Accelerating Dynamic MRI using Patch-based Spatiotemporal Dictionaries

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INTRODUCTION:

Compressed sensing (CS) is a promising method to accelerate dynamic imaging (dMRI) by employing the sparsity model to represent spatial-temporal correlations [1-3]. The selection of a suitable sparsifying transform is crucial for the reconstruction process in CS. Several methods have been proposed to apply dictionary learning (DL) in MRI reconstructions [4][5]. However, these methods simply use the dictionaries to exploit the sparseness either in the spatial direction or in the temporal direction only. Most recently, a spatiotemporal dictionary model is developed for dMRI with an additional low-rank constraint, but it may not capture the local abrupt motion because the dictionary consists of all the temporal data points [6]. In this abstract, a patch-based spatiotemporal DL model is proposed for dynamic image reconstruction from undersampled k-space data. The whole image sequence is divided into some segments that are composed of several consecutive images. Each segment is then divided into many overlapping patches along both spatial and time axes. These patches are expected to be sparsely represented over a redundant three-dimensional dictionary. The proposed model is shown to be able to capture the local features spatially and temporally using *in vivo* cardiac cine data.

THEORY AND METHOD:

Let $\mathbf{X} = [\mathbf{X}_1; \mathbf{X}_2; \ldots ; \mathbf{X}_T]$ denote the dynamic image sequence and $\mathbf{X}_t$ (t = 1, 2, ... , T) represent the t-th frame. Consider a segment $\mathbf{X}_{t,M}$ that contains M consecutive images, i.e. $\mathbf{X}_{t,M} = [\mathbf{X}_t; \mathbf{X}_{t+1};\ldots; \mathbf{X}_{t+M-1}]$. Define an operator $\mathbf{R}_{ijk}$ that extracts a three dimensional patch from $\mathbf{X}_{t,M}$ which is located at (i, j, k) and with a predefined size of (n_f, n_p, n_t). Suppose that the patch can be sparsely represented over a dictionary $\mathbf{D}_t$, i.e. $\mathbf{R}_{ijk}\,\mathbf{X}_{t,M} \approx \mathbf{D}_t\boldsymbol{\alpha}_{ijk}$, where $\boldsymbol{\alpha}_{ijk}$ is sparse. The dictionary $\mathbf{D}_t$ has a size of $P\times Q$, where $P = n_f \times n_p \times n_t$ and Q is the number of atoms. The subscript t below $\mathbf{D}$ indicates that the dictionary is temporal dependent. The dMRI reconstruction problem is formulated as:

$$\left\{\mathbf{X}_{t,M},\mathbf{D}_t,\mathbf{A}_t\right\} = \arg\min \mathrm{TV}\left(\mathbf{X}_{t,M}\right) + \lambda_1\left\|\mathbf{F}_t\mathbf{X}_{t,M} - \mathbf{Y}_{t,M}\right\|_2^2 + \lambda_2\sum_{(i,j,k)}\left\|\mathbf{R}_{ijk}\mathbf{X}_{t,M} - \mathbf{D}_t\boldsymbol{\alpha}_{ijk}\right\|_2^2,\ \text{s.t. } \left\|\boldsymbol{\alpha}_{ijk}\right\|_0 \le K,\ \ \forall i,j,k \quad \text{for } t = 1,2,\cdots,T$$

where $\mathrm{TV}(\cdot)$ stands for total variation (TV) operation along the spatial dimension, $\mathbf{Y}_{t,M} = [\mathbf{Y}_t; \mathbf{Y}_{t+1}; \ldots ;\mathbf{Y}_{t+M-1}]$, $\mathbf{Y}_t$ is the undersampled k-space data of the t-th frame image $\mathbf{X}_t$, $\mathbf{F}_t$ denotes the corresponding undersampled Fourier transforms, λ_1 and λ_2 are tuning parameters. We apply the alternating optimization framework to solve the above problem. The minimization procedure is divided into two steps. In the first step, $\mathbf{X}_{t,M}$ is fixed. The problem is simplified to a DL problem. We use the K-SVD algorithm to seek for the solutions [7]. As for the second step, $\mathbf{D}_t$ and $\mathbf{A}_t$ are both fixed. The problem becomes a TV minimization problem, which is solved by the split Bregman method [8]. In the initialization stage, we use the overcomplete discrete cosine transform (DCT) dictionary and the sliding window reconstruction results as the initial value of $\mathbf{D}_t$ and $\mathbf{X}$ respectively.

RESULTS AND DISCUSSION:

We use a set of dynamic cardiac cine data to evaluate the performance of the proposed method. The data were acquired from a 1.5T scanner using the steady-state free precession (SSFP) sequence with a flip angle of 50 degree and TR = 3.45msec. The field of view (FOV) was 345mm × 270mm and the slice thickness was 10 mm. The heart frequency was 66 bpm and the retrospective cardiac gating was used. The original data size is 256×256×25 (#PE×#FE×#frame). The cardiac region with a size of 128×128×25 is extracted for simulation. We employ the Cartesian random down sampling pattern along the PE direction. The central part of the k-space in each frame is fully sampled with a total of eight PE lines. The net reduction factor is 4. In DL, the size of an atom (P) is $n_f \times n_p \times n_t$ = 4×4×5 = 80 and the number of atoms (Q) is set to 400. The number of frames in one segment (M) is 7 and the sparsity constraint (K) is set to 5. Reconstruction using k-t FOCUSS is also performed for comparison [2].

The reconstruction results of the fifth frame are shown in Fig. 1. The zoomed-in figures of the cardiac region indicate that the proposed method preserves more details and obtains lower noises in the image. The temporal profiles at a fixed position in the FE direction are compared in Fig. 2. The proposed method captures more temporal variations than k-t FOCUSS.

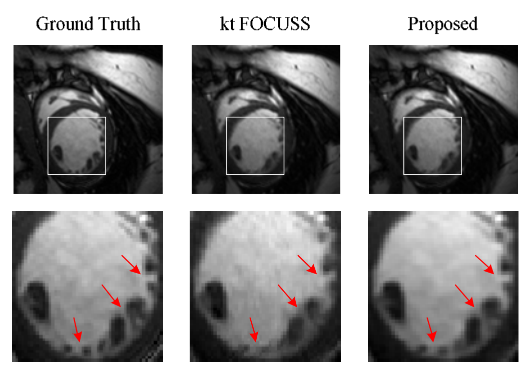

Fig.1. Reconstructions (top) and zoomed-in ROI (bottom)

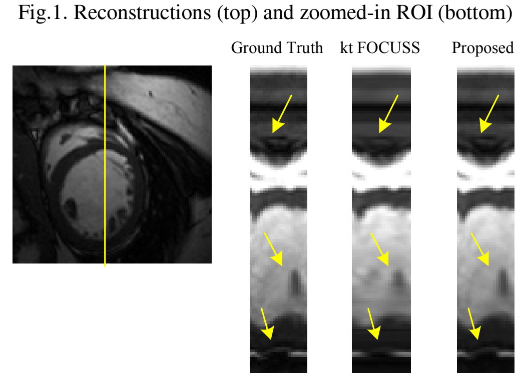

Fig.2 Comparison of the temporal profiles

CONCLUSION:

We propose a patch-based DL model for dMRI reconstruction which uses a set of temporal-dependent three-dimensional dictionaries to provide sparse representations for compressed sensing reconstruction. Simulation results demonstrate that the proposed method can preserve both spatial structures and temporal variations in cardiac cine images.

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