Data-adaptive reconstruction algorithms for accelerated dynamic MRI: an open-source MATLAB package

Sajan Goud Lingala[1], Yasir Mohsin[2], Sampada Bhave[2], Xin Miao[3], Yi Guo[1], Krishna Nayak[1], Edward DiBella[4], Mathews Jacob[3]

[1]*Ming Hsieh Dept of Electrical Engineering, University of Southern California, Los Angeles, California ,*[2]*Electrical and Computer Engineering, University of Iowa, Iowa city, Iowa,* [3]*Biomedical Engineering, University of Southern California, California,* [4]*Radiology, University of Utah*

Introduction: Dynamic MRI (DMRI) is relevant in cardio-vascular, pulmonary, contrast enhanced, flow, and vocal tract imaging applications. The emergence of highly accelerated DMRI based on sparse sampling and constrained reconstruction has created an exciting opportunity to improve the achievable spatio-temporal resolution, volumetric coverage, and signal-to-noise ratio. Here, we present an open-source MATLAB package of data-adaptive reconstruction algorithms [1-10] for accelerated DMRI. This package contains **five** data-adaptive constrained reconstruction algorithms [5-10], which adapt the representation to the data in four different ways that are appropriate for different DMRI applications, as discussed below. We provide easy to run demo code for all algorithms, using retrospective under-sampling of simulated and fully sampled *in vivo* DMRI raw data.

MATLAB package for data-adaptive reconstruction: The package is hosted at https://research.engineering.uiowa.edu/cbig/content/software. We briefly describe the objective function of all the algorithms provided in the package. We denote $\Gamma\,(\boldsymbol{x},t)$ as the dynamic image series, and $\boldsymbol{b}$ as the vector containing all the measured k-t data, and A the forward model accounting for coil sensitivity encoding and Fourier under-sampling.

(a) k-t SLR (sparsity, and global low rank constrained reconstruction) : k-t SLR [5,6] is formulated as a spectral and sparsity regularized optimization problem, where the Schatten p-norm (p<1) is used as a surrogate for the rank of the matrix, and the spatio-temporal total variation norm is used to exploit sparsity of underlying dynamic data: $min_{\Gamma}||A(\boldsymbol{\Gamma})-\mathbf{b}||_2^2+\lambda_1|\boldsymbol{\Gamma}||_p^p+\lambda_2 TV(\boldsymbol{\Gamma})$. Representative examples using a numerical first-pass cardiac phantom, in vivo myocardial perfusion data are provided with k-t SLR.

(b) k-t SLLR (sparsity, and patch-based locally low rank constrained reconstruction): k-t SLLR [7] is formulated to exploit patch-based local low rank structure, in addition to exploiting transform domain sparsity: $min_{\Gamma}||A(\boldsymbol{\Gamma})-\mathbf{b}||_2^2+\lambda_1\sum_{b\epsilon\Omega}||\mathbf{C_b}\boldsymbol{\Gamma}||_p^p+\lambda_2 TV(\boldsymbol{\Gamma})$; (2)

where $\mathbf{C_b}$ is the operator to extract the bth patch from $\boldsymbol{\Gamma}$ and reform it into a Casorati matrix, and Ω is the total number of patch matrices extracted from $\boldsymbol{\Gamma}$. Representative examples using cardiac cine data provided by the 2014 ISMRM reconstruction challenge committee are provided with k-t SLLR (also see fig 1).

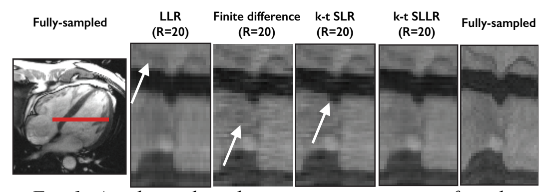

Fig. 1: Accelerated cardiac cine reconstructions from k-t SLLR, k-t SLR, LLR, Total Variation sparsity reconstructions at rate x20 *using 2D variable density random under-sampling.*

(c) BCS (blind compressed sensing): BCS [8,9] models the dynamic signal time profile as a sparse linear combination of learned temporal basis functions from a dictionary. BCS estimates the temporal basis functions ($\mathbf{V}_{RXN}$), and the sparse spatial weights/model coefficients ($\mathbf{U}_{MXR}$) jointly from the under-sampled data, where M, N and R are respectively the number of voxels per frame, total number of times frames, and number of basis functions. The optimization is formulated as: $min_{\mathbf{U},\mathbf{V}}||A(\mathbf{UV})-\mathbf{b}||_2^2+\lambda_1\left|\left|\mathbf{U}\right|\right|_1^1+\lambda_2\left|\left|\mathbf{V}\right|\right|_2^2$;

Representative examples using dynamic lung data, myocardial perfusion data, are provided with BCS (also see fig 2).

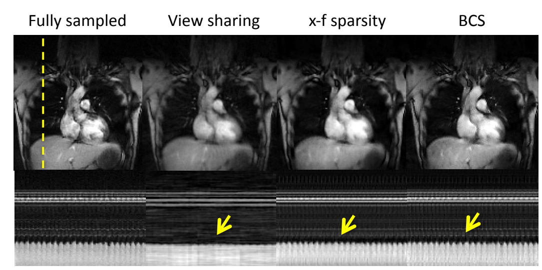

Fig. 2: Accelerated dynamic lung MRI reconstructions from BCS compared to view-sharing and CS with x-f sparsity using 16 spokes/frame with radial trajectories.

(d) DC-CS (deformation corrected-compressed sensing): DC-CS [10] is a generalized deformation corrected compressed sensing frame-work that simultaneously estimates, and corrects for inter-frame motion, while impose constraints on the deformation corrected data-set. The optimization is formulated as: $min_{\boldsymbol{\Gamma},\boldsymbol{\theta}}||A(\Gamma)-\mathbf{b}||_2^2+\lambda\phi(\tau_\theta\cdot\Gamma)$;

where τ_θ is the non-rigid image warping operator; $\boldsymbol{\theta}(\boldsymbol{x},t)$ are the deformation parameters that describe voxel wise displacements due to motion, which are estimated from under-sampled data. $\phi(u)$ denotes an arbitrary sparsity/compactness prior (eg. transform sparsity, low rank prior) applied on the deformation corrected dataset $\tau_\theta\cdot\Gamma$. Representative examples using free breathing myocardial perfusion data are provided with DC-CS (also see fig 3).

(e) PRICE (Patch regularization for Implicit motion compensation): PRICE [11] is a spatio-temporal patch smoothness regularization scheme, which implicits compensates for inter-frame motion. It avoids expensive motion estimation steps, and has computational complexity comparable to simple constraints such as TV regularization. The formulation and optimization of PRICE are detailed in [11]. Representative examples using cardiac cine, and myocardial perfusion data are provided with PRICE (also see fig 3).

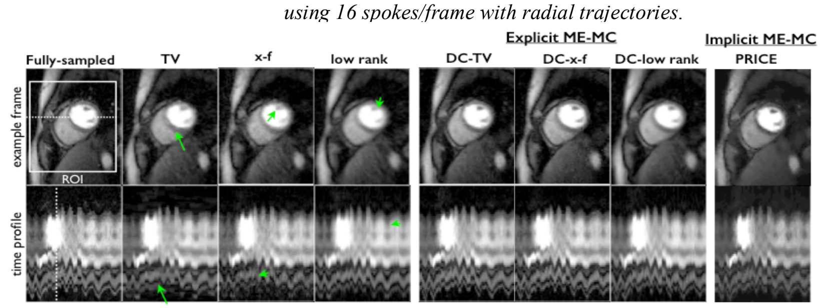

Fig. 3: Accelerated myocardial perfusion MRI from explicit motion estimation correction schemes (DC-CS with different sparsity/compactness priors), and implicit motion correction scheme (PRICE) at x *5.6 fold using pseudo radial under-sampling.*

Discussion: Data adaptive reconstruction algorithms have demonstrated superior performance over conventional pre-determined transform sparsity constraints. Reconstruction formulations are typically non-convex and are challenging to optimize, and challenging to prove convergence. The provided package includes a variety of strategies that have been found to be robust in practice, and incorporate efficient continuation via variable splitting, majorize-minimize techniques, etc. This is a "first" release of the package, and we intend to include additional data-driven reconstruction algorithms, additional example applications, and performance improvements in the future.

References: [1] A. Gupta et al, ISMRM, p.10, 2001, [2] Z-P. Liang, et al, IEEE-ISBI: pp:181-182, 2007, [3] Y. Bresler et al, IEEE-ISBI: pp. 980-83, 2007, [4] H. Jung et al, MRM; pp.103-116, 2009, [5] S.G. Lingala, et al, IEEE-TMI, 30: pp.1042-54, 2011, [6] S.G. Lingala, et al, Phys Med. Biology, 58(20): pp.7309-27, 2013, [7] X. Miao, et al, ISMRM, p 571, 2015, [8] S.G. Lingala, et al, IEEE-TMI, 32(6): pp.1132-45, 2013, [9] S. Bhave, et al, MRM, early view, doi:10.1002/mrm.25722, [10] S.G. Lingala, et al, IEEE-TMI, 34(1): pp.72-85, 2015. [11] Y. Mohsin et al, ISMRM, p0747, 2014. [12] Y. Mohsin et al, ISMRM, p2684, 2015.