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Utilizing Induced Voxel Correlation in fMRI Analysis

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Utilizing Induced Voxel Correlation in fMRI Analysis

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OUTLINE

1. Reconstruction-Preprocessing

2. Induced Correlation

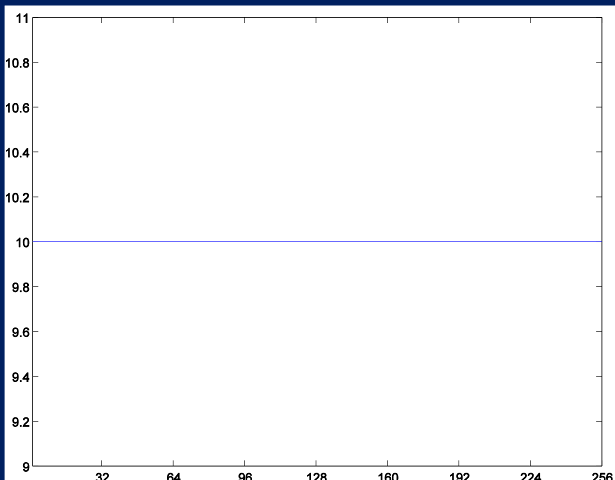
3. Utilizing Induced Correlation

4. Results

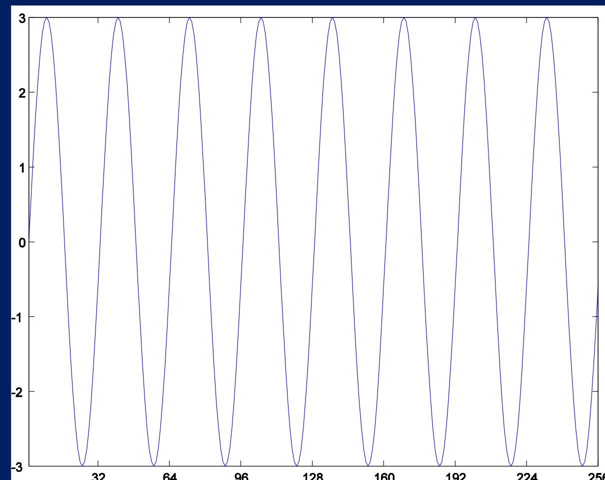
5. Discussion

Reconstruction: 1D FT

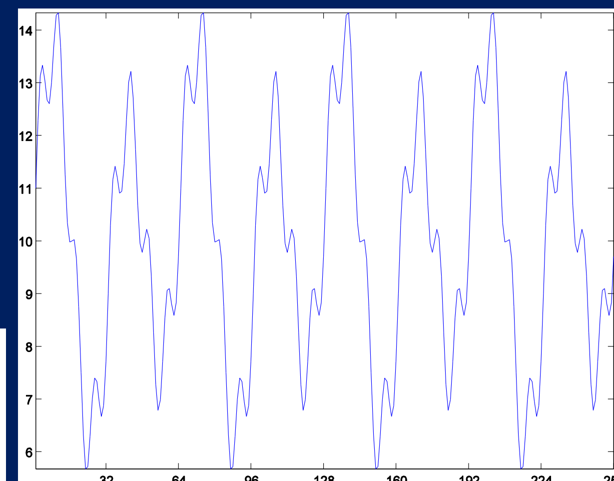
(n=256, Δt=2 s)



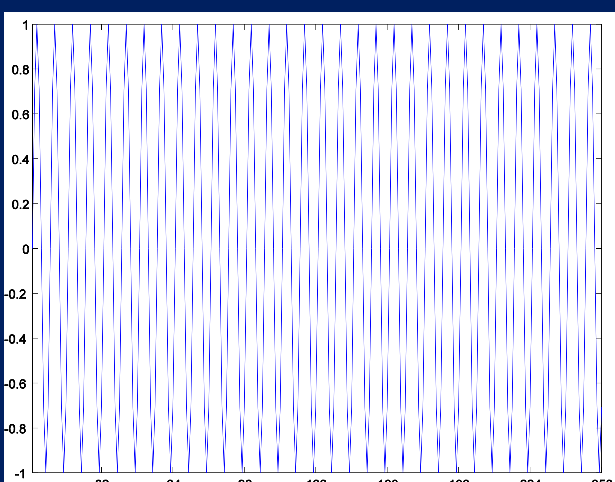
$10\cos(2\pi 0/512t)$



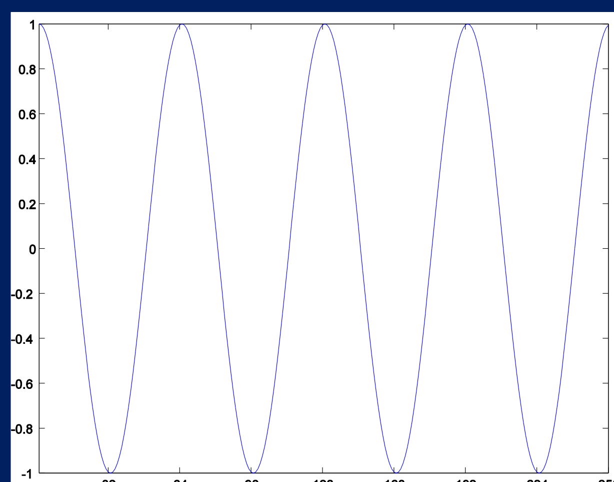
$3\sin(2\pi 8/512t)$



sum



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

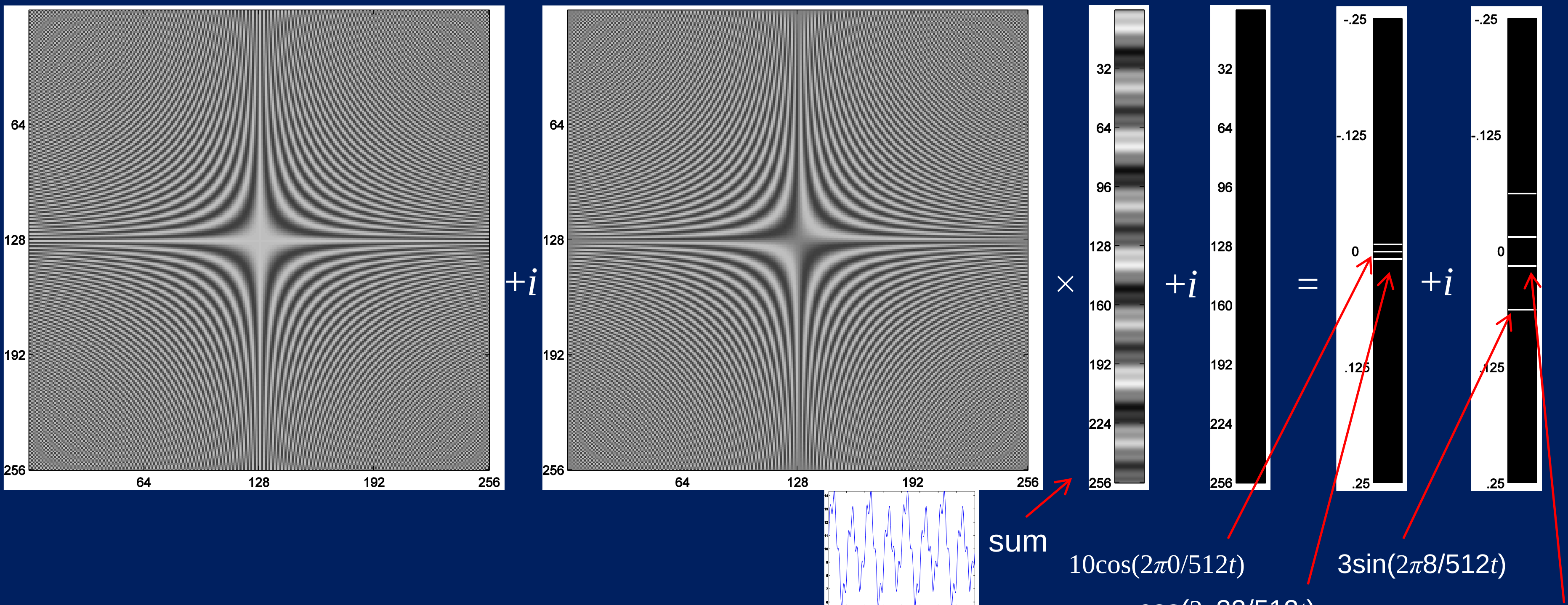


$\sin(2\pi 4/512t)$

Reconstruction: 1D FT

$(n{=}256,\ \Delta t{=}2\ \text{s})$

$$(\overline{\Omega}_R + i\,\overline{\Omega}_I) \times (y_R + i\,y_I) = (f_R + i\,f_I)$$



There are lines at the frequency locations.

Real part (image) represents constituent cosine frequencies.

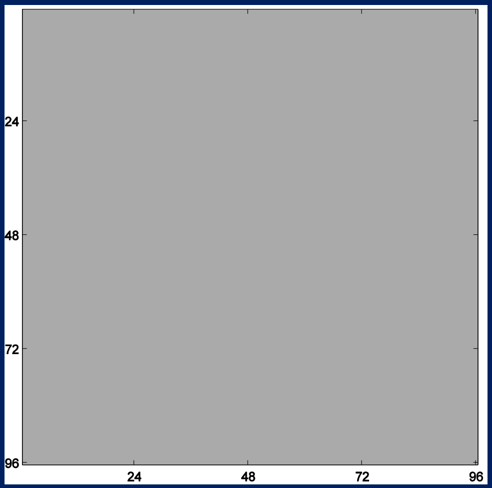
Imaginary part (image) represents constituent sine frequencies.

Intensity of the lines represents amplitude of that frequency.

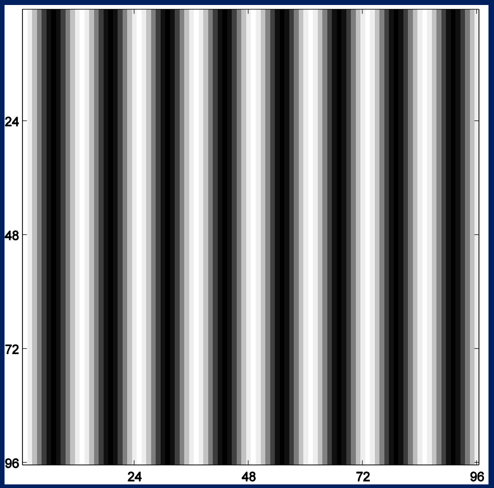
(FOV=192 mm)

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

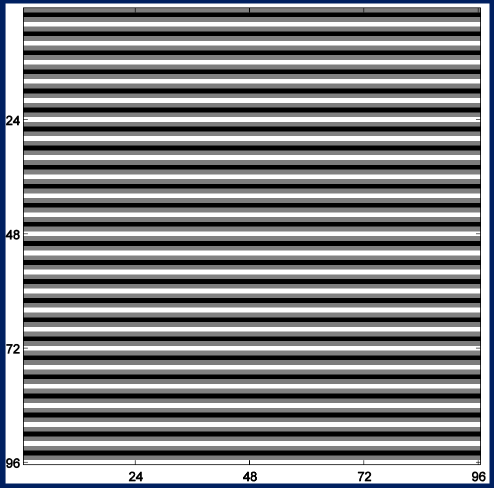
Reconstruction: 2D FT



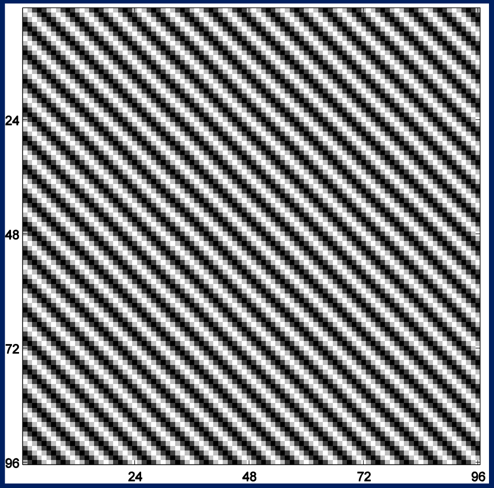
$10\cos(2\pi 0/96x)$



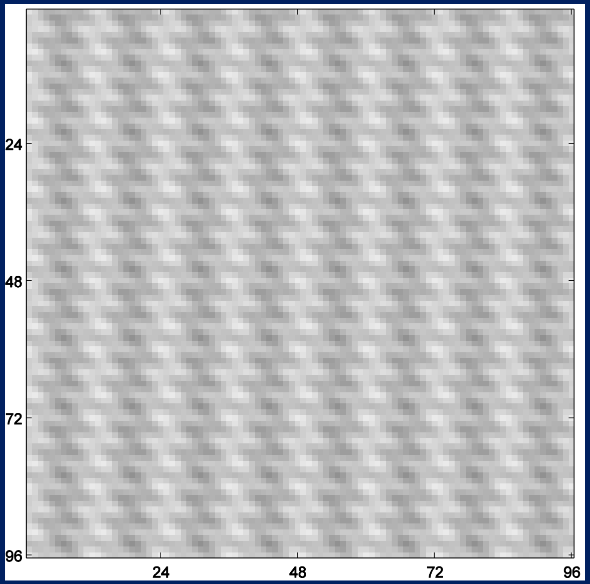
$1.5\cos(2\pi 8/96x)$



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



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



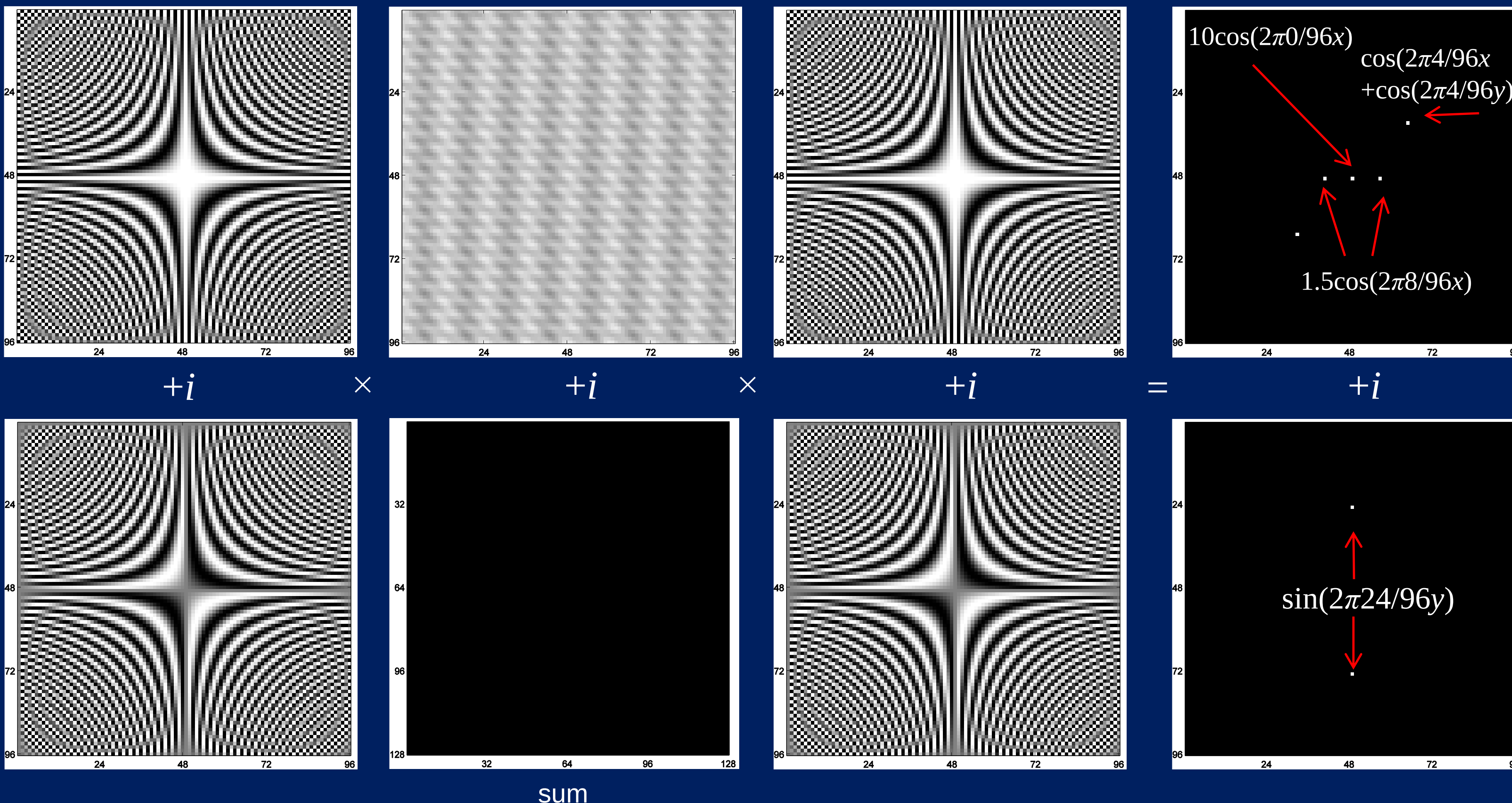
sum

(FOV=192 mm)

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

Reconstruction: 2D FT

$$(\bar{\Omega}_{yR}+i\,\bar{\Omega}_{yI}) \times (V_R+i\,V_I) \times (\bar{\Omega}_{xR}+i\,\bar{\Omega}_{xI})^T = (F_R+i\,F_I)$$



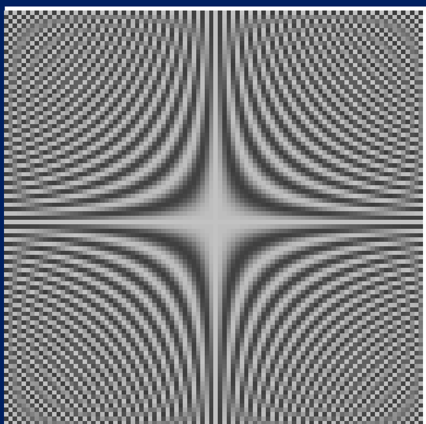
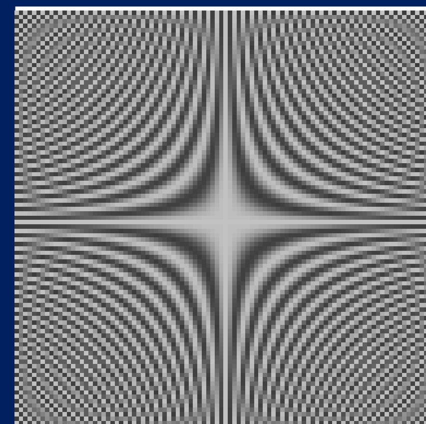
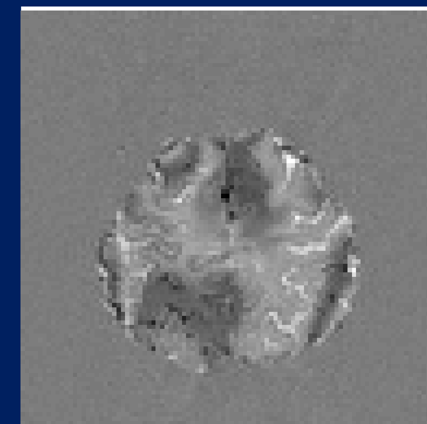
Measure

(FOV=192 mm)

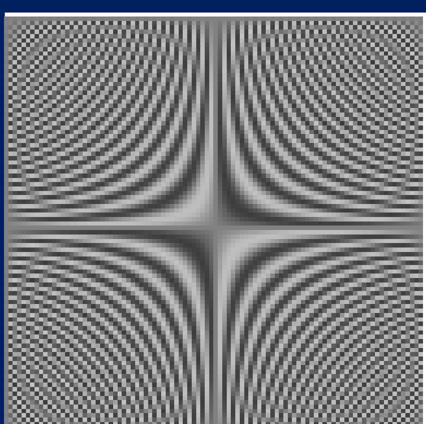
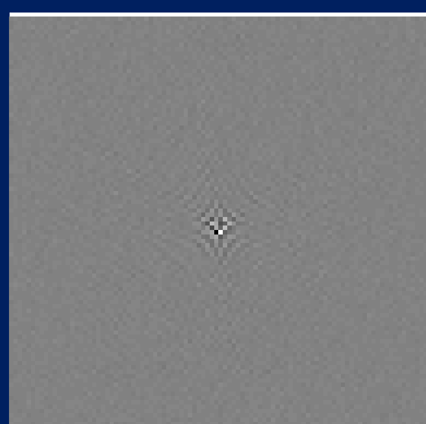
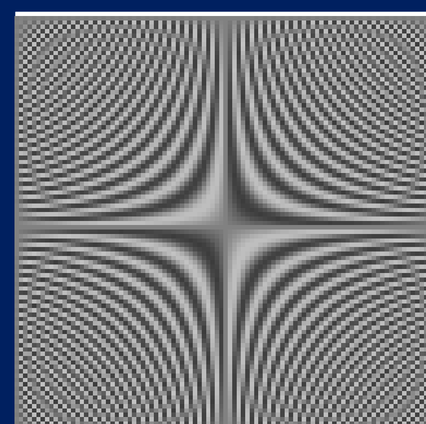
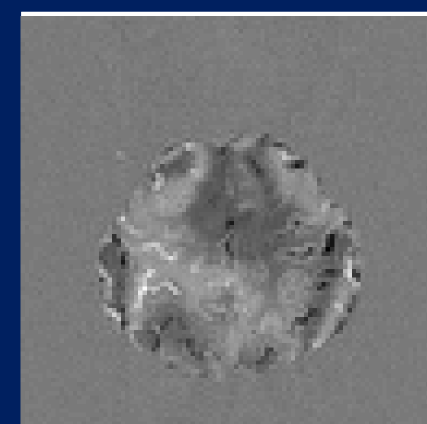
($n_x = n_y = 96$, $\Delta x = \Delta y = 2$ mm)

Reconstruction: 2D IFT

$$(\Omega_{yR} + i\,\Omega_{yI}) \quad \times \quad (F_R + i\,F_I) \quad \times \quad (\Omega_{xR} + i\,\Omega_{xI})^T \quad = \quad (V_R + i\,V_I)$$

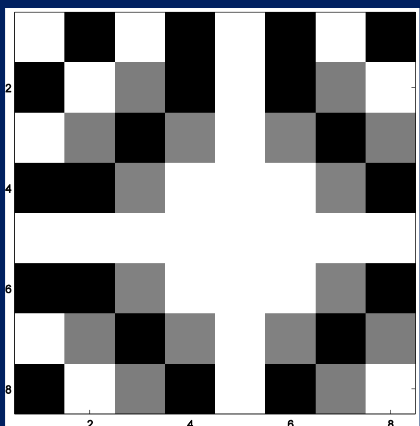
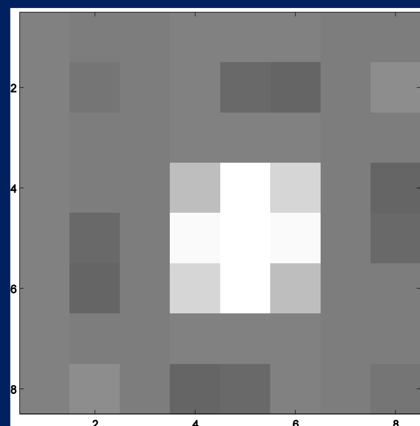
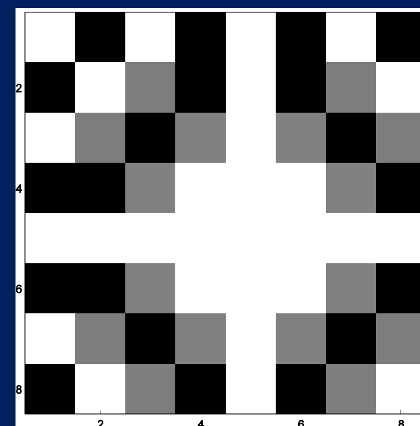
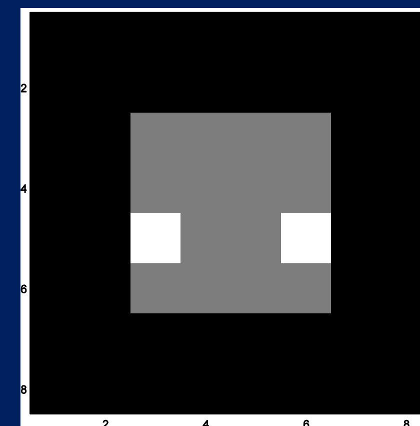
$+i \quad \times \quad +i \quad \times \quad +i \quad = \quad +i$

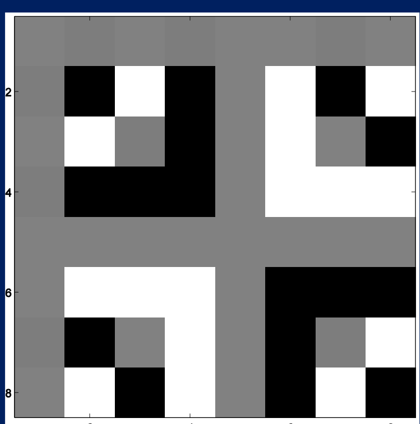
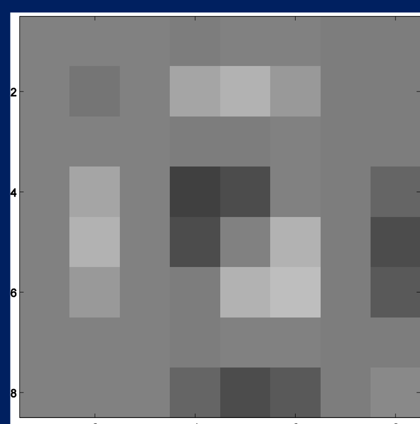
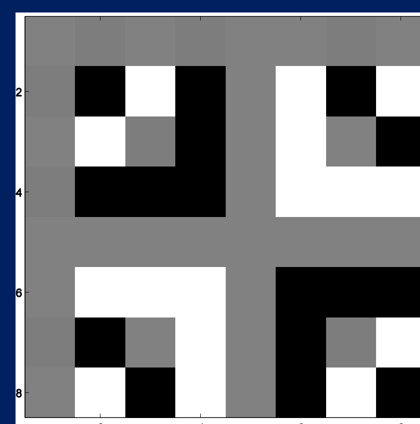
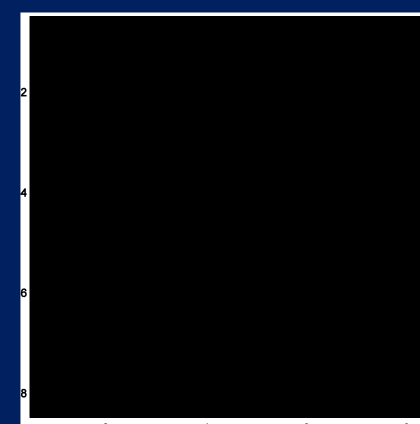
Spatial Frequencies

Reconstruction: 2D IFT

$$(\Omega_{yR} + i\,\Omega_{yI}) \quad \times \quad (F_R + i\,F_I) \quad \times \quad (\Omega_{xR} + i\,\Omega_{xI})^T \quad = \quad (V_R + i\,V_I)$$

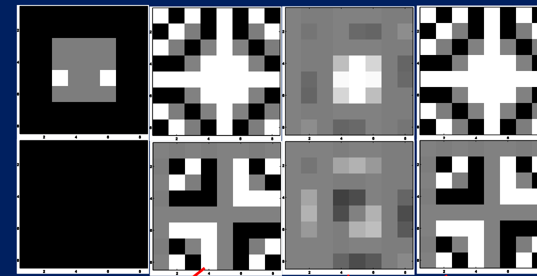





$+i \quad \times \quad +i \quad \times \quad +i \quad = \quad +i$

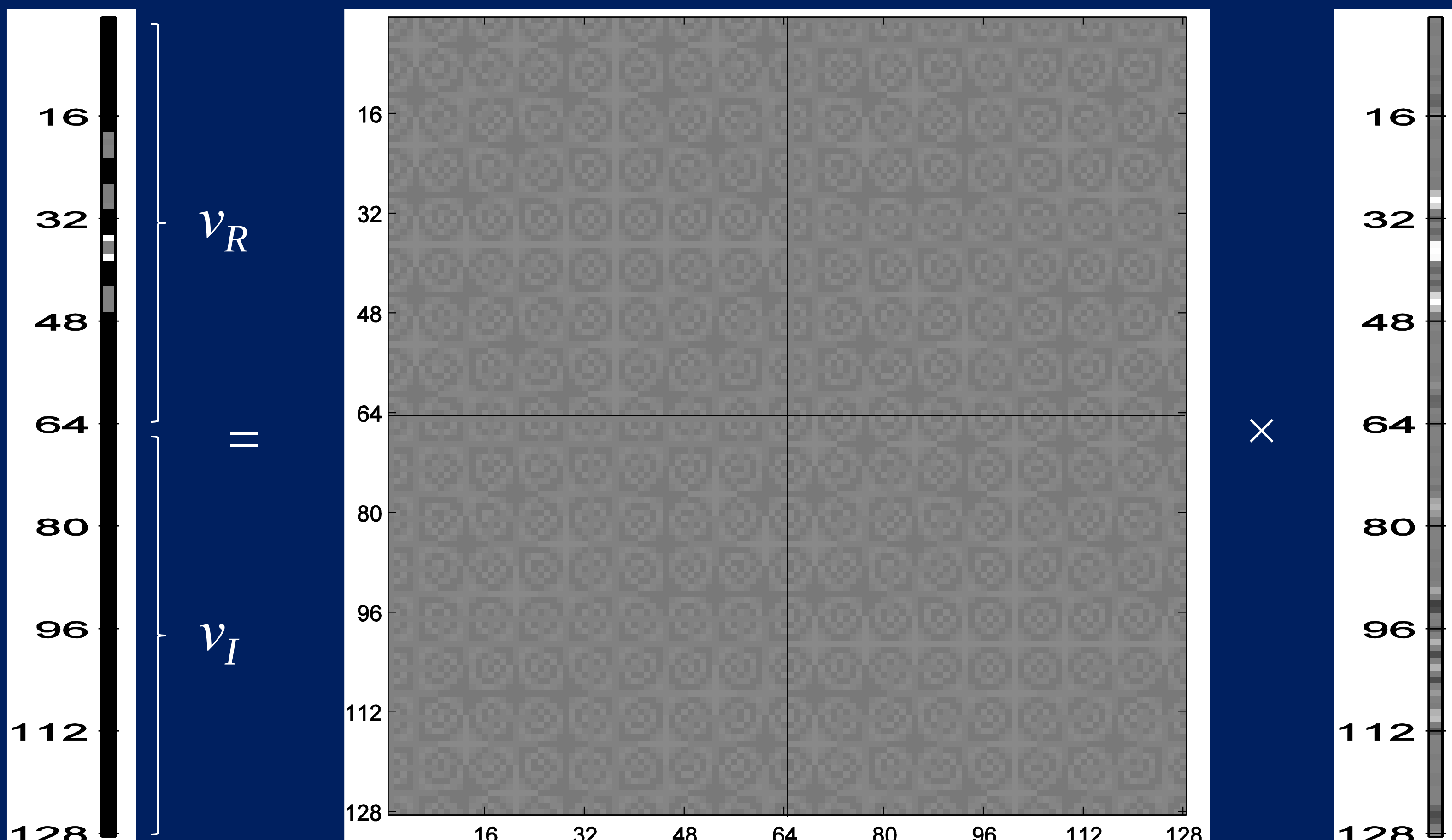





Spatial Frequencies

Reconstruction: 2D IFT Isomorphism

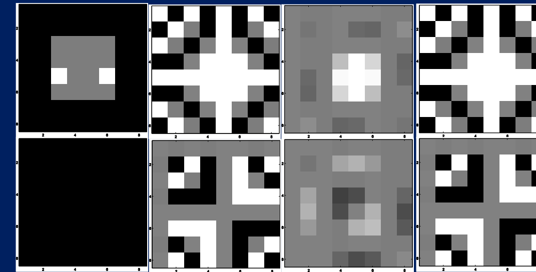


$$v = \Omega \times f$$



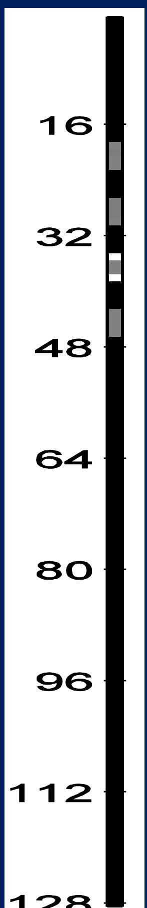
Rowe, Nencka, Hoffmann: JNSM, 159:361-369, 2007.

Reconstruction: Processing Image



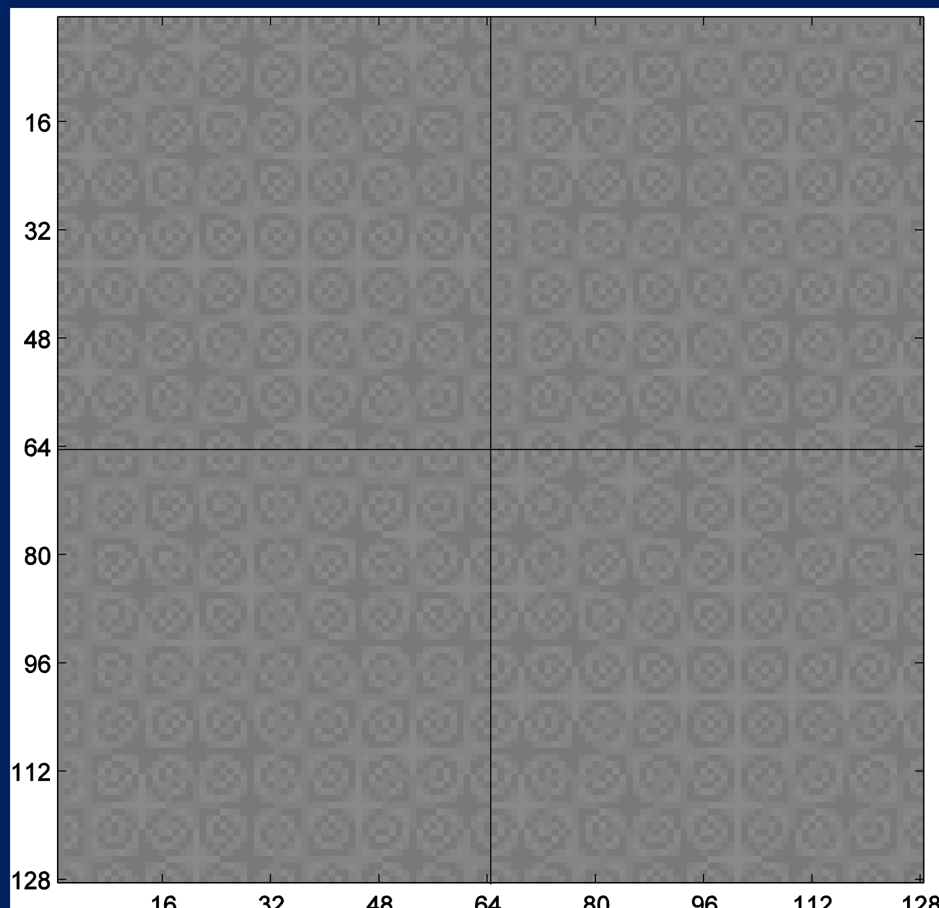
$$v = O_I \times \Omega_a \times O_I \times f$$

adjusted



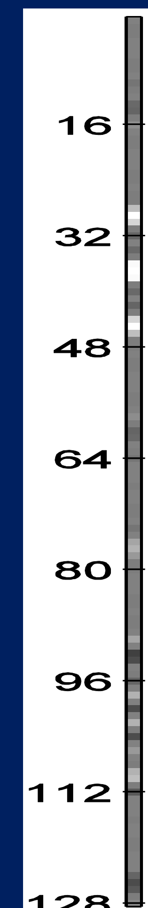
$= O_I \times$

image processing



$\times O_I \times$

k-space processing



Nencka,Hahn,Rowe:JNSM,181:268-82,2009.

Reconstruction: Processing Image

$$v = O_I \times \Omega_a \times O_k \times f$$

These operators are:

$$f = P_C \, \mathcal{R} \, C \, \mathcal{F}$$

Permute RI…RI→RR…II

Reverse rows

Censor uturns

k-space vector

$$O_k = \mathcal{A} \, \mathcal{Z} \, \mathcal{H} \, \underbrace{P_R^{-1} \Omega_{row}^{-1} \Phi \Omega_{row} P_R}_{\text{Nyquist}}$$

Apodize

Zero-fill

Homodyne

unpermute rows

IFT rows

shift rows

FT rows

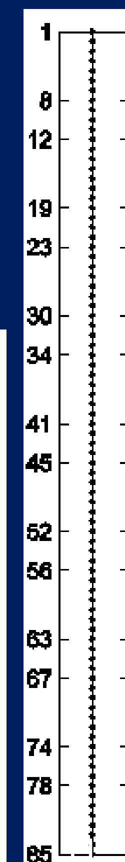
permute rows

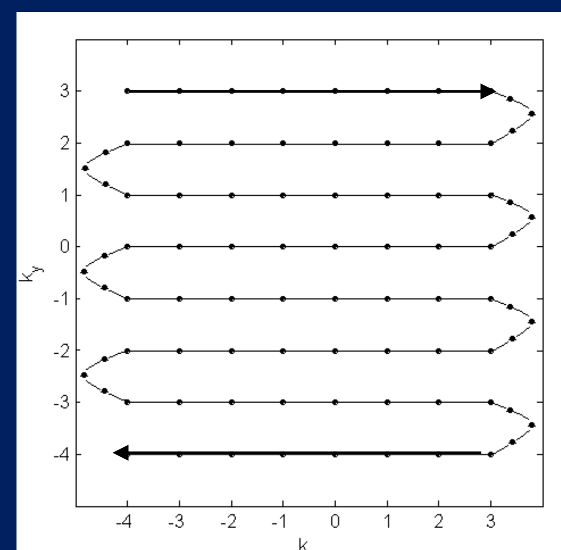
$\Omega_a = \Omega$ adjusted for ΔB and for T_2^*.

$$O_I = I_2 \otimes S_m$$

Image smoothing

$\mathcal{F}$





Nencka, Hahn, Rowe: JNSM, 181:268-282, 2009.

Induced Correlation: Mean and Covariance

If $E(f)=f_0$, then for Of, $E(Of)=Of_0$.

If $\mathrm{cov}(f)=\Gamma$, then for Of, $\mathrm{cov}(Of)=O\Gamma O^T$.

This means that with $\nu=\underbrace{O_I\Omega_a O_k}_{O} f$.

$$E(\nu) = O_I \Omega_a O_k f_0$$

$$\mathrm{cov}(\nu) = (O_I \Omega_a O_k)\Gamma(O_k^T \Omega_a^T O_I^T) = \underset{2p\times 2p}{\Sigma}$$ ← Spatial Covariance

$$\mathrm{cor}(\nu) = R_\Sigma$$ ← Spatial Correlation

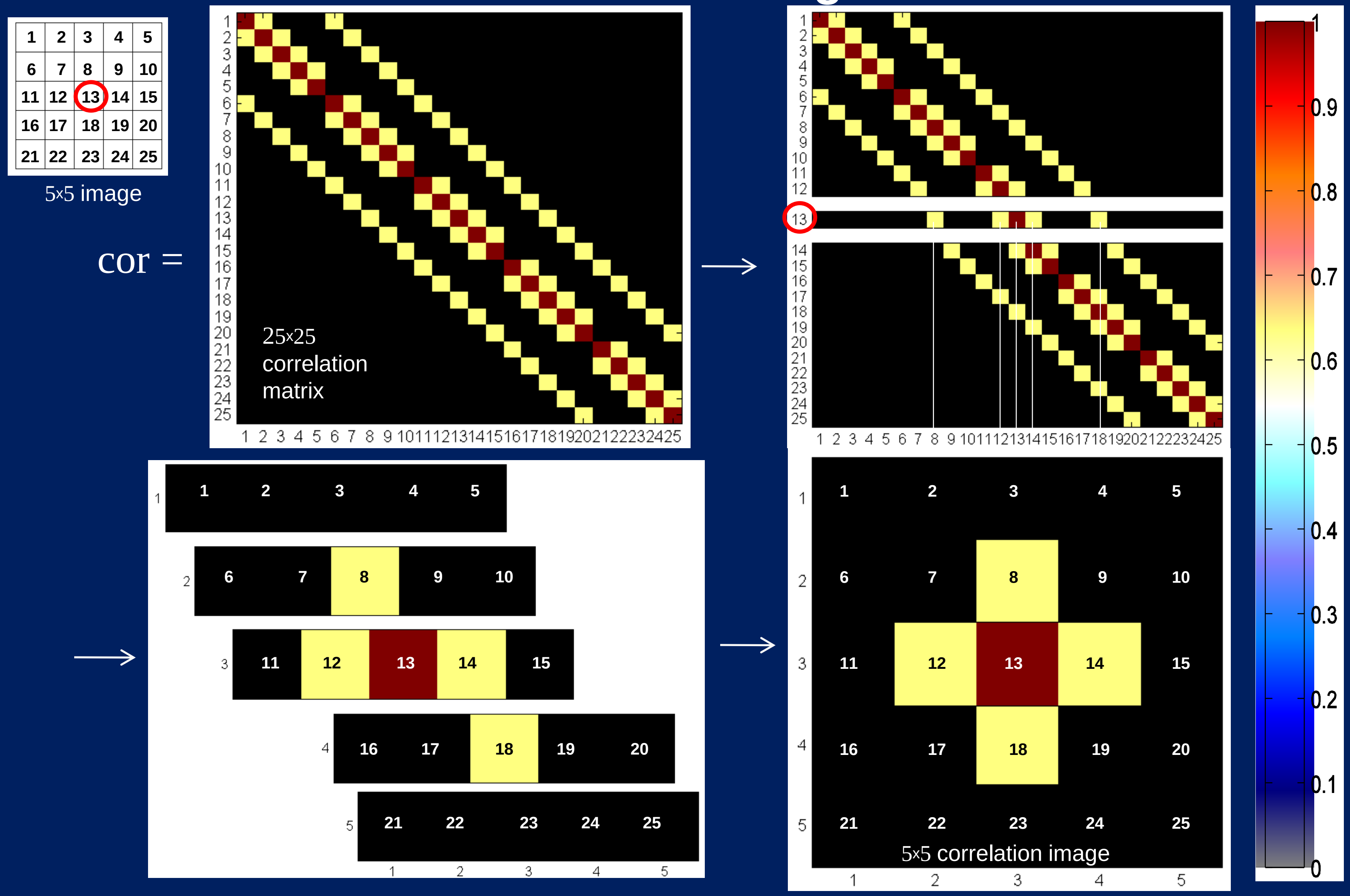
So even if $\Gamma = \sigma_k^2 I$, it is not necessarily true that $\Sigma = \sigma_I^2 I$!

This has H_0 fMRI noise and fcMRI connectivity implications!

Nencka, Hahn, Rowe: JNSM, 181:268-282, 2009.

Nencka, Rowe: OHBM, 2007.

Induced Correlation: Matrix to Image

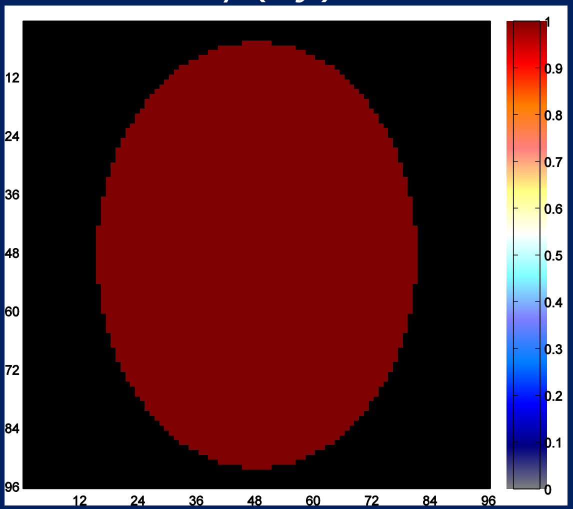


Rowe

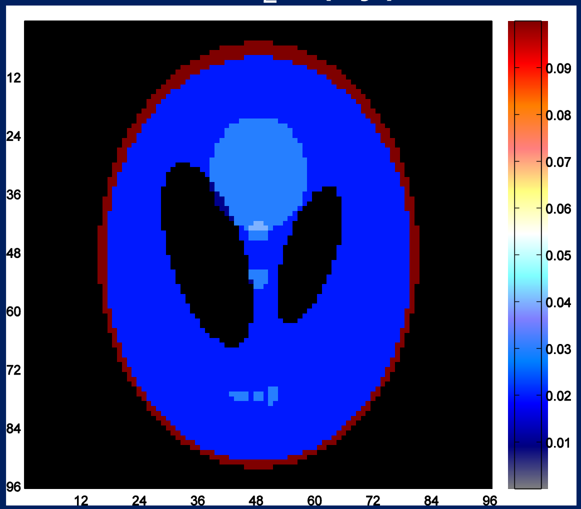
$$f(t) = \int\int \rho(x,y) e^{-t/T_2^*(x,y)} e^{-i\gamma\Delta B(x,y)t} e^{-i2\pi(k_x x + k_y y)} dxdy$$

Induced Correlation: Simulation Parameters

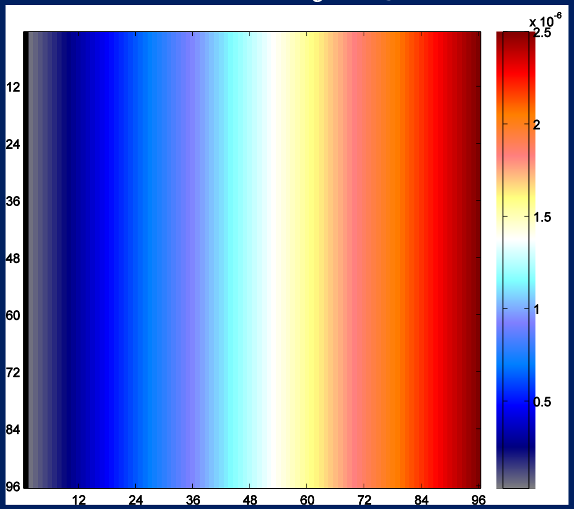
$\rho(x,y)$



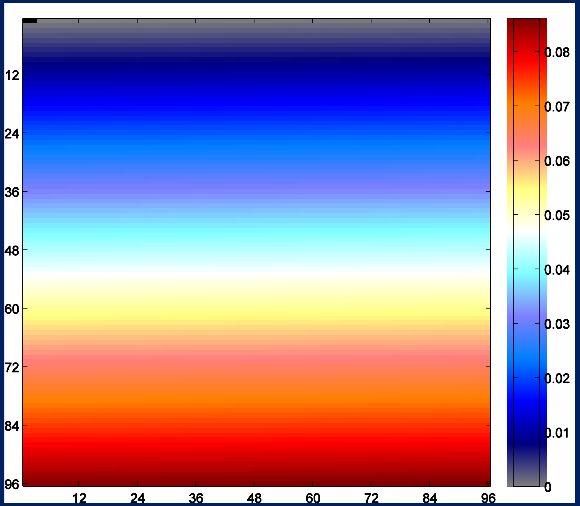
$T_2^*\ (x,y)$



$\boldsymbol{\Delta B_0}\ (x,y)$



Δt



$\mathcal{H} \neq \mathrm{I}$

16 over scan lines

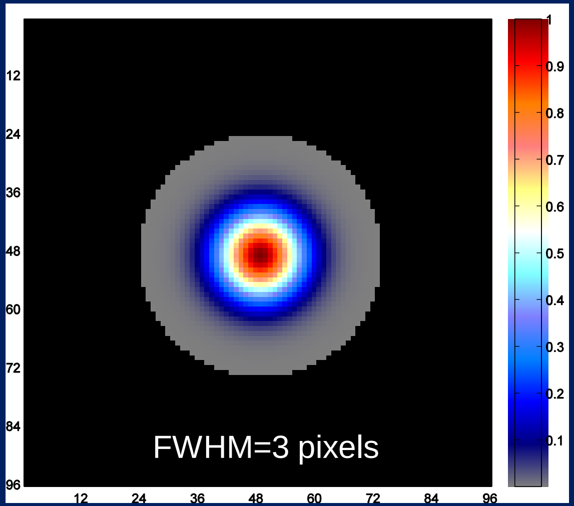
BW=250 kHz

Δt =4 μs

EES=0.96 ms

TE=50.0 ms

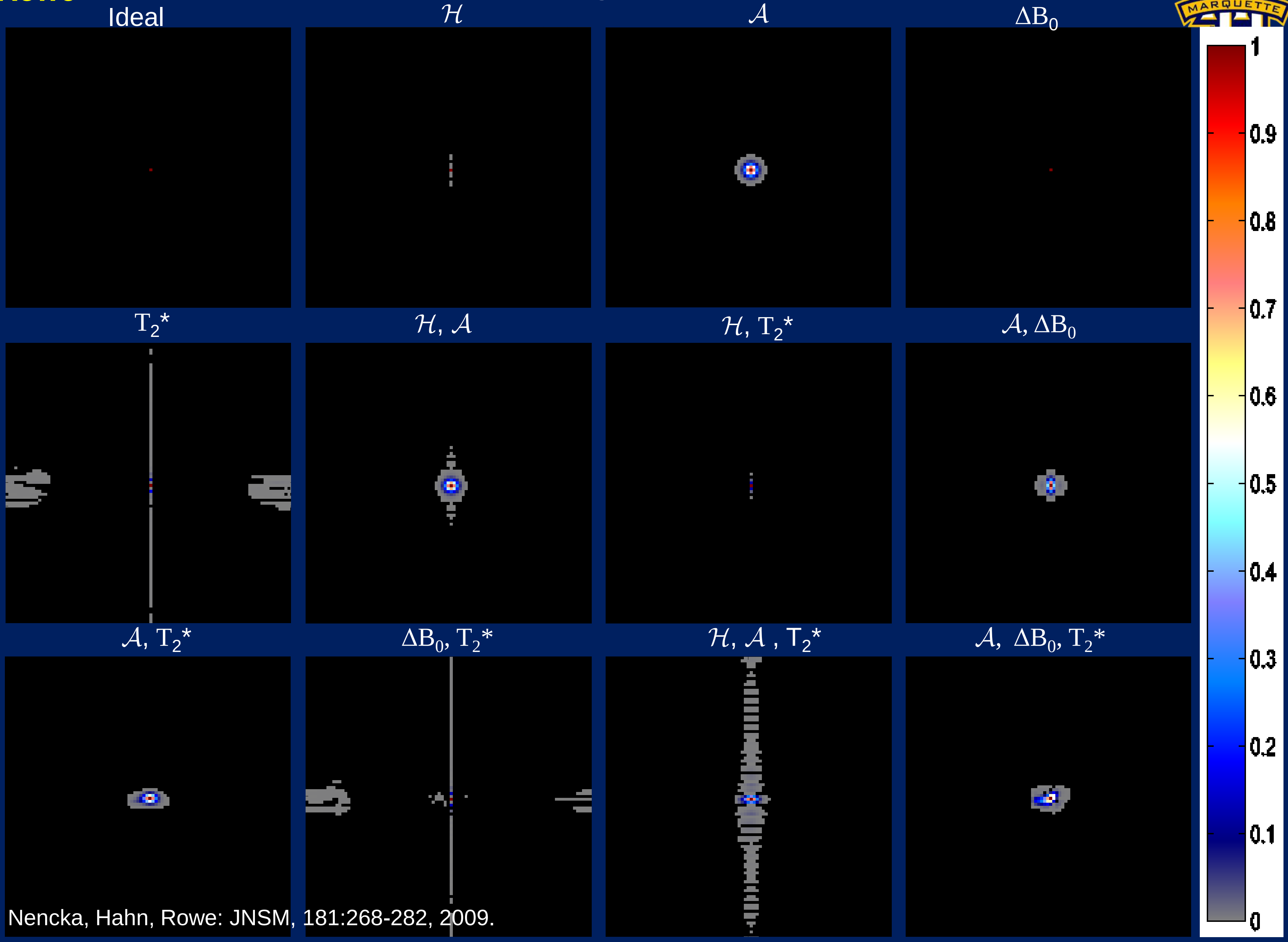
$\mathcal{A} \neq \mathrm{I}$



Nencka, Hahn, Rowe: JNSM, 181:268-282, 2009.

Rowe

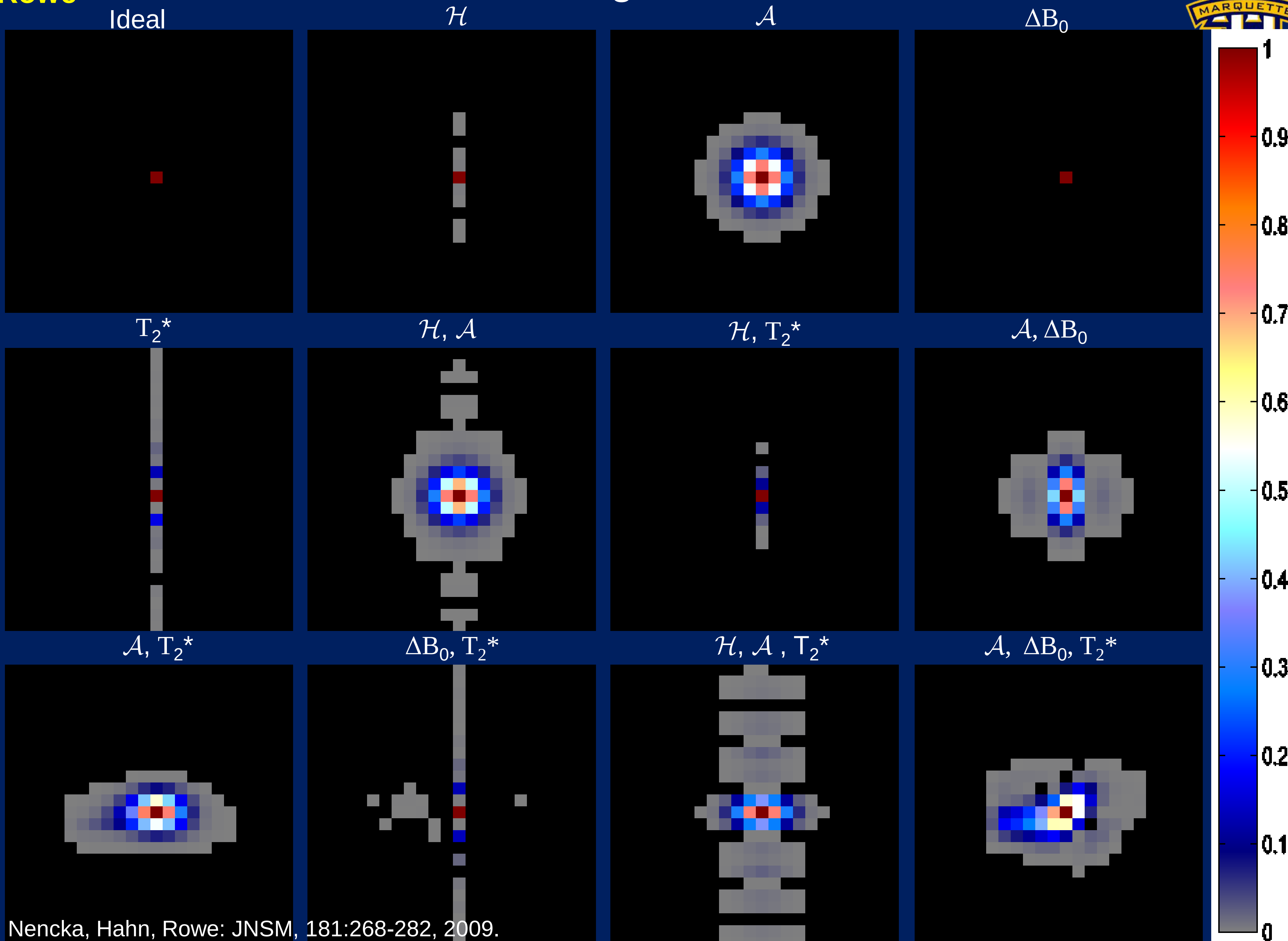
Induced Correlation: Magnitude²



Nencka, Hahn, Rowe: JNSM, 181:268-282, 2009.

Rowe

Induced Corrrelation: Magnitude² Zoomed



Nencka, Hahn, Rowe: JNSM, 181:268-282, 2009.

here is a for each voxel

a

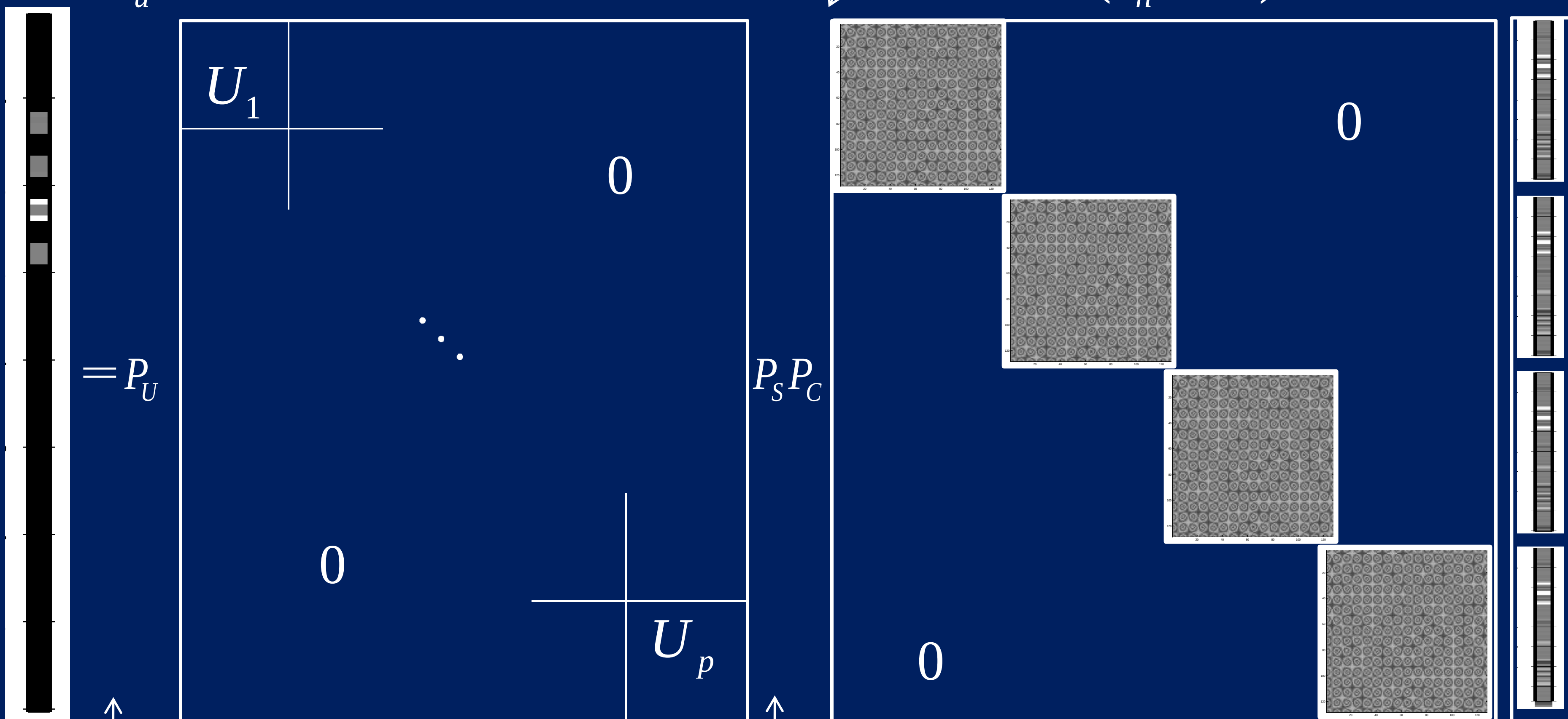
Induced Correlation: SENSE Multi Coil Combine

processing on unfolded image vector

processing on each coil image vector

insert processing on each coil k-space vector

$$y = P_u \quad U \quad P_S P_C \quad (I_n \otimes \Omega) \quad f$$



permute

Single image vector

unfold matrix U's have S and Ψ

permute to by folded voxel

reconstruct n=4 images

k-space vector of n images

Bruce, Karaman, Rowe: MRI, Accepted, 2011.

Induced Correlation: SENSE Multi Coil Combine

$$y = \underbrace{O_I \; P_u \; U \; P_S P_C \; (I_n \otimes \Omega_a O_k)}_{O} \; f$$

k-space vector
censor uturns
row reverse
permute

$$f = P_C \mathcal{R} C \mathcal{F}$$

$$O_k = \mathcal{A}\,\mathcal{Z}\,\mathcal{H}\,\underbrace{P_R^{-1}\Omega_{row}^{-1}\Phi\Omega_{row}P_R}$$

where

$f = (f_1, \ldots, f_n)'$ are coil k-space

O_k is k-space preprocessing

Ω_a is adj. inverse Fourier matrix $\Omega_a = \Omega$ adjusted for ΔB and for T_2^*

P_u, P_S, P_C, permutation matrices $\quad O_I = I_2 \otimes S_m$

Image smoothing

U SENSE unfolding matrix

O_I is image space preprocessing

Bruce, Karaman, Rowe: MRI, Accepted, 2011.

Induced Correlation: SENSE Multi Coil Combine

Statistical Expectation and Covariance.

If $E(f)=f_0$, then for Mf, $E(Mf)=Mf_0$.

If $\mathrm{cov}(f)=\Gamma$, then for Mf, $\mathrm{cov}(Mf)=M\Gamma M'$.

This means that with $y = Of$,

$$E(y) = Of_0 \quad \text{and} \quad \underset{2p\times 2p}{\mathrm{cov}(y) = O\Gamma O' = \Sigma}$$

→ $$\mathrm{cor}(\nu) = D_\Sigma^{-1/2}\Sigma D_\Sigma^{-1/2}$$

So even if $\Gamma = \sigma^2 I$, it is not necessarily true that $\Sigma = \sigma^2 I$!

This has H_0 fMRI noise and fcMRI connectivity implications!

Bruce, Karaman, Rowe: MRI, Accepted, 2011.

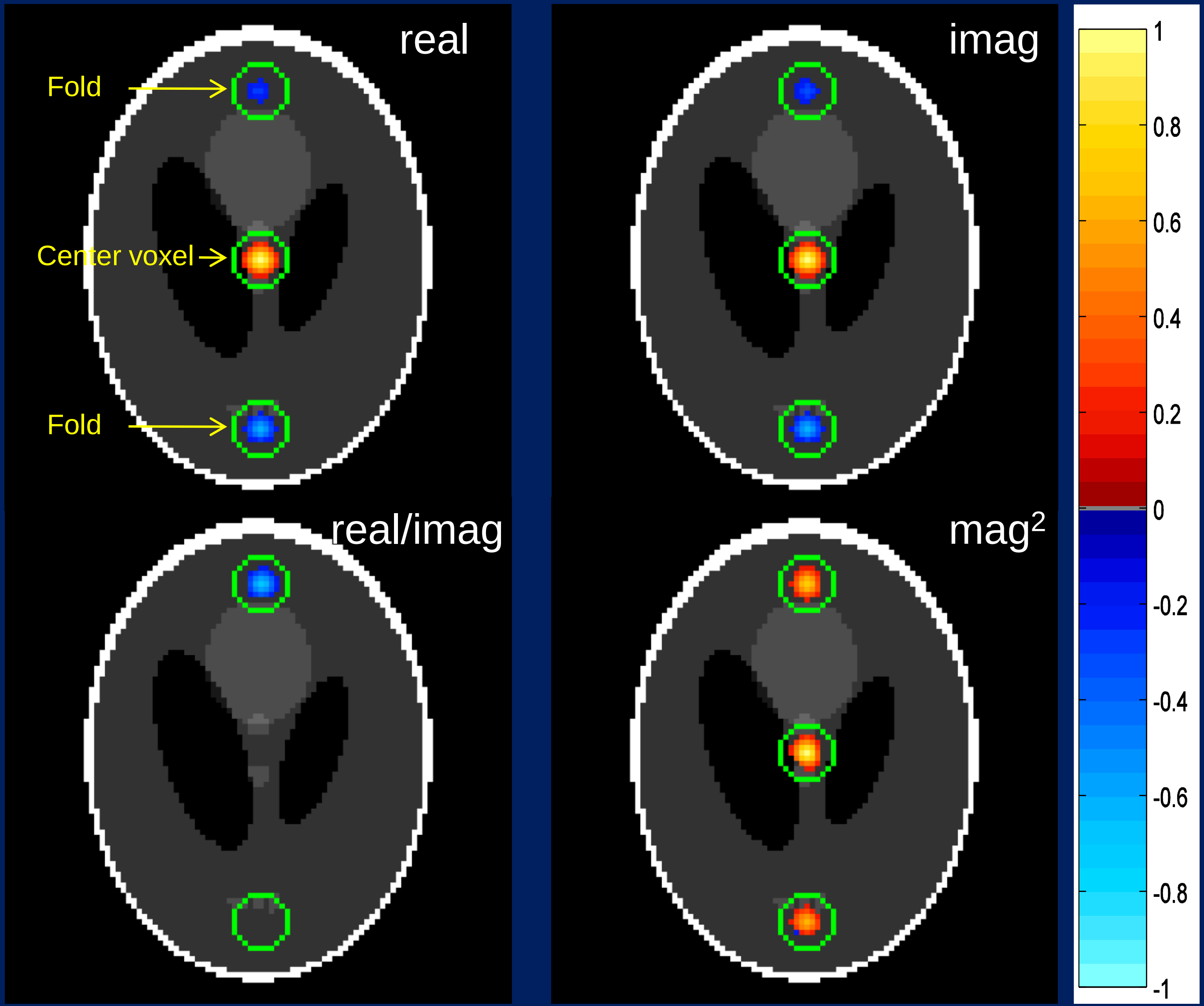
Nencka, Hahn, Rowe: JNSM, 181:268-282, 2009.

Correlations induced about the center voxel.

Induced Correlation: SENSE Multi Coil Combine

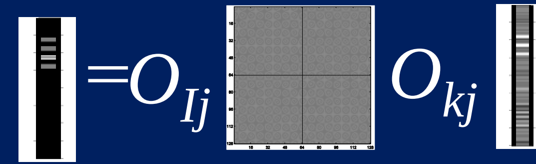
N_X=96
N_Y=96
$n = 4$
$A = 3$
FWHM=3

Functional connectivity implications



TH=0.01

Bruce, Karaman, Rowe: MRI, Accepted, 2011.



Induced Correlation: Extend to Time Series

Reconstruction of n images described as:

$$\underset{2np\times 1}{v} = I \; R \; K \; f$$

I, R, K: diagonal

$$K = BlkDiag(O_{Kt})$$
$$R = BlkDiag(\Omega_{at})$$
$$I = BlkDiag(O_{It})$$

$$\underset{2np\times 1}{\begin{pmatrix} v_1 \\ \vdots \\ v_n \end{pmatrix}} = \underset{2np\times 2np}{\begin{pmatrix} O_{I1}\Omega_{a1}O_{k1} & & 0 \\ & \ddots & \\ 0 & & O_{In}\Omega_{an}O_{kn} \end{pmatrix}} \underset{2np\times 1}{\begin{pmatrix} f_1 \\ \vdots \\ f_n \end{pmatrix}}$$

f_1: image 1 k-space vector

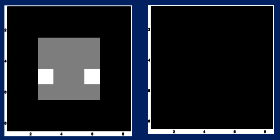
f_n: image n k-space vector

$2np\times 1$: image-space vector of n images

$2np\times 2np$: Reconstruction k-space operation matrix for n images

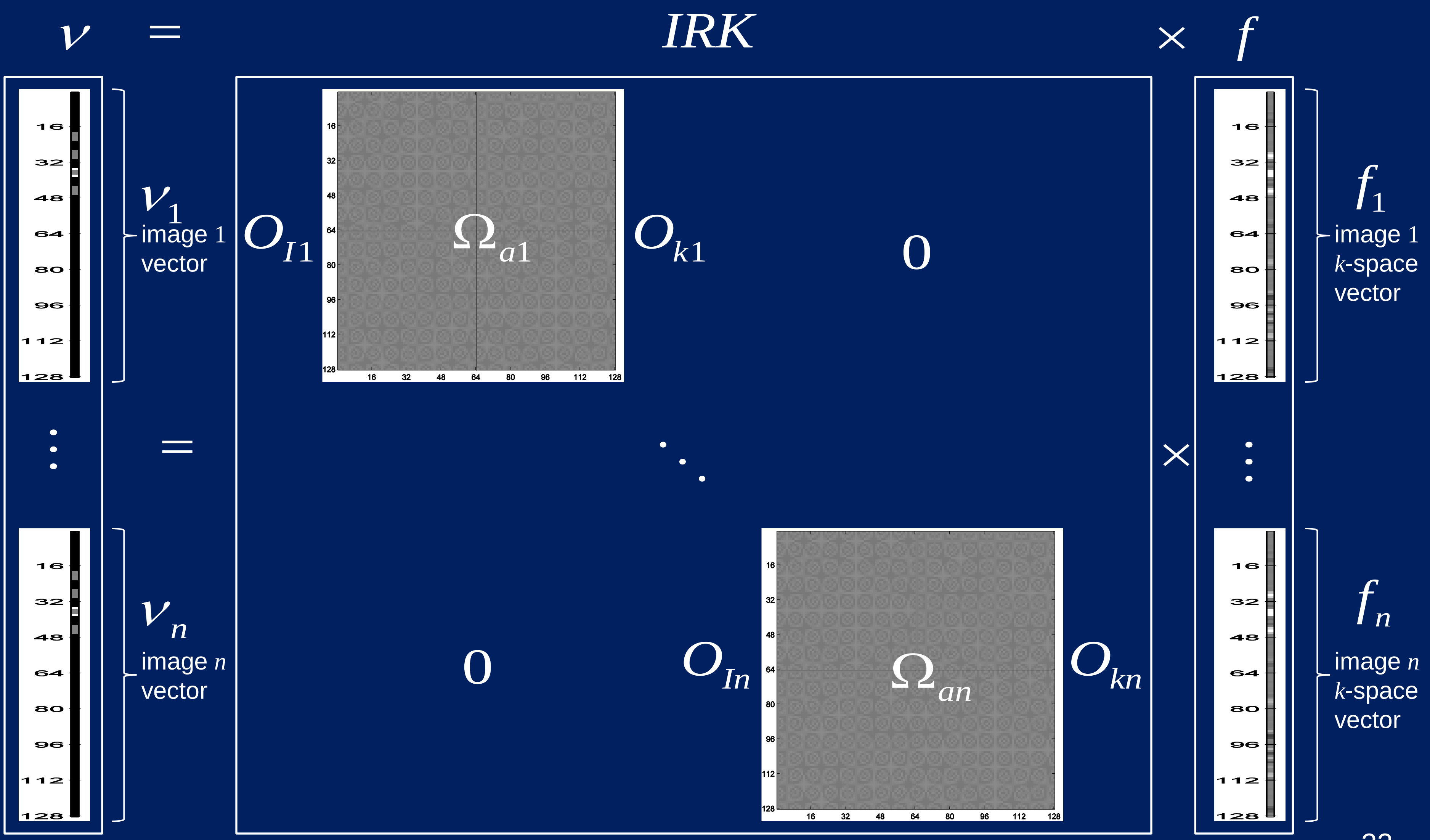
$2np\times 1$: k-space vector of n images

Nencka, Rowe: In Progress.



real imaginary

Induced Correlation: Extend to Time Series



Nencka, Rowe: In Progress.

Induced Correlation: Extend to Time Series

(dyn ΔB_0, Δx, Δt, freq filt)

$$y = T \cdot P \cdot IRK \cdot f$$

voxel 1 temporal processing

$$\underset{2np\times 1}{\begin{pmatrix} y_1 \\ \vdots \\ y_p \end{pmatrix}} = \underset{2np\times 2np}{\begin{pmatrix} O_{T1} & & 0 \\ & \ddots & \\ 0 & & O_{Tp} \end{pmatrix}} P \underset{2np\times 2np}{\begin{pmatrix} O_{I1}\Omega_{a1}O_{k1} & & 0 \\ & \ddots & \\ 0 & & O_{In}\Omega_{an}O_{kn} \end{pmatrix}} \underset{2np\times 1}{\begin{pmatrix} f_1 \\ \vdots \\ f_n \end{pmatrix}}$$

voxel p series filter

permute from measurements by image to by voxel

$$y = \begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix}$$

voxel 1 temporally processed series

n reals

$$y_j = \begin{pmatrix} y_{Rj} \\ y_{Ij} \end{pmatrix} \begin{matrix} \}\ n\times 1 \\ \}\ n\times 1 \end{matrix}$$

voxel j temporally processed series

$$j = 1, \ldots, p$$

Nencka, Rowe: In Progress.

Induced Correlation: Mean and Covariance

If $E(f)=f_0$, then for $E(Of)=Of_0$.

If $\mathrm{cov}(f)=\Gamma$, then for $\mathrm{cov}(Of)=O\Gamma O^T$.

This means that with $y=\underbrace{TPIRK}_{O}f$.

$$E(y)=TPIRKf_0$$

$$\mathrm{cov}(y)=(TPIRK)\Gamma(K^T R^T I^T P^T T^T)=\underset{2np\times 2np}{\Sigma}$$

Spatio-Temporal Covariance
HUGE

$$\mathrm{cor}(y)=R_\Sigma$$

Spatio-Temporal Correlation

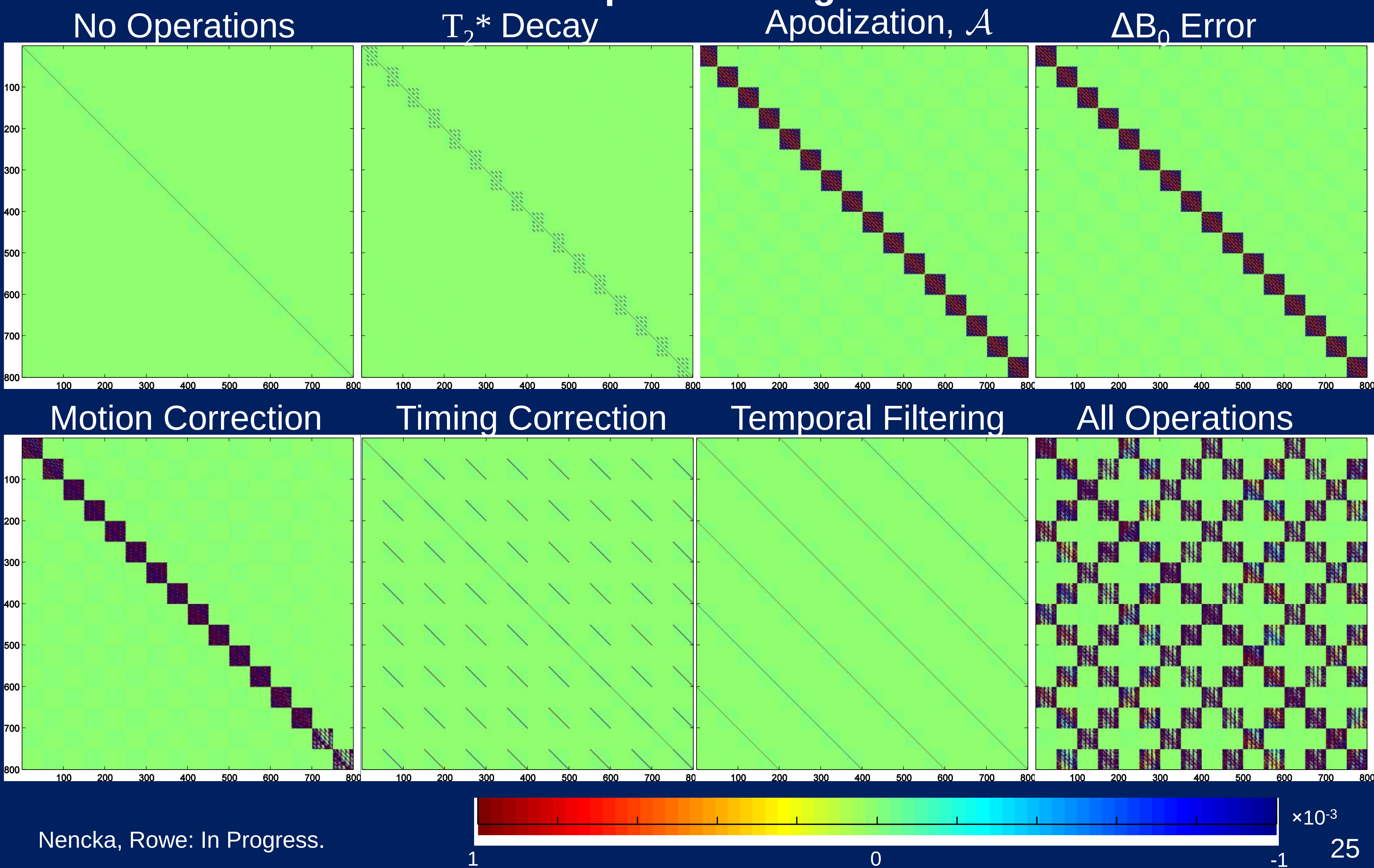
So even if $\Gamma=\sigma_k^2 I$, it is not necessarily true that $\Sigma=\sigma_I^2 I$!

This has H_0 fMRI noise and fcMRI connectivity implications!

Nencka, Rowe: In Progress.

$$\underset{800\times 800}{O} = TPIRK$$

Induced Correlation: Example 5×5 image 8 TRs 2 slices

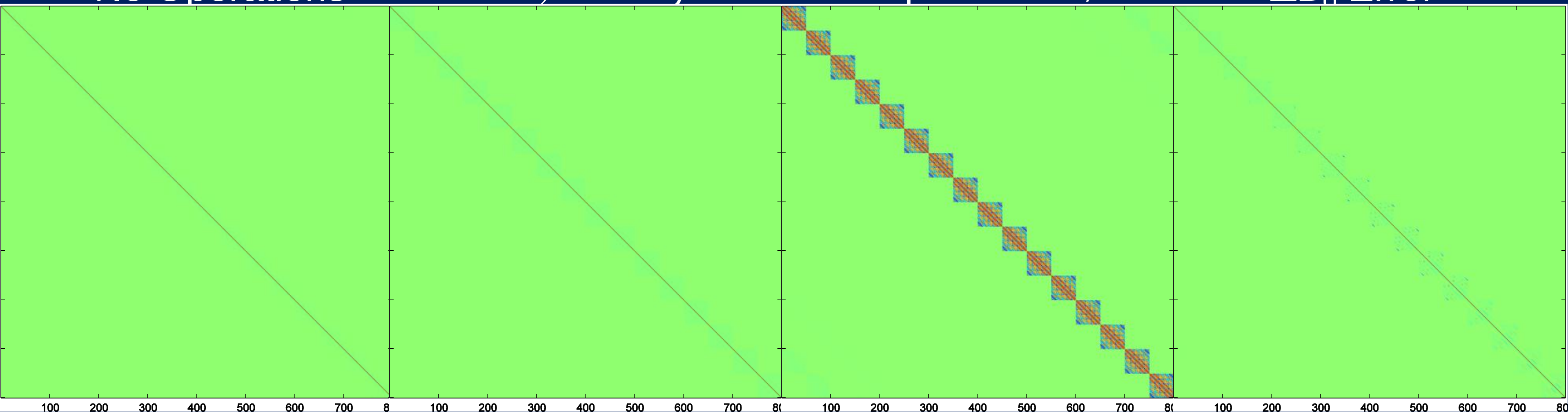


Nencka, Rowe: In Progress.

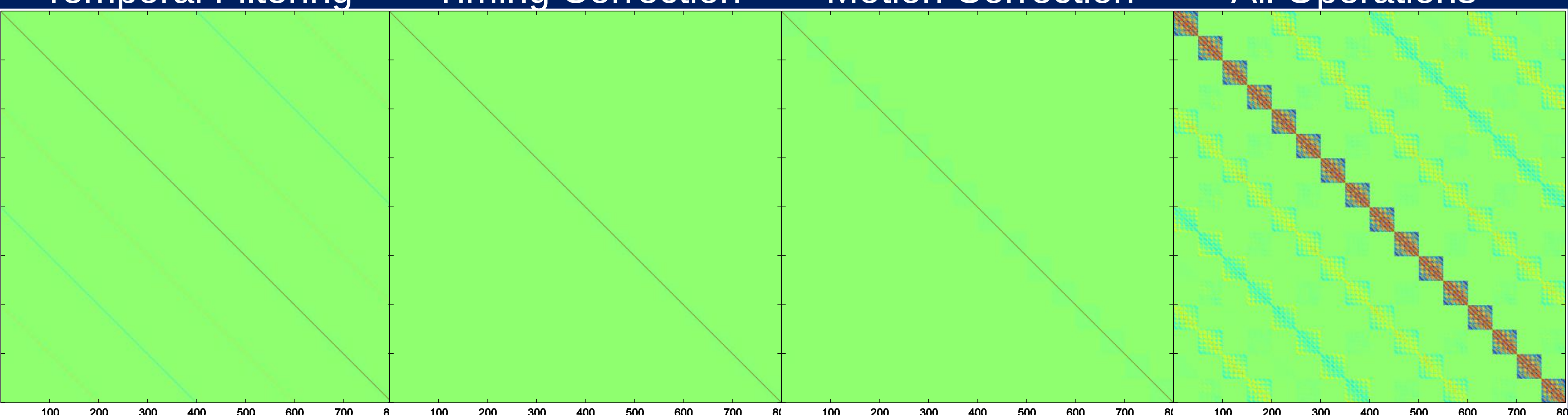
$$\underset{800\times800}{\Sigma} = OIO^T \rightarrow \underset{800\times800}{R_\Sigma}$$

Induced Correlation: Example 5×5 image 8 TRs 2 slices

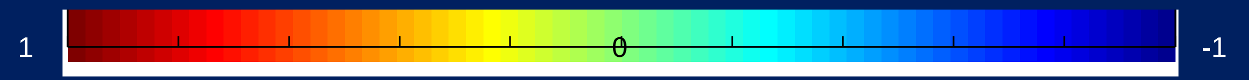
No Operations | T_2* Decay | Apodization, $\mathcal{A}$ | ΔB_0 Error



Temporal Filtering | Timing Correction | Motion Correction | All Operations

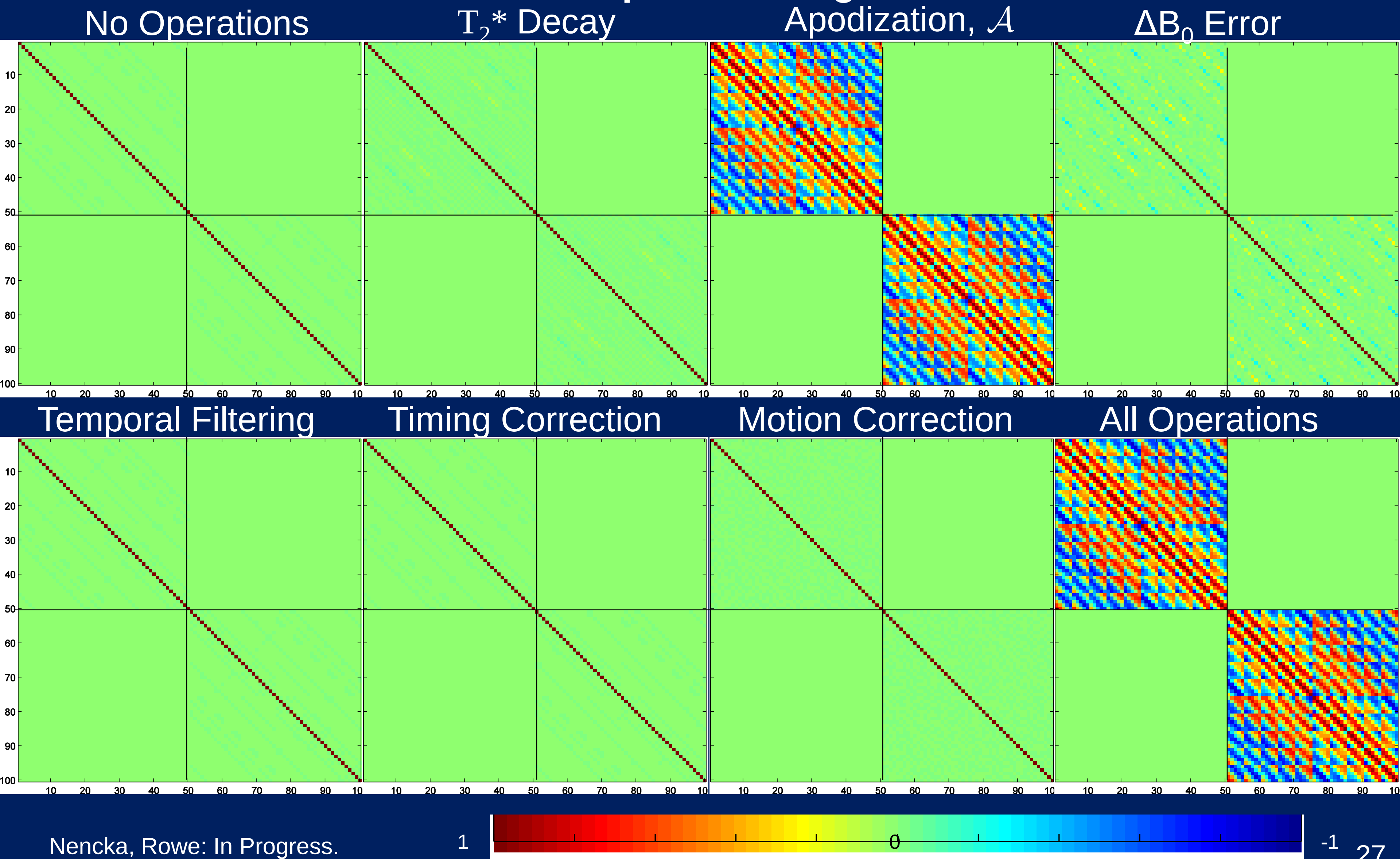


Nencka, Rowe: In Progress.



$$\underset{100\times 100}{\Sigma} = OIO^T \rightarrow \underset{100\times 100}{R_S}$$

Induced Correlation: Example 5×5 image 8 TRs 2 slices

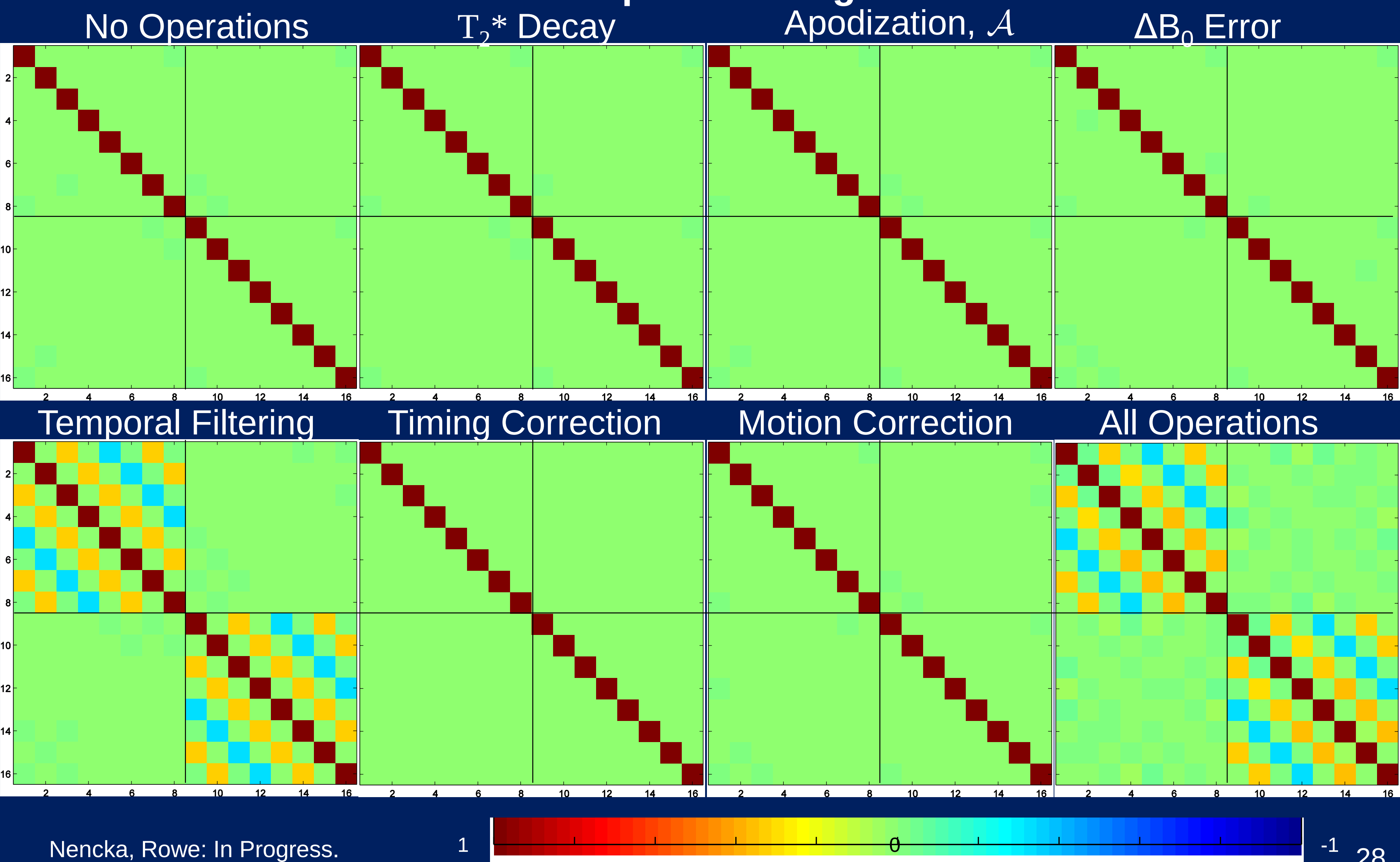


Nencka, Rowe: In Progress.

Rowe

$$\underset{16\times16}{\Sigma} = OIO^T \rightarrow \underset{16\times16}{R_T}$$

Induced Correlation: Example 5×5 image 8 TRs 2 slices



Nencka, Rowe: In Progress.

Utilizing Induced Correlation:

Since for all voxels is

$$\underset{2np\times 2np}{\Sigma} = \begin{pmatrix} \begin{array}{c|c} \Sigma_1 & \\ \hline & \end{array} & & \Sigma_{jk} \\ & \ddots & \\ \Sigma'_{jk} & & \begin{array}{c|c} & \\ \hline & \Sigma_p \end{array} \end{pmatrix} \Rightarrow$$

Then for voxel j, the R-I cov is

$$\underset{2n\times 2n}{\Sigma_j} = \begin{pmatrix} \Sigma_{jR} & \Sigma_{jRI} \\ \Sigma'_{jRI} & \Sigma_{jI} \end{pmatrix}$$

and the magnitude[2] covariance is

$$\begin{aligned} \delta_j &= tr(\Sigma_j) + \mu'_j \mu_j \\ \Lambda_{jj} &= 2tr(\Sigma'_j \Sigma_j) + 4\mu'_j \Sigma_j \mu_j \quad , \\ \Lambda_{jk} &= 2tr(\Sigma'_{jk} \Sigma_{jk}) + 4\mu'_j \Sigma_{jk} \mu_k \end{aligned}$$

Nencka, Hahn, Rowe: JNSM, 181:268-282, 2009.

Utilizing Induced Correlation:

Complex-Valued

$$C_j = \begin{pmatrix} \cos\theta_{j1} & & 0 \\ & \ddots & \\ 0 & & \cos\theta_{jn} \end{pmatrix} \quad S_j = \begin{pmatrix} \sin\theta_{j1} & & 0 \\ & \ddots & \\ 0 & & \sin\theta_{jn} \end{pmatrix}$$

$$\begin{pmatrix} y_{jR} \\ y_{jI} \end{pmatrix} = \begin{pmatrix} C_j X \beta_j \\ S_j X \beta_j \end{pmatrix} + \begin{pmatrix} \eta_{jR} \\ \eta_{jI} \end{pmatrix}, \qquad \eta_j \sim N(0, \Sigma_j)$$

Compute activation individually for each voxel.

Incorporate Induced Covariance

Magnitude-Only (assuming high SNR)

$$m_j = X\beta_j + \varepsilon_j, \qquad \varepsilon_j \sim N(0, \Lambda_j)$$

Compute activation individually for each voxel.

Can form larger spatio-tempporal model.

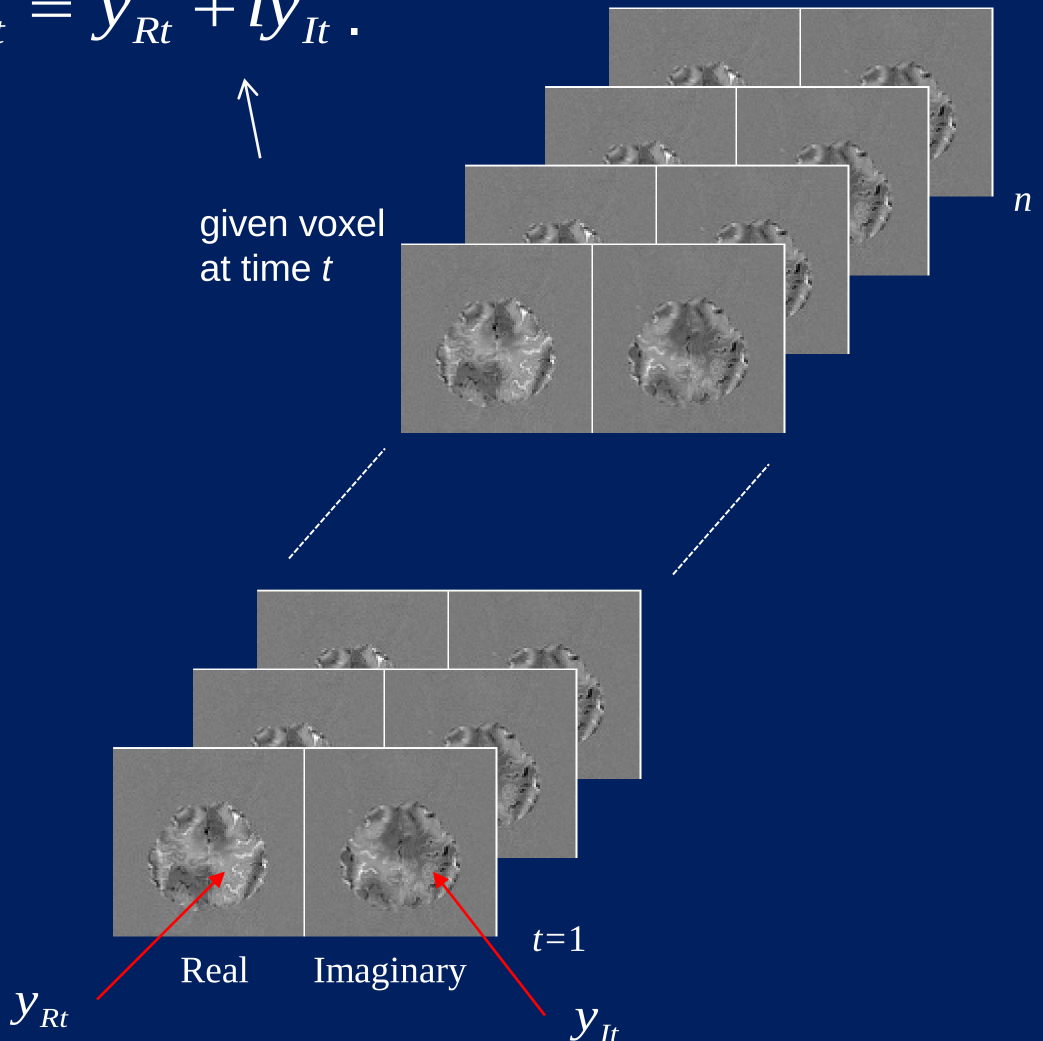
Nencka, Hahn, Rowe: JNSM, 181:268-282, 2009.

Rowe: NIMG, 25:1310-1324, 2005b.

Utilizing Induced Correlation: Complex fMRI

The fMRI data is truly complex-valued images and voxel time series, $y_t = y_{Rt} + iy_{It}$.

given voxel
at time *t*

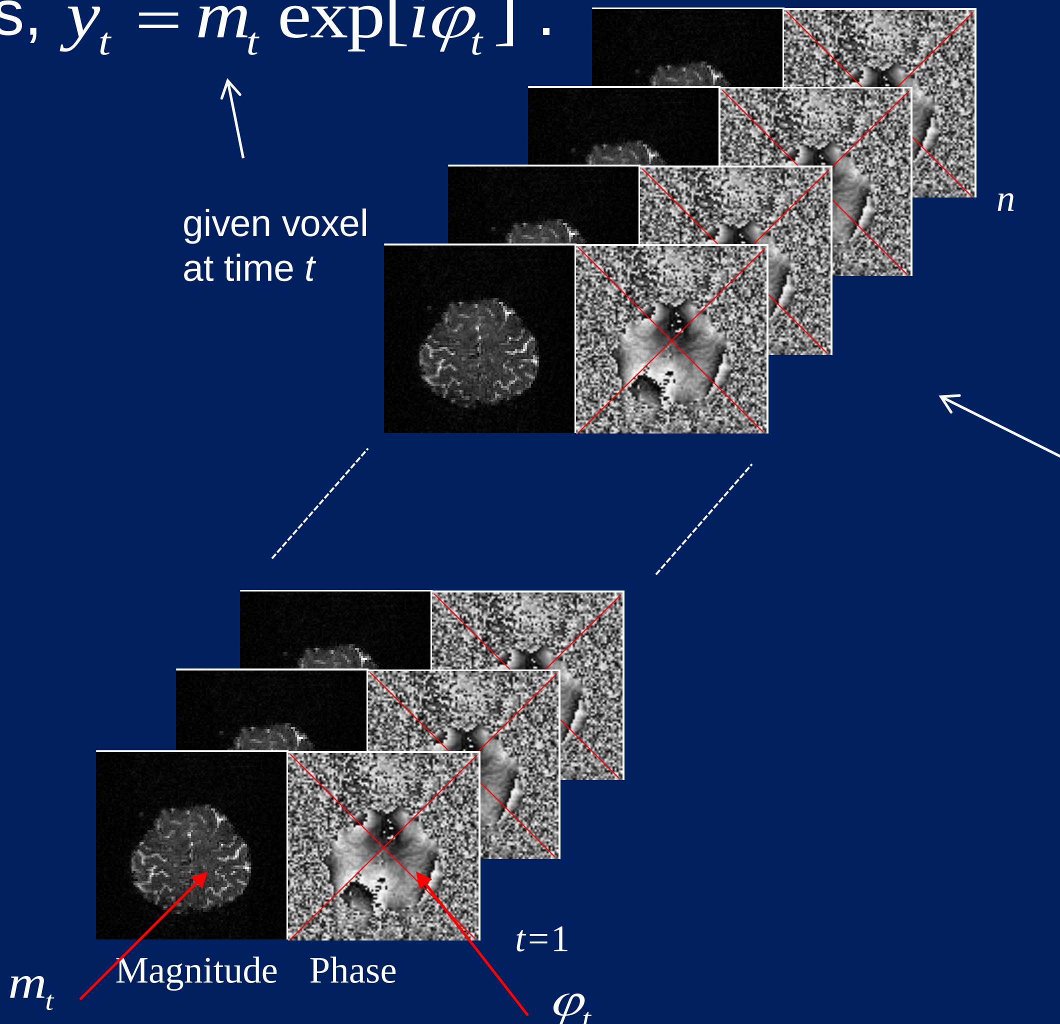


Cartesian coordinates
Real-Imaginary

Utilizing Induced Correlation: Magnitude-Only fMRI

Complex-valued images to magnitude and phase images and time series, $y_t = m_t \exp[i\varphi_t]$.

Polar Coordinates
Magnitude-Phase



Phase discarded!
(in nearly all fMRI)

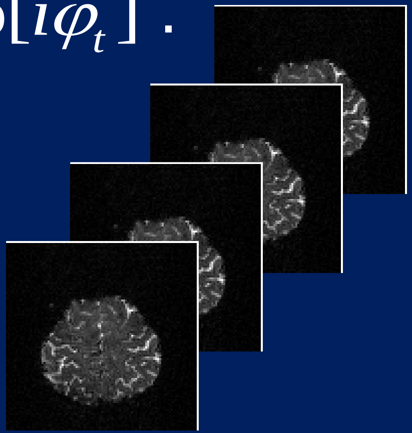
½ of numbers
are discarded
(and processed)

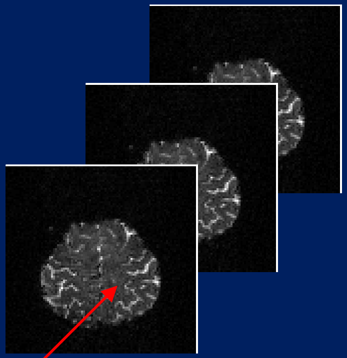
Biological information
in phase through space!
And also through time.

Utilizing Induced Correlation: Magnitude-Only fMRI

Complex-valued images to magnitude and phase images and time series, $y_t = m_t \exp[i\varphi_t]$.

given voxel
at time *t*





m_t Magnitude Phase

Magnitude-Only

m_t

Phase discarded!
(in nearly all fMRI)

½ of numbers
are discarded
(and processed)

Biological information
in phase through space!
And also through time.

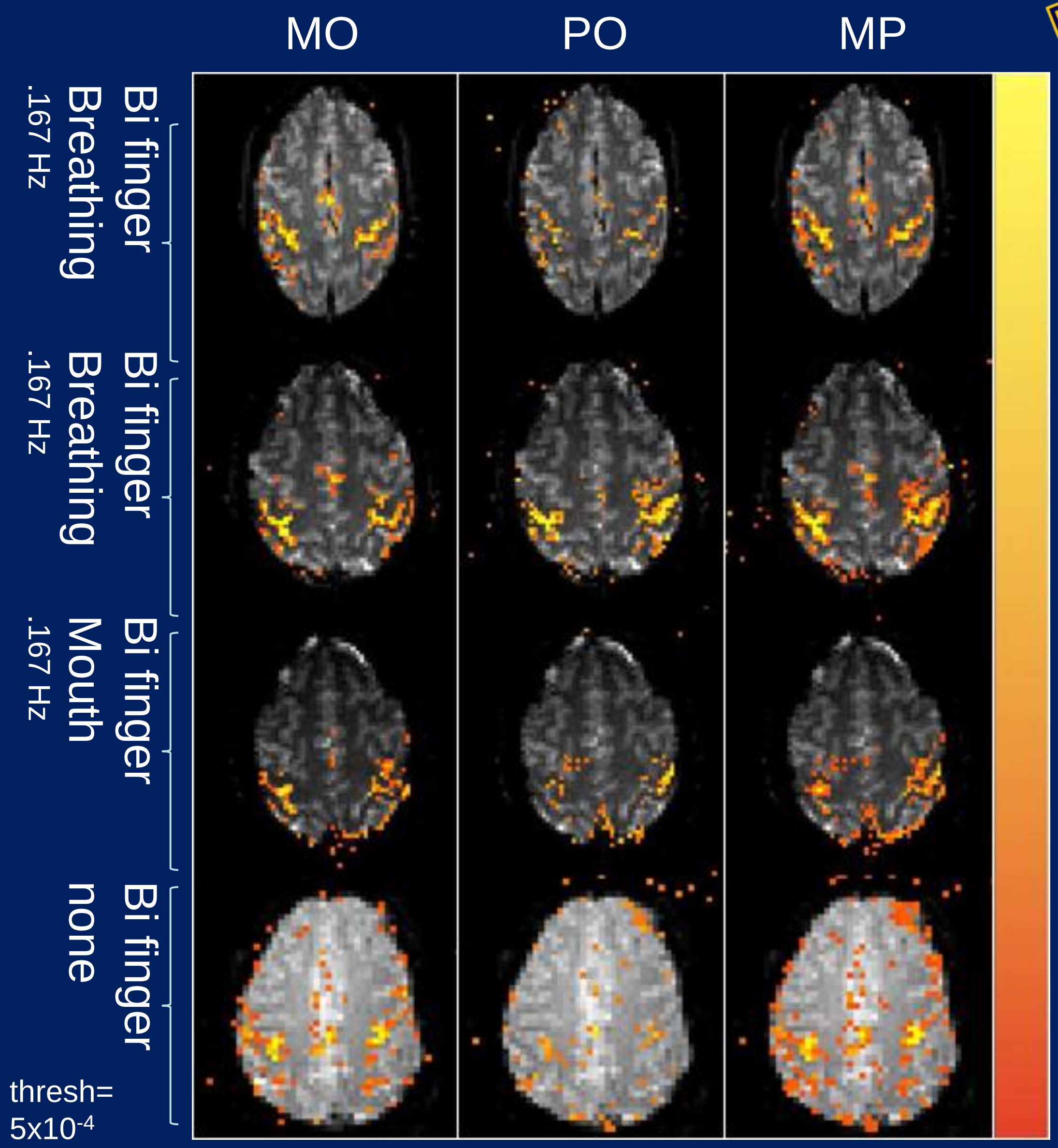
Results: Independent

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



Rowe: NIMG, 25:1310-1324, 2005.
Rowe: MRM, to appear, 2009.

Hahn, Nencka, Rowe: NIMG, 742-752, 2009.
Hahn, Nencka, Rowe: HBM, Online, 2011.

$$\Delta B_t = \frac{\arg\left(I_t \sum_{j=1}^{n} \left(\frac{I_j^*}{|I_j|} \right) \right)}{\gamma \mathrm{TE}}$$

Discussion:

When DATA ANLYSTS preprocess RESEARCHERS data,

THEY change the mean and covariance structure.

Many preprocessing operations have been shown

to modify or induce a correlation.

WE need to utilize this correlation in OUR analysis model!

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