Highly accelerated dynamic imaging reconstruction using low rank matrix completion and partial separability model

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TARGET AUDIENCE: Scientists and clinicians interested in highly accelerated dynamic MRI

PURPOSE: The current fast imaging techniques [1-5] have shown success in improving the temporal resolution of dynamic MRI. However, it is still challenging to improve both the spatial and temporal resolutions simultaneously. Joint use of partial separability (PS) and spatial-spectral sparsity constraints [6,7] has been demonstrated useful for reconstruction from undersampled data. However, the PS model fails when the navigation data is not available. This abstract presents a new approach to highly accelerated dynamic MRI. In data acquisition, k-space data is moderately randomly undersampled at the center k-space navigator locations, but highly undersampled at the outer k-space for each temporal frame. In reconstruction, the under-sampled navigator dataset is structured into a single matrix which is assumed to be of low rank. Then the navigator data is reconstructed using structured low-rank matrix completion [8]. After all the unacquired navigator data is estimated, the PS model [5-7] is used to obtain the entire dynamic image series from highly undersampled data.

THEORY AND METHODS: The main goal of the proposed method is to recover the dynamic image sequence $\gamma(\mathbf{x},t)$ from highly under-sampled Fourier measurements, where **x** and *t* represent spatial location and time respectively. We adopt the PS model which assumes $\gamma(\mathbf{x},t)$ to be spatial-temporal partially separable [5-7]: $\boldsymbol{\Gamma}^{M\times N}=[\gamma(\mathbf{x},t_1),\cdots,\gamma(\mathbf{x},t_N)]=\mathbf{U}_s^{M\times R}\mathbf{V}_t^{R\times N}$, where $\mathbf{U}_s$ and $\mathbf{V}_t$ represent the spatial coefficient matrix and the temporal basis, and *R* is the rank of Γ. Conventional PS methods continuously and densely acquire navigator data at central k-space to estimate $\mathbf{V}_t$. However, in cases when the (**k**-*t*) data is highly undersampled [9,10], acquiring navigator data would become the bottleneck of high accelerations (shown in Fig. 1). Locally low rank in either image or k-space has been used in parallel imaging reconstruction [8,11], dynamic imaging [12,13], and parameter mapping [14]. Here, we assume the navigator data in the **k**-t domain is of locally low rank. As a result, estimating the unacquired navigator data becomes a low rank matrix completion problem, as has been stressed in [8]. Then the temporal basis $\mathbf{V}_t$ can be obtained from the *R* dominant right singular vectors through the singular value decomposition (SVD) [6]. We further assume the dynamic image series to be sparse in the spatial and temporal frequency domain [7,8]. $\mathbf{U}_s$ is calculated by the following optimization function: $\widehat{\mathbf{U}}_s=\operatorname{argmin}\|\mathbf{d}-\mathbf{E}\mathbf{U}_s\mathbf{V}_t\|_2^2+\lambda\|vec(\mathbf{U}_s\mathbf{V}_t\mathbf{F}_t)\|_1$, where **d** represents the undersampled k-space data, **E** represents an operator which integrates both the Fourier transform with a specified undersampling trajectory in (**k**,*t*)-space, and $\mathbf{F}_t$ is the temporal Fourier transform.

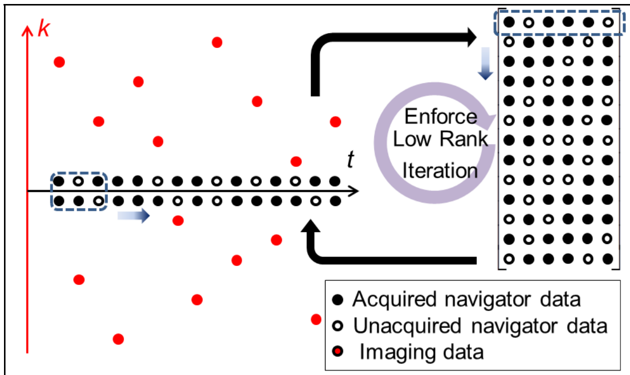

Fig.1. Distribution of navigator data and imaging data in the (**k**,*t*)-space for a dynamic object.

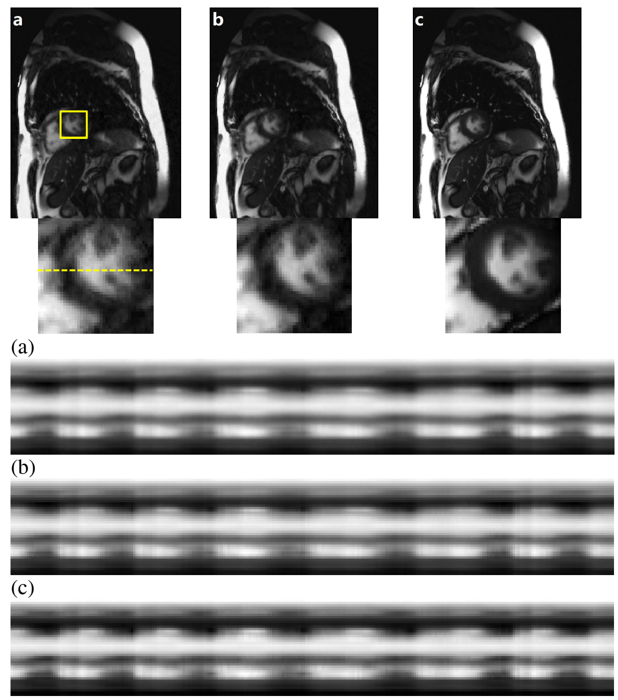

Fig.2. The reconstructed image frame and temporal profile using the proposed method and the reference. Conventional PS method fails and thus is not shown. (a),(b) ROI of the reconstructions from the proposed method with reduction factors of 44.4 and 36.4 respectively (3 and 4 lines in imaging data area each frame). (c) Reference.

RESULTS: The proposed method was evaluated on a numerical human cardiac MR phantom with retrospective undersampling. Imaging parameters were TR = 3ms, 200 phase encodings, and 256 samples per readout. The k-space data was generated from the Fourier transform of the phantom, and then retrospectively undersampled. The central two phase encoding lines in the (**k**,*t*)-space were considered as navigation locations. The k-space data in the navigation location has a random undersampling factor of 1.3. The k-space data outside the navigation location is randomly undersampled with a much higher reduction factor (only 3 and 4 lines at each frame, corresponding to net reduction factors of 44.4 and 36.4, respectively). In Fig. 2, we show a frame of reconstructed images and the ROI temporal profiles using the proposed method, compared with those from the reference image.

CONCLUSION: We have proposed an approach to reconstruct highly undersampled dynamic MRI with high spatial and temporal resolution. The approach effectively exploits locally low rankness within the navigator region to recover the full from undersampled navigator data, and combines PS and sparsity constraints in the same framework. The proposed method has shown to achieve high quality, artifacts-free reconstructions with reduction factors up to 44, when conventional PS method fails.

REFERENCES: [1] Korosec FR, et al., MRM, 36:345–351, 1996. [2] Barger AV, et al., MRM, 48:297–305, 2002. [3] Mistry N, et al., MRM, 59:289–297, 2008. [4] Tsao J, et al., MRM, 50:1031–1042, 2003. [5] Brinegar C, et al., MRM, 64:1162–1170, 2010. [6] Liang ZP, ISBI: 988-991, 2007. [7] Zhao B, et al., IEEE Trans. Med. Imag., 31(9):1809-1820, 2012. [8] Shin PJ, et al., MRM, 72(4)959-970, 2014. [9] Xu B, et al., MRM, 69(2), 2013. [10] Lyu J, et al., ISMRM, 333, 2014. [11] Trzasko JD, et al., 517, ISMRM, 2012. [12] Gao H, et al., UCLA CAM Report, 2011: 11-26, Los Angeles, CA. [13] Lingala SG, et al., IEEE Trans. Med. Imag., 30(5), 2011. [14] Zhang T, MRM, DOI: 10.1002/mrm.25161, 2014.