6308

Motion Compensated Free Breathing Myocardial Perfusion MRI Using Iterative Non Local Shrinkage

Yasir Q Mohsin[1], Sajan Goud Lingala[2], Edward DiBella[3], and Mathews Jacob[1]

[1]*Electrical Engineering, University of Iowa, Iowa city, IA, United States,* [2]*Electrical Engineering, University of Southern California, Los Angeles, California, United States,* [3]*Department of Radiology, University of Utah, S.L.City,UT, United States*

Target Audience – This work caters to researchers and clinicians interested in free breathing myocardial perfusion MRI with high spatio-temporal resolution and slice coverage.

Purpose: The main focus of this abstract is to recover myocardial perfusion imaging (MPI) data from highly under-sampled measurements. Compressed sensing schemes that exploit sparsity in Fourier and gradient domains are widely used in MPI to improve resolution and coverage [1] [2]. While these methods demonstrate successful recovery when inter frame motion is minimal, they often result in unacceptable spatio-temporal blurring and residual alias artifacts in the presence of respiratory motion and cardiac motion due to inaccurate gating. Methods that combine motion estimation and compensation (ME-MC) have been shown to improve the results in this context [4] [7], but they come with considerably increased computational complexity. In addition, the joint estimation of the motion model parameters and the signal involves a complex non-convex optimization criterion, which is challenging to solve efficiently. The main objective of this work is to introduce a motion compensated MPI recovery scheme that does not require the motion parameters to be explicitly estimated, and hence is considerably more efficient than explicit ME-MC schemes.

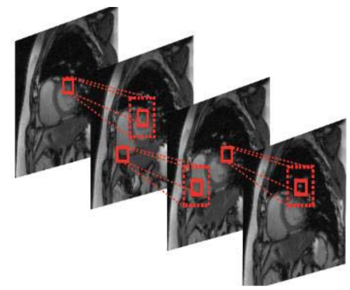

Fig1: Illustration of the proposed patch based regularization scheme. The regularization term penalizes the differences between each patches and other patches in its neighborhood using a robust distance metric. This approach provides motion compensated recovery without the need to explicitly estimate the motion as in traditional ME-MC methods.

Methods: Reconstruction: Motivated by our recent work on patch based regularization in 2-D, we formulate the recovery of the dynamic MRI data from under sampled data as a 3-D patch based regularization scheme.

$$\mathbf{f}^* = \arg\min_{\mathbf{f}} \|\mathcal{A}(\mathbf{f}) - \mathbf{b}\|^2 + \lambda \sum_x \sum_{y\in\mathcal{N}(x)} \varphi\left(P_x(f) - P_y(f)\right)$$

Here, f is the dynamic dataset and $P_x(f)$ is a rectangular image patch centered at the pixel x, while $N(x)$ denotes a search neighborhood around x (see Fig1). The regularization term in the above equation is the sum of distances between each patch $P_x(f)$ and patches $P_y(f)$ in its neighborhood. The neighborhood is chosen to compare patches in adjacent frames, thereby providing implicit motion compensation (see Fig1). We use robust distance metrics φ that saturate with distance to encourage smoothing between similar patches, while discouraging the averaging of dissimilar patches. Our earlier research showed that current non-local algorithms can be explained as the first iteration of an iterative reweighted algorithm to solve the above cost function [3]. The iterative strategy, with proper continuation, is seen to considerably improve performance over current non-local methods. In this work, we use a novel iterative non-local shrinkage algorithm, which is considerably faster than iterative reweighted non-local means [3]; it also provides more accurate solutions. The advantage of our approach lies in the reduced computational complexity compared to the current ME-MC schemes, which require explicit motion estimation. In addition, since the regularization penalty is considerably simpler, we use efficient continuation strategies to encourage the convergence to the global minimum of the criterion.

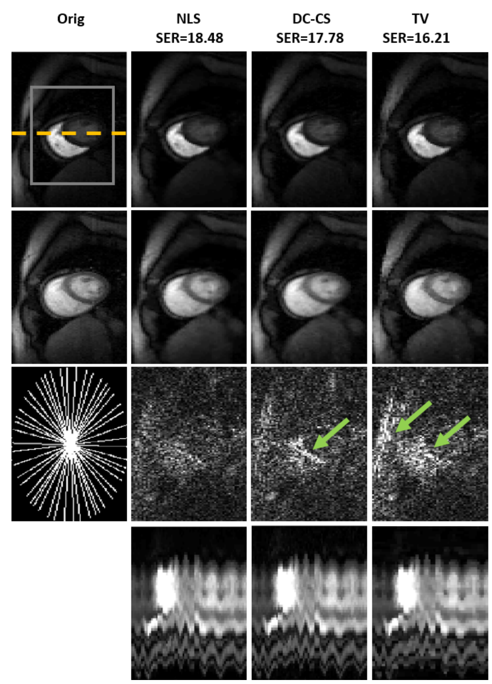

Fig2: ECG gated myocardial perfusion MRI data recovered from 24 lines. For each scheme two frames are shown along with an error image and time profile along the dotted line. The NLS reconstructions shows better depiction of myocardial borders in comparison to DC–CS and TV reconstructions. The SER is computed on the ROI shown in the top left image.

Experimental data used for validation: We perform the recovery of a retrospectively undersampled Cartesian dataset as well as a radial MPI datasets to determine the utility of this algorithm. In the first experiment, the fully sampled single slice data from a fully sampled myocardial perfusion MRI acquisition (Saturation recovery FLASH sequence, TR/TE =2.5/1ms, saturation recovery time = 100ms, 3 slices, phase encodes x frequency encodes: 90 x 190, temporal resolution: 1 beat, spatial resolution: 2.5 mm x 2.5 mm x 8 mm) was retrospectively undersampled using golden angle radial trajectory. The data contained motion primarily due to breathing and inconsistent gating, and also had additional integer shifts to amplify motion (see Fig 2). A golden angle pseudo radial k-t sampling pattern with 24 rays/frame was used for undersampling. The second experiment uses a radially sampled prospective free breathing stress myocardial perfusion data acquired using the TR/TE ≈ 2.6/1.2 ms, 3 slices per beat, flip angle of 14 degrees, 2.3 x 2.3 x 8 mm pixel size, FOV: 280 mm2, bandwidth 1002 Hz/pixel, 72 radial rays per frame with angle rotations of π / 288 radians across frames. For subsampling, we considered 24 rays per frame that were distributed approximately in a golden angle manner. The data was coil compressed to a single coil using the coil compression strategy in [6].

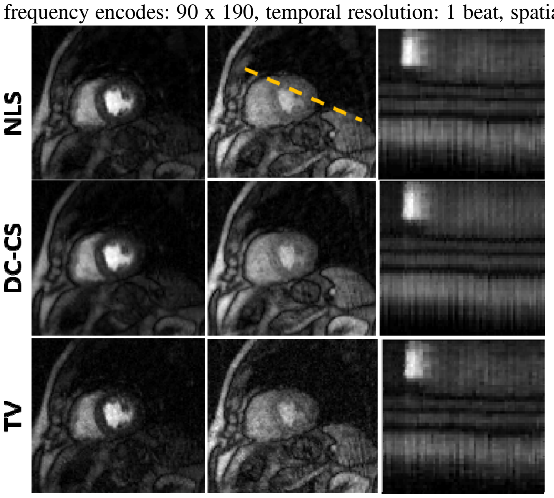

Fig3: comparison on shallow breathing prospective radial using 24 rays/frame. For each scheme two frames are shown and one time profile along the dotted line. We can see that NLS preserves well the motion.

Results: The results of the Cartesian undersampling experiment are shown in (Fig2), where we compare the proposed algorithm against the deformation corrected compressed sensing scheme (DC-CS) [4] and classical temporal total variation based scheme (TV). The run time of our algorithm was considerably shorter (~5 min) than the DC-CS scheme (40.2 min). We also observe that NLS reconstructions shows better depiction of myocardial borders in comparison to DC-CS and TV. The experiments on radial data are shown in (Fig3). The visual comparison depicts that NLS considerably improves image quality over TV in terms of reduced spatio-temporal blurring, and motion artifacts. While the NLS and DC-CS are similar in image quality, the former scheme is considerably more computationally efficient.

Conclusion – The experiments demonstrate the potential of the non-local regularization scheme in providing fast and implicit motion compensated recovery of dynamic MRI data with considerably lower computational complexity than ME-MC schemes, which rely on explicit motion estimation and compensation.

References [1] Adluru G1 et al, J Magn Reson Imaging. 29(2):466-73 2009. [2] Otazo et al. first-pass cardiac perfusion MRI Article first published online: 2010 [3] Yang et al, IEEE TIP, 22 (8), 3192-203, 2013. [4] Lingala et al; IEEE TMI 2014, early view. [5] E. DiBella et al; 1–10, 2011. [6] M. Buehrer et al; MRM 57, 6, 1131–1139, 2007. [7] E. DiBella et al; J Cardiovasc Magn Reson 15.1 (2013): 26.