Accelerated Cardiac Cine Using Locally Low Rank and Total Variation Constraints

Xin Miao¹, Sajan Goud Lingala², Yi Guo², Terrence Jao¹, and Krishna S. Nayak^{1,2}

¹Biomedical Engineering, University of Southern California, Los Angeles, CA, United States, ²Electrical Engineering, University of Southern California, Los Angeles, CA, United States

INTRODUCTION: Simultaneously achieving high spatial and temporal resolution remains a challenge in 3D cardiac cine imaging. Constrained reconstruction promoting the low rank property of dynamic image matrices has been proposed for accelerated dynamic MRI [1,2]. Recently, locally low rank (LLR) constraint was proposed to exploit spatially-varied local rank-deficiency [3]. Moreover, the combination of global low rank with sparsity constraints has been shown in various forms to improve image recovery rate and reconstruction performance [1,4]. In this study, we combine LLR with temporal total variation constraints (LLR+tTV), and evaluate against current state-of-art methods on the reconstruction of highly undersampled cardiac cine images.

METHODS: Datasets: Six fully-sampled cardiac cine datasets distributed by the 2013 ISMRM Recon Challenge committee [5] were used in this study. The data was acquired using a 2D cine breath-held bSSFP sequence with 32-channel cardiac receiver coils. Three of the datasets were midventricular short-axis, and the other three were vertical long-axis. Approximate parameters: image matrix 210×426, spatial resolution 1×1 mm², 30 timeframes per cardiac cycle. The datasets were retrospectively under-sampled in two dimensions using two sampling patterns: a variable-density random and Cartesian golden-angle radial. Acceleration factors (R) ranged from 10 to 50. Image Reconstruction: The cost function of the LLR and temporal TV regularized optimization problem was formulated as: $\Gamma^* = \underset{\Gamma}{\operatorname{arg\,min}} \| FS(\Gamma) - m \|_2^2 + \lambda_1 \Phi(\Gamma) + \lambda_2 \| \nabla_t \Gamma \|_1, \quad \Phi(\Gamma) = \sum_{b \in \Omega} \| C_b(\Gamma) \|_p$

$$\Gamma^* = \operatorname*{arg\,min}_{\Gamma} \parallel FS(\Gamma) - m \parallel_2^2 + \lambda_1 \Phi(\Gamma) + \lambda_2 \parallel \nabla_{\tau} \Gamma \parallel_1, \quad \Phi(\Gamma) = \sum_{b \in \Omega} \parallel C_b(\Gamma) \parallel_p$$

where Γ is the image to be reconstructed, m is the multi-coil k-space measurement, F is the Fourier sampling operator, S are the coil sensitivity maps computed from time-averaged data using ESPIRiT [6], $||.||_p$ is the non-convex Schatten p-norm (p=0.5 in this study), a surrogate to rank [1], C_b is the operator to extract b'th patch matrix (5×5×Nt in size) from Γ , Ω is the total number of overlapping patches and ∇_t is the finite difference operator along time. The proposed method was compared against: 1) temporal TV constraint alone ($\lambda_1 = 0$), 2) LLR constraint alone ($\lambda_2 = 0$) [3] and 3) kt-SLR method, in which Φ is replaced with global low rank constraint using Schatten p-norm [1]. To improve reconstruction speed compared to Ref [1], alternating direction methods of multipliers (ADMM) with variable splitting [7] was used to solve the optimization problem. Image Quality Assessment: Three metrics were chosen for quantitative evaluation against fully-sampled reference images: rMSE, structural similarity index (SSIM) [8] and high frequency error norm (HFEN), which was used to evaluate the reconstruction of edges and fine structures [9]. All metrics were computed within the manually defined region of interest (the heart) and averaged among timeframes. Regularization parameters for each algorithm were optimized by referring to rMSE.

RESULTS: Fig. 1 compares x-t plots of the reconstruction result from the four methods in two representative datasets. At an acceleration factor of 20, LLR showed considerable edge blurring, tTV produced patchy artifact, kt-SLR had less TV-related artifacts but presented more edge blurring than LLR+tTV. Compared to the other three methods, LLR+tTV better preserved the fine structure (mitral valve) in the long-axis case (arrows in FIG. 1b). When the acceleration factor increased to 50, the artifacts described above were amplified. The patchy artifacts in tTV reconstruction (arrows in FIG. 1c and 1f) affected the visualization of the myocardial borders (dotted curves in the reference x-t plots). In contrast, LLR+tTV more reliably preserved the myocardial borders. Quantitative evaluation matches these qualitative observations. As depicted in Fig.2, LLR+tTV reconstruction had consistently superior rMSE, SSIM and HFEN scores compared to the other three methods. The metric advantage of LLR+tTV was more significant in cases with higher level of under-sampling. The score difference for individual time frames was consistent with the average of the entire time series (not shown). No essential difference was found between cases with 2D random and Cartesian golden-angle radial under-sampling.

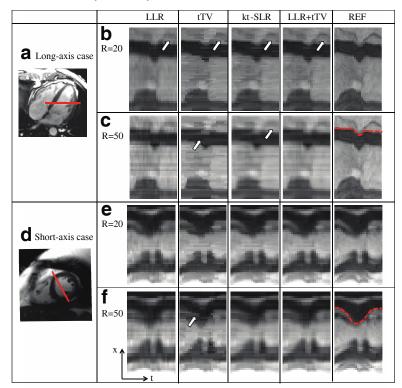


Figure 1 Comparison of the four methods based on x-t plots. Datasets were under-sampled with 2D random sampling pattern. Reference images (a,d) indicate the position of 'x' in b-f.

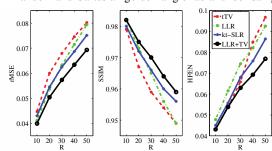


Figure 2 Quantitative evaluation of one example dataset. rMSE, SSIM and HFE as a function of acceleration factor shows consistently superior performance of LLR+tTV.

CONCLUSION: When performing highly accelerated cardiac cine with 2D random or Cartesian golden-angle radial sampling, the combination of LLR and temporal TV constraints provides superior image quality (preservation of fine structures, and endoand epi-cardial boundaries) compared to prior approaches, suggesting this as a promising approach for 3D cine CMR.

REFERENCES: [1] S. G. Lingala, IEEE-TMI 30(5): 1042–1054, 2011 [2] J. P. Haldar and Z.-P.Liang, Proc. ISBI, 2010 [3] J. Trzasko, ISMRM 2011, p. 4371 [4] B. Zhao, IEEE-TMI 31(9): 1809-1820, 2012 [5] www.ismrm.org/challenge [6] M. Uecker, MRM 2014 [7] S. Ramani, IEEE-TMI 30(3): 694-706, 2011 [8] Z. Wang, Image Processing, IEEE Transactions 13(4): 600-612, 2004 [9] S. Ravishankar, and Y. Bresler, IEEE-TMI 30(5): 1028-1041, 2011