Is My Correlation of Biological Origin?

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June 14, 2013

Outline:

1. Biological Associations
    - Between Brain Regions
    - Within Brain Regions
    - Physiological Signals
2. Induced Correlation
    - Within Slice Local Correlation
    - Within Slice Distant Correlation
    - Between Slice Distant Correlation
    - Temporal Correlation
3. Discussion

1. Biological Associations: Between Discovered

Biological association between regions of brain have been seen.

1. Biological Associations: Between Discovered

Functional Connectivity in the Motor Cortex of Resting Human Brain Using Echo-Planar MRI

Bharat Biswal, F. Zerrin Yetkin, Victor M. Haughton, James S. Hyde

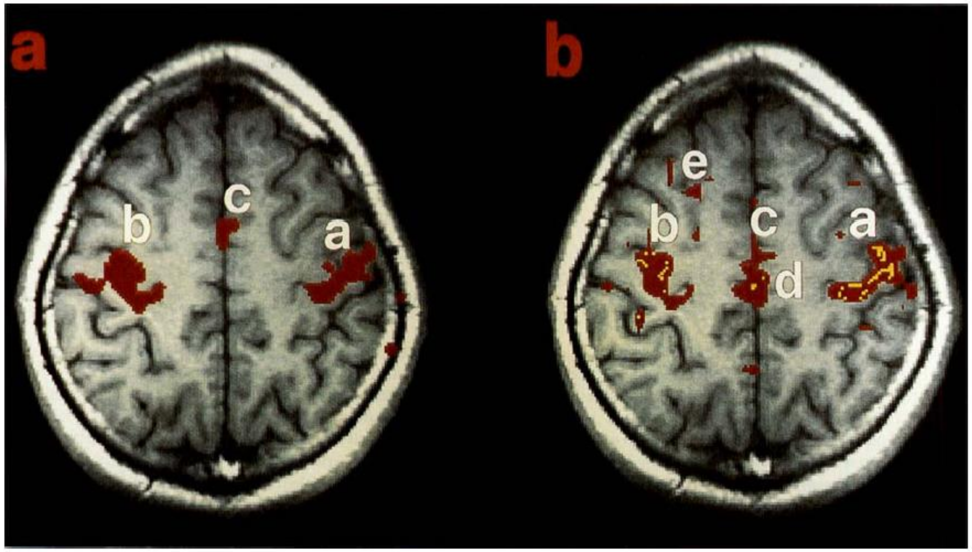


FIG. 3. (Left) FMRI task-activation response to bilateral left and right finger movement, superimposed on a GRASS anatomic image. (Right) Fluctuation response using the methods of this paper. See text for assignment of labeled regions. Red is positive correlation, and yellow is negative.

MRM 34:537–541 (1995)

From the Biophysics Research Institute Medical College of Wisconsin, Milwaukee, Wisconsin

1. Biological Associations: Within Applied

Biological Associations within regions have been used to detect Neurological Disease.

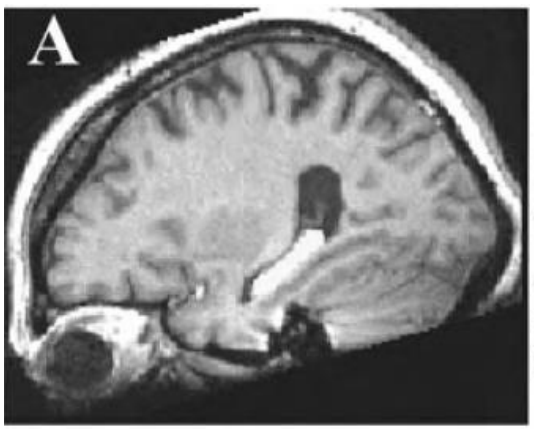
1. Biological Associations: Within Applied

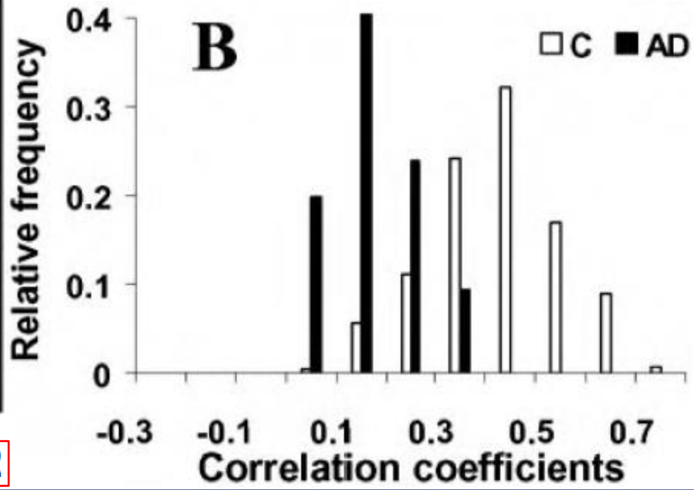
Alzheimer Disease: Evaluation of a Functional MR Imaging Index as a Marker[1]

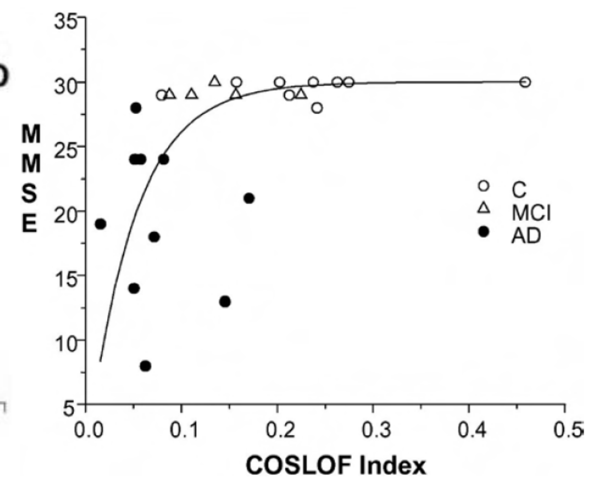
Shi-Jiang Li, PhD
Zhu Li, MD
Gaohong Wu, PhD
Mei-Jie Zhang, PhD
Malgorzata Franczak, MD
Piero G. Antuono, MD

[1] From the Biophysics Research Institute
Medical College of Wisconsin, Milwaukee, WI

$$\mathrm{COSLOF} = \frac{2}{K(K-1)} \sum_{i,j=1,i>j}^{K} cc_{ij},$$







Radiology · October 2002

1. Biological Associations: Physiological Signals

It has been noticed that there are physiological signals that need to be subtracted.

1. Biological Associations: Physiological Signals

Magnetic Resonance in Medicine 44:162–167 (2000)

Image-Based Method for Retrospective Correction of Physiological Motion Effects in fMRI: RETROICOR

Gary H. Glover,[1*] Tie-Qiang Li,[1] and David Ress[2]

[1]Department of Radiology, Stanford University School of Medicine, Center for Advanced MR Technology at Stanford, Stanford, California.

ELSEVIER

NeuroImage

www.elsevier.com/locate/ynimg
NeuroImage 31 (2006) 1536 – 1548

Separating respiratory-variation-related fluctuations from neuronal-activity-related fluctuations in fMRI

Rasmus M. Birn,* Jason B. Diamond, Monica A. Smith, and Peter A. Bandettini

Laboratory of Brain and Cognition, National Institute of Mental Health, NIH, 10 Center Dr., Bldg. 10, Rm. 1D80 Bethesda, MD 20892-1148, USA

2. Induced Correlation:

It has been noticed that the data has an intrinsic correlation and is spatially dependent.

2. Induced Correlation: Within Local

ELSEVIER NeuroImage
32 (2006) 1656 – 1668

Reducing inter-scanner variability of activation in a multicenter fMRI study: Role of smoothness equalization

Lee Friedman,[a,*] Gary H. Glover,[b] Diana Krenz,[c] and Vince Magnotta[d]
The FIRST BIRN [1]

In summary, we have described important scanner differences in activation effect size and smoothness that will affect the results of multicenter fMRI studies. Vendor differences in image smoothness were documented and are likely due to differences in k-space filtering regimes. We have shown that smoothness equalization can reduce scanner differences in activation effect size within a field strength and also reduce the field strength effect on activation effect size.

2. Induced Correlation: Within Local

◆ Human Brain Mapping 30:13–23 (2009) ◆

Integrated Local Correlation: A New Measure of Local Coherence in fMRI Data

Gopikrishna Deshpande, Stephen LaConte, Scott Peltier, and Xiaoping Hu*

WHC Department of Biomedical Engineering, Georgia Institute of Technology and Emory University, Atlanta, Georgia

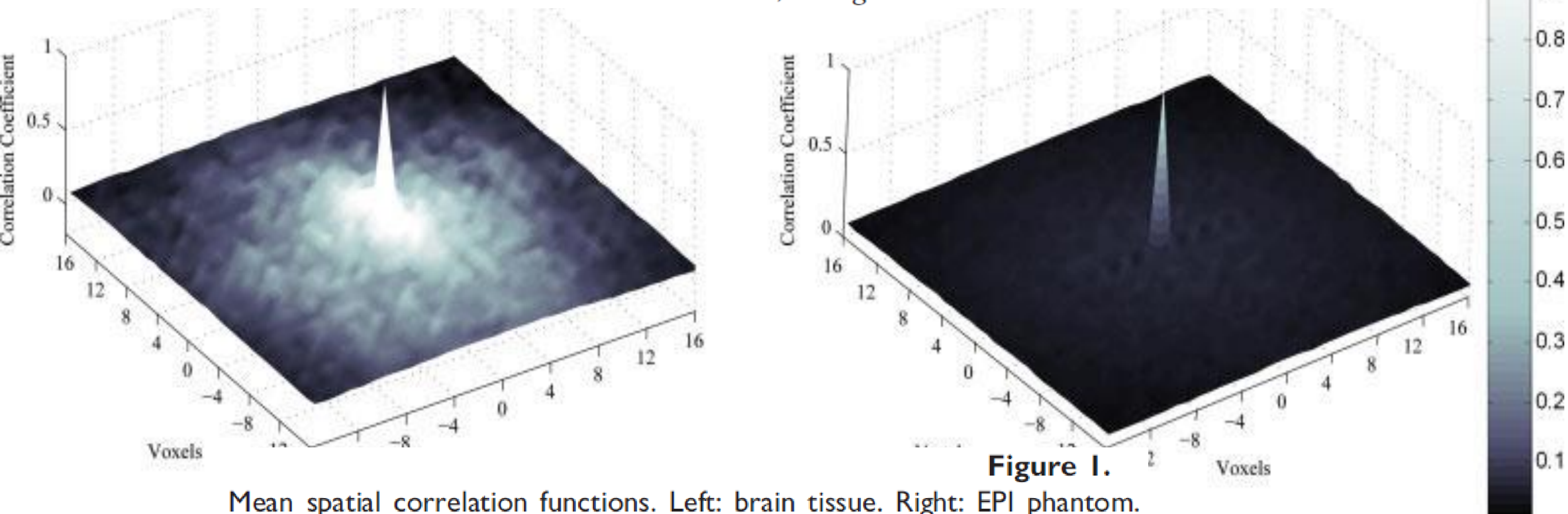
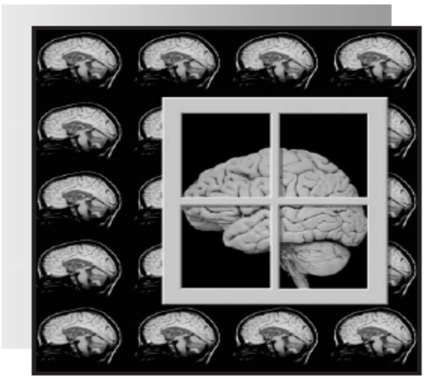


Figure 1.
Mean spatial correlation functions. Left: brain tissue. Right: EPI phantom.

2. Induced Correlation: Within



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Evaluating fMRI Preprocessing Pipelines

Review of Preprocessing Steps for BOLD fMRI

IEEE ENGINEERING IN MEDICINE AND BIOLOGY MAGAZINE MARCH/APRIL 2006

BY STEPHEN C. STROTHER

The preprocessing steps interact with virtually every decision made in designing and performing an fMRI experiment.

Empirical Evaluation of Preprocessing.

2. Induced Correlation:

Efforts to precisely mathematically quantify the effects of processing.

2. Induced Correlation:

Generally ignored

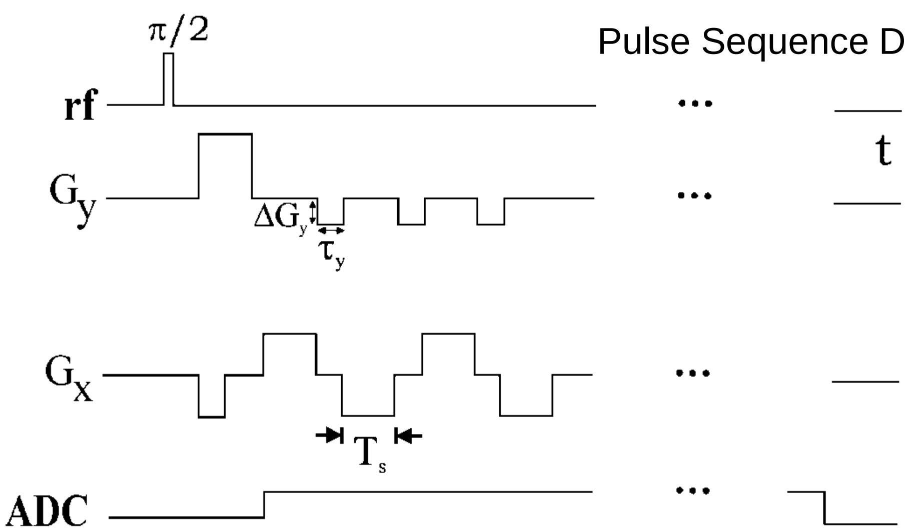
Signal at t

$$\mathcal{S}(t)=\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}\underbrace{\rho(x,y)e^{-t/T_2^*(x,y)}e^{-i\gamma\Delta B(x,y)t}}_{\rho^*(x,y)}e^{-i2\pi(k_x x+k_y y)}dxdy$$

where $k_x(t)=\frac{\gamma}{2\pi}\int_0^t G_x(\tau)d\tau$ and $k_y(t)=\frac{\gamma}{2\pi}\int_0^t G_y(\tau)d\tau$ are known.

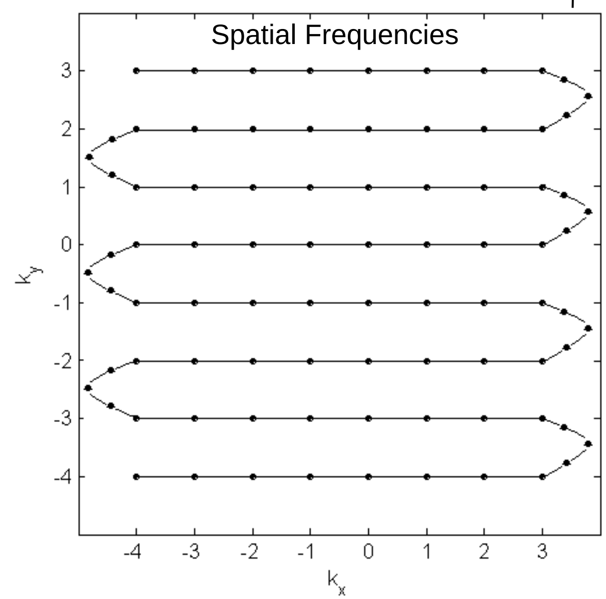
By changing G_x and G_y over time . . . we cover k-space.

Pulse Sequence Diagram



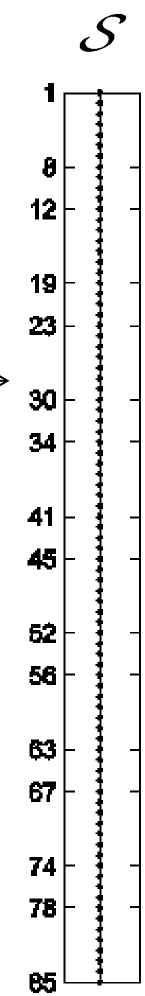
Adapted from Haacke et al., 1999.

string out



8×8 image

R-I Points



R-I Vector

2. Induced Correlation: Representation

JOURNAL OF NEUROSCIENCE METHODS

159 (2007) 361–369

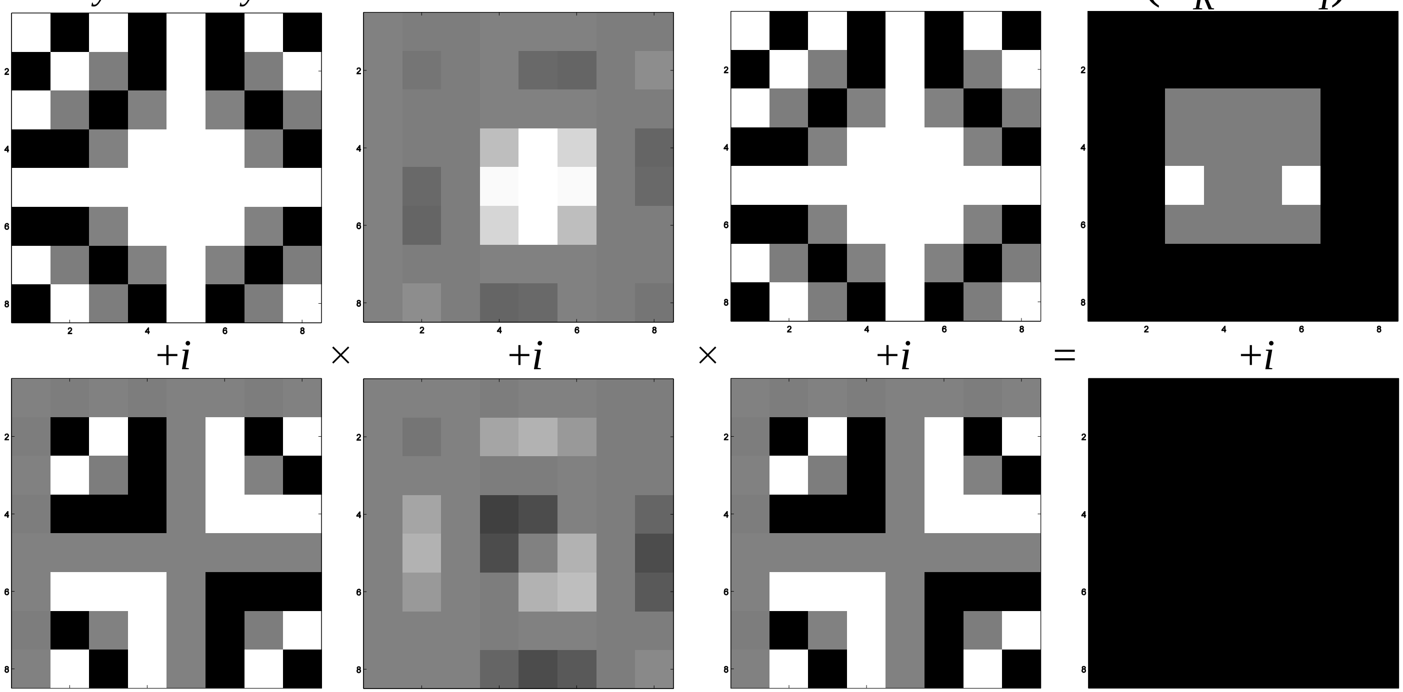
Signal and noise of Fourier reconstructed fMRI data

Daniel B. Rowe[a,b,*], Andrew S. Nencka[a], Raymond G. Hoffmann[b]

[a] Department of Biophysics, Medical College of Wisconsin, Milwaukee, WI, USA

[b] Division of Biostatistics, Medical College of Wisconsin, Milwaukee, WI, USA

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

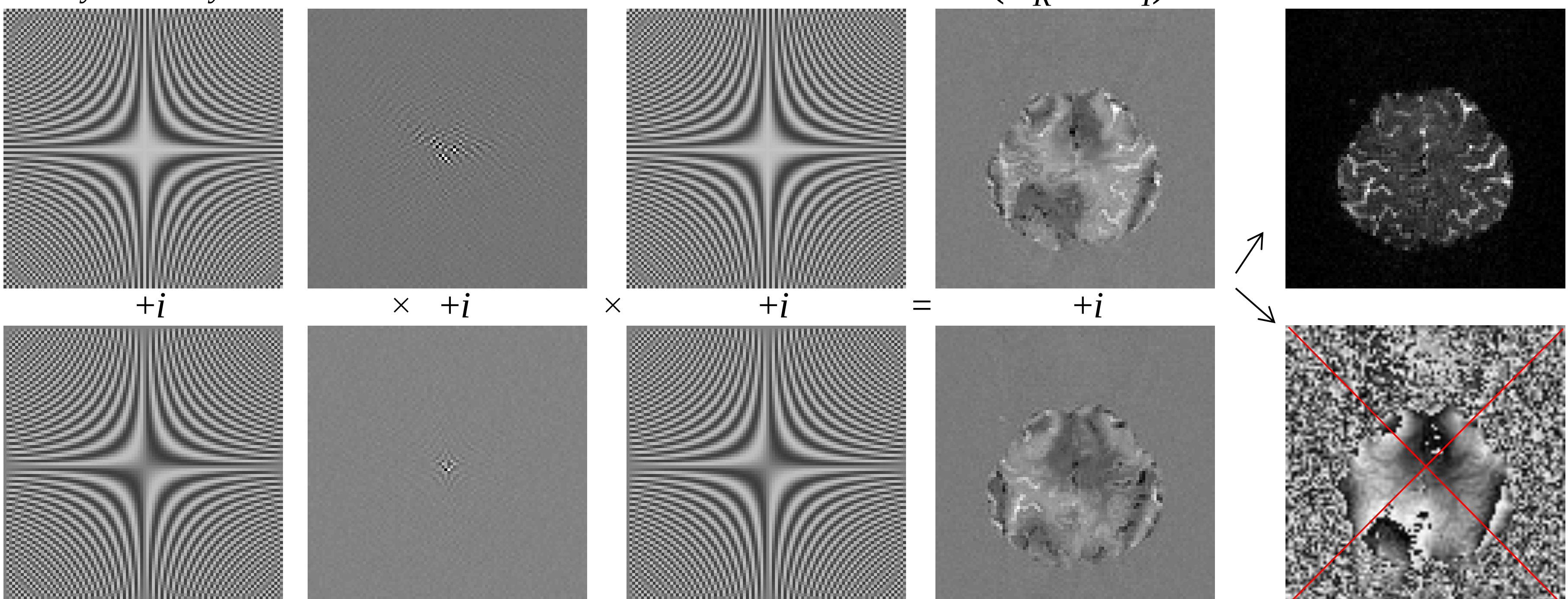


Spatial Frequencies

Complex Image

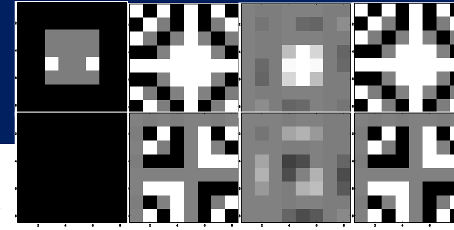
2. Induced Correlation: Representation

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



Spatial Frequencies

Complex Image



2. Induced Correlation: Representation

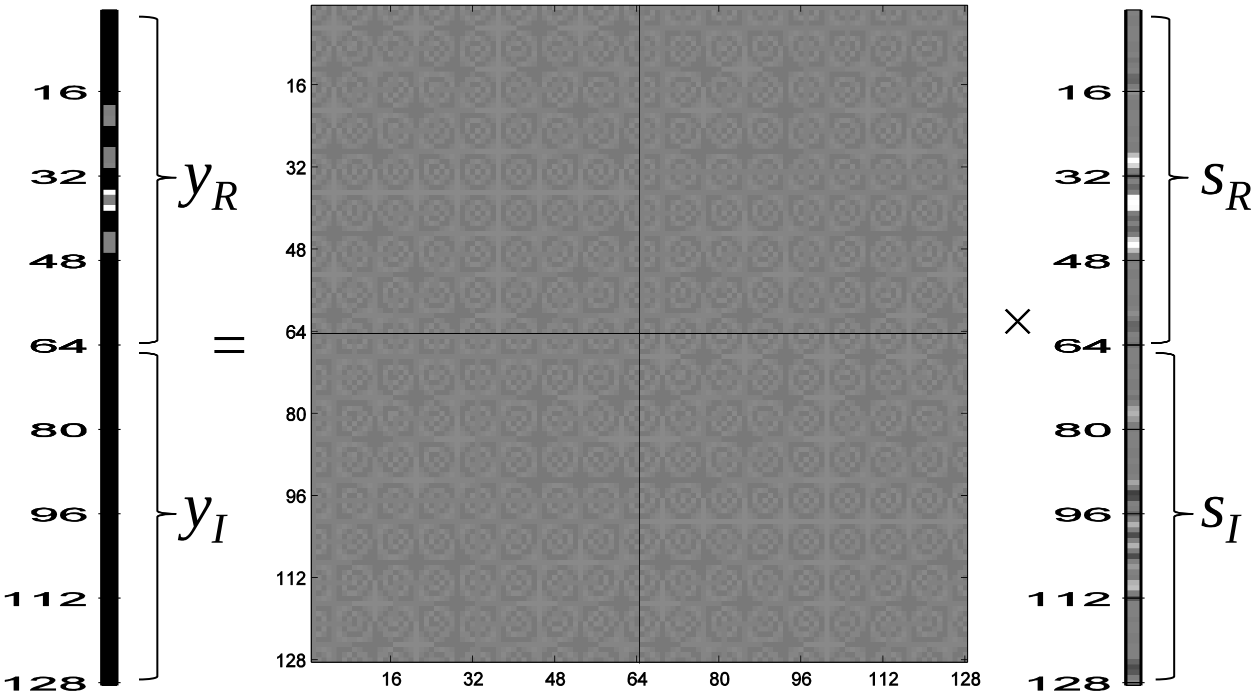
Signal and noise of Fourier reconstructed fMRI data

Daniel B. Rowe [a,b,*], Andrew S. Nencka [a], Raymond G. Hoffmann [b]
[a] Department of Biophysics, Medical College of Wisconsin, Milwaukee, WI, USA
[b] Division of Biostatistics, Medical College of Wisconsin, Milwaukee, WI, USA

JOURNAL OF NEUROSCIENCE METHODS
159 (2007) 361–369

real rows on imag rows

real rows on imag rows



If $E(s) = s_0$

and

$\text{cov}(s) = \Gamma$

then if

$y = \Omega s$,

$E(y) = \Omega s_0$

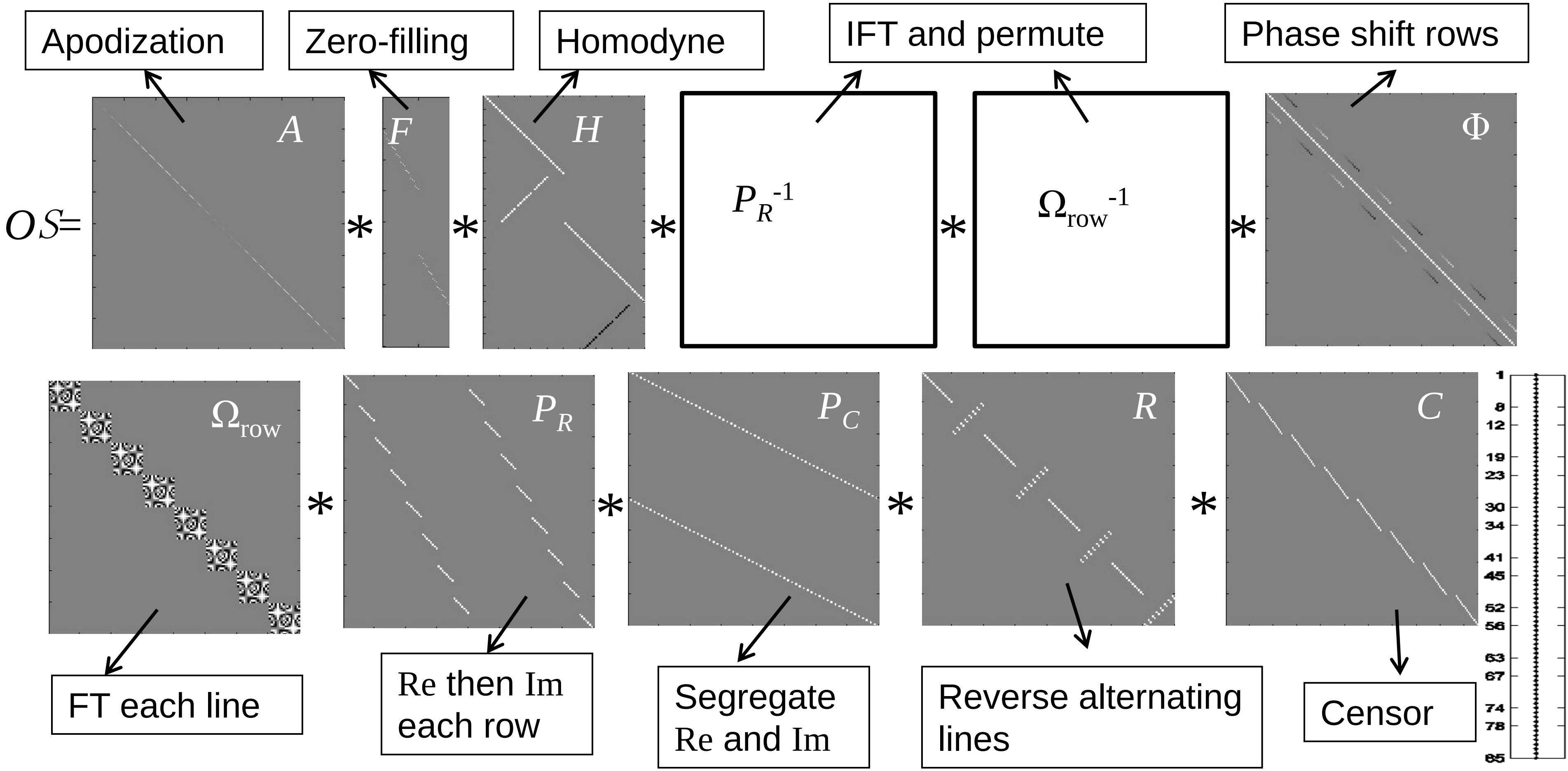
and

$\text{cov}(y) = \Omega \Gamma \Omega'$.

$$\Omega \sigma^2 I \Omega' = \frac{\sigma^2}{p_x p_y} I$$

Now we can do statistics!

2. Induced Correlation: Data Processing



And there are MANY more!

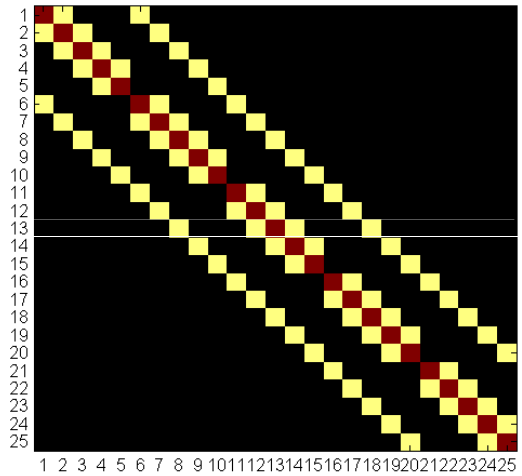
2. Induced Correlation: Representation

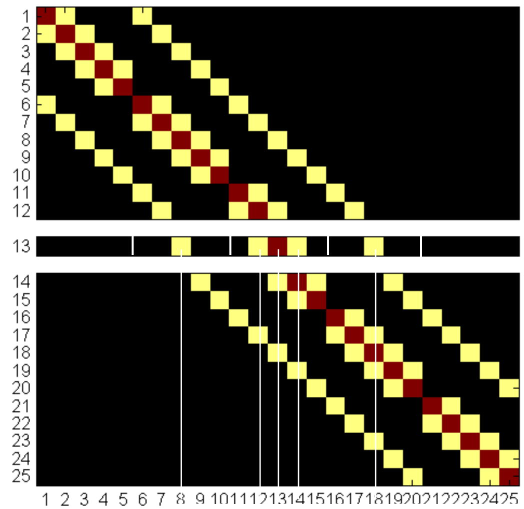
1	2	3	4	5
6	7	8	9	10
11	12	13	14	15
16	17	18	19	20
21	22	23	24	25

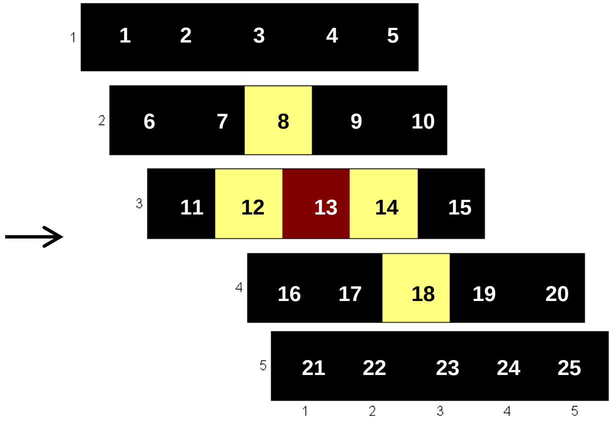
5×5 image

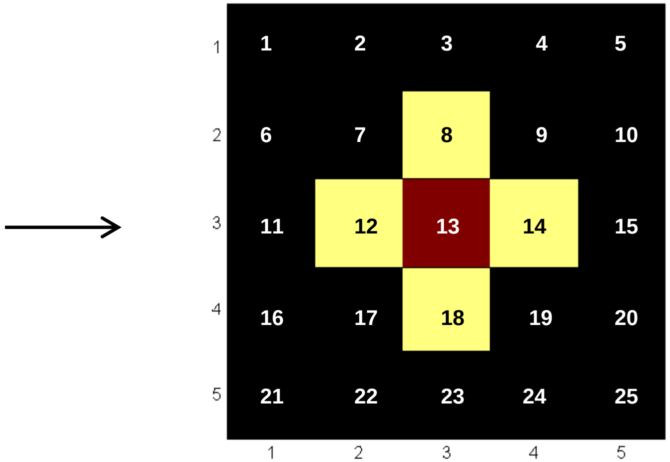
$\mathrm{cor}(y) =$

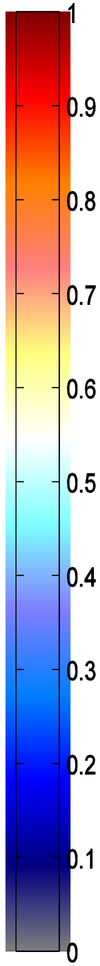
25×25 correlation matrix











5×5 correlation image

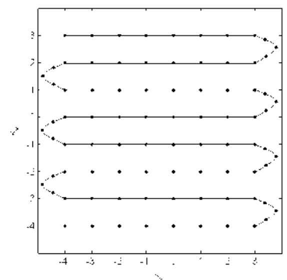
2. Induced Correlation: Within Local

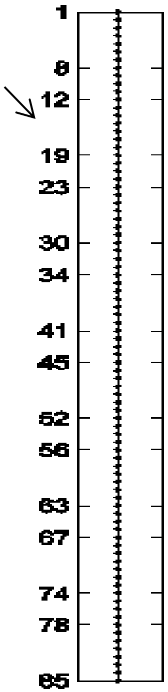
JOURNAL OF NEUROSCIENCE METHODS
181 (2009) 268–282

A Mathematical Model for Understanding the STatistical effects of *k*-space (AMMUST-k) preprocessing on observed voxel measurements in fcMRI and fMRI

Andrew S. Nencka[a], Andrew D. Hahn[a], Daniel B. Rowe[a,b,*]

[a] Department of Biophysics, Medical College of Wisconsin, Milwaukee, WI, USA
[b] Division of Biostatistics, Medical College of Wisconsin, Milwaukee, WI, USA





S

spatial frequencies

$$y = \underbrace{S_m \Omega_a A F H P_R^{-1} \Omega_{row} \Phi P_R P_C R C}_{O} S$$

spatial frequencies

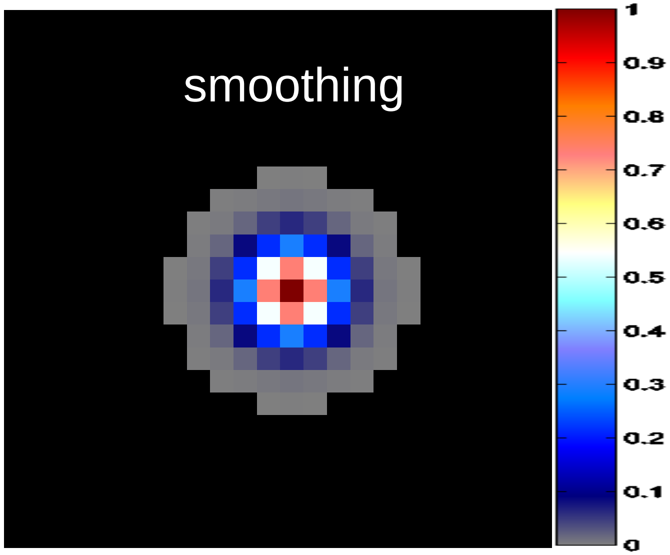
processing & reconstruction

$$y = OS$$

$$E(y) = OS_0$$

$$\mathrm{cov}(y) = O \Gamma O'$$

$$\mathrm{cor}(y) = D^{-1/2} O \Gamma O' D^{-1/2}$$



2. Induced Correlation: Within Distant

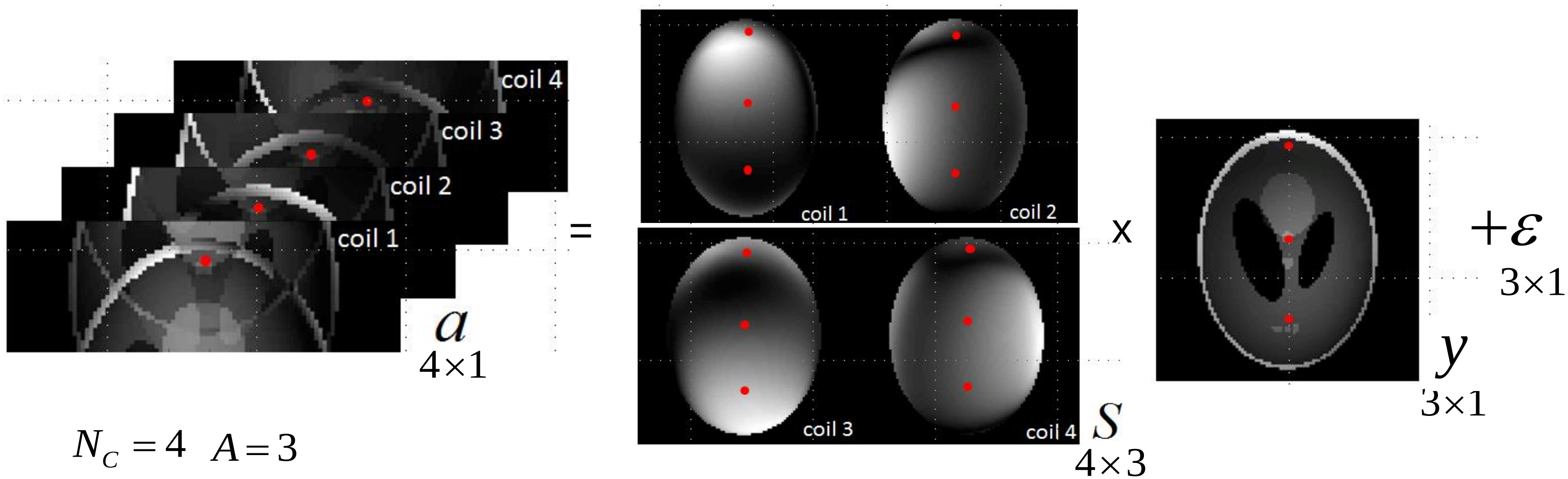
MAGNETIC RESONANCE IMAGING

29 (2011) 1267 – 1287

A statistical examination of SENSE image reconstruction via an isomorphism representation

Iain P. Bruce[a], M. Muge Karaman[a], Daniel B. Rowe[a,b,*]

[a]Department of Mathematics, Statistics, and Computer Science, Marquette University, Milwaukee, WI 53201, USA
[b]Department of Biophysics, Medical College of Wisconsin, Milwaukee, WI 53226, USA



$N_C = 4 \quad A = 3$

For each voxel: $y = (S'\Psi^{-1}S)^{-1}S'\Psi^{-1}a = ua$

can insert processing on unfolded image vector

can insert processing on each coil image vector

can insert processing on each coil k-space vector

$$\nu = P_U \; U \; P_{CS} \; \Omega \; s$$

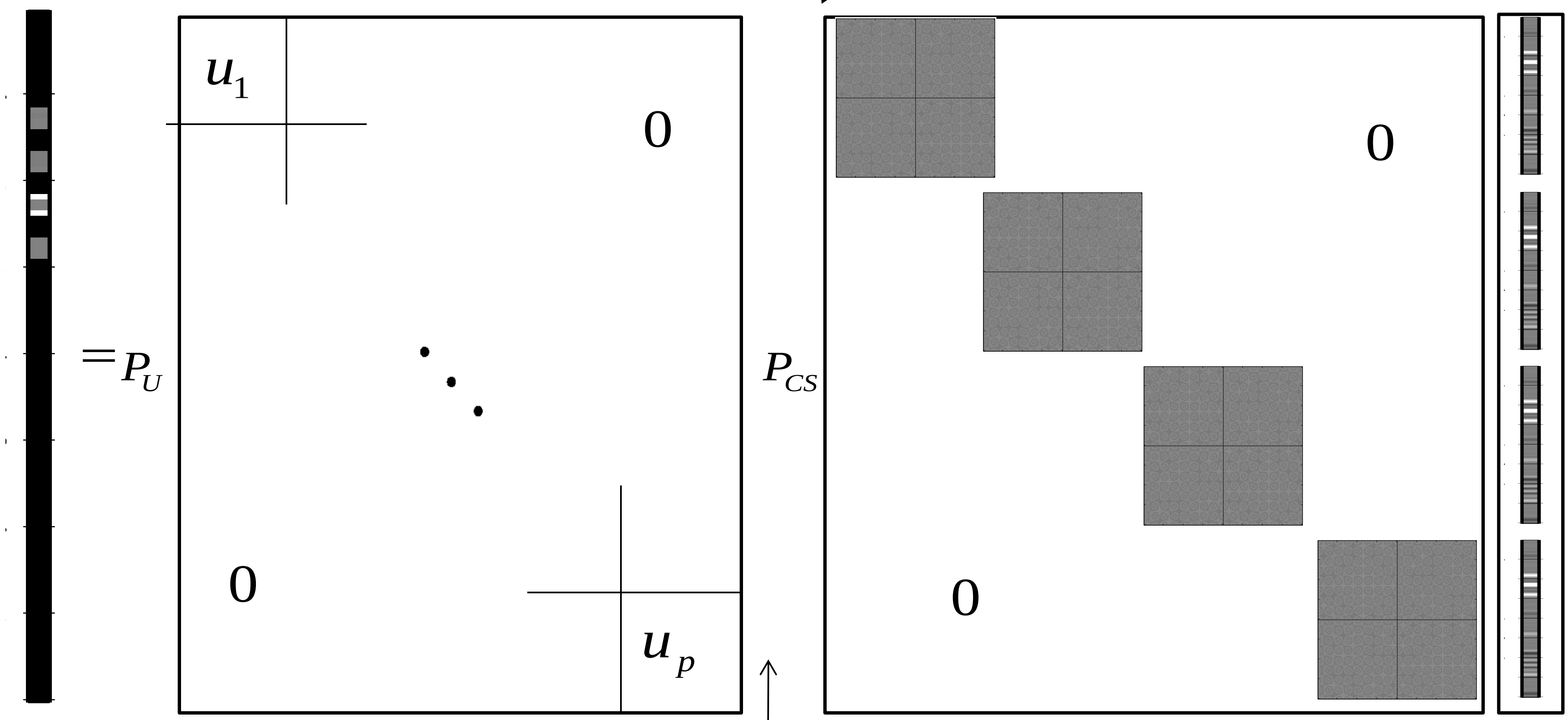


image vector

unfold matrix
u's have S and Ψ

permute to by
folded voxel

reconstruct N_c=4 images

k-space vector
of N_c images

Bruce, Karaman, Rowe: MRI, 1267-1287, 2011.

2. Induced Correlation: Within Distant

Magnetic Resonance Imaging

29 (2011) 1267 – 1287

A statistical examination of SENSE image reconstruction via an isomorphism representation

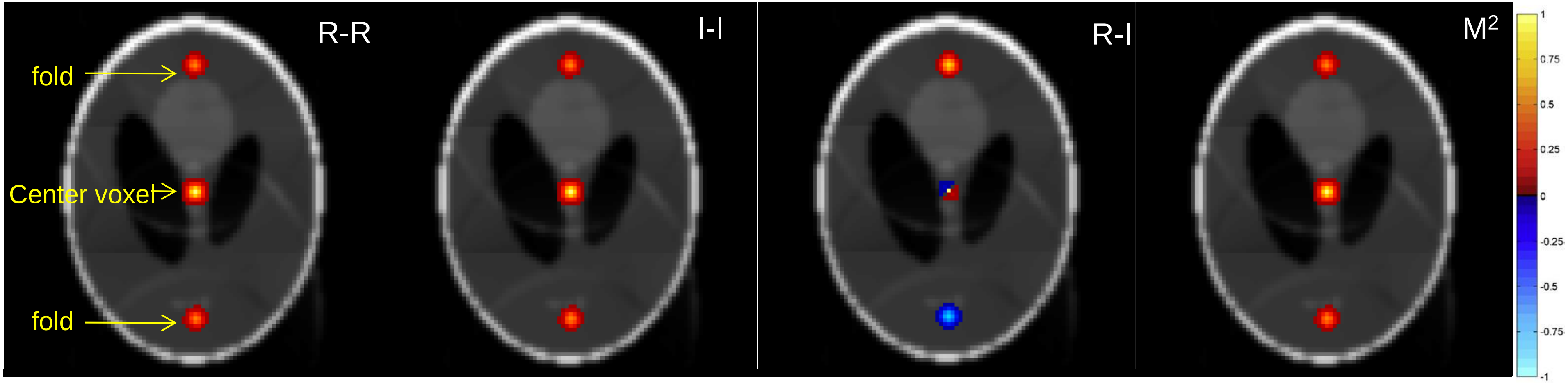
Iain P. Bruce [a], M. Muge Karaman [a], Daniel B. Rowe [a, b, *]

$$y = \underbrace{O_I P_U U P_S P_C (I_{nC} \otimes \Omega) O_K}_{O} s \qquad y = Os \qquad \Sigma = \mathrm{cov}(y) = O \Gamma O'$$

y ← k-space vectors for all voxels

O ← processing & reconstruction

$$O_I = S_m$$



2. Induced Correlation: Within Distant

GRAPPA: Submitted Unpublished Results

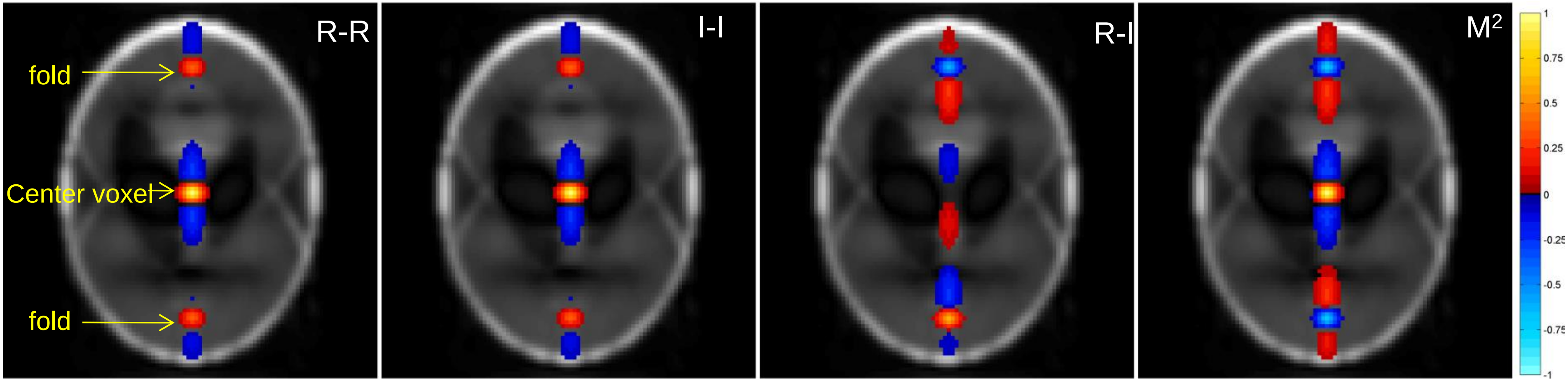
Iain P. Bruce[1] and Daniel B. Rowe[1,2]
[1]Marquette University, [2]Medical College of Wisconsin

$$y = \underbrace{O_I C(I_n \otimes \Omega O_K) P_{C2} P_{G2} G P_{G1} P_{C1}}_{O} s \qquad y = Os \qquad \Sigma = \mathrm{cov}(y) = O\Gamma O'$$

s ← k-space vectors for all voxels

O ← processing & reconstruction

$$O_I = S_m$$



2. Induced Correlation: Between

Separation of Two Simultaneously Encoded Slices with a Single Coil

Daniel B. Rowe[1,2], Andrew S. Nencka[2], Andrzej Jesmanowicz[2], and James S. Hyde[2]

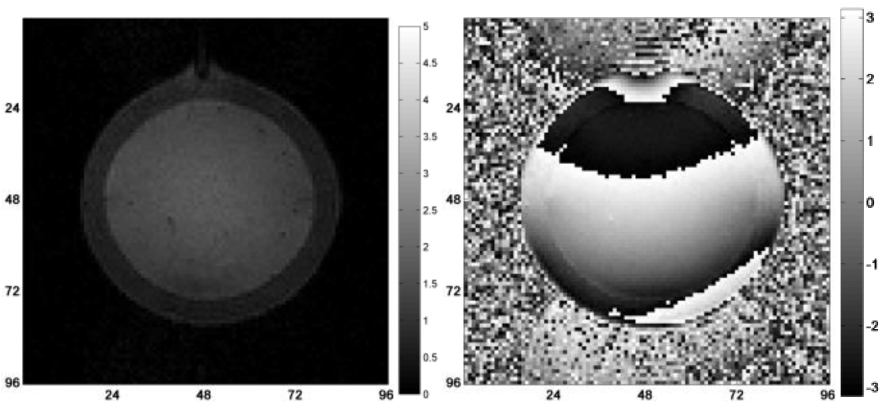
[1]*Department of Mathematics, Statistics, and Computer Science, Marquette University*

ISMRM 21st Annual Meeting & Exhibition
Salt Lake City, Utah, USA
20-26 April 2013
"Discovery, Innovation & Application – Advancing MR for Improved Health"

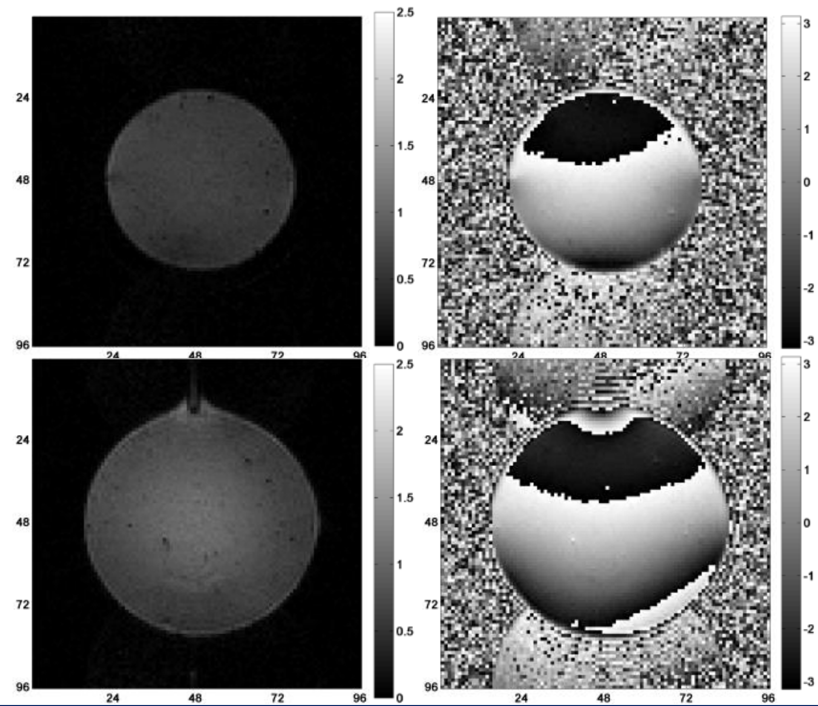
Proc. Intl. Soc. Mag. Reson. Med. 21 (2013), 0123.

$$\begin{pmatrix} y_R \\ y_I \end{pmatrix} = \begin{pmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \end{pmatrix} \begin{pmatrix} \rho_1 \cos\theta_1 \\ \rho_1 \sin\theta_1 \\ \rho_2 \cos\theta_2 \\ \rho_2 \sin\theta_2 \end{pmatrix} + \begin{pmatrix} \varepsilon_R \\ \varepsilon_I \end{pmatrix}$$

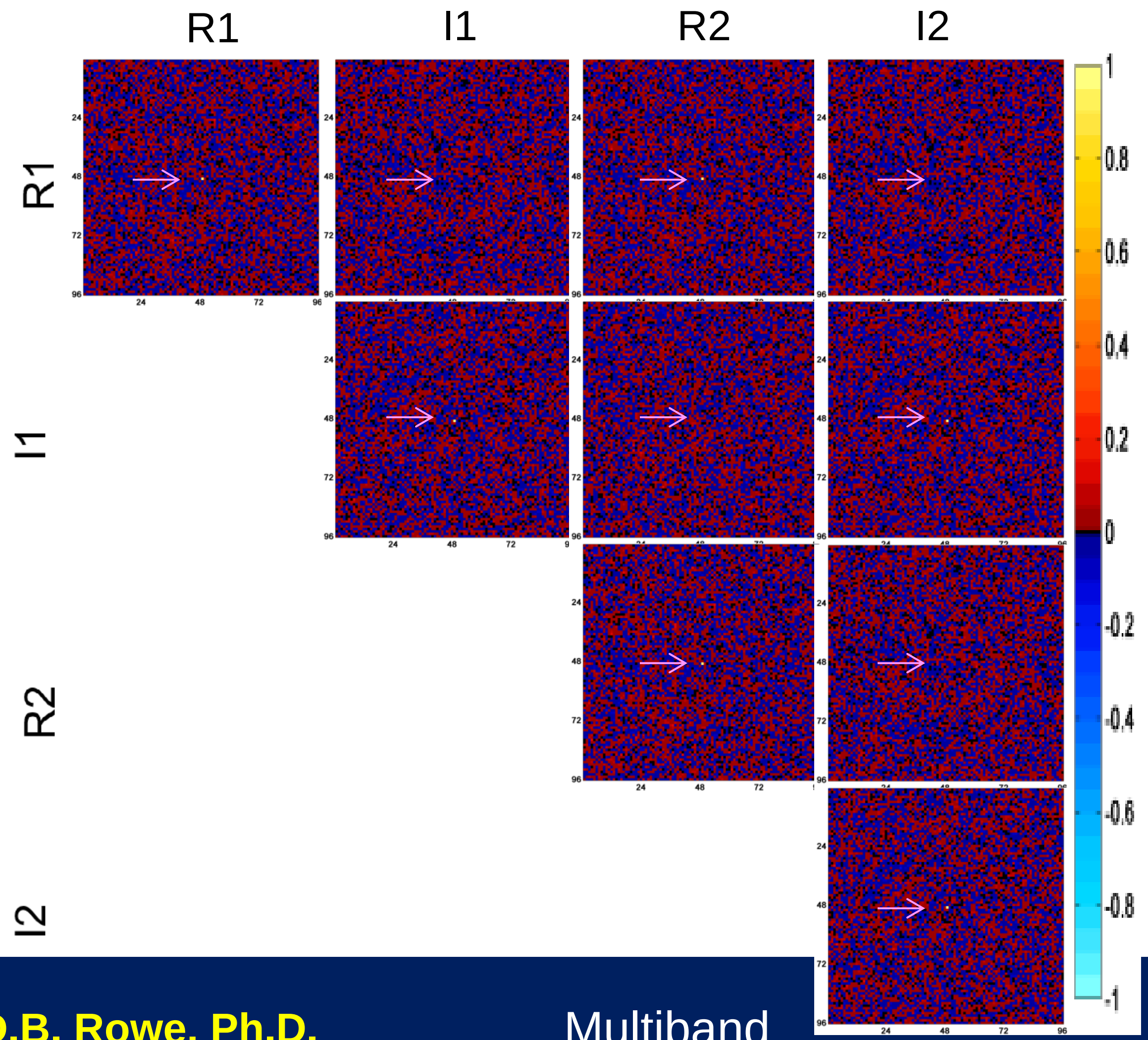
Aliased Image, Aliasing Matrix, True Unaliased Images, Measurement Error



separated



2. Induced Correlation: Between

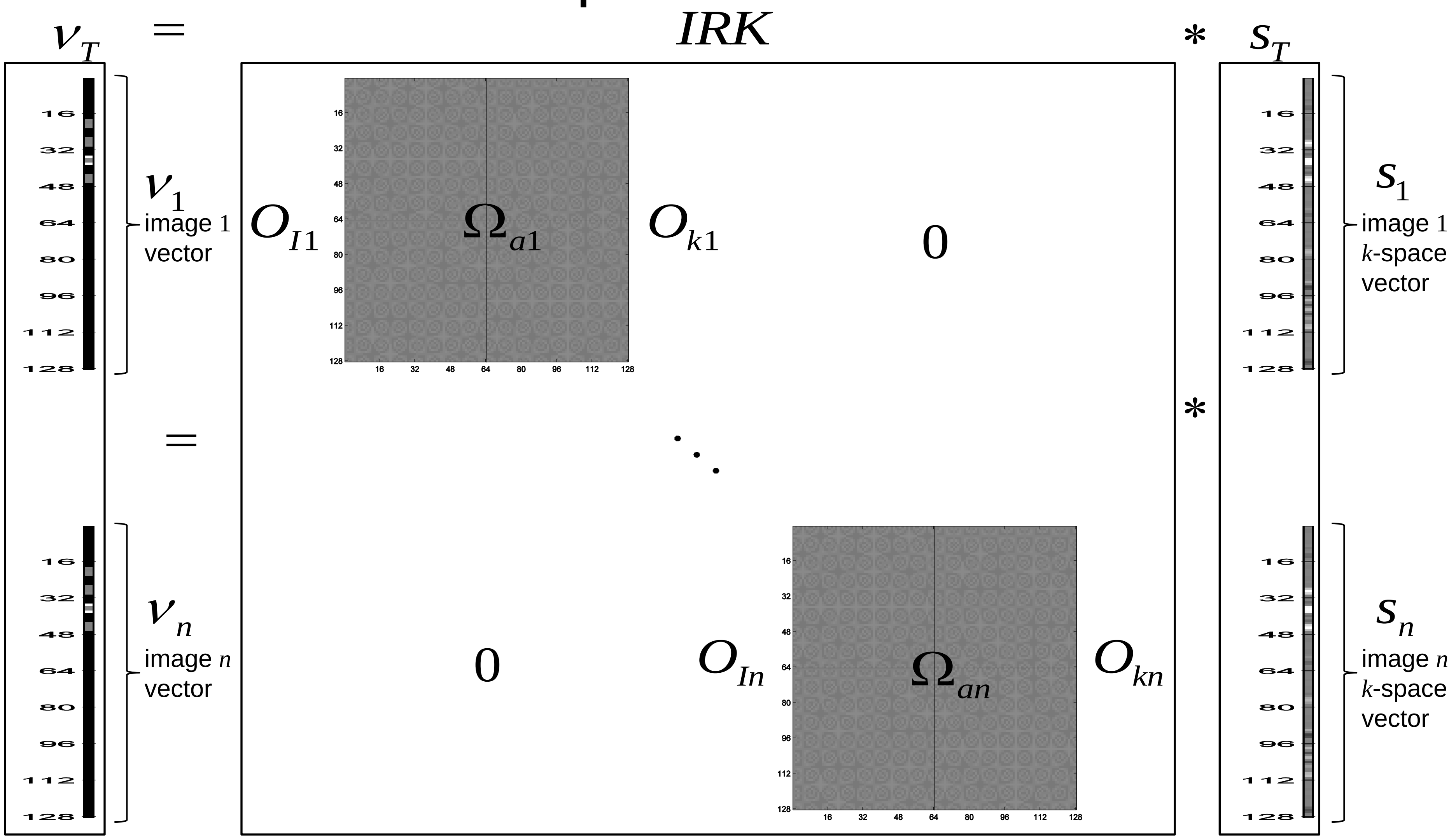


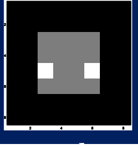
Rowe, Jesmanowicz, Bruce, Hyde, Nencka
In Submission, 2013.

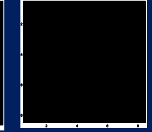
$$\mathrm{cov}(y) = \Sigma$$

$$\Sigma = \frac{\sigma^2}{4} \begin{array}{c c} & \begin{array}{cccc} R1 & I1 & R2 & I2 \end{array} \\ \begin{array}{c} R1 \\ I1 \\ R2 \\ I2 \end{array} & \begin{pmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \end{pmatrix} \end{array}$$

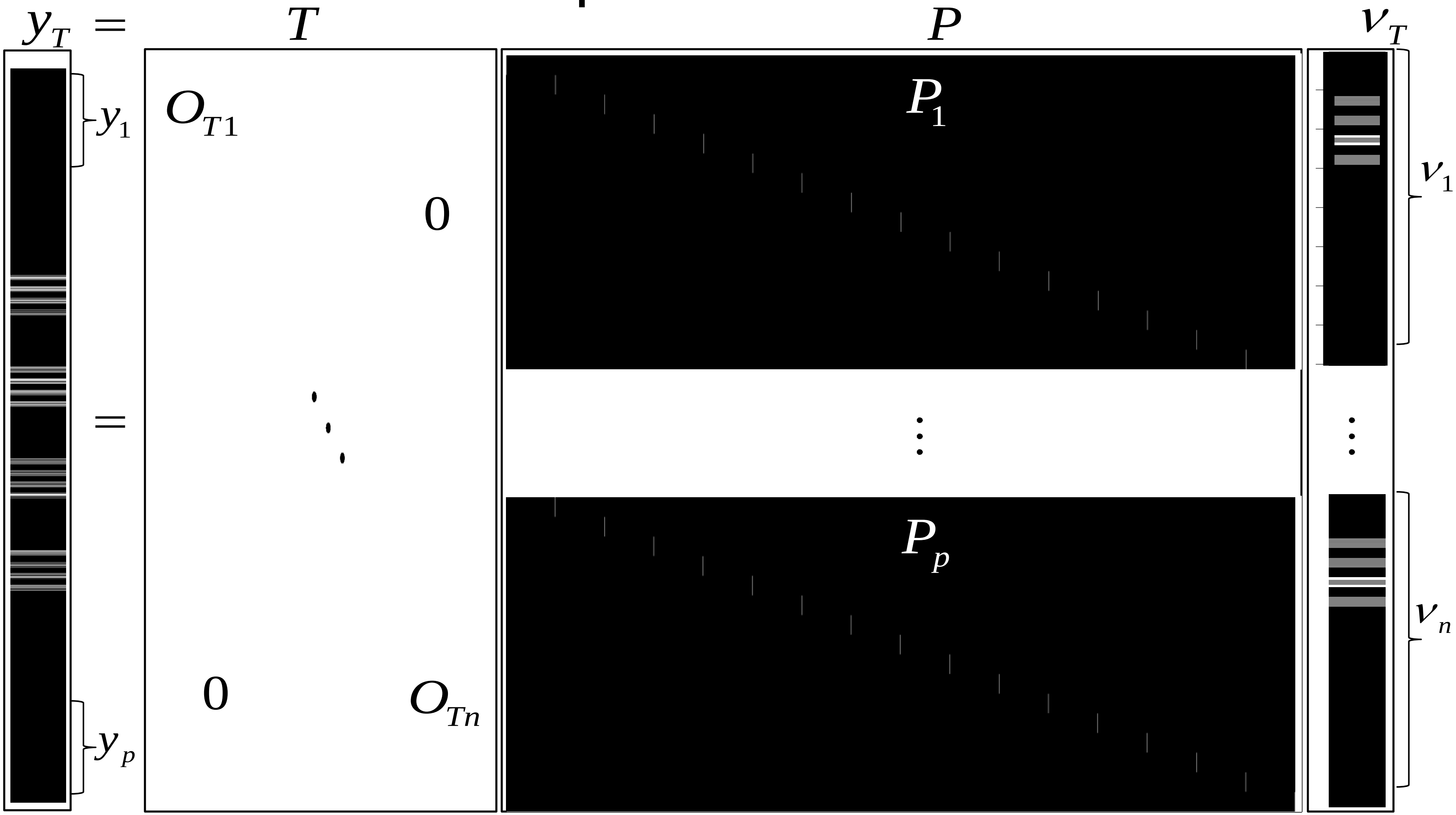
2. Induced Correlation: Temporal







2. Induced Correlation: Temporal



ordered by voxel

Karaman, Nencka, Rowe: In Progress.

2. Induced Correlation: Temporal

ISMRM 21st Annual Meeting & Exhibition
Salt Lake City, Utah, USA
20-26 April 2013

TEMPORAL PROCESSING OF FMRI DATA INDUCES FUNCTIONAL CORRELATIONS AND POTENTIALLY ALTERS FUNCTIONAL ACTIVATIONS

M. Muge Karaman[1], Andrew S. Nencka[2], and Daniel B. Rowe[1,2]

[1]*Department of Mathematics, Statistics, and Computer Science, Marquette University, Milwaukee, WI, United States,* [2]*Department of Biophysics, Medical College of Wisconsin, Milwaukee, WI, United States*

Proc. Intl. Soc. Mag. Reson. Med. 21 (2013) 2232

$$s_T = (s_1', \ldots, s_n')'$$

$$y_T = O_T s_T$$

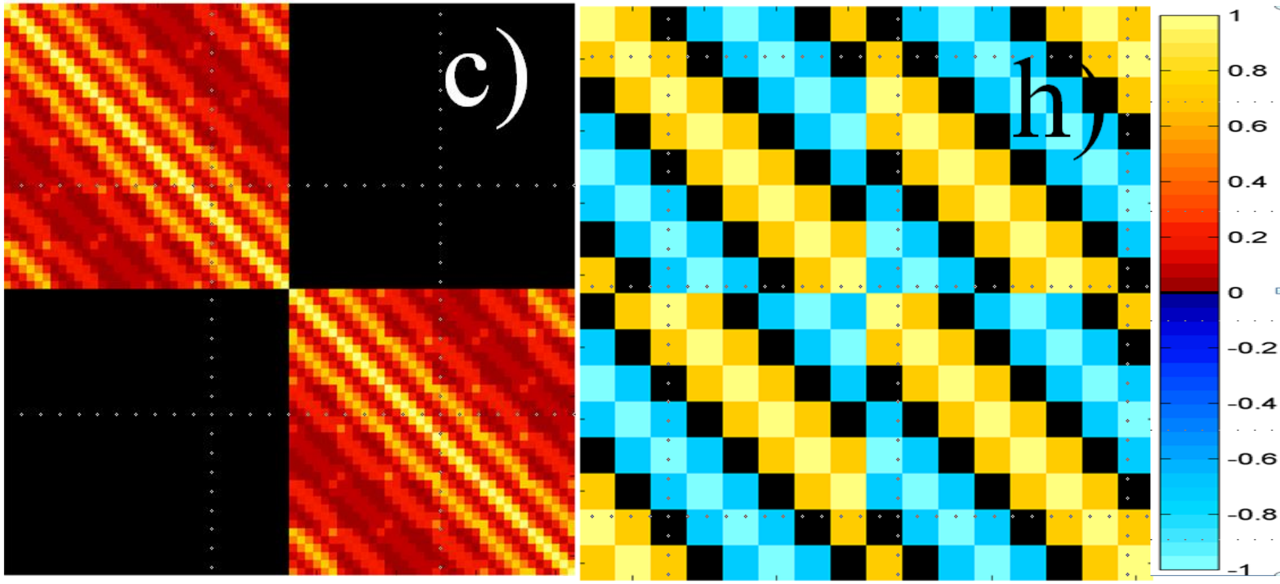
$$O_T = TIRK$$

$$E(s_T) = s_{T0}$$

$$\mathrm{cov}(s_T) = \Gamma$$

$$E(y_T) = O_T s_{T0}$$

$$\Sigma = O_T \Gamma O_T'$$



3. Discussion

Neuroscientists rely upon Statisticians to model and analyze their data.

Statisticians aim for a model that best describes the data.

Statisticians get data that is processed without their knowledge.

The results and interpretations are confounded by induced correlations that are of no biological origin.

The preprocessing needs to be characterized and accounted for when making biological interpretations.

We should model and analyze the original data that we measure, not a processed version of our data.