

# Field-corrected imaging for sparsely-sampled fMRI by exploiting low-rank spatiotemporal structure

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## INTRODUCTION

Magnetic field gradients near air-tissue interfaces cause signal dropout, hampering BOLD fMRI. To make the data less prone to  $T_2^*$  susceptibility artifacts, it is desirable to reduce the readout duration. This can be achieved by undersampling  $k$ -space, which has been investigated for dynamic MRI [1-3] and recently proposed for fMRI [4,5]. In this work, we demonstrate a field-corrected imaging approach to sparsely sampled fMRI, coined functional LOW Rank Approximations (fLORA). Specifically, we exploit partial separability (PS)-induced low rank structure of fMRI data via group-sparsity, combined with magnetic field inhomogeneity compensation.

## THEORY

The acquired fMRI signal during a readout with trajectory defined by  $\mathbf{k}$  is conventionally modeled in the presence of field inhomogeneity as

$$d(\mathbf{k}, t) = \int \rho(\mathbf{r}, t) e^{-(TE \pm t)(R_2^*(\mathbf{r}) + j\omega(\mathbf{r}))} e^{-j2\pi \mathbf{k} \cdot \mathbf{r}} d\mathbf{r} + \zeta(\mathbf{k}, t), \quad (1)$$

where  $\rho(\mathbf{r}, t)$  denotes the desired spatial function at particular time point  $t$ ,  $R_2^*(\mathbf{r})$  and  $\omega(\mathbf{r})$  are the transverse relaxation rate and field inhomogeneity present at  $\mathbf{r}$ ,  $\zeta(\mathbf{k}, t)$  is the modeled measurement noise, and the positive/negative sign is chosen for spiral-out/spiral-in trajectories respectively. We assume that the data  $d(\mathbf{k}, t)$  is available over a set of points that sparsely sample  $k$ -space. Based on the low-rank structure of fMRI data, we propose the following PS-based spatial-temporal decomposition:

$$\rho(\mathbf{r}, t) = I_{ref}(\mathbf{r}) \sum_{l=1}^L p_l(\mathbf{r}) q_l(t), \quad (2)$$

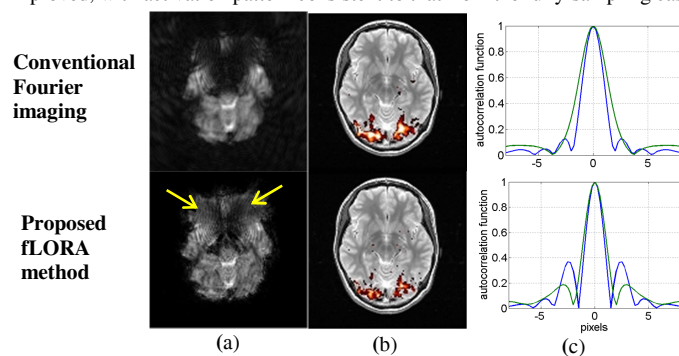
where  $I_{ref}(\mathbf{r})$  is a reference image that contains *a priori* boundary information,  $p_l(t)$  and  $q_l(t)$  can be viewed as the  $l$ -th spatial and temporal basis functions. Model (2) is a special case of PS-based model [3] with inclusion of the reference, while the generalized series model [6] is a special case of (2). In matrix notations, we denote  $\mathbf{P}_{ij} = p_j(\mathbf{r}_i)$  and  $\mathbf{Q}_{ij} = q_j(t_i)$ , respectively. Given the signal model (2), we estimate the temporal basis  $\hat{\mathbf{Q}}$  via  $L$ -th rank SVD decomposition of fMRI data. Image reconstruction is then formulated as solving the following regularized optimization problem

$$\hat{\mathbf{P}} = \arg \min_{\mathbf{P}} \|\mathbf{d} - A\{\mathbf{P}\}\|_2 + \lambda_1 \|\mathbf{R}_1\{\mathbf{P}\}\|_{1,2} + \lambda_2 \|\mathbf{R}_2\{\mathbf{P}\}\|_1, \quad \|\mathbf{R}_1\{\mathbf{P}\}\|_{1,2} = \sum_{l=1}^{N_t} \sqrt{\sum_{m=1}^{N_w} |(\mathbf{P}\hat{\mathbf{Q}})_{ml}|^2}, \quad \|\mathbf{R}_2\{\mathbf{P}\}\|_1 = \sum_{l=1}^{N_t} \sum_{m=1}^{N_w} |(\mathbf{W}\mathbf{P}\mathbf{Q})_{ml}|, \quad (3)$$

where  $\mathbf{d}$  is the measured data vector,  $\mathbf{W}$  denotes 2D wavelet transform, and  $N_t, N, N_w$  are the number of time frames, voxels, and wavelet coefficients, respectively. Given  $\hat{\mathbf{Q}}$ ,  $A$  is the linear matrix operator which defines the data measurement and sampling in the presence of field inhomogeneity, while  $\mathbf{R}_1\{\mathbf{P}\}$  and  $\mathbf{R}_2\{\mathbf{P}\}$  penalties impose group sparsity typical for fMRI data. The penalty  $\mathbf{R}_1\{\mathbf{P}\}$  constrains the degree of BOLD fMRI temporal variation spatially, motivated by the fact that fMRI temporal changes are usually localized in several brain regions. The penalty  $\mathbf{R}_2\{\mathbf{P}\}$  is motivated by the fact that the functional image at each time frame is itself sparse, since BOLD signal is at most a few percent of the maximal baseline low-frequency intensity. The non-smooth convex optimization problem (3) is solved by employing Nikolova's gradient descent approach [7]. Having estimated spatial basis  $\hat{\mathbf{P}}$ , the final reconstructed image is obtained as  $\hat{\rho} = \mathbf{I}_{ref} \hat{\mathbf{P}} \hat{\mathbf{Q}}$ .

## METHODS & RESULTS

We applied the proposed method to BOLD fMRI data on human volunteers. A single-shot variable-density spiral-out sequence was performed at  $(128 \times 128)$  resolution with prospective undersampling rate of four. BOLD functional data (30 slices, 4 mm slice thickness, TR = 3.1 s, TE = 68 ms, 83 time frames, FOV = 22 cm, 8 coils) were obtained using synchronized visual and auditory stimulation. A block design consisted of eight "on" and eight "off" blocks, each lasting for 15 sec. The reference was obtained with a fully-sampled Archimedean spiral acquisition at a single time point, and the field map was derived from a second such acquisition with TE 2ms longer. Figure 1 shows functional images and activation maps, estimated from conventional zero-filling and the proposed method. The new method gains spatial resolution, both visually and quantitatively (the width of the main lobe of autocorrelation function reduced approximately twice). In addition, signal dropout was reduced in the orbitofrontal brain region, as shown by arrows. To further validate the method in terms of activation pattern, retrospective undersampling was simulated in the presence of field inhomogeneity with spiral-out and spiral-in acquisitions. Figure 2 shows estimated functional images with activation maps overlain. Results show consistent performance of the method: signal artifacts due to magnetic susceptibility were corrected while resolution of the images and activation maps was improved, with activation pattern consistent to that from the fully-sampling case.



**Figure 1.** Experimental results: (a) functional images and (b) activation maps estimated from Fourier and proposed methods. Autocorrelation functions along horizontal/vertical directions (in blue/green) of reconstructions are shown in (c).

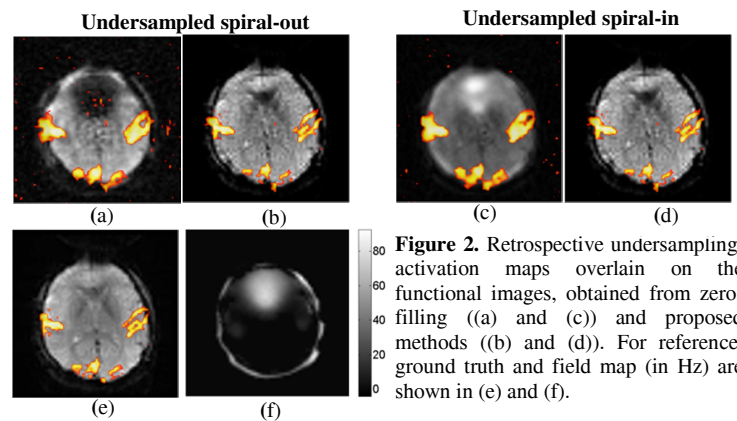
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## CONCLUSIONS

A field-corrected imaging approach to sparsely-sampled fMRI data has been presented. The method exploits the specific low-rank structure of fMRI data via group sparsity and incorporates field inhomogeneity into iterative image reconstruction. Experimental results demonstrate the ability of the method in obtaining higher-resolution functional images and activation maps with artifact correction due to susceptibility-induced field gradients.

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**Figure 2.** Retrospective undersampling: activation maps overlain on the functional images, obtained from zero-filling ((a) and (c)) and proposed methods ((b) and (d)). For reference, ground truth and field map (in Hz) are shown in (e) and (f).