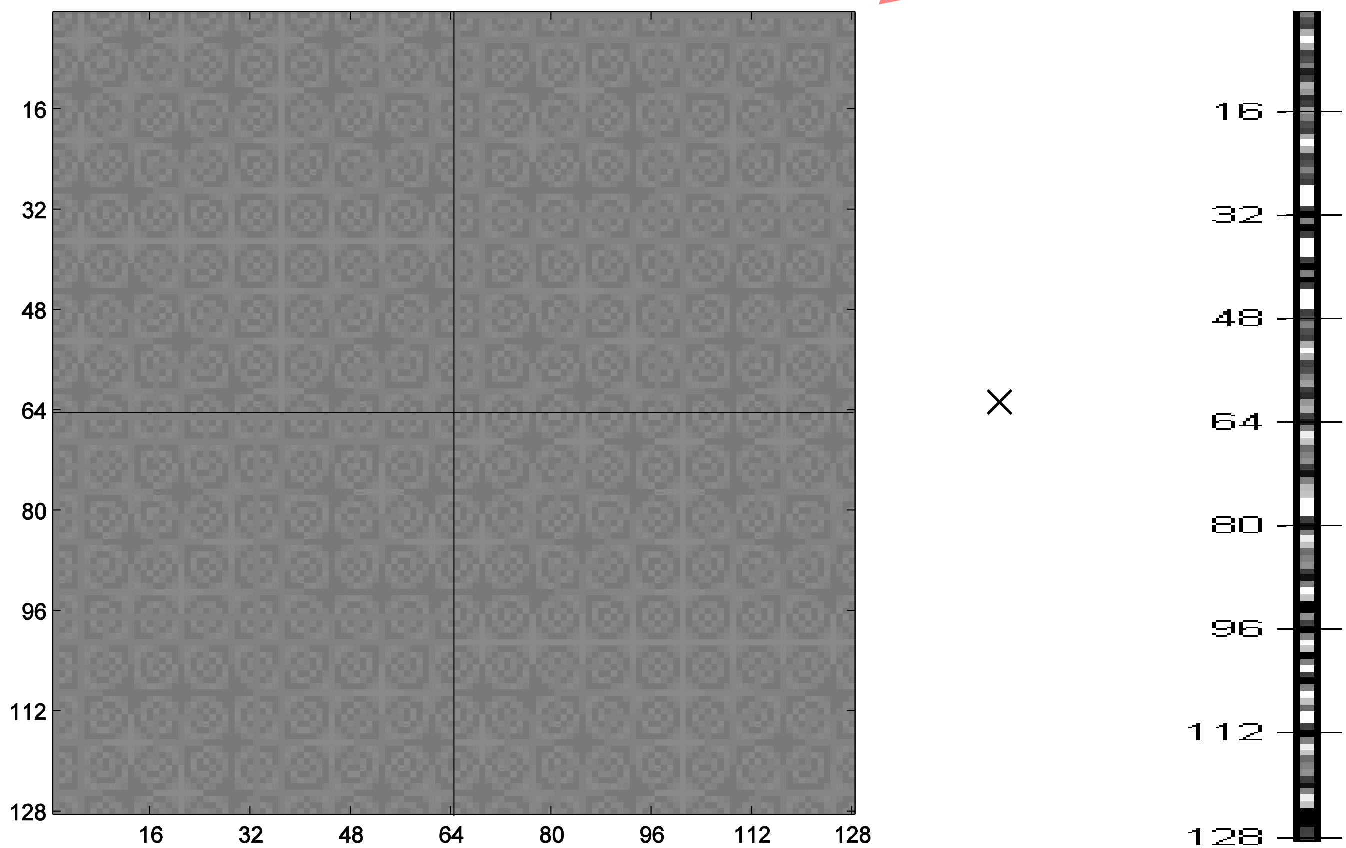


Image Reconstruction

We can stack freq. rows of reals over rows of imaginaries, make one IFT reconstruction matrix from the two,



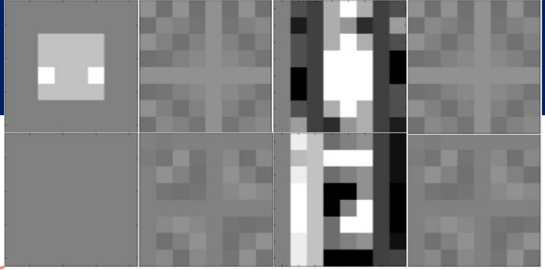
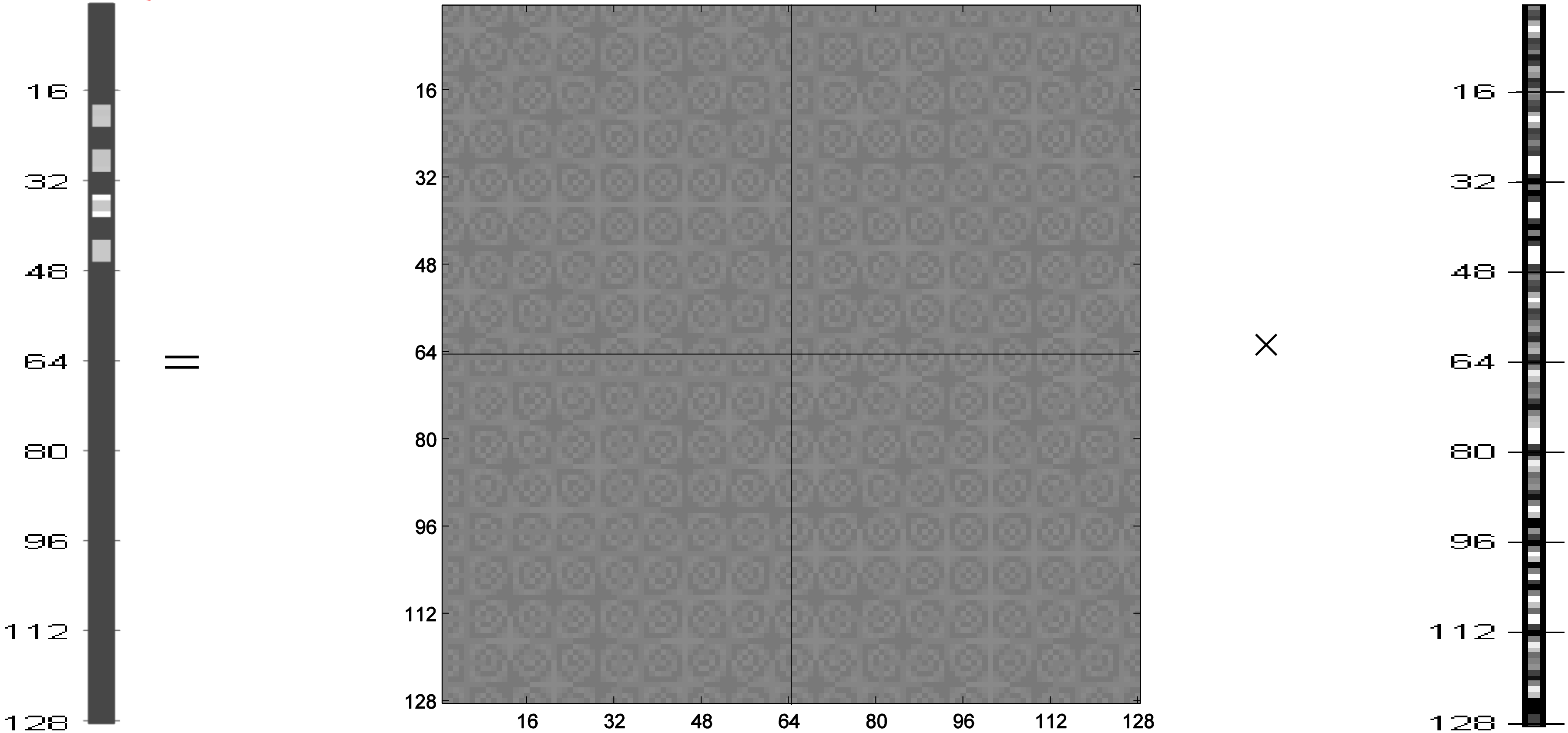


Image Reconstruction

We can stack freq. rows of reals over rows of imaginaries,
make one IFT reconstruction matrix from the two,
to get the rows of reals over rows of imaginaries.



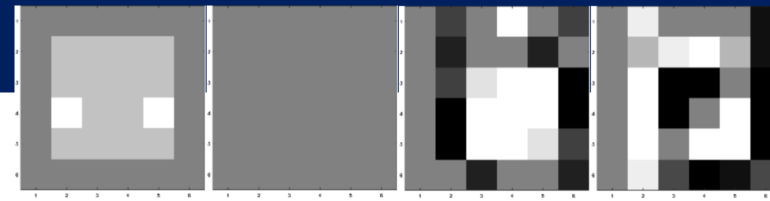
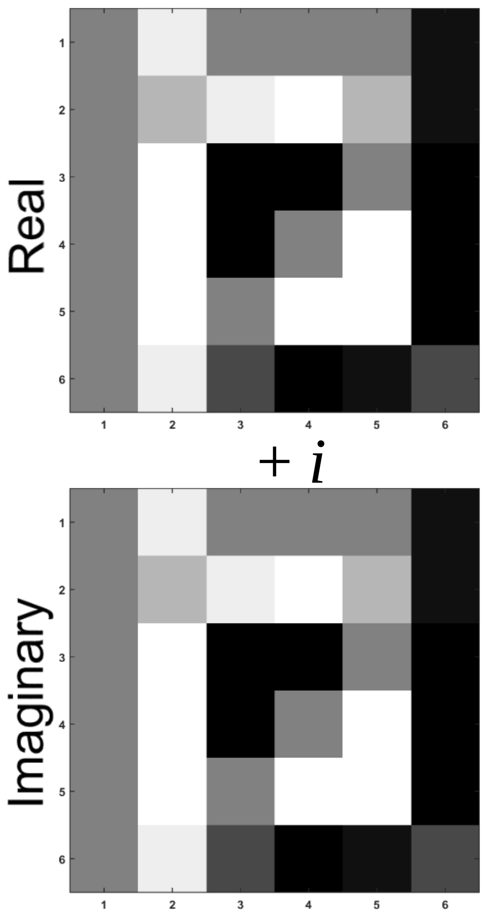


Image Processing

Many processing operations are performed by the scanner, by physicists, and by engineers before statistical analysis.



<u>*k*-space Processing</u>
Nyquist Ghost Correction
Static B0 Field Correction
Zero Fill Interpolation
Non-Cartesian Interpolation
Ramp Sampling Interpolation
Homodyne Interpolation
Apodization
And many more…

<u>Image Reconstruction</u>
2D inverse Fourier transform
SENSE/GRAPPA
Simultaneous Multi-Slice

<u>Image Processing</u>
Image Smoothing
Global Normalization
Motion Correction
And many more…

<u>Time Series Processing</u>
Filtering
Smoothing
Dynamic B0 Correction
Slice Timing
And many more…

Show ones in blue.

Image Processing

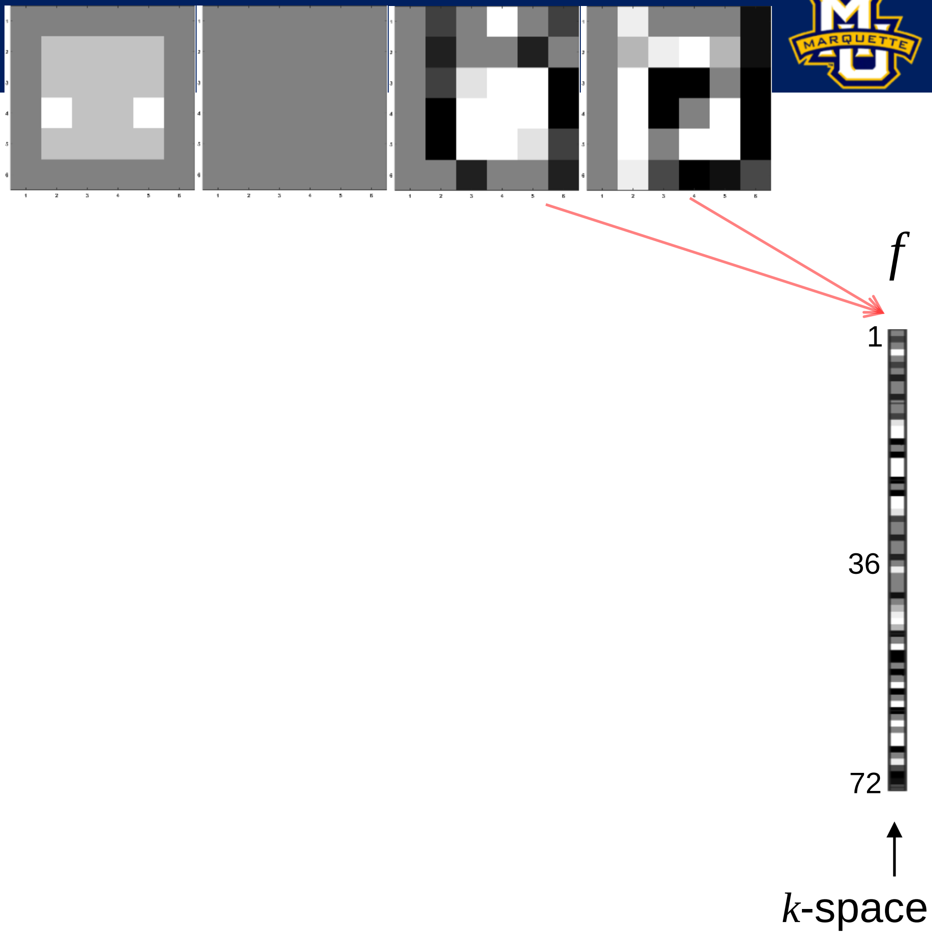
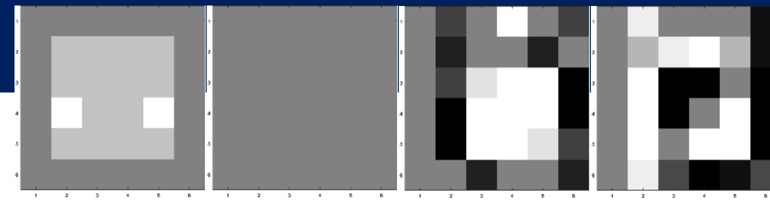


Image Processing



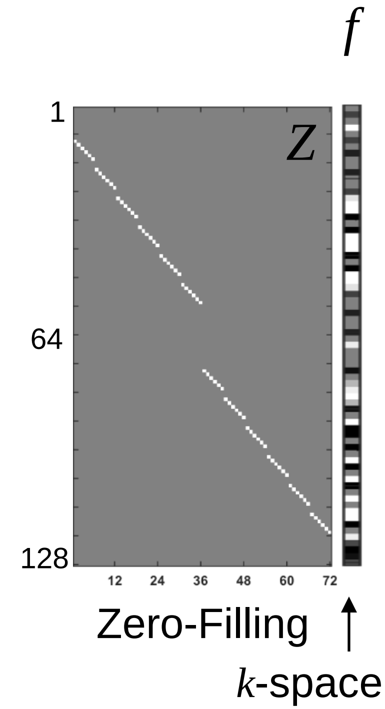
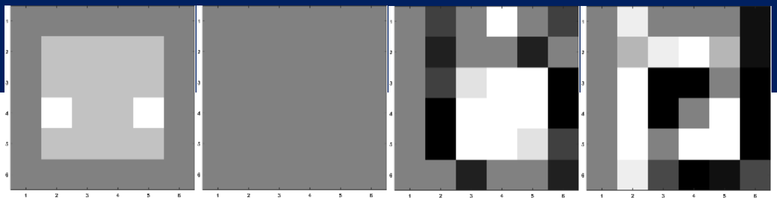


Image Processing



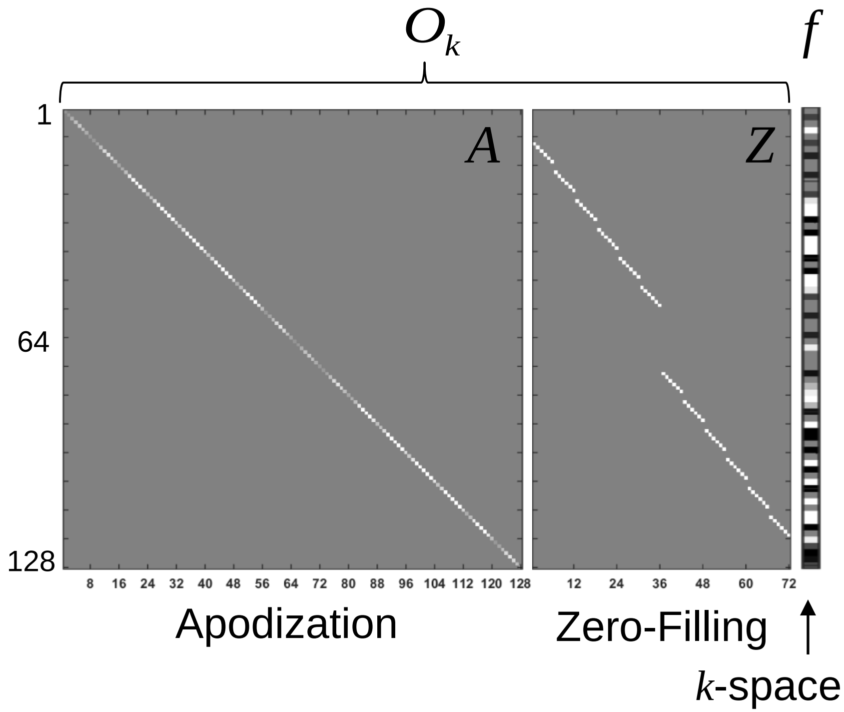
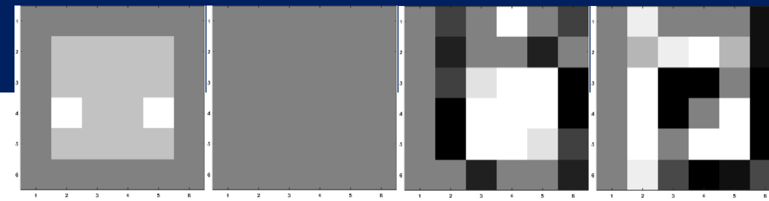
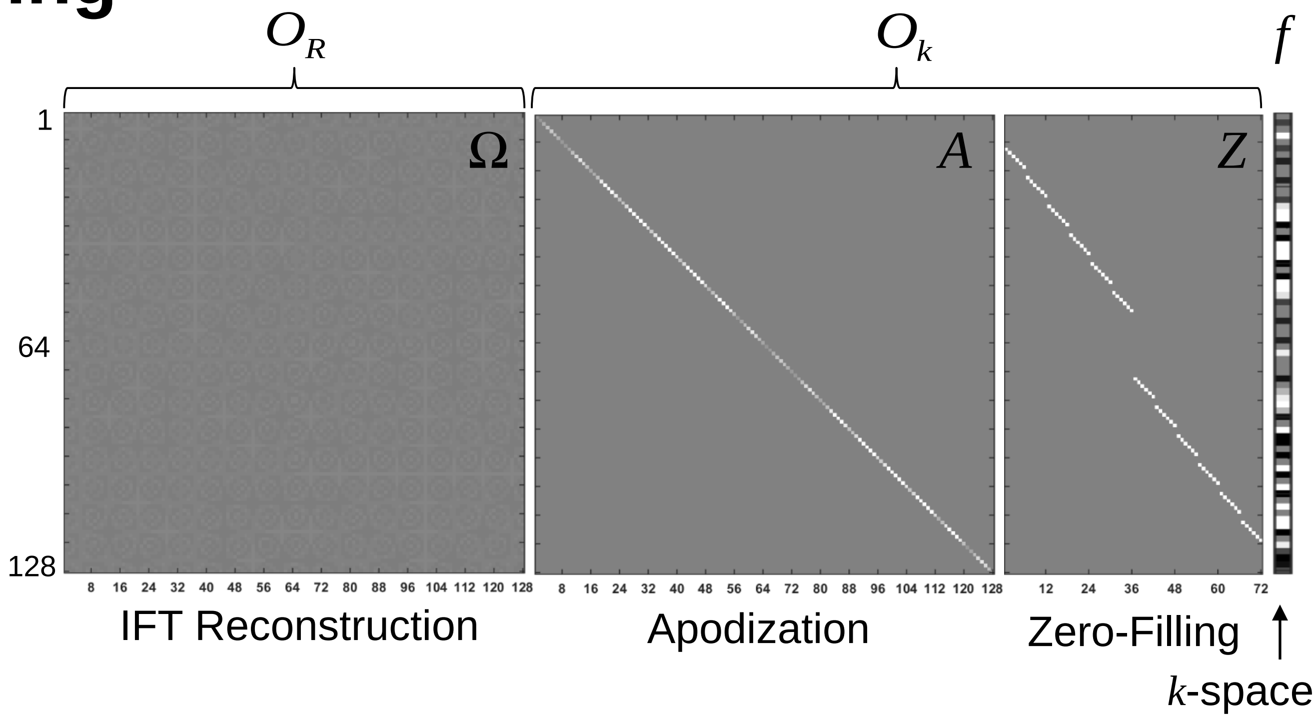


Image Processing





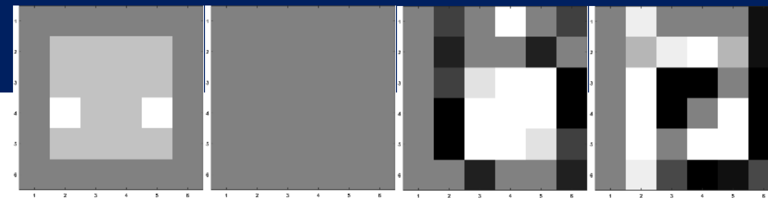
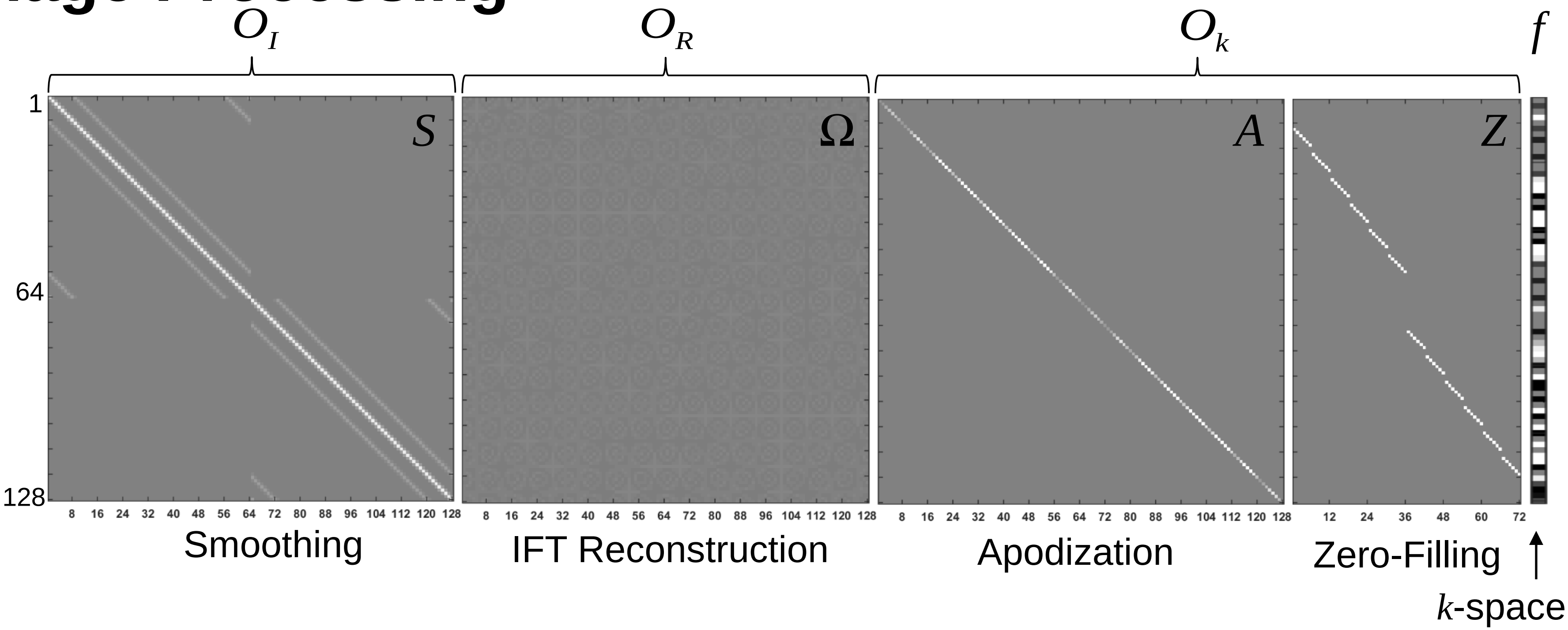


Image Processing



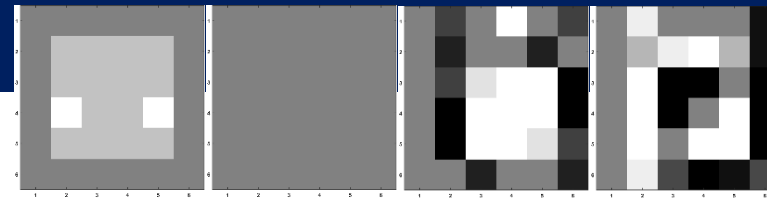
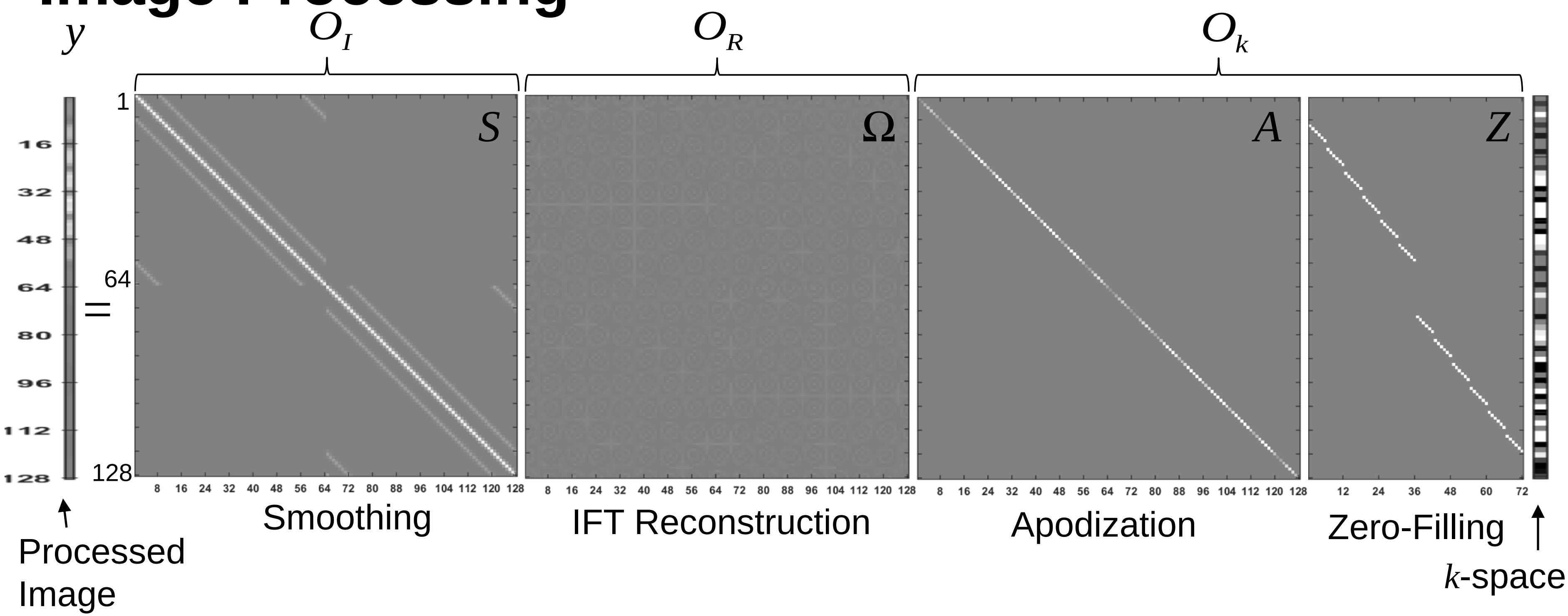


Image Processing



$y=Of$

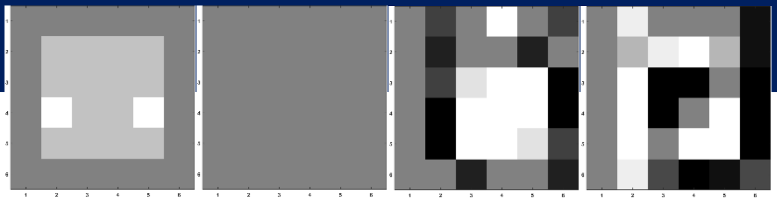
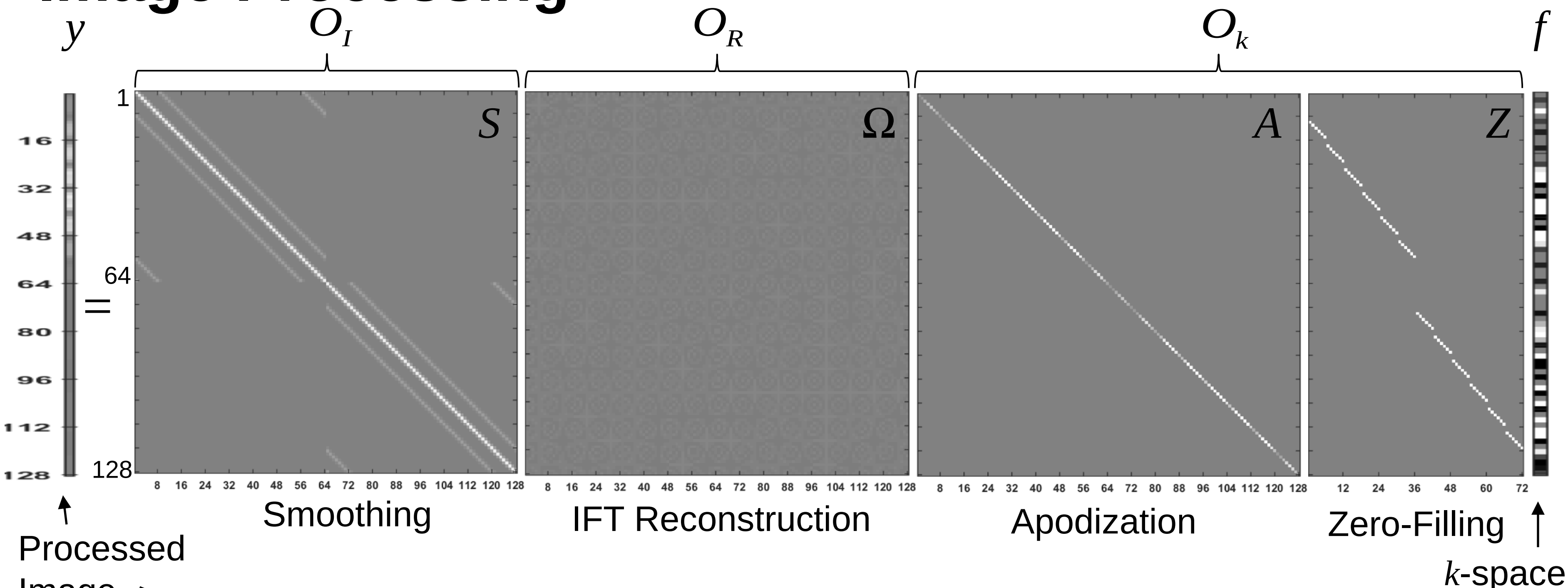
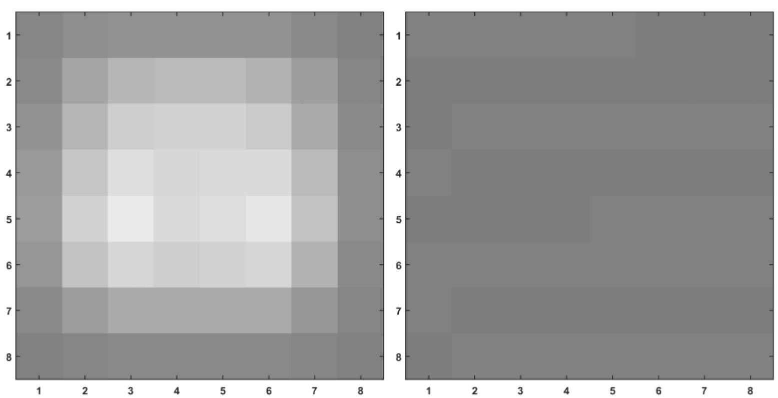


Image Processing



$y = Of$



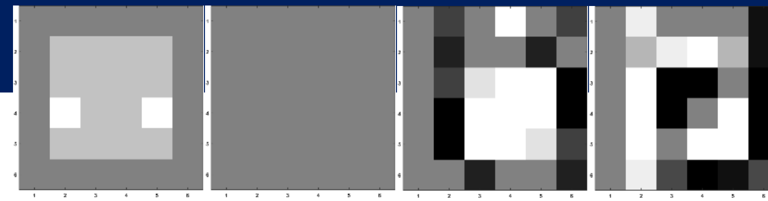


Image Processing

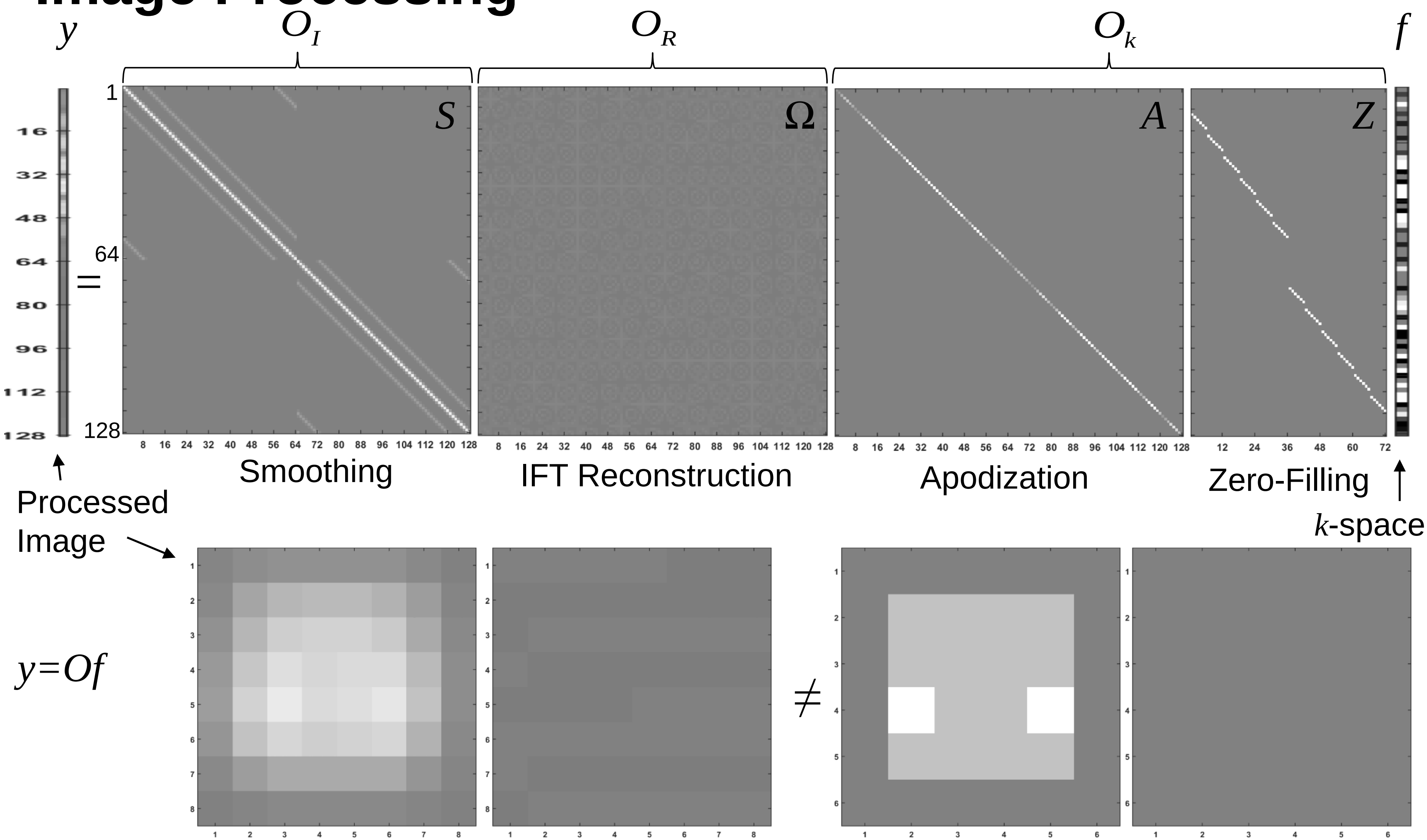


Image Processing

We measure an array of complex-valued numbers,
perform complex-valued image reconstruction to this array,
to generate complex-valued images in real and imaginary,
along the way, there is complex-valued image processing.

What are the implications of what was done to the data?

Implications

In statistics, we know the rule that says:

If a vector f has a mean δ, and a covariance Γ,

Then $y=Of$ has a mean $\mu=O\delta$, and a covariance $\Sigma=O\Gamma O^T$.

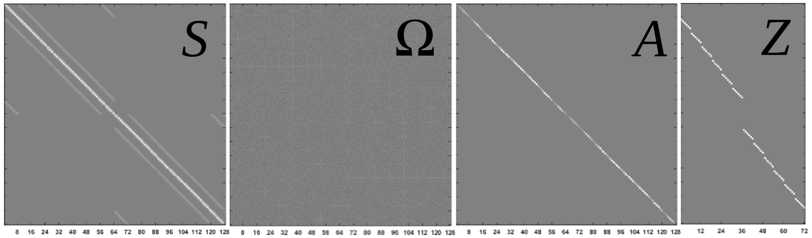
Then Σ can converted into a correlation matrix $R=D^{-1/2}\Sigma D^{-1/2}$.

Where $D^{-1/2}=1/\sqrt{diag(\Sigma)}$.

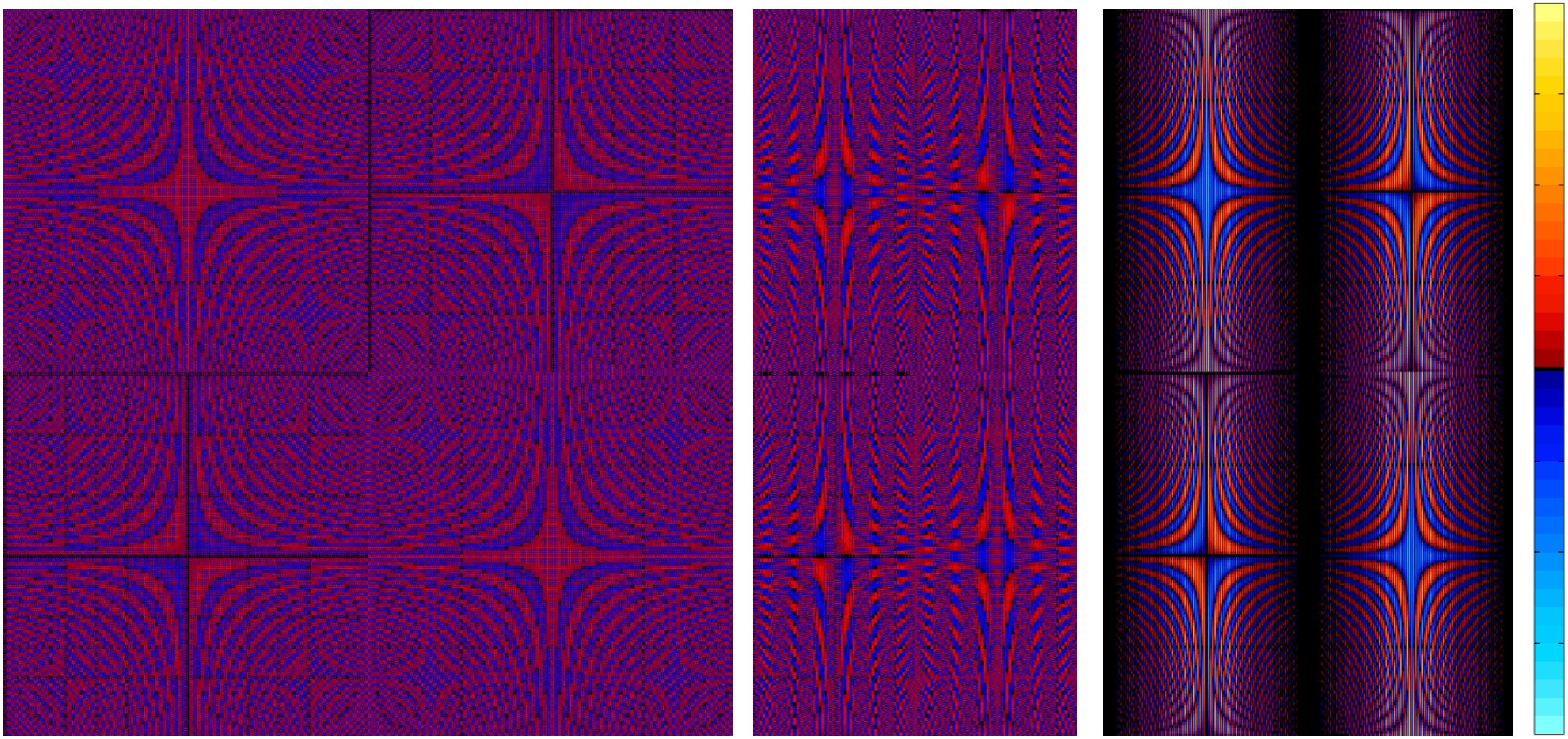
Assume k-space measurements independent so $\Gamma=I$.

Implications

Operators, O.



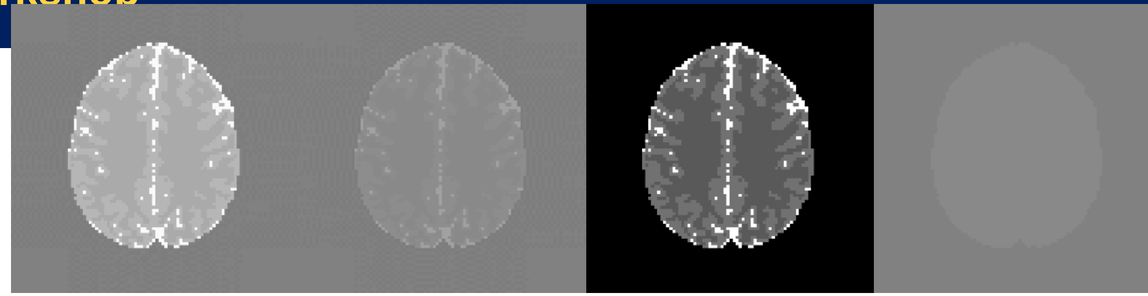
Ω ΩZ $S\Omega AZ$



Implications

Mean, $\mu=Of$.

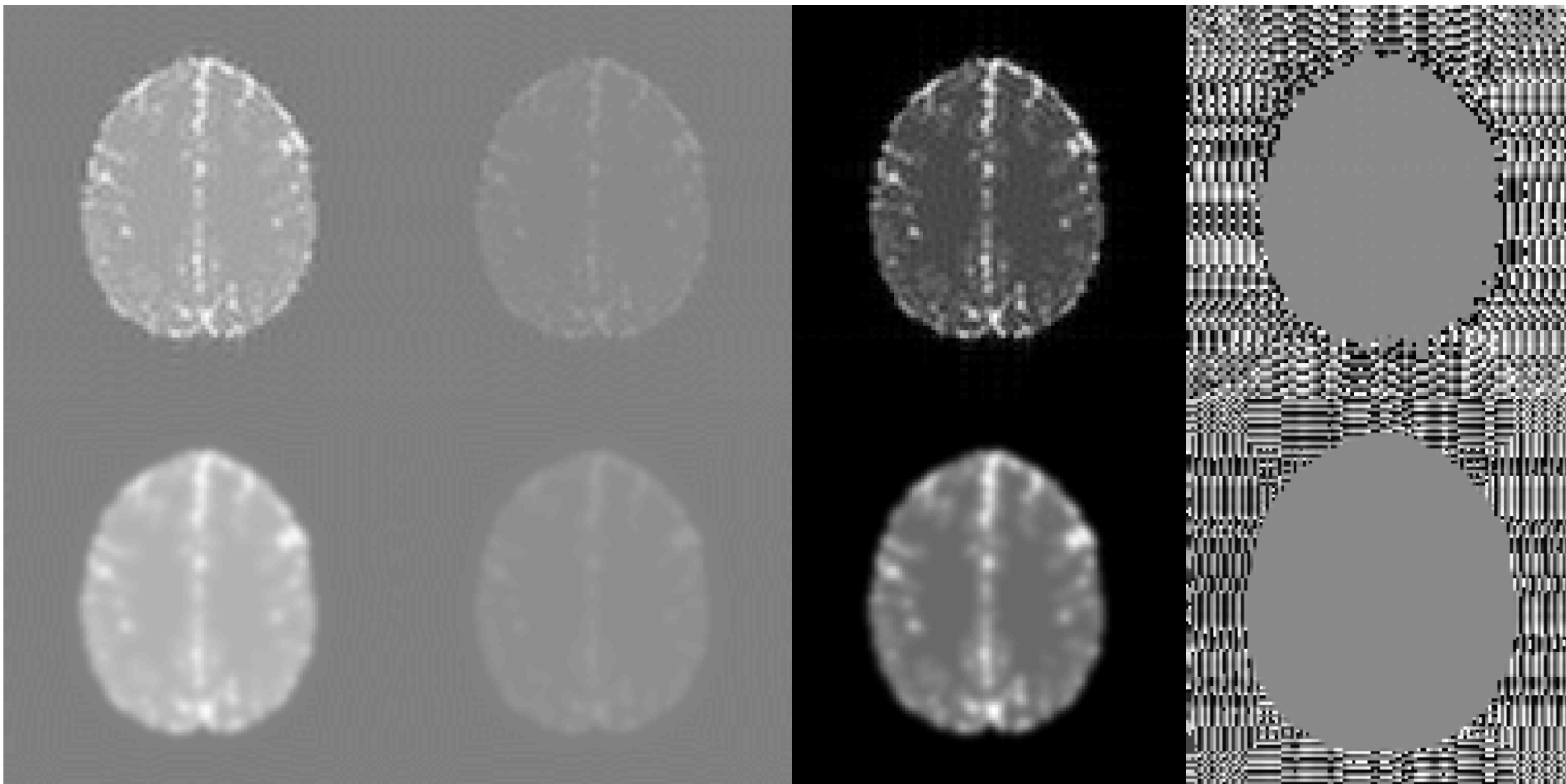
True Values



R I M P

ΩZ

$S\Omega AZ$



Implications

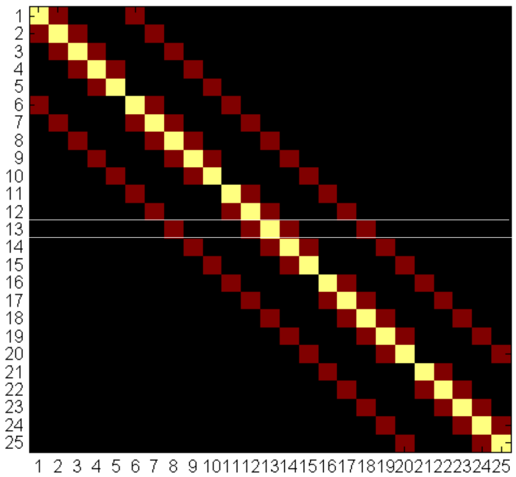
Correlation matrix and correlation image.

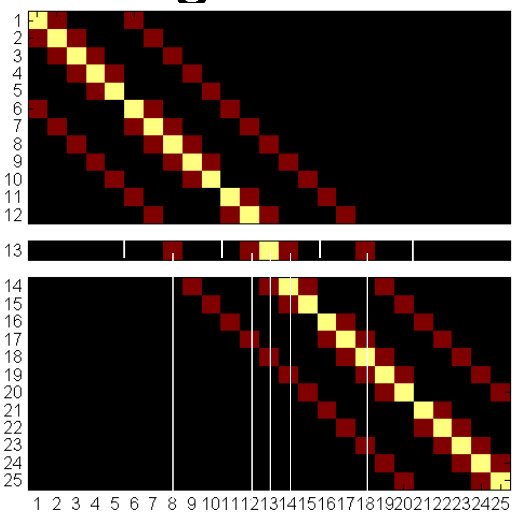
1	2	3	4	5
6	7	8	9	10
11	12	13	14	15
16	17	18	19	20
21	22	23	24	25

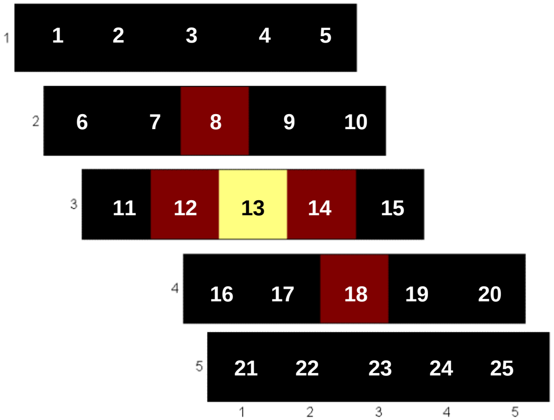
5×5 image

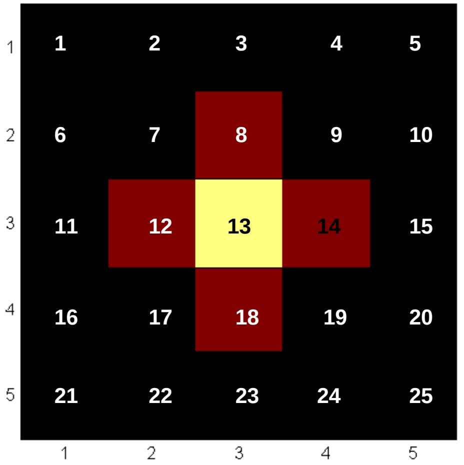
$\text{cor}(y) =$

25×25 correlation matrix

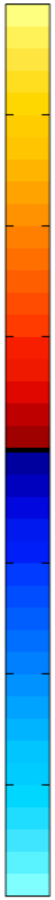




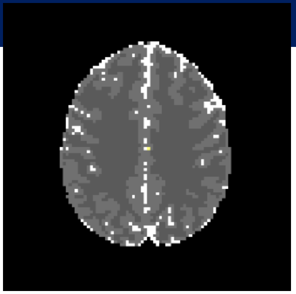




5×5 correlation image



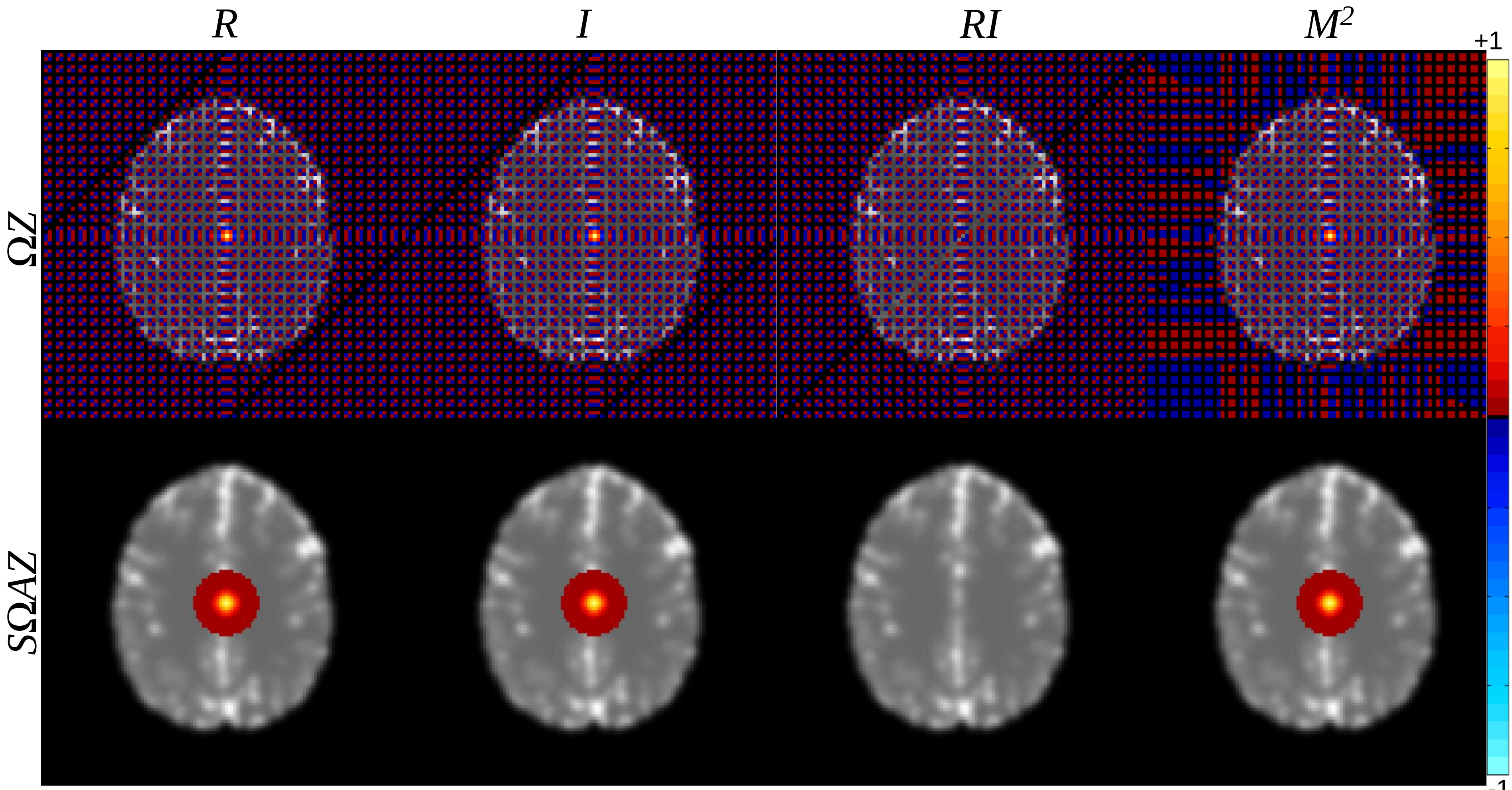
True Values



Implications

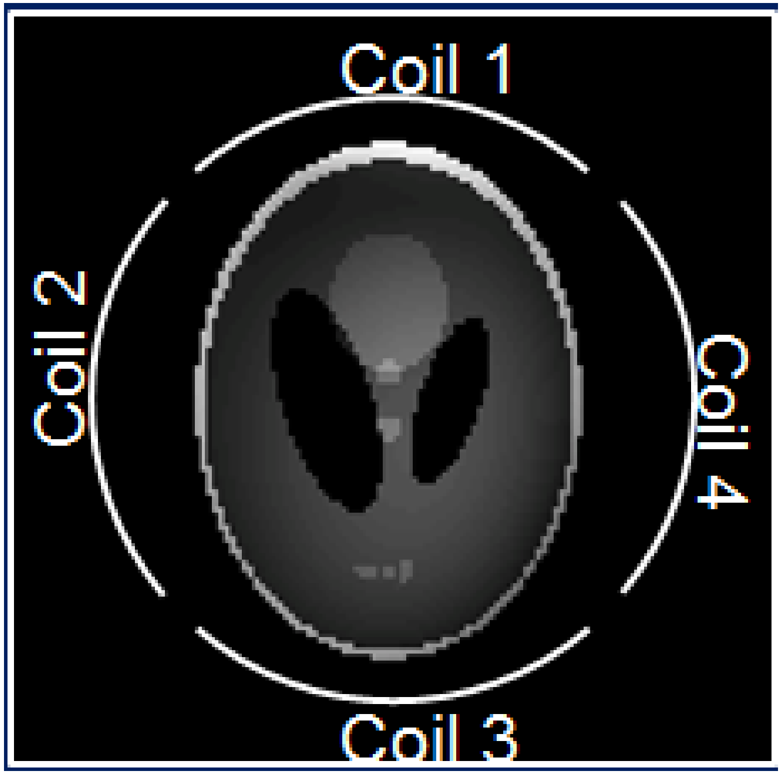
Correlation, $R = D^{-1/2} \Sigma D^{-1/2}$.

$$R = \begin{bmatrix} R_{RR} & R_{RI} \\ R_{IR} & R_{II} \end{bmatrix}$$

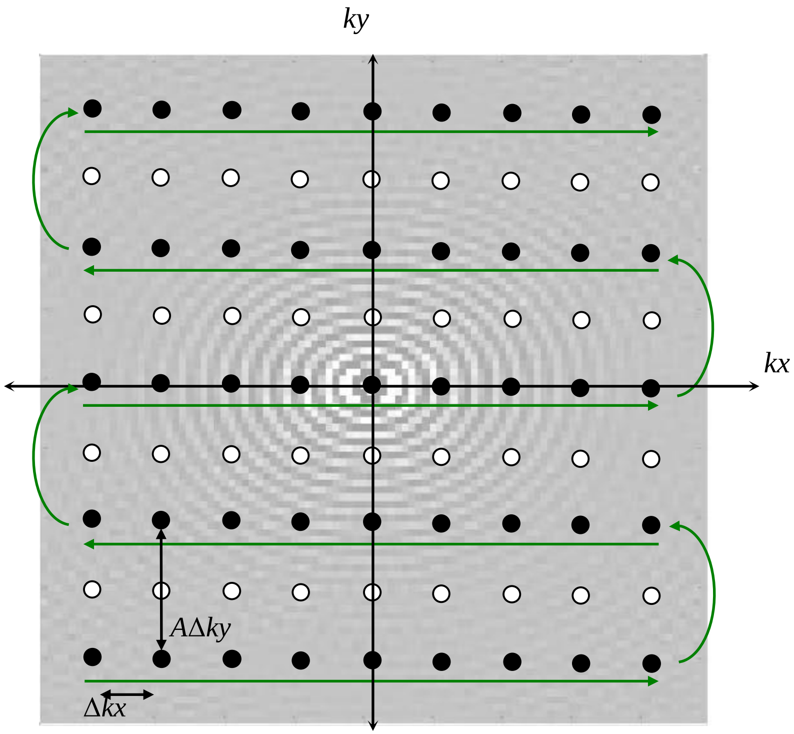


Reconstruction

Parallel Imaging In-Plane Acceleration
SENSE/GRAPPA



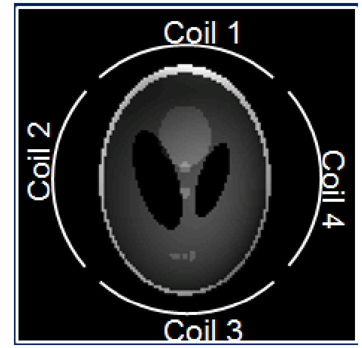
$N_C = 4$



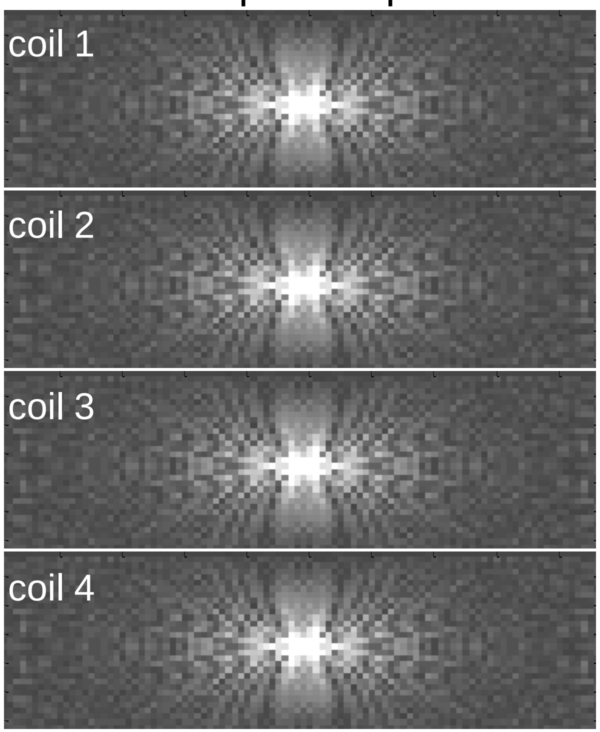
Accelerated Acquisition (A=2)

Reconstruction

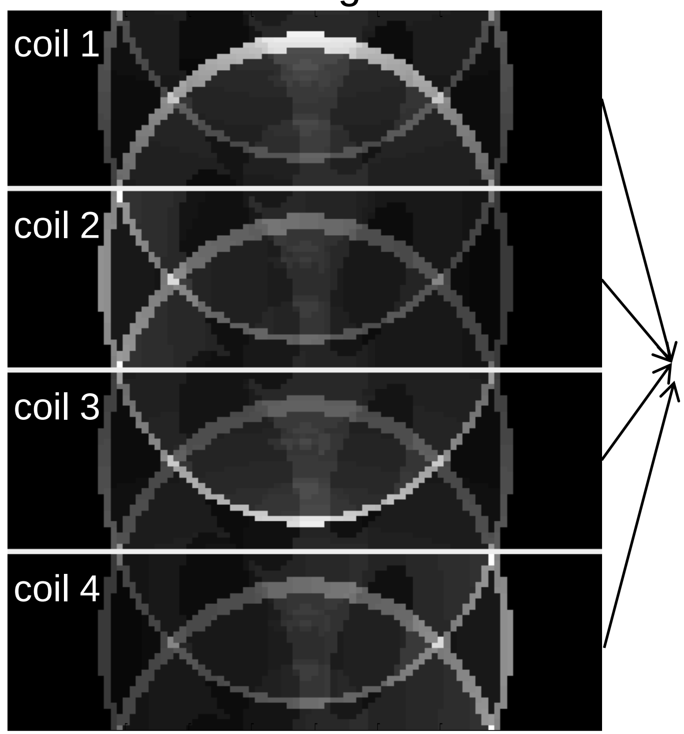
SENSE



sub-sampled k-space



aliased image

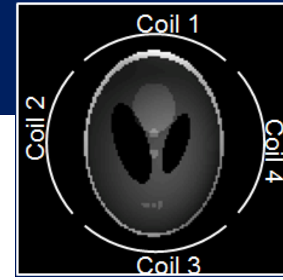


combined image

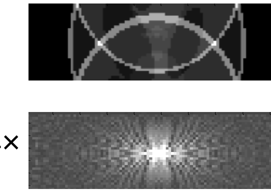
$N_C = 4 \quad A = 3$

Reconstruction/Processing

SENSE



4×



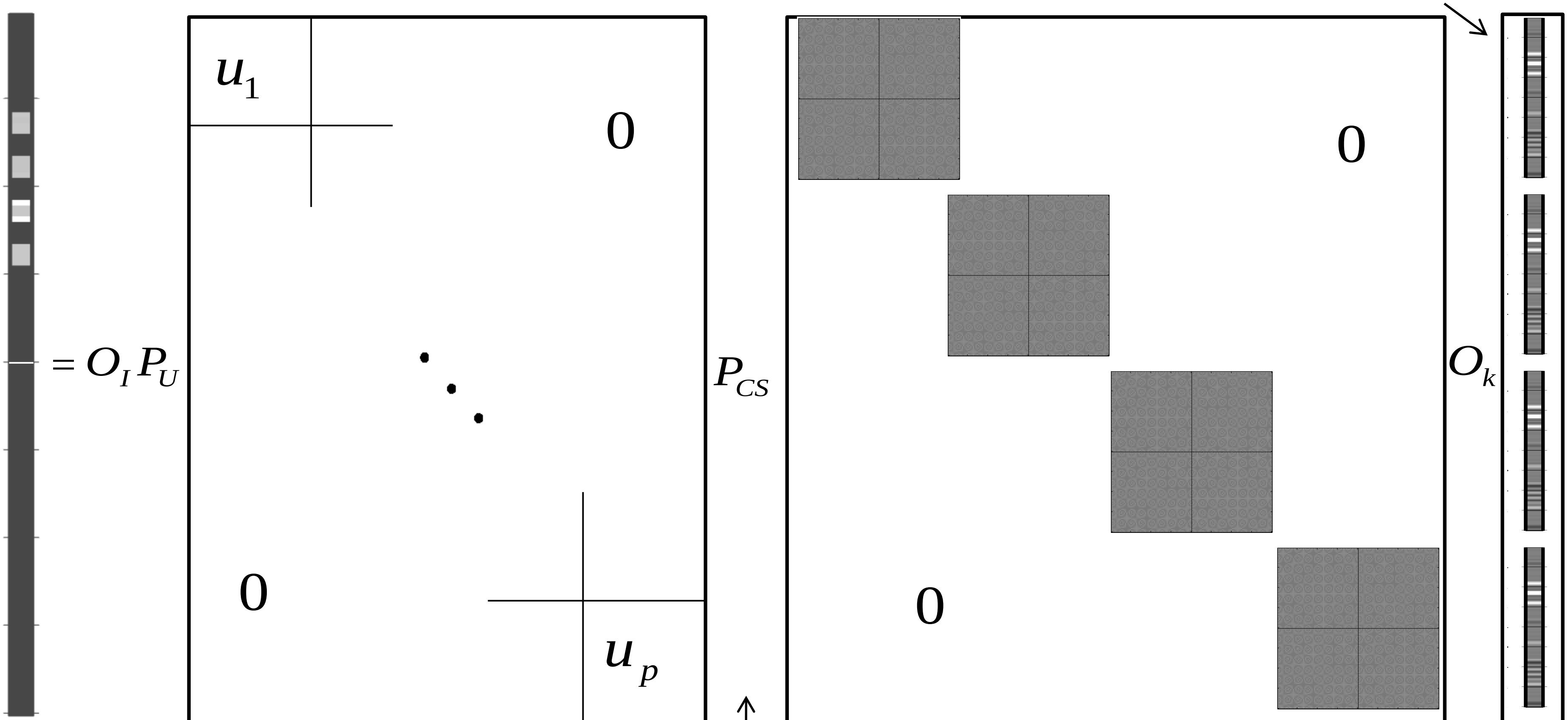


image image
Vector, complex

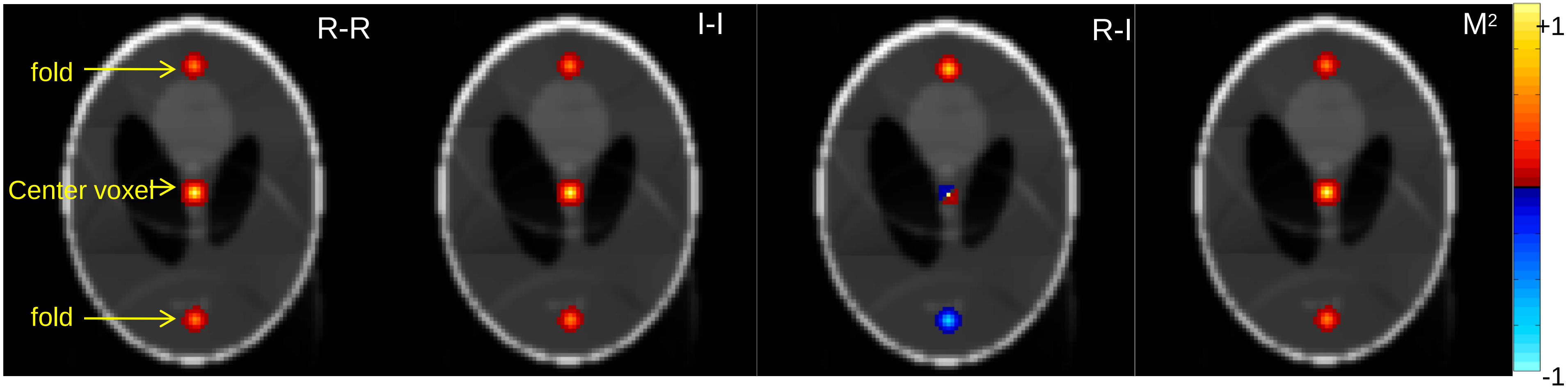
permute to by
folded voxel

reconstruct N_c=4 images

k-space
vector of
N_c images

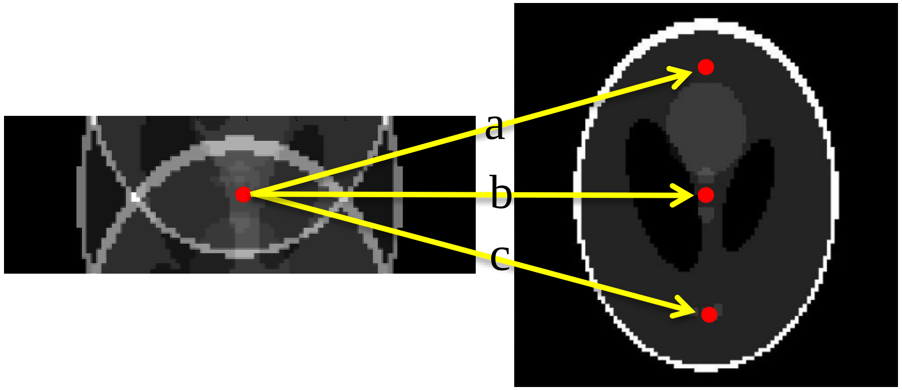
Implications

SENSE reconstruction induces long-range correlation.



Theoretical A=3 with smoothing

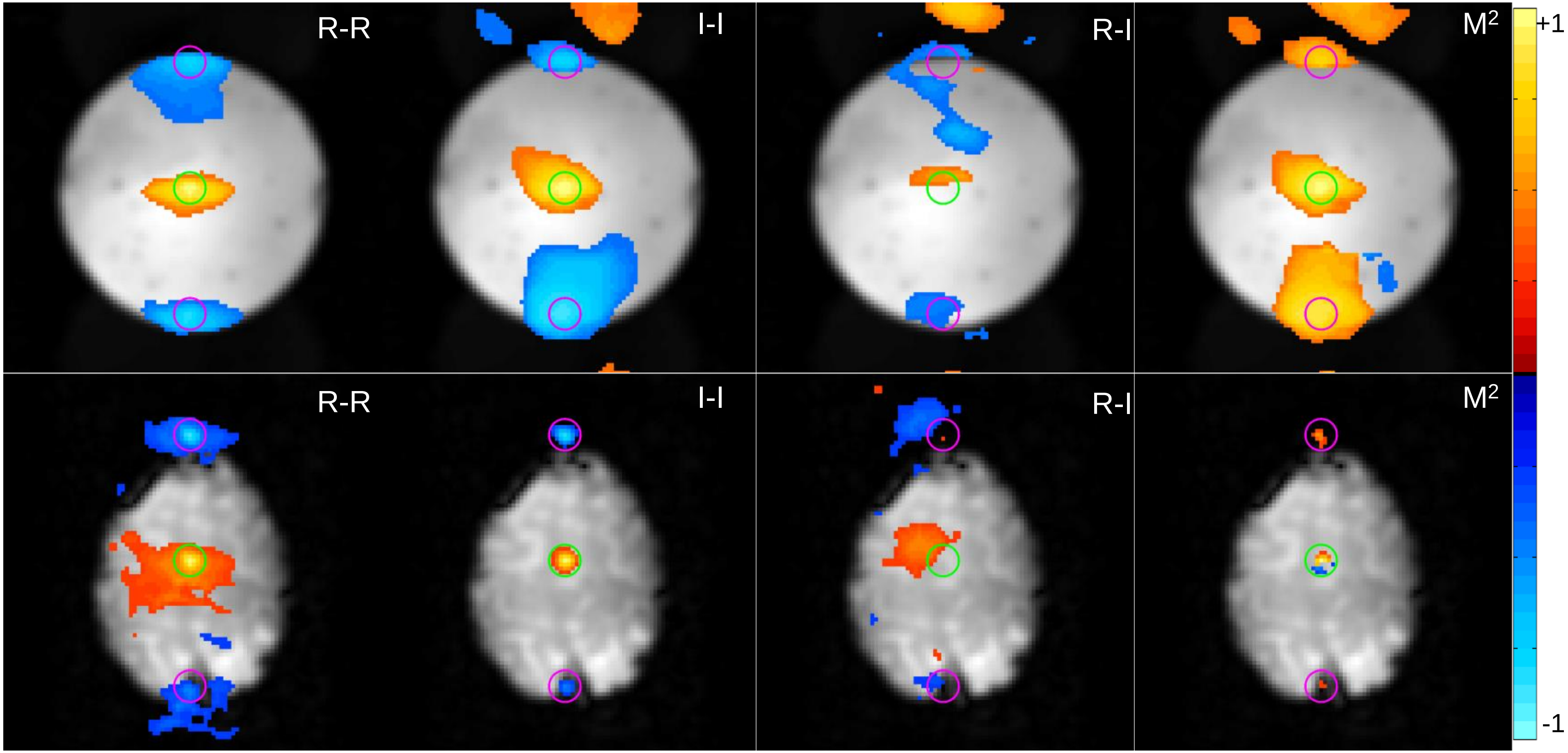
Basically multiplying voxel values a_t by same 3 numbers over time to lead to correlated voxels.

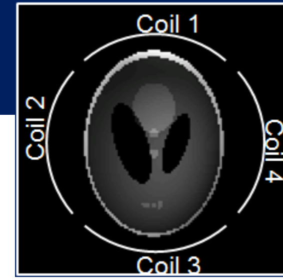


Implications

SENSE Reconstruction induces long-range correlation.

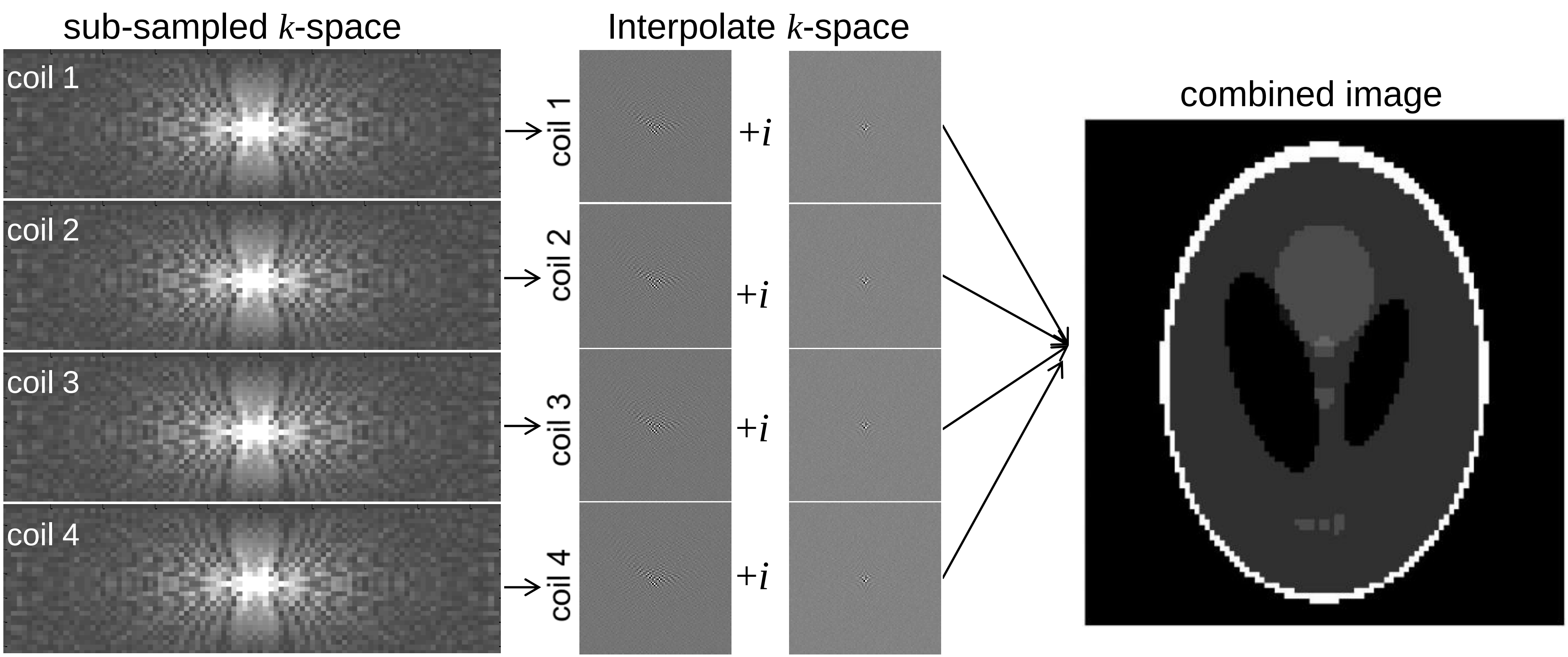
Experimental Results SENSE A=3 smoothed



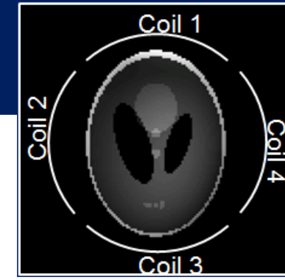


Reconstruction

GRAPPA



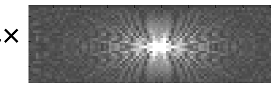
$N_C = 4 \quad A = 3$



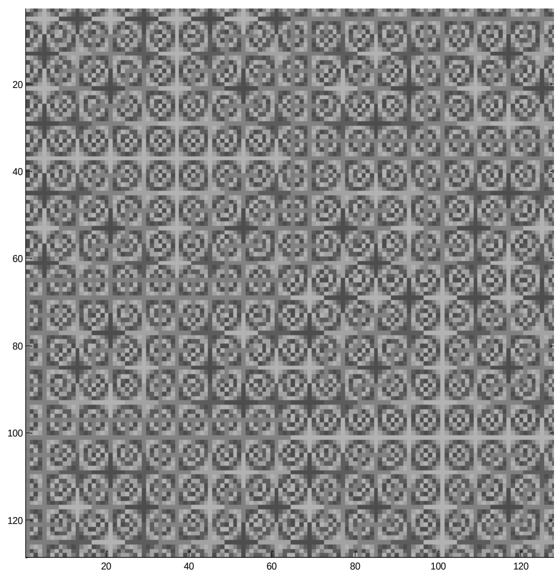
Reconstruction/Processing

GRAPPA

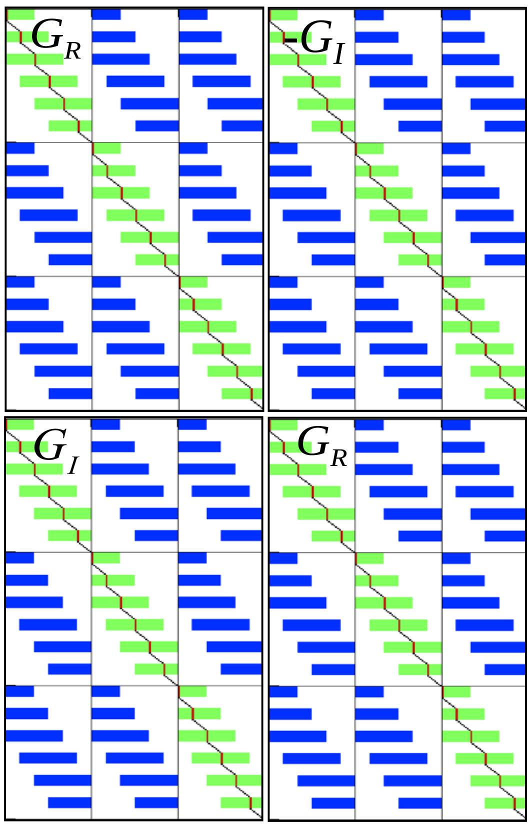
4×



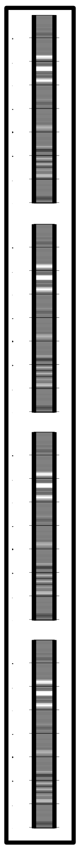
$= O_I$



$C \quad P$



$P \quad O_k$



single image Vector, complex

inverse FT reconstruction

linear combination

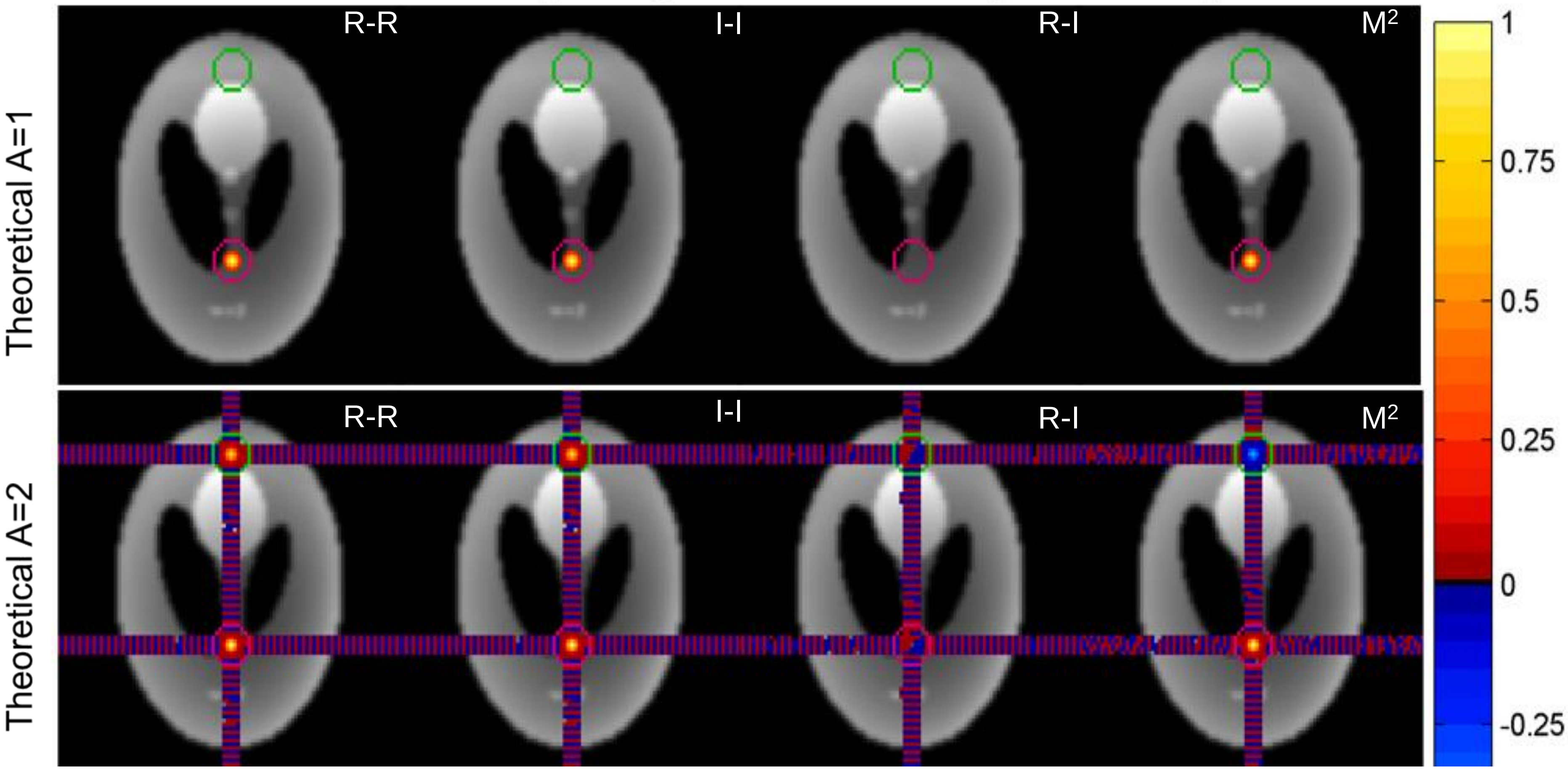
permute to by folded voxel

GRAPPA interpolation

k-space vector of N_c images

Implications

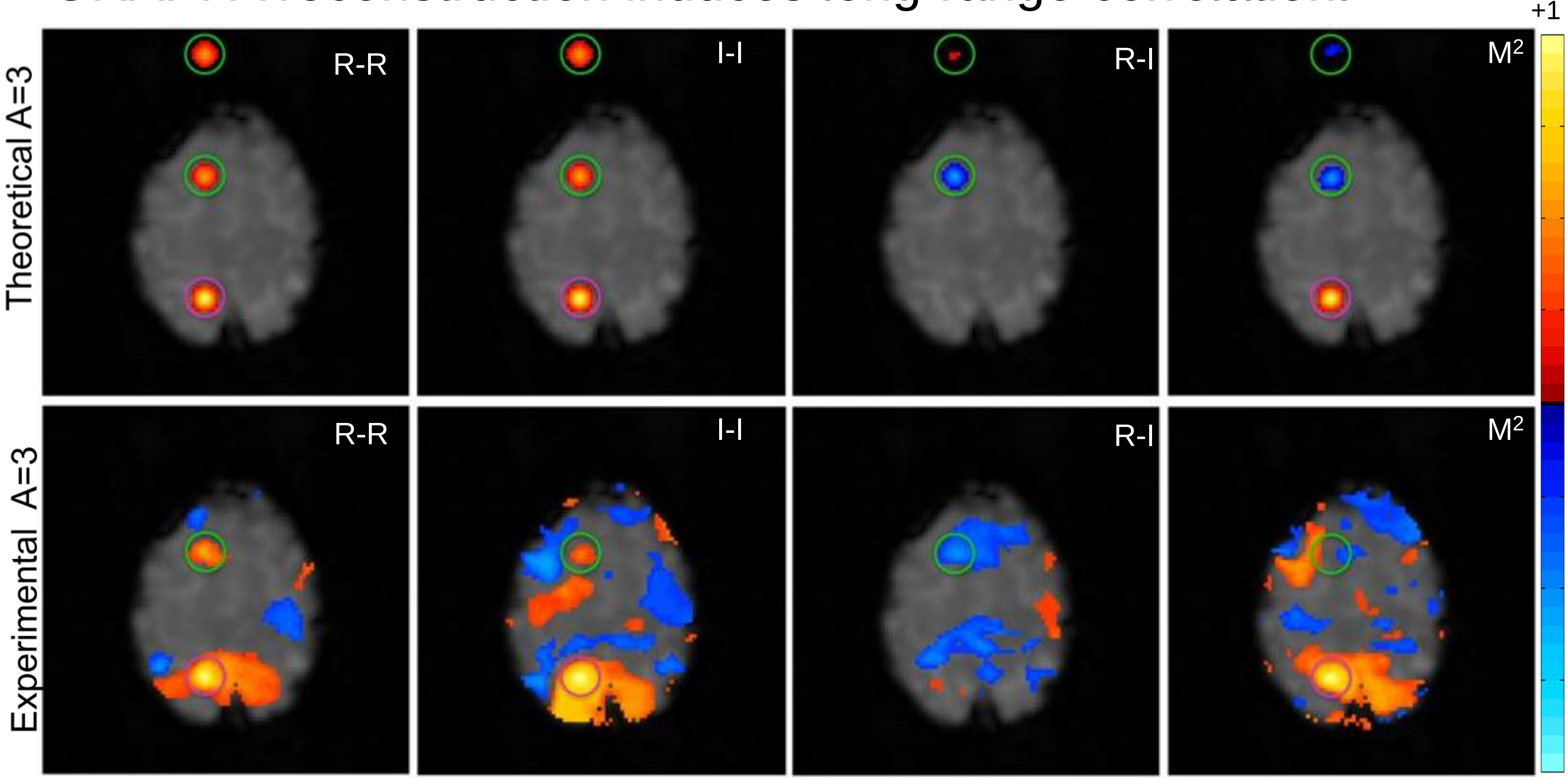
GRAPPA reconstruction induces long-range correlation.



GRAPPA A=2 with smoothing

Implications

GRAPPA reconstruction induces long-range correlation.

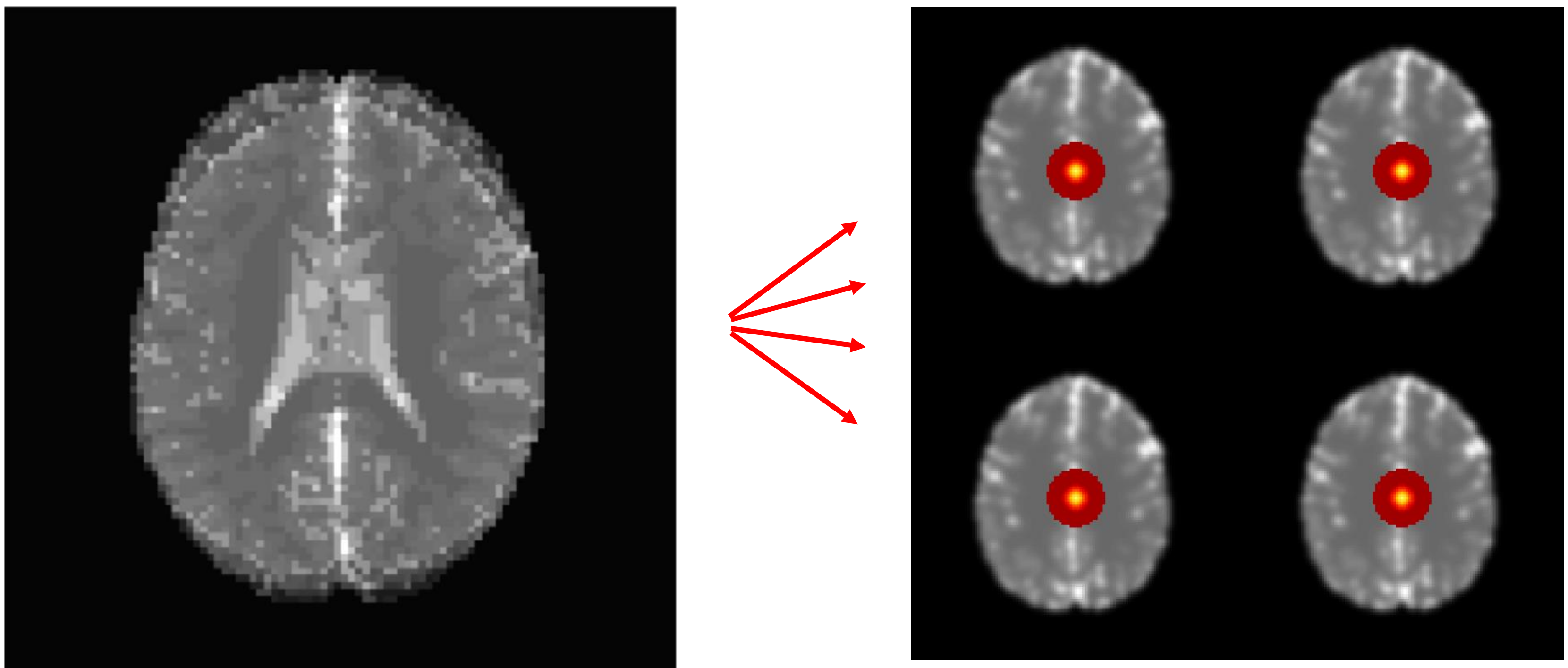


GRAPPA A=3 with smoothing

Reconstruction

Simultaneous Multi-Slice (Multiband)

The exact same math for SENSE and GRAPPA has been used for separating overlapping slices.

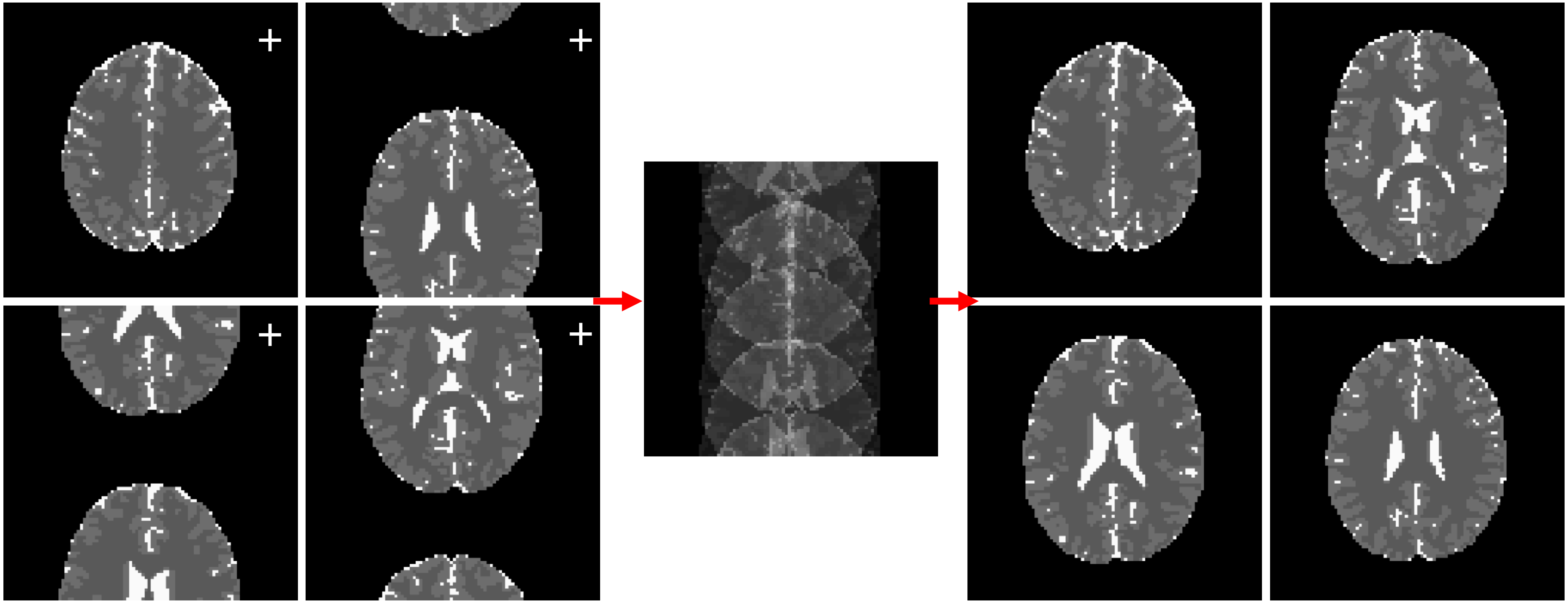


Illustration

Reconstruction

Simultaneous Multi-Slice (Multiband)

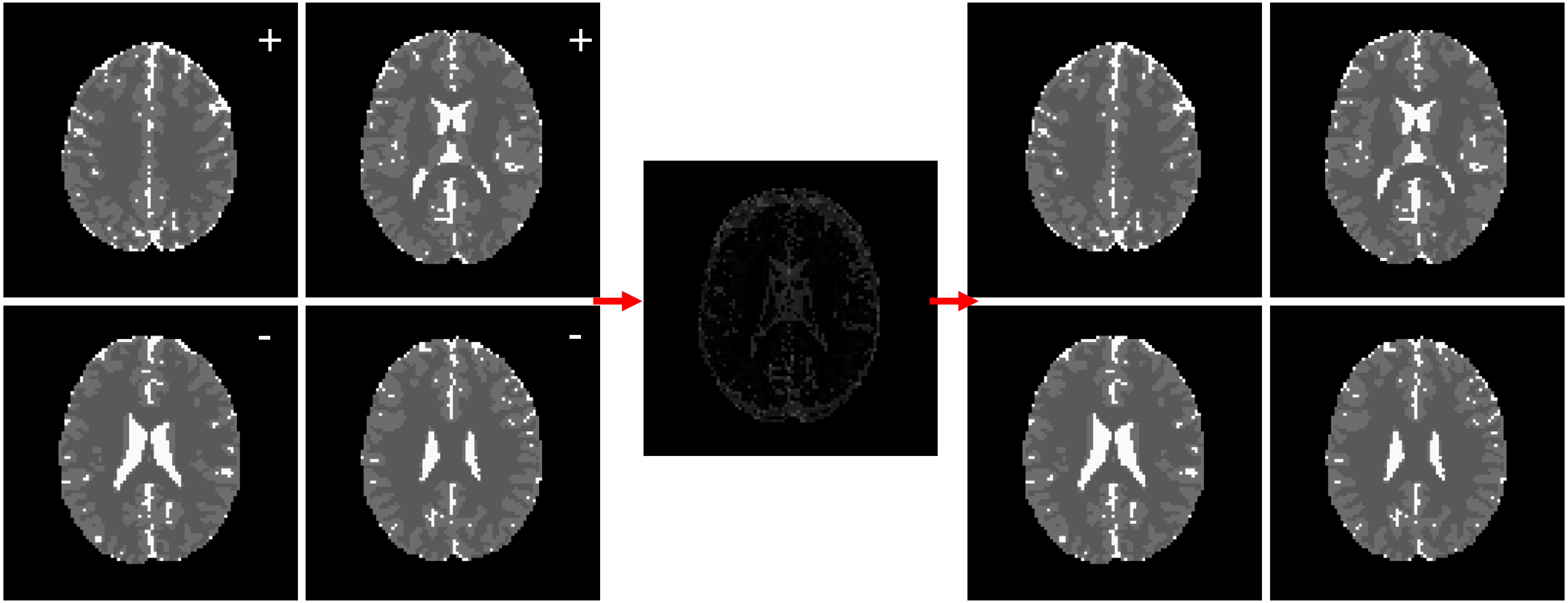
Efforts have been made to decrease voxel signal overlap with some success. CAIPI FOV shifts.



Reconstruction

Simultaneous Multi-Slice (Multiband)

Have developed the SPECS technique with CAIPI, extended to Hadamard encoding.



3. Materials and Methods

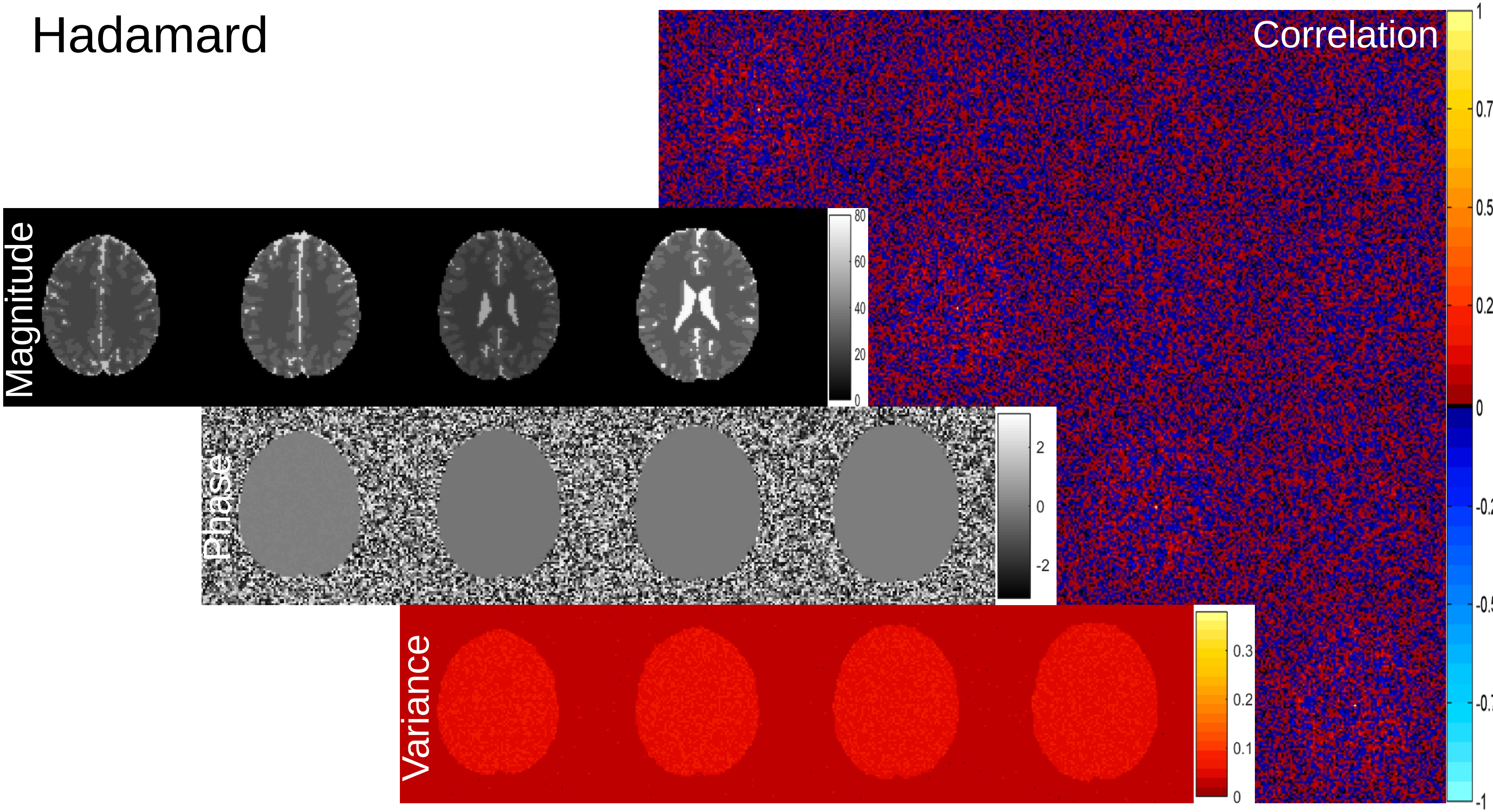
In order to demonstrate the SPECS Hadamard model with encoding with the aliasing, a T_2* weighted 96×96 digital phantom is generated with 720 TRs for 4 slices. For the optimal separation, a unique magnitude and phase is added to each slice, with an average SNR = 50.

One voxel region in each slice, with the locations rotating clockwise, has a block design task simulated of sixteen 22-second periods, added to its magnitude with a CNR = ½.

In both models the initial off-task portion of the time-series is used for the calibration images in the slice separation.

4. Results

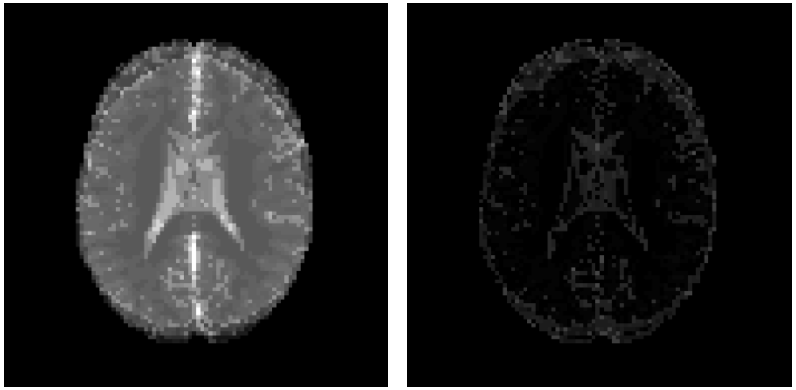
Hadamard



Results

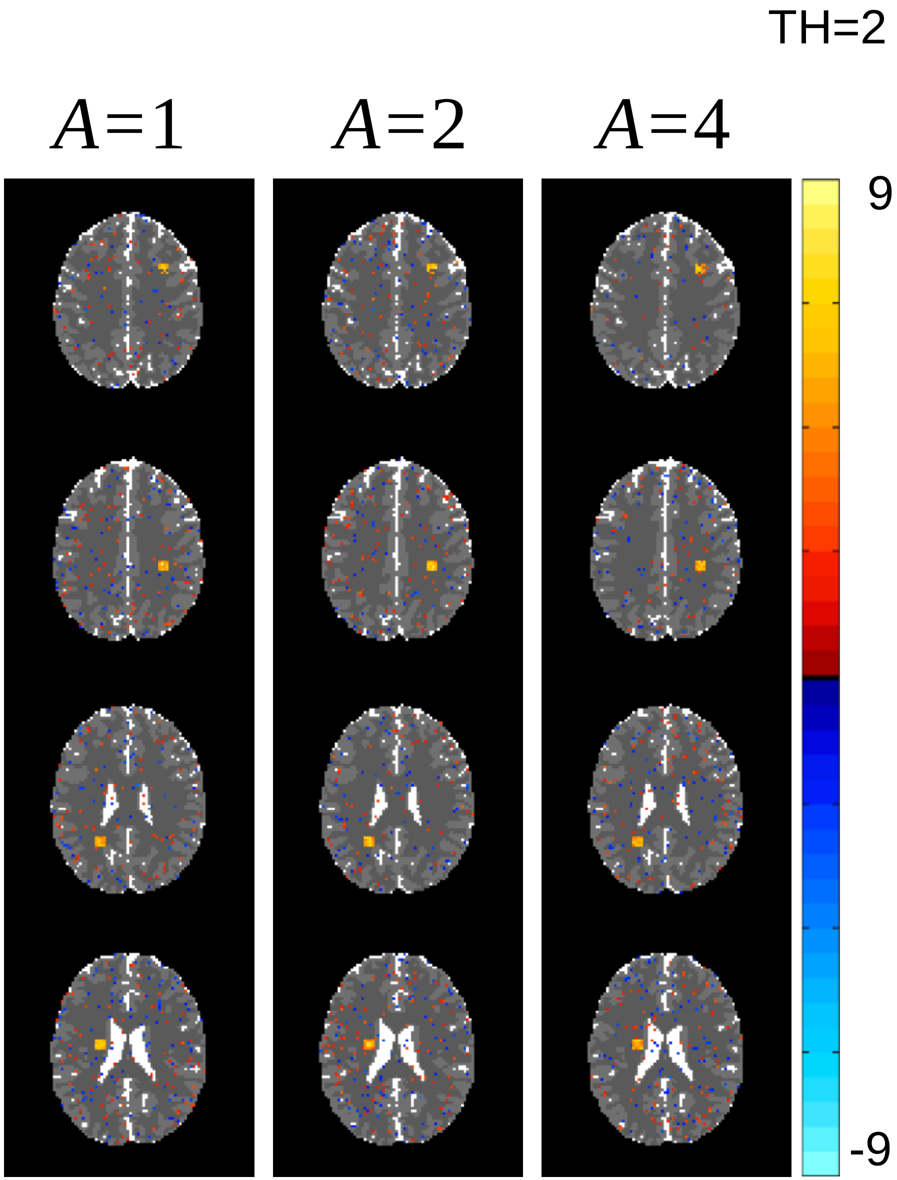
SPECS-Hadamard

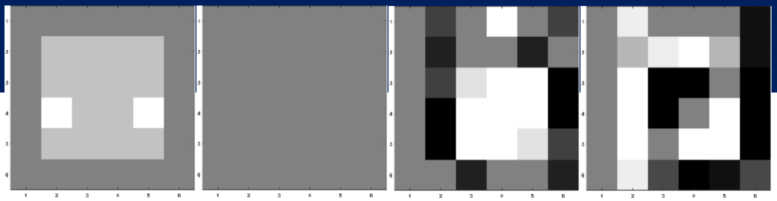
2 complex acquisitions



4 separated complex slices

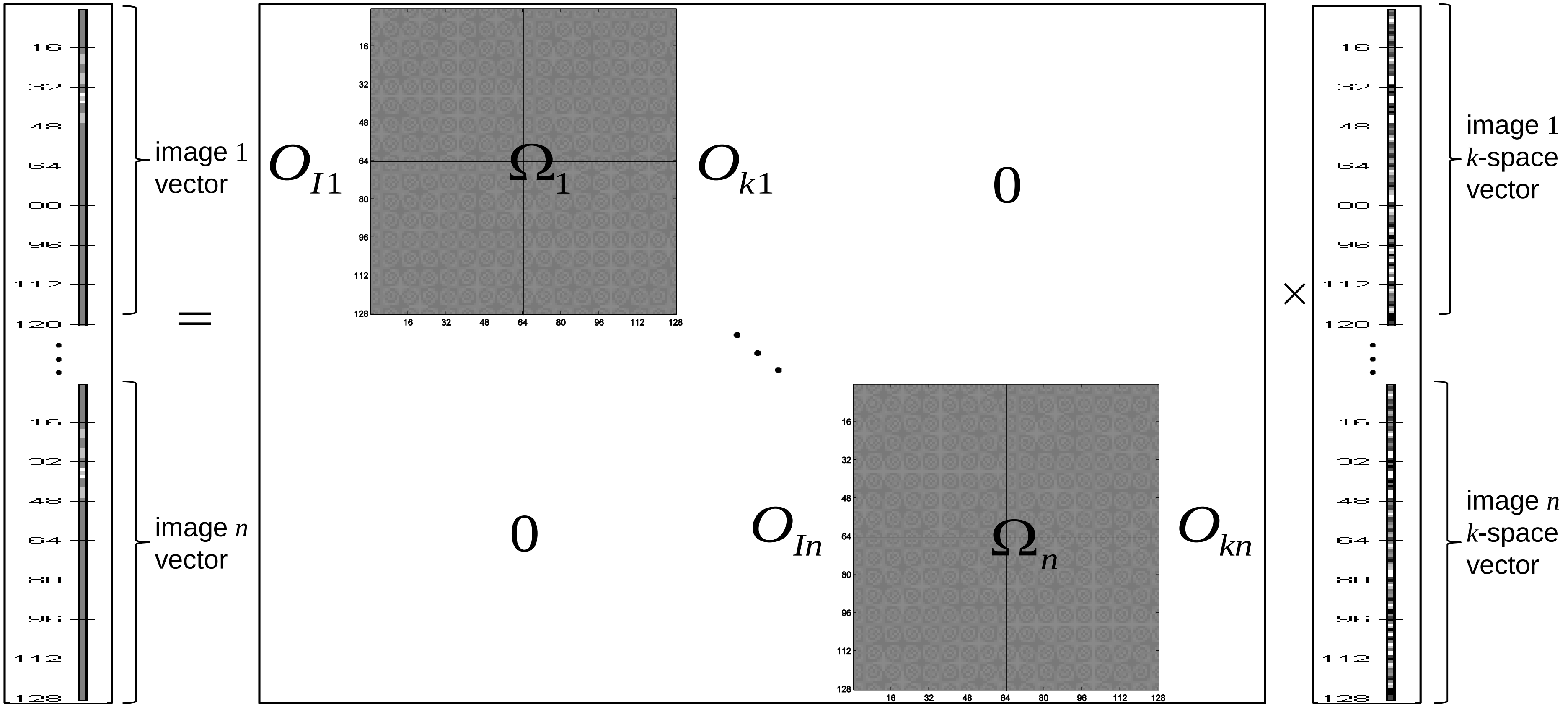
Complex-valued Activation

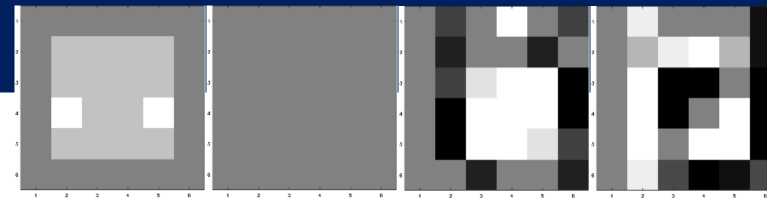




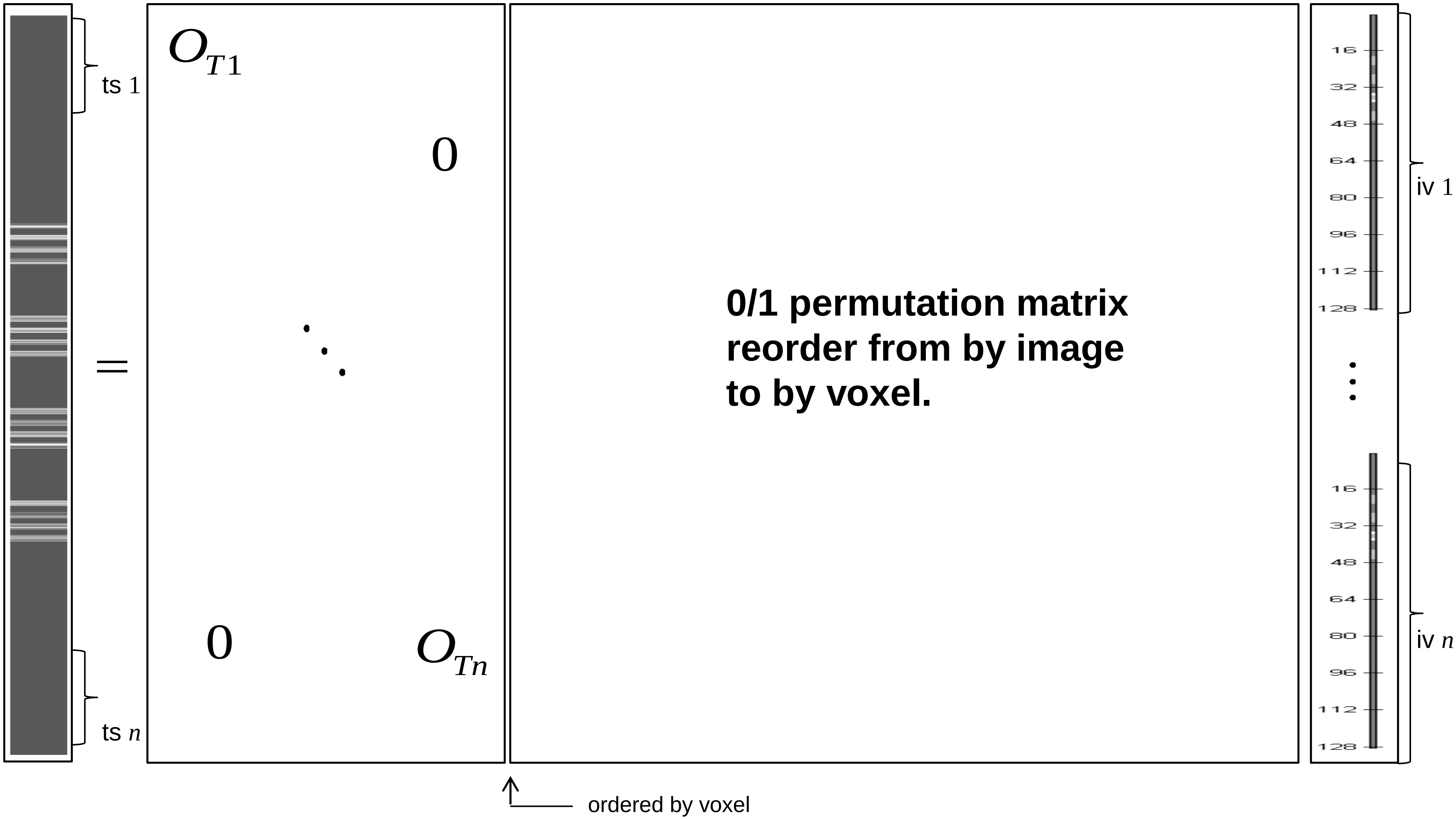
Results

Expand processing to include Time Series





Results


ts 1
ts n
=
O_{T1}
0
0
O_{Tn}
0/1 permutation matrix
reorder from by image
to by voxel.
iv 1
iv n
16
32
48
64
80
96
112
128
ordered by voxel

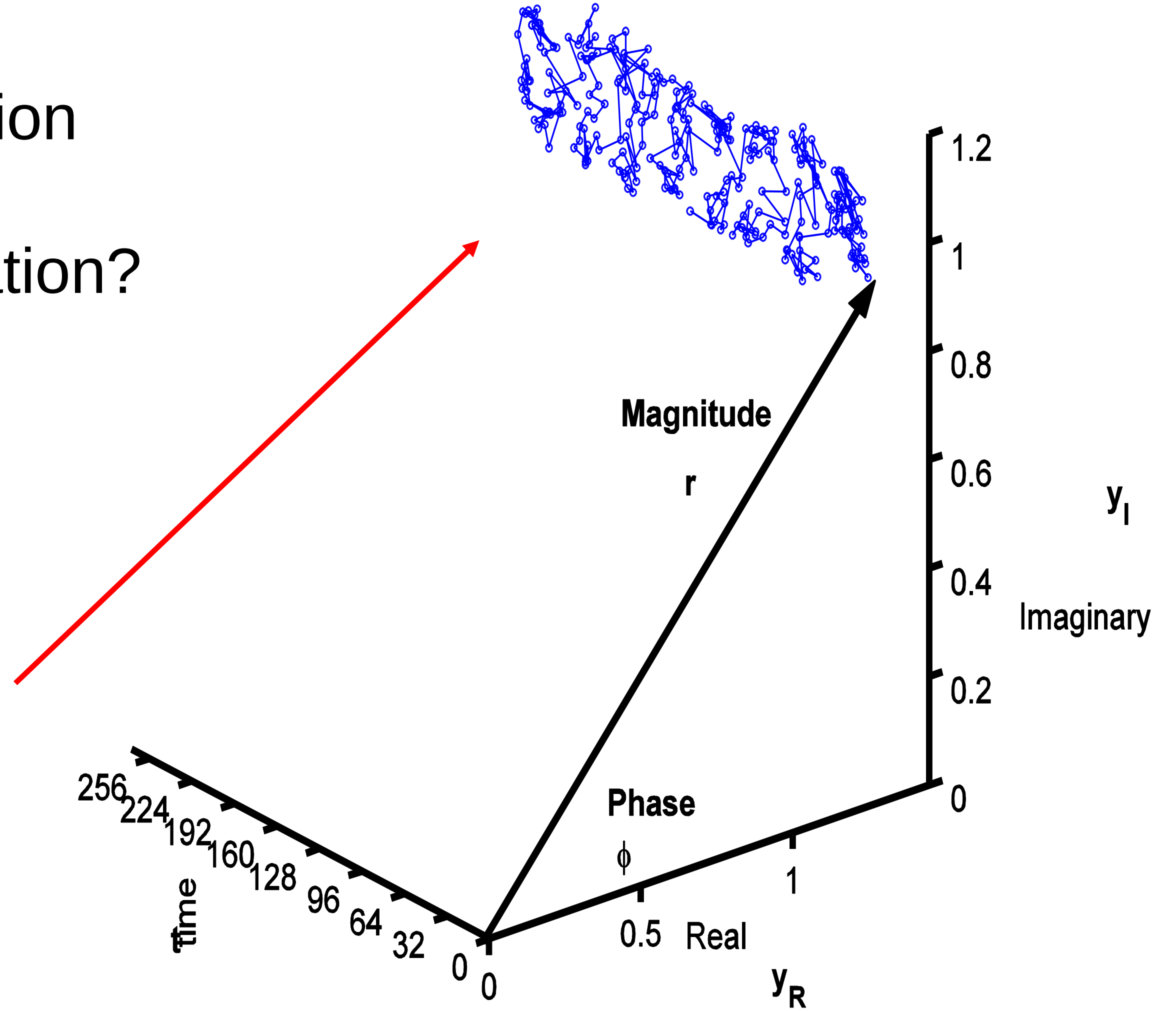
Discussion

This opens up the opportunity for complex-valued analysis!

Complex-valued activation
and/or
Complex-valued correlation?

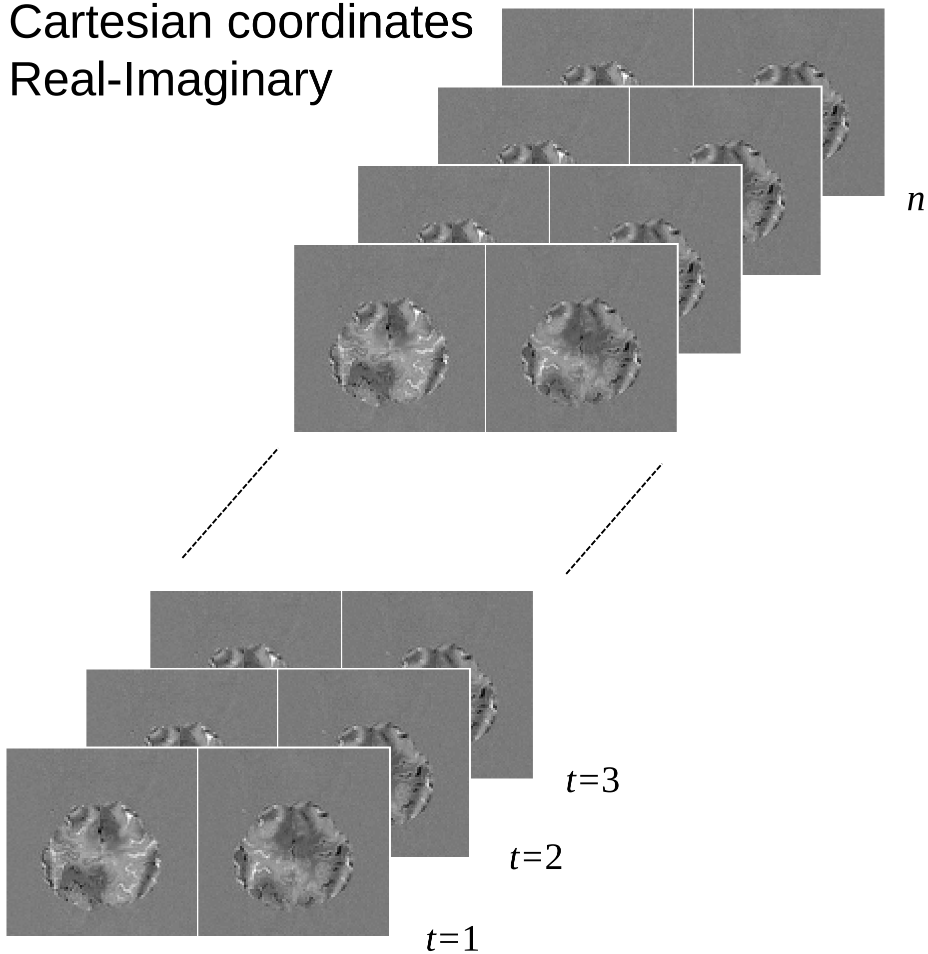
Magnitude and Phase
or equivalently
Real and Imaginary

Lengthening & Rotation
with task!

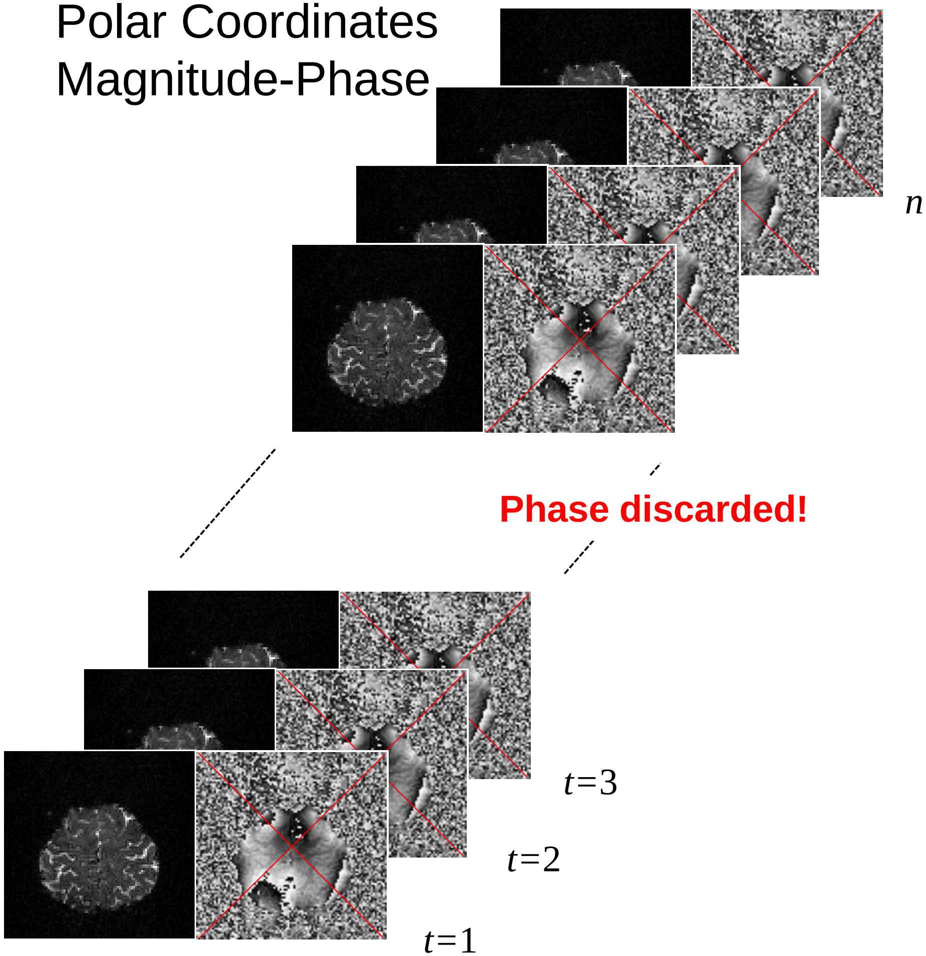


Discussion

Cartesian coordinates
Real-Imaginary



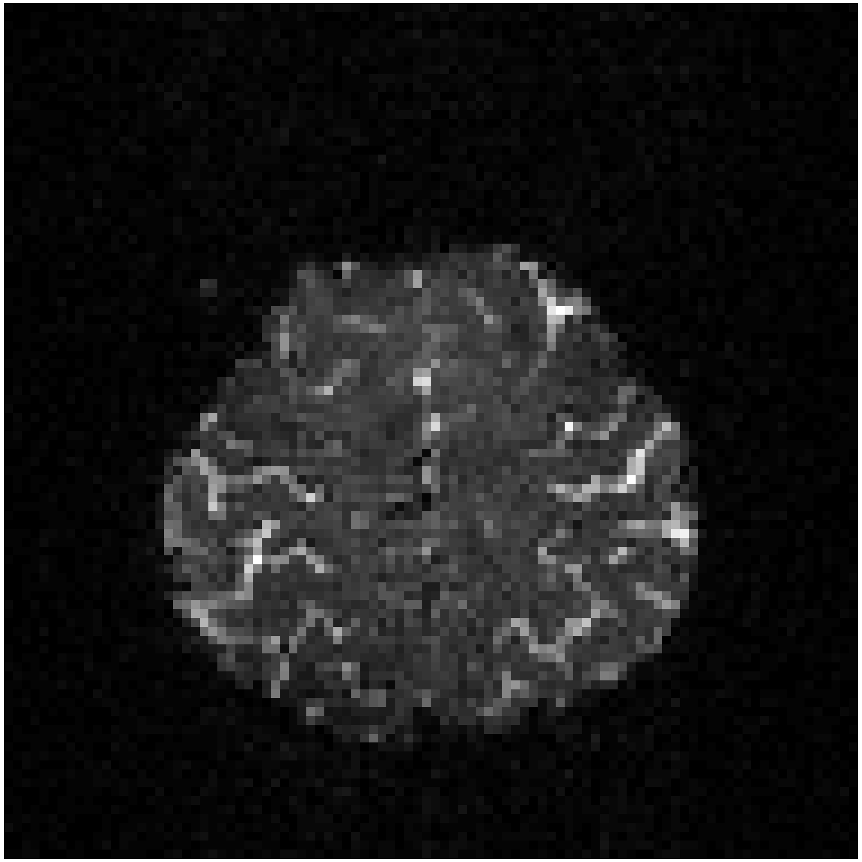
Polar Coordinates
Magnitude-Phase



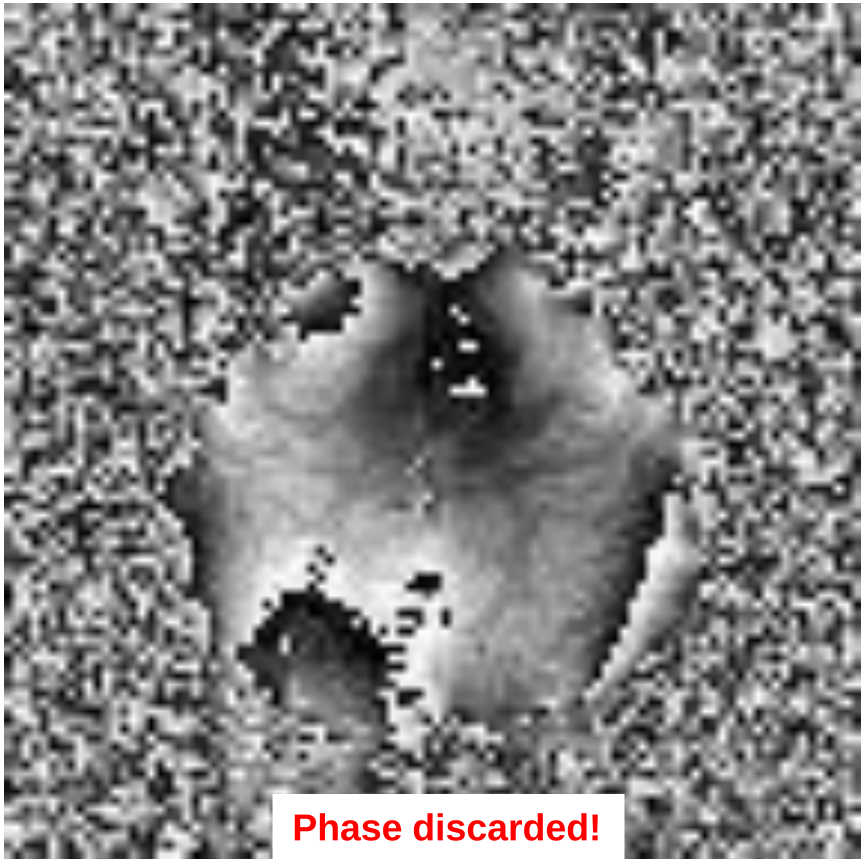
Discussion

There is biological information in the phase!

GRE EPI Image



Magnitude Image

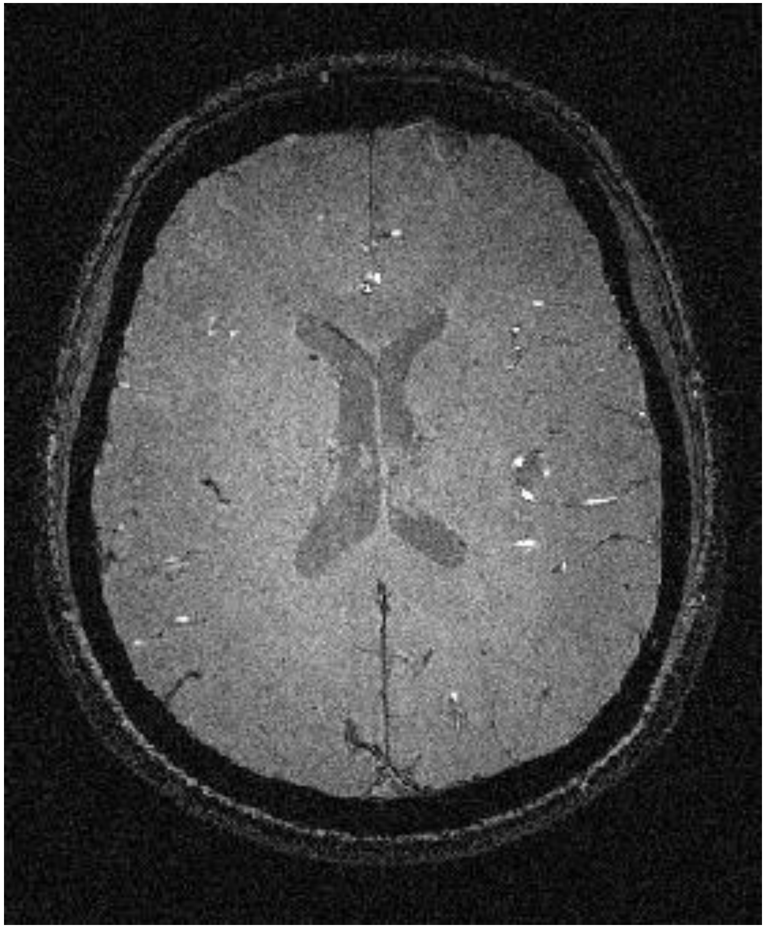


Phase Image

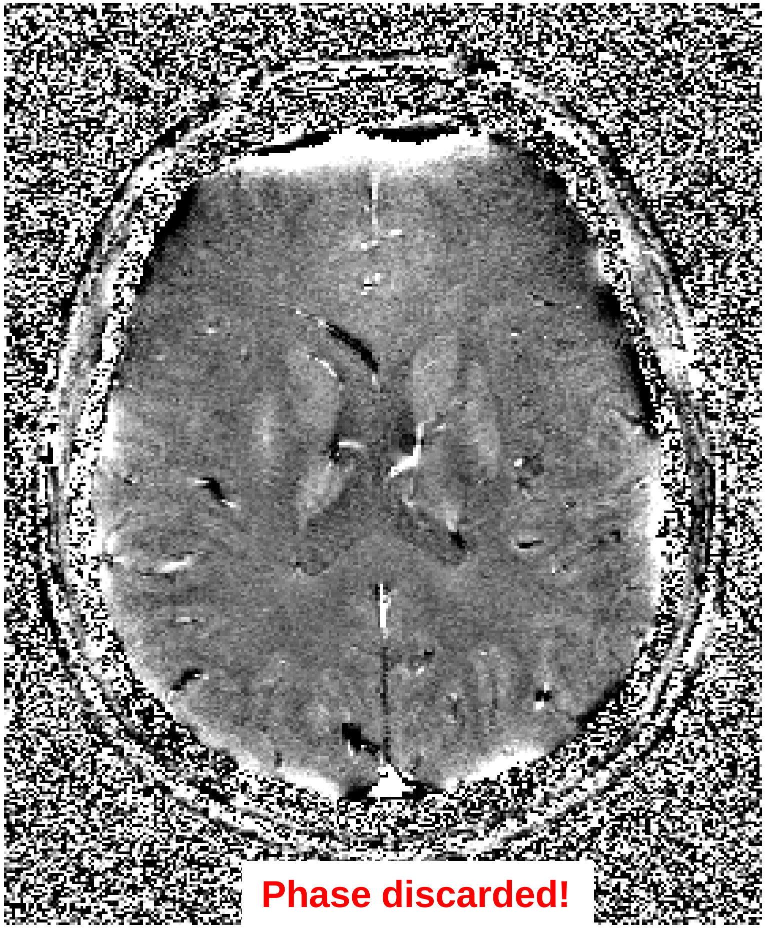
Discussion

There is biological information in the phase!

"SWI" Anatomical Image



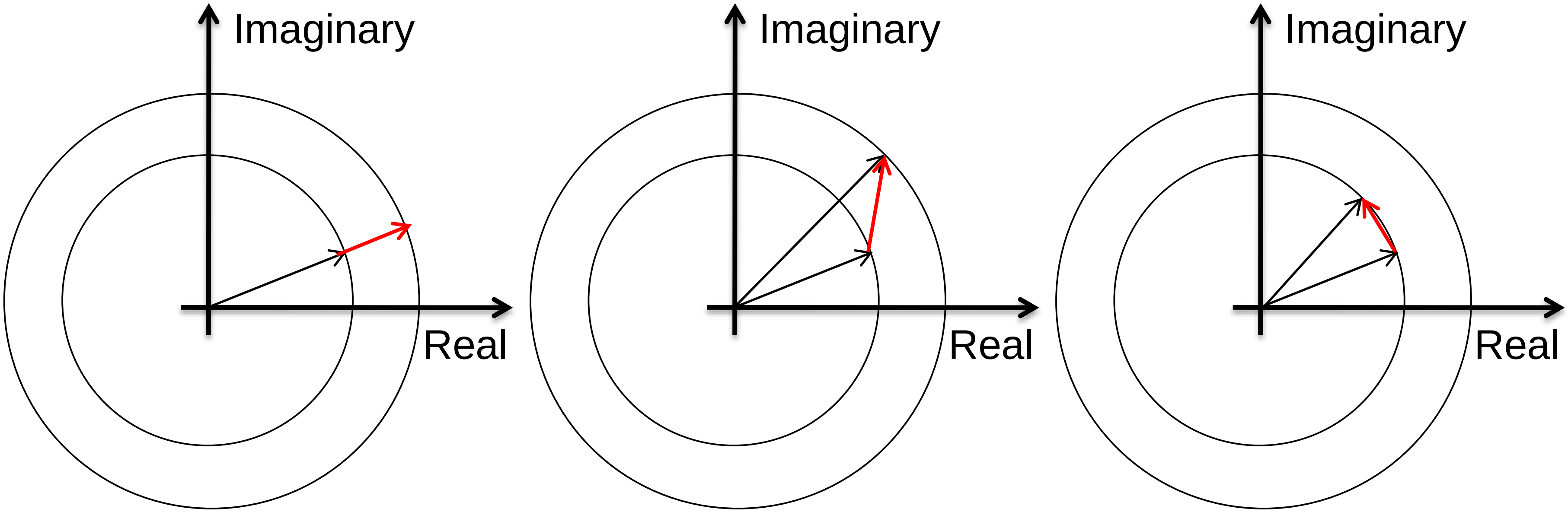
Magnitude Image



Phase Image

Discussion

Complex-valued fMRI models can be developed.



- Complex Magnitude w/ Constant Phase (CP) Activation
- Complex Magnitude and/or Phase (MP) Activation
- Real Magnitude-Only (MO/UP) Activation (Discard Phase)
- Real Phase-Only (PO) Activation (Discard Magnitude)

Discussion

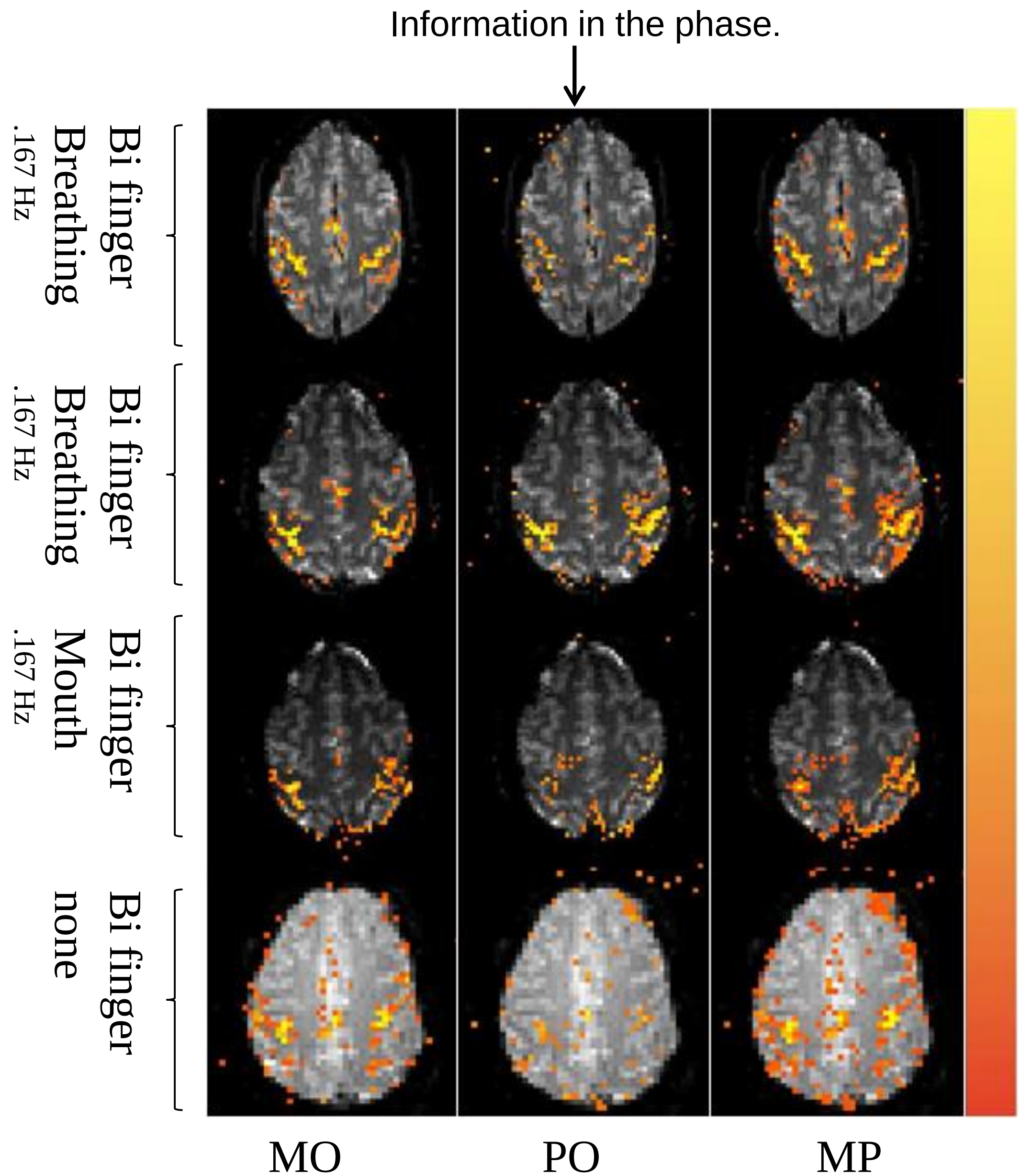
3.0T GE LX

20s off+16×(8 s on 8 s off), 276 TRs
12 axial slices, 96 × 96, FOV = 24 cm
TH = 2.5 mm, TR = 1 s, TE = 34.6 ms
FA = 45◦, BW = 125 kHz, ES = .708 ms

20s off+16×(8 s on 8 s off), 276 TRs
10 axial slices, 96 × 96, FOV = 24 cm
TH = 2.5 mm, TR = 1 s, TE = 42.8 ms
FA = 45◦, BW = 125 kHz, ES = .768 ms

20s off+16×(8 s on 8 s off), 276 TRs
10 axial slices, 96 × 96, FOV = 24 cm,
TH = 2.5 mm, TR = 1 s, TE = 42.8 ms
FA = 45◦, BW = 125 kHz, ES = . 768 ms

20s off+10×(8 s on 8 s off), 180 TRs
9 axial slices, 64 × 64, FOV = 24 cm
TH = 3.8 mm, TR = 1 s, TE = 26.0 ms
FA = 45◦, BW = 125 kHz, ES = .680 ms



Discussion

Care needs to be taken when we obtain data.

We should get data in its originally measured form.

We should do any required processing ourselves.

Our models should incorporate processing.

Thank You!

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SAMSI 2015 CCNS
Working Group on Image Reconstruction and Processing
Thursdays 2 pm ET