Processing Induced Spatial Correlations Are Quantified With A Temporal Frequency Representation in Complex-Valued fMRI

Mary C. Kociuba[1] and Daniel B. Rowe[1,2]

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

Background & Purpose: During signal acquisition, local and systematic noise obscures the signal due to unpredictable external factors. To attenuate the noise, various spatial and temporal operations are applied during signal processing. These operations induce spatiotemporal correlations into neural regions that were previously uncorrelated.[1,2] Signal processing applied to the acquired signal can be represented as real-valued matrix operators, with the signal processing and image reconstruction methods presented as a series of linear matrix multiplications. Spatial correlations are typically described with the magnitude component of the time-series, although it has been shown that complex-valued temporal frequencies describe correlations between voxels in the cerebral cortex for non-task data.[3] In this study, the temporal frequency framework is expanded to define how preprocessing induced spatial correlations arise. Through identifying artificial correlations, this frequency description is the first step in accounting for correlations arising from spatial and temporal operators applied to *k*-space and image space data, as well as image reconstruction methods. Quantifying and compensating for preprocessing induced correlations will yield more accurate clinical conclusions and produce more reliable results from the data.

Theory: The image vector *v* is reconstructed with $v = (I_n \otimes \Omega)\, s$, where *s* is the complex-valued observed *k*-space signal vector for *p* voxels and *n* TRs, and Ω is the inverse Fourier reconstruction operator.[4] The permutation matrix *P*, reorders the vector by voxel rather than image, $y = Pv$, so the real-valued temporal frequencies *f*, are represented, $f = (I_p \otimes \bar{\Omega}_T)Pv$, with the temporal forward Fourier transform matrix, $\bar{\Omega}_T$. The voxel time-series for voxel *j*, y_j, is reconstructed with a temporal IFT matrix, Ω_T, from the spatial frequencies f_j, $y_j = \Omega_T f_j$, with the demeaned time-series $\tilde{y}_j$ and $\tilde{y}_j = \Omega_T \tilde{f}_j$. Using the same notation for voxel *k*, the spatial covariance between *j* and *k* is represented as $\mathrm{cov}(y_j, y_k) = \frac{1}{2n}\tilde{y}_j{}'\tilde{y}_k = \frac{1}{2n}\left(\Omega_T \tilde{f}_j\right)'\left(\Omega_T \tilde{f}_k\right) = \frac{1}{4}\left(\tilde{f}_{jR}'\tilde{f}_{kR} + \tilde{f}_{jI}'\tilde{f}_{kI}\right)$. Note, the covariance corresponds to the jk^{th} entry in the spatial covariance $p{\times}p$ matrix, Σ, and is presented as summation of the overlap of the real and imaginary components of temporal frequencies. The diagonal matrix of spatial variances *D* is used to construct the spatial correlation $R = D^{-1/2}\Sigma D^{-1/2}$. To show the efficacy of the framework, consider a series of operations O applied to the data, the unprocessed and processed voxel time-series are written as $y = (I_p \otimes \Omega_T)f$ and $y_s = O(I_p \otimes \Omega_T)f$. The spatiotemporal covariance matrix for *y*, is $\mathrm{cov}[y] = \Gamma$ and the covariance matrix is altered from processing, $\mathrm{cov}[y_S] = O\Gamma O'$. This linear relationship between the time-series and spatial frequency domain is the basis for the study.

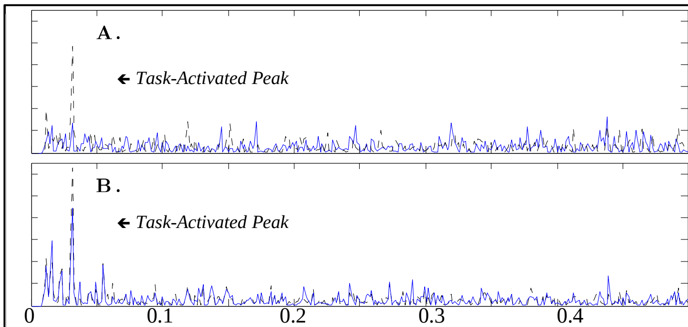

Figure 1: Potential correlation coefficient contributions at each temporal frequency for v_a(black) and v_b(blue) **A.** before and **B.** after spatial smoothing.

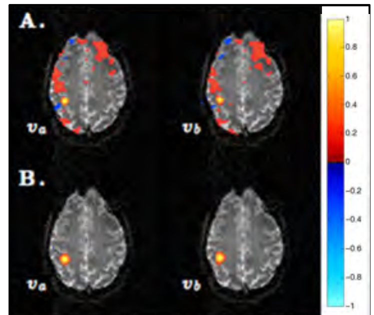

Figure 2: **A.**MO and **B.**CV spatial correlation maps for v_a and v_b.

Methods: Experimental fMRI data is collected with a single subject on a 3.0 T scanner from a finger tapping experiment, performed for sixteen 22-second periods, with an echo planar pulse sequence (TR/TE = 1000/39 ms, BW = 125 kHz, 4 mm thick axial slices, matrix = 96×96, no. of slices = 10, FOV = 24 cm, flip angle = 45°, TRs = 720). The *k*-space data were Nyquist ghost corrected, IFT reconstructed, and TOAST dynamic B0 corrected.[5] The utility of the framework is demonstrated with spatial smoothing operator S_m, applied to the real and imaginary components separately, with a FWHM = 3 voxels Gaussian kernel, such that $O = P'(I_{2n} \otimes S_m)P$. Two neighboring voxels of interest, v_a and v_b, are chosen to analyze the impact of preprocessing on their temporal frequency spectrums, and the magnitude-only (MO) and complex-valued (CV) spatial correlations.

Results & Discussion: The matrix description of the spatial covariance, $\mathrm{cov}[y] = \Gamma$, allows one to measure the effect of the signal processing on the spatial covariance, $\mathrm{cov}[y_S] = O\Gamma O'$. Comparing Fig. 1A to Fig. 1B, shows how the preprocessing may lead to inaccurate conclusions by altering the frequency content; both spectrums share a more similar pattern, and v_b exhibits a task-activated peak, after processing. The frequency summation notation allows the temporal frequency spectrum to be easily divided, such that potential correlation contributions are quantified, as shown in Fig. 2. Note, the sum the correlation coefficients is 1 for each voxel. A specific band in the temporal frequency spectrum can be identified as a significant contributor to the induced correlation, in fMRI bands near the task-activated peak are of interest. This framework also allows for complex analysis of the data, as shown in the MO and CV correlations in Fig. 2, incorporating the phase component in the correlation reduces undesirable variability in the estimates, by increasing the biological information used in the analysis.

Conclusion: The adaptable framework presented describes the nature of the processing induced spatial correlations in terms of temporal frequencies, and the advantage of using the phase in fMRI analysis. Defining the extent processing induced correlations alter the data is critical to development of methods to regress out artificial correlations, such that accurate clinical conclusions are derived from the data.

References: **1.** Friston et al., NeuroImage 2000. **2.** Nencka et al., J. Neurosci. Meth. 2009. **3.** Cordes et al., J. of Am. NeuroRadiology 2000. **4.** Rowe et al., J. Neurosci. Meth. 2007. **5.** Hahn et al., HBM 2011. **6.** Cordes et al., J. of Am. NeuroRadiology **7.** Glover et al., MRM 2000.

Processing Induced Spatial Correlations Are Quantified with a Temporal Frequency Representation in Complex-Valued fMRI

Mary C. Kociuba[1] and Daniel B. Rowe[1,2]

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

SYNOPSIS

To attenuate noise inherent within the acquired signal, spatial and temporal operations are incorporated into the image reconstruction process. Such operations induce spatiotemporal correlations into previously uncorrelated neural regions.[1,2] Spatial correlations are typically described with the magnitude-only (MO) data, although it has been shown that complex-valued (CV) temporal frequencies describe correlations between voxels in the cerebral cortex for non-task MO data.[3] In this study, a linear framework is developed to define the consequence of processing induced spatial correlations. This CV notation is advantageous for identifying portions of the temporal spectrum that contribute to the spatial covariance, and the application to CV data contributes to the validation of the statistical power of CV models in fRMI studies.

METHODS

DATA ACQUISITION & PROCESSING: A subject performed a finger tapping task for 16-22s periods, (TR/TE=1000/39ms, BW=125kHz, 4mm axial slices, matrix=96×96, slices=10, FOV=24cm, flip angle=45°, TRs=720) on a 3.0T GE MR750 scanner. The k-space signal was Nyquist ghost and dynamic B_0-field corrected,[5] IFT reconstructed, and high-pass(<0.009 Hz)/low-pass(>0.08 Hz) band filtered. To demonstrate the framework, CV and MO data is processed separately with a spatial smoothing operator, Gaussian kernel, FWHM=3 voxels.

VOXELS OF INTEREST (VOIs): Four voxels were chosen based on CV activation locations: voxel a is in the left motor cortex region, voxel b and c are in the right motor cortex region, and voxel d is in the white matter. Only voxels a and c exhibit an initial task-activation peak.

A TEMPORAL FREQUENCY DESCRIPTION OF CORRELATION: A CV time-series for any voxel j, y_j, is reconstructed with the IFT matrix, Ω, from the spatial frequencies f_j, $y_j=\Omega f_j$. With a demeaned CV time-series and similar notation for another voxel k, the spatial covariance between voxel j and k is

$$\mathrm{cov}(y_j,y_k)=(2n)y_j'y_k=1/(2n)(\Omega f_j)'(\Omega f_k)=1/4(f_{jR}'f_{kR}+f_{jI}'f_{kI}).$$

This covariance corresponds to the jk^{th} entry in the spatial covariance matrix, Σ, and is presented as the summation of the overlap of the real and imaginary components of temporal frequencies. A diagonal matrix of spatial variances, D, is constructed from the spatial correlation $R=D^{-1/2}\Sigma D^{-1/2}$. A series of operations, O, is applied to the data, the unprocessed and processed CV voxel time-series are written as $y=(I_p\otimes\Omega)f$ and $y_s=O(I_p\otimes\Omega)f$, specifically a spatial smoothing operator S_m, is applied with a permutation matrix, P, such that $O=P'(I_{2n}\otimes S_m)P$. So covariance for y, is $\mathrm{cov}(y)=\Sigma$, and the covariance altered from processing is $\mathrm{cov}(y_S)=O\Sigma O'$. To show the efficacy of this Fourier description of correlation, both MO and CV data is analyzed.

FREQUENCY BAND DIVISIONS: The spatial covariance matrix can be written as a summation of covariance bands $\Sigma=\Sigma_{B1}+\ldots+\Sigma_{Bb}$, to identify the portion of the spectrum which contributes most significantly to correlation. Three frequency bands are analyzed: B1:0.0009-0.024 Hz, B2:0.026-0.037 Hz, B3:0.038-0.08 Hz with the task-activated peak observed in B2.

SPECTRAL DECOMPOSITION: The spectral decomposition for each VOI illustrates the potential correlation contribution, r_ℓ, of the ℓ^{th} element in the temporal frequency spectrum, $r_\ell=(f_{jR_\ell}^2+f_{jI_\ell}^2)/(f_{jR}'f_{jR}+f_{jI}'f_{jI})$.
Note, r_ℓ describes the correlation contribution such that $\sum_{\ell=1}^{n} r_\ell=1$.

RESULTS AND DISCUSSION

MAGNITUDE-ONLY(MO) DATA

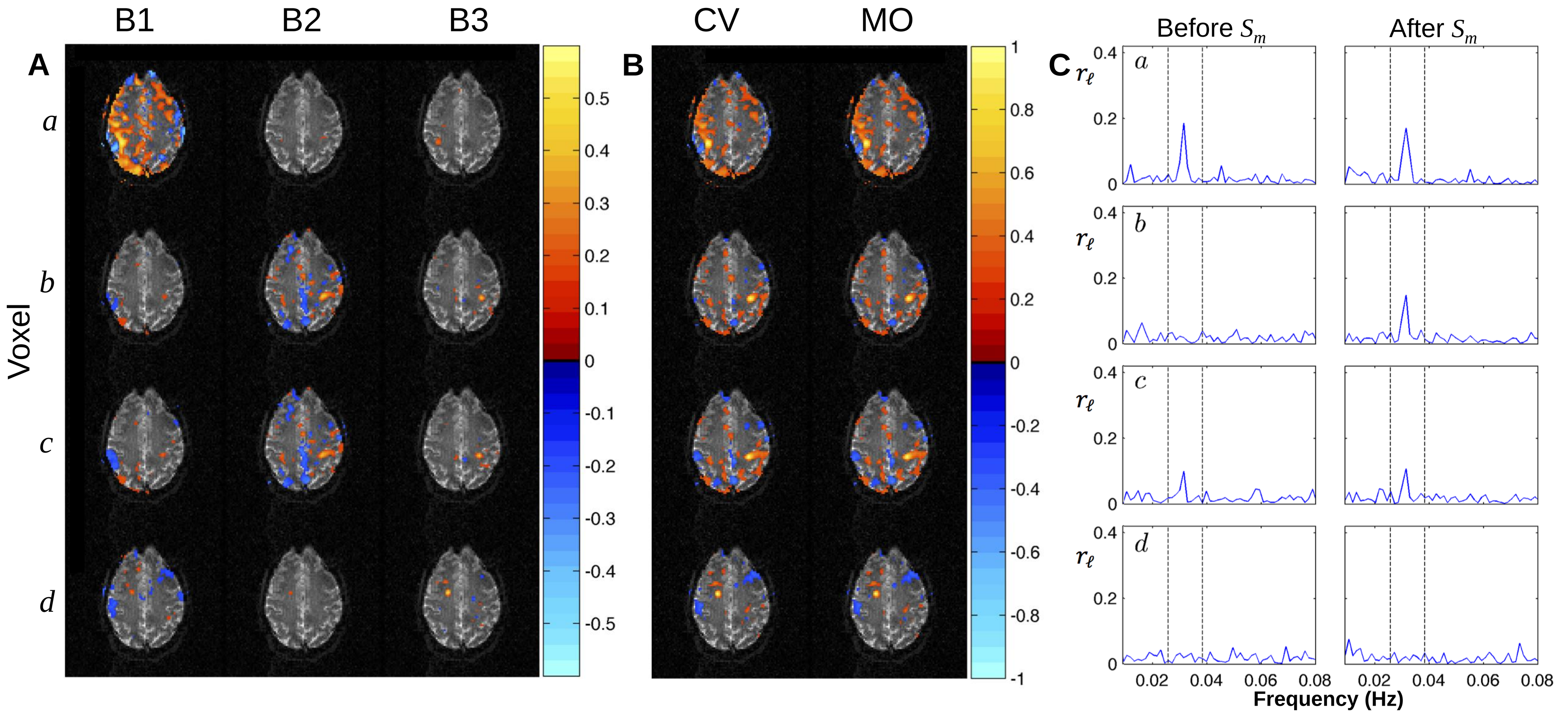

Fig. 1 MO data **(A)** spatial correlation maps after spatial smoothing by VOI and band, B1:0.0009-0.024 Hz, B2:0.026-0.037 Hz, B3:0.038-0.08 Hz, **(B)** the total MO and CV correlation maps, and **(C)** the spectral decomposition as the correlation contributions, r_l, before and after spatial smoothing. Vertical lines correspond to band divisions.

COMPLEX-VALUED (CV) DATA

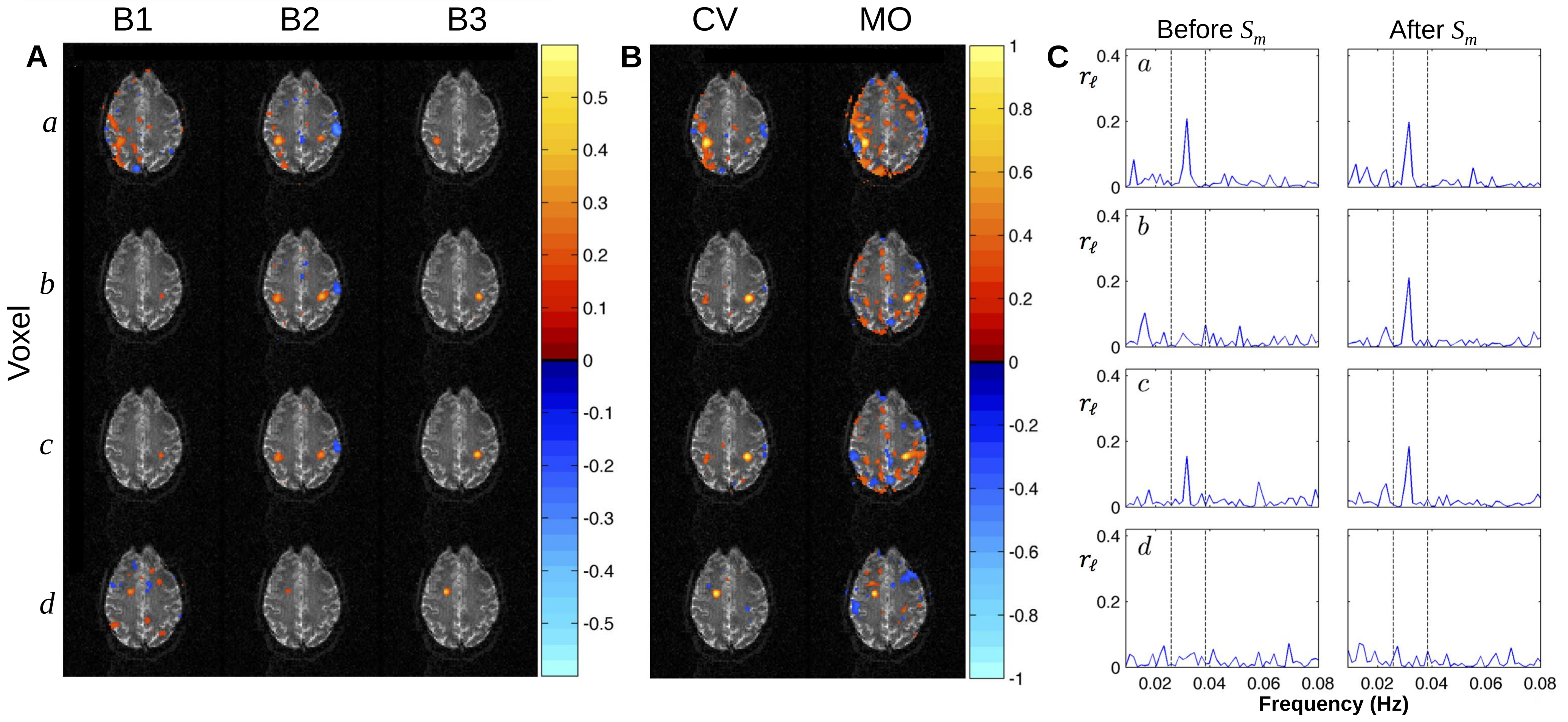

Fig. 2 CV data **(A)** spatial correlation maps after spatial smoothing by VOI and band, B1:0.0009-0.024 Hz, B2:0.026-0.037 Hz, B3:0.038-0.08 Hz, **(B)** the total MO and CV correlation maps, and **(C)** the spectral decomposition as the correlation contributions, r_l, before and after spatial smoothing. Vertical lines correspond to band divisions.

- As observed in Fig. 1A-B & 2A-B, discarding the phase in the analysis results in noisier MO correlation maps with less distinguishable motor cortex.
- Fig. 1C & 2C show the CV correlation contributions have stronger activation peaks in B2, where voxels a and c exhibit a significant correlation contribution.
- Voxel b has no initial activation peak, however its proximity voxel c, results in an induced task activation peak from spatial smoothing. Now, voxel b also shares overlapping frequency content with voxel a, in an nonadjacent region, and the two voxels now have a functional relation as a result of processing.
- The application of MO and CV data to the model illustrates the increased sensitivity of a CV analysis. This CV temporal Fourier frequency description of correlation more accurately quantifies the origin of induced correlation, with a reduction in noise in the computations, compared to MO models.

REFERENCES

1. Friston et al., NeuroImage 2000. **2.** Nencka et al., J. Neurosci. Meth. 2009. **3.** Cordes et al., J. of Am. NeuroRadiology 2000. **4.** Rowe et al., J. Neurosci. Meth. 2007. **5.** Hahn et al., HBM 2011. **6.** Cordes et al., J. of Am. NeuroRadiology **7.** Glover et al., MRM 2000.