Accelerated fMRI using Low-Rank Model and Sparsity Constraints

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Introduction:

Significant efforts have been made to accelerate data acquisition for fMRI using fast scanning [1-3] and/or parallel imaging [4-5]. Sparse sampling offers a new opportunity to further accelerate fMRI [6-8]. In this work, we present a new method to reconstruct fMRI image series from sparsely sampled (**k**,t)-space data. The proposed method combines two modeling constraints: a Partial Separability (PS) constraint [9] exploiting the low-rank structures in fMRI image series and a sparsity constraint. Simulations based on experimental finger tapping fMRI data demonstrate accurate reconstruction of the gray-scale images and the activation regions from highly undersampled data by the proposed method.

Proposed Method:

Model and Formulation: We consider the following data acquisition model

$$d_q(\mathbf{k}_m) = \int I_q(\mathbf{x}) e^{-j2\pi \mathbf{k}_m \mathbf{x}} d\mathbf{x} + n_q(\mathbf{k}_m), \quad (1)$$

where I_q is the qth frame in an fMRI image series, $d_q(\mathbf{k}_m)$ denotes its corresponding **k**-space measurements and n_q is assumed to be complex white Gaussian noise. After proper discretization, the model in Eq. (1) can be expressed as $\mathbf{d} = \Omega(\mathbf{F}_s\mathbf{X}) + \mathbf{N}$, where $\mathbf{d} \in C^{MQ\times 1}$ contains the data for all the frames, $\mathbf{F}_s \in C^{N\times N}$ is a Fourier encoding matrix, Ω is a (**k**, t)-space sampling operator, $\mathbf{X} = [\mathbf{x}_1,\ldots,\mathbf{x}_Q] \in C^{N\times Q}$ contains the image series to be reconstructed and **N** contains noise. Using the PS model, we can represent **X** as $\mathbf{X} = \mathbf{UV}$ [10-11], where $\mathbf{U} \in C^{N\times L}$ and $\mathbf{V} \in C^{L\times Q}$ are two low-rank matrices. Accordingly, we propose to reconstruct **X** using the following formulation

$$\hat{\mathbf{U}}, \hat{\mathbf{V}} = \arg\min_{\mathbf{U},\mathbf{V}} \left\| \Omega(\mathbf{F}_s\mathbf{UV}) - \mathbf{d} \right\|_2^2 + \lambda\Phi(\mathbf{U},\mathbf{V}), \quad (2)$$

where $\Phi(\mathbf{U},\mathbf{V})$ is a penalty function that promotes the sparsity of **X** in a certain transform domain. In this work, we choose $\Phi(\mathbf{U},\mathbf{V}) = \|\mathbf{U}\|_1$, where the l_1-norm here for a matrix is defined as $\|\mathbf{A}\|_1 = \sum_{mn} |[\mathbf{A}]_{mn}|$. This penalty is motivated by the observation that vectors in **U** (obtained from fully sampled images) highly resemble the spatial components from a typical fMRI data analysis (e.g., ICA analysis as reviewed in [12]) and these components are usually sparse [13].

Algorithm: A specially designed data acquisition scheme, as illustrated in Fig. 1, is used to decouple the joint estimation in Eq. (2) into an efficient sequential estimation of **V** and **U** [9-11]. The repeatedly sampled phase encodings near the center of **k**-space (also referred to as navigator signals [9-11]) are used to estimate **V**. Specifically, the navigator signals are stacked in a matrix, to which SVD is applied and the first L right singular vectors are selected to form an estimate of **V**, denoted as $\mathbf{V}_t$. With $\mathbf{V}_t$ determined, the original problem in Eq. (2) can be rewritten as

$$\hat{\mathbf{U}} = \arg\min_{\mathbf{U}} \left\| \Omega(\mathbf{F}_s\mathbf{UV}_t) - \mathbf{d} \right\|_2^2 + \lambda \|\mathbf{U}\|_1, \quad (3)$$

which can be solved by a number of computationally efficient algorithms developed in the context of sparse signal recovery. Here, we use an algorithm based on additive half-quadratic representation with continuation. Detail of this algorithm can be found in [11].

Results:

We evaluated the proposed method using experimental fMRI data acquired on a 3T SIEMENS Skyra scanner with a 16-channel head coil. A periodic block design paradigm with a finger tapping task was used. Data was acquired using a 2D EPI sequence with: TR/TE = 2000/27ms, matrix size = 88×88, and 32 slices. Parallel imaging acquisition with an acceleration factor of two was used and GRAPPA [14] reconstruction was applied. The sum-of-squares images were then treated as the reference and used to simulate undersampled data. Fig. 2 shows some representative results from the proposed method at an undersampling factor of 5, compared to the fully sampled data. The activation regions detected (using SPM8) are overlaid on the corresponding reconstructed images. As can be seen, the results from the proposed method match well with those from the fully sampled data.

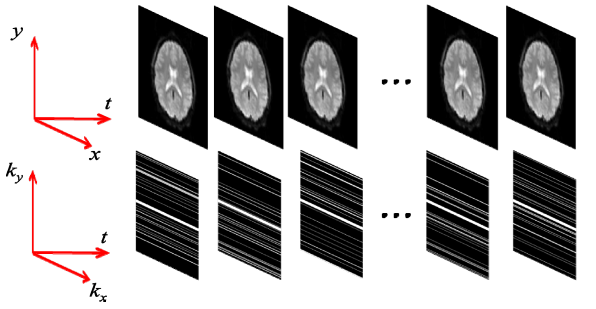

Fig.1: Illustration of the proposed data acquisition scheme.

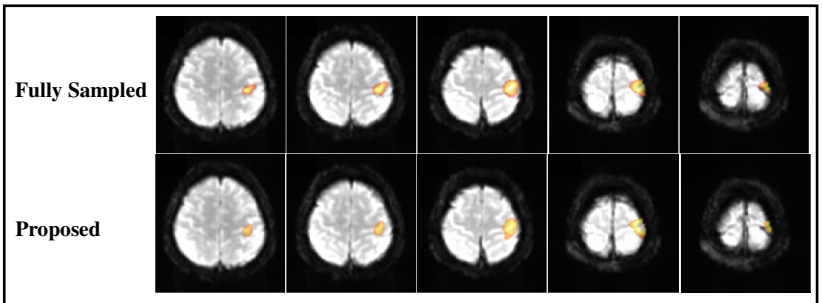

Fig.2: Comparison of the reconstructions and activation maps from the fully sampled data with those from the proposed method.

Conclusion: We proposed a new method for accelerating fMRI experiments using sparse sampling of (**k**, t)-space. The performance of the proposed method has been evaluated using retrospective undersampling of fMRI experimental data. The proposed method produced accurate reconstruction of both the gray-scale images and the activation maps compared to those from fully sampled data. More fMRI studies will be conducted to determine more rigorously the benefits of the proposed method.

References: [1] Mansfield et al., JCAT, 1995. [2] Feinberg et al., PLoS, 2010. [3] Liu et al., MRM, 1993. [4] Afacan et al., MRM, 2012. [5] De Zwart et al., MRM, 2002. [6] Madore et al., MRM, 1999. [7] Jung et al., ISBI, 2009. [8] Jeromin et al., BMEO, 2012. [9] Liang, ISBI, 2007. [10] Haldar et al., ISBI, 2010. [11] Zhao et al., IEEE TMI, 2012. [12] Calhoun et al., NeuroImage, 2009. [13] Flandin et al., NeuroImage, 2007. [14] Griswold et al., MRM, 2002.

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