An Analytic Magnitude and Phase fMRI Activation Model Applied to ASL

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Synopsis
A computationally fast high ISNR magnitude and phase activation model is presented then applied to an ASL fMRI visual experiment. In fMRI, Fourier encoded k-space measurements, inverse Fourier reconstructed images, and voxel time series are complex-valued (real and imaginary or magnitude and phase). Nearly all fMRI studies derive functional activation from magnitude-only time series while discarding the phase time series. A GLM magnitude and/or phase activation model has been introduced and shown to have higher sensitivity. However, the existing method to compute magnitude and phase activation utilizes an iterative MLE algorithm while here we use a large ISNR exact solution.

Introduction
In fMRI, Fourier encoded k-space measurements are complex-valued: the inverse Fourier transform image reconstruction process produces complex-valued images. Voxel time series from a set of complex-valued images are also complex-valued (real and imaginary or magnitude and phase). Nearly all fMRI studies derive functional activation based on magnitude-only data time series [1,2]. The phase time series (half of the data values) are usually discarded. It is known that there is biological information contained within the phase time series [3,4]. Recently GLM activation models from complex-valued data have been introduced to detect changes in the magnitude and phase [5,6]. and shown to have higher sensitivity [7]. There has been increasing interest in detecting task related magnitude and phase changes in fMRI [8]. The current method to compute magnitude and phase activation [8] utilizes an iterative MLE algorithm. We present an analytic, computationally fast high ISNR magnitude and phase activation model then demonstrate its performance on an ASL fMRI visual stimulation experiment.

Theory
In a voxel, the observed complex-valued data at time t can be described as

\[
\begin{bmatrix}
\rho_t \\
\iota_t
\end{bmatrix} = \begin{bmatrix}
\rho_t \cos \theta_t \\
\rho_t \sin \theta_t
\end{bmatrix} + \begin{bmatrix}
\eta_t \\
\overline{\eta}_t
\end{bmatrix}
\]

where \( t = 1,\ldots,n \) and the measurement errors are specified to be normally distributed with a mean of zero and variance \( \sigma_t^2 \) and \( \sigma^2 \) and shown to have higher sensitivity [7]. There has been increasing interest in detecting task related magnitude and phase changes in fMRI [8]. The current method to compute magnitude and phase activation [8] utilizes an iterative MLE algorithm. We present an analytic, computationally fast high ISNR magnitude and phase activation model then demonstrate its performance on an ASL fMRI visual stimulation experiment.

Experiment
ASL images were collected from a human subject using the pseudo-CASL sequence (spin-echo spiral acquisition with TR=4000 ms, TE=15 ms, slice thickness = 7 mm, FOV = 24 cm). The labeling pulses consisted of a train of Hanning window shaped pulses (pulse width \( T_p = 500 \mu s \), pulse spacing \( T_s = 290 \mu s \), flip angle \( T_F = 22 \degree \), not a constant moment \( T_C = 103 \mu s \) GLM) applied for 3600 ms. The scans were collected during a visual stimulation paradigm (8 Hz flashing checkerboard: six cycles of 50 s rest - 50 s active). Five slices were prescribed encompassing the visual cortex and 150 TRs were collected. The experiment was performed using a post inversion delay of 1200 ms for arterial suppression.

References

Acknowledgements
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Results
The complex-valued time courses were phase centered by subtracting their mean and spatially smoothed. A complex GLM for the unsubtracted design matrix columns displayed as rows in Figure 1 [10].

Figure 1: ASL signal design matrix. Figure 2: Activation map.

Linear and quadratic bregle bend regressors were incorporated in order to capture trends of no interest. The linear models were estimated from Magnitude-Only, Phase-Only and Magnitude-Phase complex data. The complex data model was evaluated using MLE [6] as well as the large SNR method presented above. F statistics and their corresponding p-values were computed over the field of view. Statistical scores were extracted from a cubic ROI (3x3x3 voxels) centered on an active area on the visual cortex and compared across analysis types. In Figure 2 is the activation map (expressed as \(-\log_{10}(p\text{-value})\) overlaid on the mean perfusion map for magnitude-only analysis (blue color scale) and complex analysis (not color scale) while overlapping pixels are green. All active pixels in the Magnitude-Only analysis were also active in the Magnitude-Phase analysis. Table 1 indicates the mean \(-\log_{10}(p\text{-value})\) over the ROI for each analysis.

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<th>PO</th>
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Table 1: Mean \(-\log_{10}(p\text{-value})\) over ROIs.

Discussion
These results confirm that (1) complex analysis is beneficial for ASL fMRI data processing (2) there is more task-related phase information in ASL data when the arterial signal is preserved and (3) the new estimation method yields results that are nearly equivalent to the iterative MLE method. Simulations not shown demonstrate nearly equivalent results down to ISNRs below 5 and an order of magnitude time reduction.

108,75,14 mm | MO | PO | MP |
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