Model-based reconstruction for physiological noise correction in functional MRI

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Introduction: Recent years have seen an explosion in the number of fMRI studies analyzing connectivity between different brain regions. These studies, which study low frequency (<0.1 Hz) temporal correlations, are confounded by under-sampled cardiac and respiratory signals that can alias into this frequency range and confound analyses of neural networks. In cardiac MRI, low rank algorithms have been proposed to perform high resolution spatiotemporal reconstructions [1, 2]. Here we propose a low rank approach combined with temporal Fourier sparsity and random sampling to estimate physiological noise with high spatiotemporal resolution.

Theory: We propose to model the spatiotemporal evolution of the magnetization in the object as being partially separable. Mathematically, we assume $m(\boldsymbol{x},t) = \sum u_r(\boldsymbol{x}) v_r(t)$, where $u_r(\boldsymbol{x})$ is the r[th] spatial basis function, $v_r(t)$is the r[th] temporal basis function, and R is the model order or rank. When the time series of images are sampled and rearranged into an $M \times N$ matrix $\mathbf{C}$, then $\text{rank}(\mathbf{C}) \leq R$. In addition, we can write $\mathbf{C} = \mathbf{UV}$ where $\mathbf{U}_{mr}=\text{u}_r(\boldsymbol{x}_m)$and $\mathbf{V}_{rn}=\text{v}_r(t_n)$. We further assume that the temporal basis functions are sparse in the Fourier domain and that the spatial basis functions are smooth. Recovering $\mathbf{C}$ can then be formulated as the following matrix completion problem:

$$\mathbf{U},\mathbf{V} = \underset{\mathbf{U},\mathbf{V}}{\text{argmin}} \parallel \mathbf{y} - S(\mathbf{UV}) \parallel_2^2 + \frac{\beta}{2} \parallel \mathbf{DF}^{-1}\text{vec}(\mathbf{U}) \parallel_2^2 + \lambda \parallel \mathbf{Q}\text{vec}(\mathbf{V}) \parallel_1,$$

where $\mathbf{y}$ is a $P \times 1$ data vector, $\mathbf{U}$ and $\mathbf{V}$ contain the spatial and temporal basis functions as described above, $S()$ is a sparse sampling operator, $\mathbf{D}$ is a 2D spatial finite differencing matrix, $\mathbf{F}$ is a matrix that applies the 2D DFT, $\mathbf{Q}$ is a matrix that applies the DFT to the temporal dimension of $\mathbf{V}$, and β and λ are regularization parameters. This cost function implicitly incorporates the rank constraint while penalizing roughness in the spatial domain and promoting sparsity in the temporal Fourier domain. We propose to combine this reconstruction approach with a random 3D EPI sampling pattern that incoherently samples the temporal functions, which helps the recovery of $\mathbf{V}$. The use of EPI allows the problem to be reduced to a stack of 2D problems by applying the inverse DFT along the frequency encoding direction.

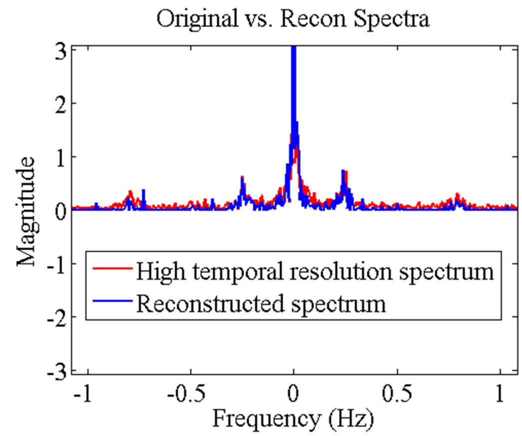

Figure 1: Comparison of ideal Fourier spectrum (blue) vs. reconstruction (red). R=24, β=1e-4, λ=6e3.

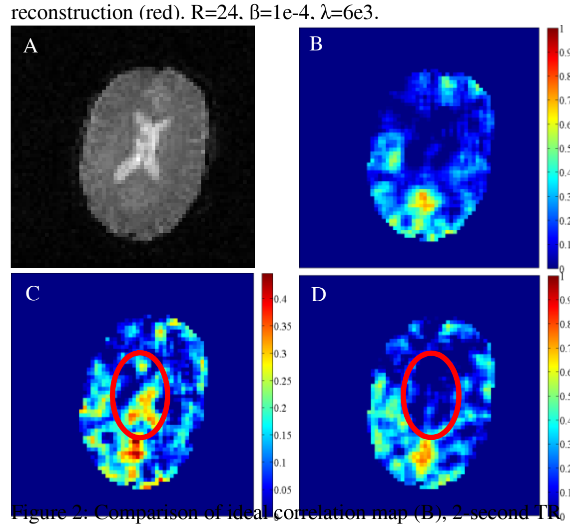

Figure 2: Comparison of ideal correlation map (B), 2-second TR map (C), and the proposed method with 1/64 of data, highlighting removal of correlations in the ventricles (D). Example fMRI image

Experiments and Results: We demonstrate the potential of this method via a 2D EPI experiment with high temporal resolution data. We evaluate the performance of the algorithm by examining functional correlations in a standard resting state connectivity experiment. One volunteer was asked to lie in the scanner and not think about anything in particular. The subject was scanned with a 2D single shot EPI sequence at a single slice with imaging parameters TR=100ms, TE=30ms, flip angle=22°, FOV=22x22cm, matrix size=64x64. The data were detrended and low pass filtered with a cutoff of 0.08 Hz and temporal correlations were calculated relative to the posterior cingulate cortex (PCC); this case served as the "ideal" map. To compare the reconstruction to the ideal map, the data was decimated by a factor of 63/64s to simulate a random 3D EPI where the frequency direction is transverse to the slice. The high temporal resolution data set was reconstructed with the low rank algorithm before detrending, low pass filtering and correlation calculations. Figure 1 compares the Fourier spectrum of the original high temporal resolution data set and the reconstructed data set, with the reconstructed data set being able to capture information from the cardiac and respiratory peaks. Figure 2 compares the correlation maps from the "ideal" data set, the reconstructed data set, and a simulated 2-second TR data set, highlighting the removal of correlations in the ventricles.

Conclusions: We have demonstrated that low rank algorithms with temporal Fourier sparsity constraints have the potential to reconstruct much of the information with only 1/64th of the data. These techniques could be useful in functional connectivity studies where temporal correlations are of interest and the physiological noise is a significant confound. They can also be applied without recording external reference signals.

References: [1] Zhao et al. IEEE-EMBS 2010. pp. 3390-3. [2] Hu, et al., IEEE TIP 21:742-753, 2012.