

Statistical Analysis of Image Reconstructed Fully-Sampled and Sub-Sampled fMRI Data

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Outline Introduction

Varied methods to produce fMRI images with varied properties.

^{3×} Reconstruction

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

Processing

Images are processed for enhancement & artifact reduction.

Implications

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

Discussion

How was our data was produced and what was done to it?



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.



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.



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



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.







(FOV=240 mm) $(n_x = n_y = 96, \Delta x = \Delta y = 2.5 \text{ mm})$

We inverse Fourier transform spatial freqs to generate image.

0.2 0.0 -0.2 0.2 +i0.2 0.0 -0.2 -0.2 spatial frequencies 0.2

Real



(FOV=240 mm) $(n_x = n_y = 96, \Delta x = \Delta y = 2.5 \text{ mm})$

We inverse Fourier transform spatial freqs to generate image.





(FOV=240 mm) $(n_x = n_y = 96, \Delta x = \Delta y = 2.5 \text{ mm})$

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(FOV=240 mm) $(n_x = n_y = 96, \Delta x = \Delta y = 2.5 \text{ mm})$

We inverse Fourier transform spatial freqs to generate image.





The machine Fourier encodes the image. Measure spatial freq.





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



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



 f_R

f

Х

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.

R

I

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 y_R

 y_I

 f_R

fi

Х



Processing

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



k-space Processing

Nyquist Ghost Correction Static B0 Field Correction Zero Fill Interpolation Non-Cartesian Interpolation Ramp Sampling Interpolation Homodyne Interpolation Apodization And many more...

Image Reconstruction

2D inverse Fourier transform In-Plane SENSE/GRAPPA Through-Plane SENSE

Image Processing

Image Smoothing Global Normalization Motion Correction And many more...

Time Series Processing

Filtering Smoothing Dynamic B0 Correction Slice Timing And many more...

Show ones in blue.



 f_R

fi

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.





Processing







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 $\Gamma = I$.

BIRS Neuroimaging Data Analysis



Implications Operators, *O*.



a) *Ο*=Ω



b) *O*=Ω*Z*







-1.1×10⁻⁴

BIRS Neuroimaging Data Analysis

Implications Mean, $\mu = Of$.

 $O=\Omega Z$







+1

Implications Correlation matrix and correlation image.





2 3 5 5×5 correlation image

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1

6 11

-1



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



a) O=Ω



c) $O=\Omega A$

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

d) $O=S\Omega$



e) $O=\Omega AZ$

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g) $O=S\Omega Z$

-1



Multi-Coil Acquisition



N_C=4, *A*=1

• S



Reconstruction

Multi-Coil Acquisition



Each coil measures *k*-space.









N_C=4, *A*=1

BIRS Neuroimaging Data Analysis Coil local so non uniform sensitivity.







Reconstruction SENSE





 S_{22} •

*S*₂₃●

Reconstruction

Multi-Coil Acquisition



Each coil measures *k*-space.











Reconstruction SENSE



D.B. R





Implications

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Implications

SENSE induces long-range in-plane correlation.

Theoretical Results

SENSE A=3 smoothed



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





+1

Implications SENSE Reconstruction induces long-range correlation.

Experimental Results SENSE *A*=3 smoothed



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Karaman, Nencka, Bruce, Rowe: Brain Connect, 4:649-661, 2014.



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Implications

GRAPPA reconstruction induces long-range correlation.

GRAPPA A=3 smoothed



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Bruce: PhD Dissertation, 2014.



Multi-Coil Acquisition Simultaneous Multi-Slice (SMS)



Each coil measures *k*-space.

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Larkman et al: JMRI, 13:313-317,2001.



Reconstruction **Multi-Coil Acquisition** • S₁₁ Simultaneous Multi-Slice (SMS) Coil 1 • S₄₃ • S₄₂ Coil 4 • S₄₁ Coil 3 • S₃₃ • S₃₂ Each coil measures *k*-space. v_j, S_{kj}

$$N_{C}=4, A=3$$
 $j=1:A, k=1:N_{c}$

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Reconstruction • S₁₁ $a_4 = S_{41}v_1 + S_{42}v_2 + S_{43}v_3$ $a_1 = \frac{S_{11}v_1 + S_{12}v_2 + S_{13}v_3}{V_1 + S_{12}v_2 + S_{13}v_3}$ Coil 1 • S₄₃ • S₄₂ • S₄₁ Coil 4 Coil 3 $a_3 = \frac{S_{31}v_1 + S_{43}v_2 + S_{33}v_3}{V_3 + S_{33}v_3}$ • S₃₃ $a_2 = \frac{S_{21}v_1 + S_{22}v_2 + S_{23}v_3}{S_{21}v_1 + S_{22}v_2 + S_{23}v_3}$ • S₃₂

Multi-Coil Acquisition Simultaneous Multi-Slice (SMS)



Each coil measures *k*-space.

$$v_{j}, S_{kj}, a_k$$

 $N_c=4, A=3 \qquad j=1:A, k=1:N_c$



Separated

Reconstruction SENSE SMS







Implications

In statistics, we know the rule that says:

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



Implications SENSE induces long-range through-plane correlation.



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Coil 1

2

Coil

Coil 3

Coil 4



Implications SENSE induces long-range in-plane correlation.





Implications SENSE induces long-range through-plane correlation.





Implications SENSE induces long-range in-plane correlation.





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.

We should develop models that incorporate processing.

We should use all of the data (magnitude and phase).



Thank You!

This work is joint with former & current PhD students: Dr. Andrew S. Nencka, Medical College of Wisconsin Dr. Andrew D. Hahn, University of Wisconsin-Madison Dr. Iain P. Bruce, Duke University Dr. M. Muge Karaman, University if Illinois-Chicago Ms. Mary C. Kociuba, Marquette University Mr. Kevin K. Liu, Marquette University