Improving temporal resolution in fMRI using low-rank plus sparse matrix decomposition

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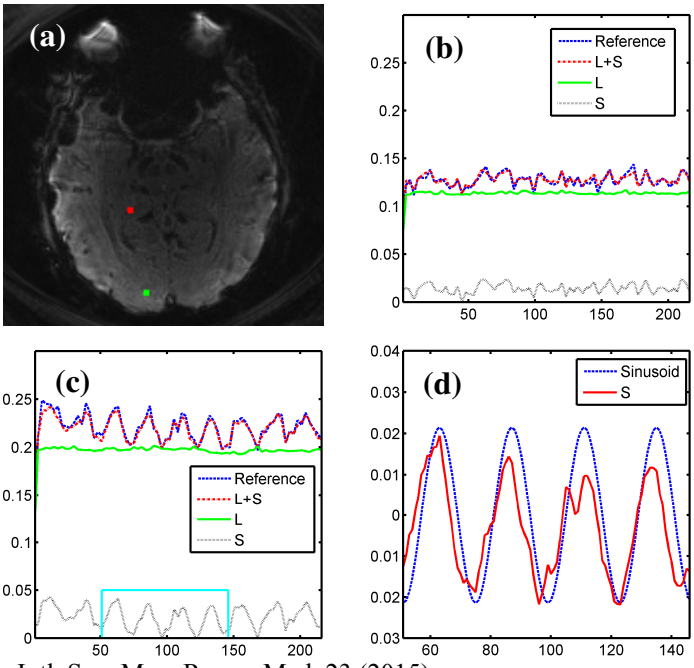
Introduction. High spatial resolution functional MRI provides greater localization of activation in the brain enabling identification of small functional-sub units, such as superior colliculus (SC).[1] However, small voxels require long readout durations that are adversely affected by T2* signal decay and off-resonance effects. Consequently, both single- and multi-shot acquisitions limit the temporal resolution of the high spatial resolution fMRI studies resulting in low temporal sampling bandwidths which leads to aliasing of physiological noise and poor sensitivity of fMRI to BOLD signal. This paper proposes on modeling the spatio-temporal fMRI signal as a low-rank (**LR**) plus (**+**) sparse (**S**) matrix decomposition that allows fMRI signal recovery from under-sampled data. The (**LR+S**) model has been previously applied for accelerating cardiac MR applications.[2] This model is well suited for fMRI signals evoked by slowly varying experiments using blocked or slow event-related designs. In the (**LR+S**) decomposition of the fMRI signal, the **LR** can model the temporally correlated background, and **S** can model the dynamic BOLD response.

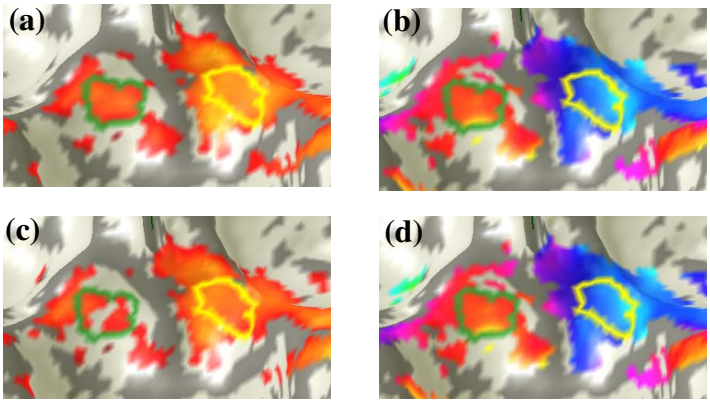
Methods. The time series of fMRI images is converted to a matrix **M** in which each column is a temporal frame. The (**LR+S**) model decomposes the matrix **M** as a superposition of a low-rank matrix **L** and a sparse matrix **S**. Low-rank matrix completion from under-sampled data is performed by minimizing the nuclear norm of the matrix, which is the analog of the $l1$-norm for signal vectors. Therefore, the **L** + **S** decomposition is performed by solving the following convex optimization problem: $\min_{\boldsymbol{L},\boldsymbol{S}} \frac{1}{2}\|\boldsymbol{E}(\boldsymbol{L}+\boldsymbol{S})-d\|_2^2 + \mu\|\boldsymbol{L}\|_* + \lambda\|\boldsymbol{S}\|_1$, where $\|\boldsymbol{L}\|_*$ is the nuclear norm of the matrix $\boldsymbol{L}$, $\|\boldsymbol{S}\|_1$is the $l1$-norm of **S**, $\boldsymbol{E}$ is the encoding or acquisition operator, and d is the under-sampled data and the parameters trade λ and μ trade-off data consistency with the solution complexity given by the sum of the nuclear- and $l1$-norm. The minimization problem is solved using iterative soft thresholding of the singular values of $\boldsymbol{L}$ and of the entries of $\boldsymbol{S}$.[2] Reference fMRI data is acquired on a Siemens 3T scanner using Archimedean spiral-out trajectory.[3] The imaging planes are oriented to cover the SC and a portion of the visual cortex. Ten quasi-axial slices with a field-of-view of 192-mm at an inplane resolution of 1.2-mm using 3-shot spiral (TR= 1 sec/shot) are acquired. For validation of the (**LR+S**) decomposition based fMRI recovery, retrospective under-sampling using variable-density spirals is performed.[4] Under-sampling corresponds to reducing the number of spiral shots used for reconstruction.

Results. Figure 1 shows results for under-sampled recovery at an acceleration of 3 with λ = 0.005 and μ = 0.001 selected empirically to yield the best recovery performance. Figure 1a shows a recovered fMRI image in which two voxels are highlighted. The red voxel lies in non-activated region and its time-series are shown in fig. 1b. The green voxel lies in the visual cortex and its time series are shown in fig. 1c. The **S** component captures the pseudo-periodic BOLD activity and the **L** component captures the temporally correlated data. Figure 1d shows the **S** component for the green voxel alongside a sinusoid at the stimulus frequency (r^2 = 0.84). Figure 2 shows the results of BOLD analysis in the SC for the under-sampled recovery and compares with that of the reference data. Figures 2a and 2c show the BOLD signal (coherence value) for the reference (0.50±0.06) and the under-sampled data (0.46±0.07), respectively. Figures 2b and 2d compare the phase distributions of the activation signals in the reference and under-sampled data, respectively. Minor differences in phase distributions are observed in the left SC and changes are negligible in the right SC.

Conclusions. Preliminary results of using the low-rank plus sparse matrix decomposition model for under-sampled recovery of in-vivo fMRI data are promising. BOLD activation signals are recovered in SC with contrast-to-noise ratio (CNR) ≥ 4.4 (85% of reference CNR) up to accelerations of 3. Evaluation of the (**LR+S**) model based fMRI technique in prospective under-sampling experiments for various under-sampling trajectories is under progress.

References: [1] Katyal *et. al. J Neurophysiol* **104**, 3074-83 (2010); [2]Otazo, R. *Magn Reso Med* **1522-2594** (2014); [3]Glover,G.H. *Magn Reso Med* **44**, 412-415 (1999); [4]Chang,C.. *Magn Reso Med* **65**, 1287-1296 (2011).





(TOP) Fig. 2: Comparison of BOLD activation analysis on superior colliculus for an under-sampled recovery at acceleration of 3. a) Coherence and b) phase map for reference data, c) Coherence and d) phase maps for under-sampled recovery.

(Left) Fig. 1: Result of under-sampled recovery on in-vivo data at an acceleration of 3. a) A sample recovered image; Time-series: b) of a non-activated voxel (red in image); c), of an activated voxel (green in image); d) sparse component with a sinusoid at the stimulus frequency with r^2 = 0.84