Block LOw-rank Sparsity with Motion guidance (BLOSM) for accelerated dynamic MRI

Xiao Chen[1], Michael Salerno[2,3], Craig H Meyer[1], and Frederick H Epstein[1]

[1]*Biomedical Engineering, University of Virginia, Charlottesville, Virginia, United States,* [2]*Medicine, University of Virginia, Charlottesville, Virginia, United States,* [3]*Radiology, University of Virginia, Charlottesville, Virginia, United States*

Background:

Many cardiac MRI (CMR) applications feature dynamic images, in which an object's signal intensity or position changes over time. Several accelerated imaging techniques utilizing k-t undersampling have been proposed which exploit spatiotemporal correlations and use a few spatiotemporal basis functions to model dynamic CMR behavior and reconstruct images[1,2]. However, these algorithms are sensitive to respiratory motion and perform poorly when signal intensity, object position and object shape change during image acquisition. In this study, we propose a novel method that divides the images into regions (blocks) and tracks the blocks' motions to exploit increased sparsity within the tracked blocks (Block LOw-rank Sparsity with Motion guidance or BLOSM). The simplified dynamics in the smaller, motion-compensated blocks are more accurately described by a limited number of basis functions, making the method insensitive to complex dynamics.

Methods:

In BLOSM, blocks of image pixels are tracked through time using motion information extracted from the acquired image data. The tracked blocks consist of structure-similar and temporally-related objects with simplified dynamic complexity. Specifically, a block $\mathbf{B}_{\mathrm{xc}}(t_1) \in \mathbb{C}^{N_b \times N_b}$ is initiated on the first image $\mathbf{m}(t_1) \in \mathbb{C}^{N_x \times N_y}$ with its center at $\mathbf{x}_\mathrm{c}$. $\mathbf{B}_{\mathrm{xc}}(t_1)$ is tracked to the next image as $\mathbf{B}_{\{\mathrm{xc+dxc}\}}(t_2)$ where $\mathrm{d}\mathbf{x}_\mathrm{c}$ is the displacement of $\mathbf{x}_\mathrm{c}$ using image registration and {} takes the integer to avoid spatial interpolation. The tracked blocks are gathered as a cluster $\Xi \in \mathbb{C}^{N_b \times N_b \times N_t}$ and rearranged to $\mathbf{Z} \in \mathbb{C}^{N_s \times N_t}$ ($N_s = N_b \cdot N_b$) for singular value decomposition (SVD) to exploit low-rank sparsity (Figure 1). Ξ has greater sparsity compared to the whole image $\mathbf{m}$, because the blocks have a smaller scope with decreased spatiotemporal variations, and motion-guidance (MG) leads to less motion contamination and simplified motion patterns.

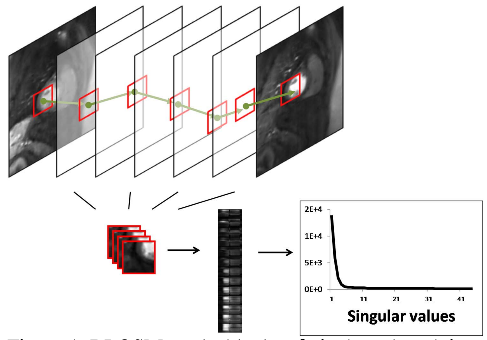

Figure 1. BLOSM tracks blocks of pixels and exploits block low-rank sparsity. A block is tracked through time. These temporally related blocks with similar spatial contents are gathered together and form a 3D cluster. The cluster is rearranged into a 2D matrix which has a high spatiotemporal correlation, and SVD is applied. Only a few of the singular values have significantly higher values than the others, presenting matrix low-rank sparsity.

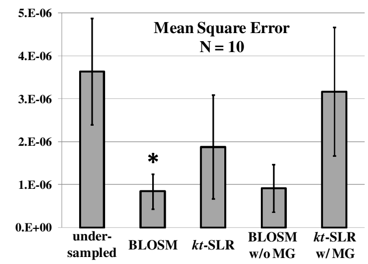

Figure 3. MSE of 10 patient datasets reconstructed using different algorithms. MSE for BLOSM was greatly reduced relative to *kt*-SLR (*P<0.01 v.s. undersampled, *kt*-SLR and *kt*-SLR w/ MG). Note that MSE was averaged over pixels and time points. Less MSE improvement for BLOSM compared to BLOSM w/o MG was observed since motion only happened at a few time points and the decrease in error was averaged out over time.

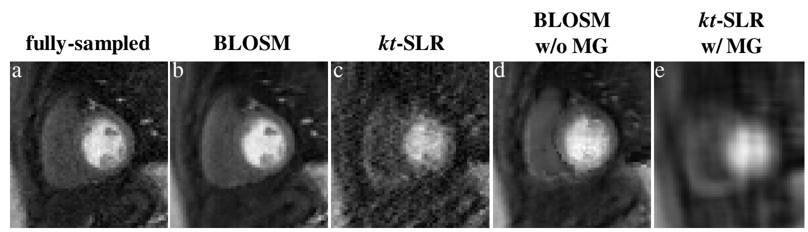

Figure 2. Example images at one time point from one patient's perfusion CMR. The heart moved at this time point due to respiratory motion. BLOSM (b) outperformed *kt*-SLR (c). Without motion-guidance (d), quality degraded severely in the image with motion. Without blocking (e), kt-SLR w/ MG suffered severe over-smoothing due to spatial interpolation.

In this study, we frame the CS problem as:

$$\mathbf{m}^* = \arg\min_{\mathbf{m},\mathcal{R}} \|\mathcal{F}_\mathrm{u}\mathbf{m} - \mathbf{d}\|_2 + \lambda \|\Phi_\mathcal{R}\mathbf{m}\|_{p*}$$

$\Phi_\mathcal{R}$ represents the block motion tracking operator where $\mathbf{m}$ is divided into blocks using motion trajectory maps R. $\|*\|_{p*}$ is a joint Schatten p-norm that exploits regional low rank and p=0.9[3]. An iterative soft-thresholding algorithm is adopted to solve the CS problem[4]. Overlapped blocks are initiated to avoid gaps and a weighted summation algorithm is used to merge blocks back to images. A coarse-to-fine strategy, which both shrinks block size and employs more refined registration methods (beginning with rigid registration and finishing with affine or non-rigid registration) during CS iteration, is used to track blocks as the algorithm iterates.

N=10 human cardiac first-pass datasets (chosen to have prominent respiratory motion) were retrospectively undersampled at an acceleration rate of 4 and reconstructed using BLOSM and *kt*-SLR[1], which uses whole image low-rank sparsity without MG. BLOSM without MG and *kt*-SLR with MG were also implemented and compared. Mean square error (MSE) was calculated for quantitative analysis.

Results:

BLOSM substantially improved image quality compared to *kt*-SLR as demonstrated both in images (Fig. 2) and MSE values (Fig. 3). The increase in quality was most obvious when respiratory motion occurred. Both the "block" and "motion-guidance" concepts in BLOSM contributed to the improvement, which was demonstrated by comparisons to BLOSM w/o MG, *kt*-SLR w/ MG and *kt*-SLR.

Conclusion and Discussions:

We have developed a novel motion-guided regional sparsity CS algorithm for dynamic MR images which can handle complex dynamics and is motion insensitive. Substantial image quality improvement was achieved by using the proposed method BLOSM for rate 4 accelerated cardiac first-pass perfusion images with respiratory motion.

References: [1] Lingala et al. IEEE 2011 30:1042-54 [2] Pedersen et al. MRM 2009 62(3):706-16 [3] Majumdar et al. MRI 2011 29(3):408-17 [4] Combettes et al. Multiscale Model Simul 2005 4:1168-1200

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