Motion Compensated Dynamic Imaging without Explicit Motion Estimation

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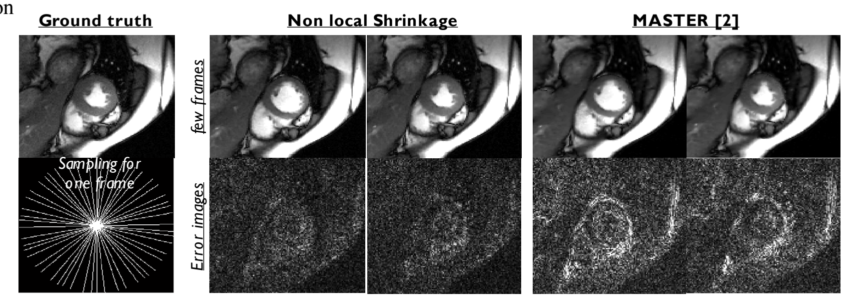
Target Audience – This work caters to researchers and clinicians interested in the recovery of dynamic MR images from highly under-sampled k-space data.

Purpose – The main focus of this abstract is to recover dynamic MRI data from highly under-sampled measurements. Compressed sensing schemes that exploit sparsity in Fourier and gradient domains have enjoyed a lot of success in breath-held cardiac MRI. However, these schemes often result in un-acceptable spatio-temporal blurring and residual alias artifacts, when applied to free breathing cardiac MRI with or without cardiac gating. The main reason is the high inter-frame motion, often introduced by respiration. Methods that combine motion estimation and compensation (ME-MC) have been shown to improve the results in this context, 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 often difficult to solve. Our main objective is to introduce a novel framework for motion-compensated dynamic MR image recovery that does not suffer from the above mentioned drawbacks.

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

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

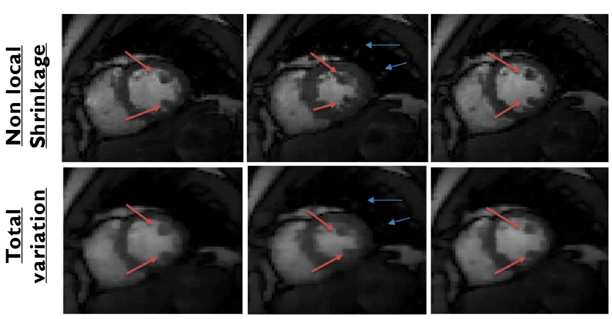
Here, f is the dynamic dataset and x specifies different voxels in the dataset. Here $P_x(f)$ is a rectangular image patch centered at the pixel x and N(x) indicates a small search neighborhood around x. We use robust distance metrics φ that saturate with distance to encourage smoothing between similar patches, while discouraging the averaging of dissimilar patches. Since the regularization penalty penalizes the distances between each patch in the image and similar patches in the adjacent frame, this algorithm provides implicit motion compensation. Our earlier research showed that current non-local algorithms can be explained as the first iteration of a iterative reweighted algorithm to solve the above cost function [1]. 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 to solve the above optimization criterion, which is around 10 times faster than our previous iterative reweighted algorithm. It is also seen to provide more accurate solutions with improved image quality.



Experiment 1 (Retrospective downsampling of a fully sampled dataset): We show example dynamic frames for the NLS and the MASTER[2] algorithms. The error images are shown in the second row. We observe that the proposed NLS scheme depicted superior quality specifically near the myocardial borders and maintained crisp features. The SER (Signal to Error) values for NLS and MASTeR were 26.94db and 23.18dB respectively.

We demonstrate the utility of the proposed scheme on two experiments. In the first experiment, we retrospectively undersample a fully sampled breath-held CINE dataset (5 coils, TE: 2:0 ms, TR: 4:1 ms, ip angle: 45_, FOV: 350_350 mm, slice thickness: 12 mm, 8 views per segment, 224 phase-encoding lines, 256 read-out samples, and 16 temporal frames). We assumed a sampling pattern with radial spokes uniformly distributed within a single frame, while subsequent frames had the pattern rotated by small random angles to ensured incoherent sampling. We reconstruct the data using the proposed scheme. and an ME-MC algorithm termed as MASTER [2]. In a second experiment, we determine the ability of the proposed scheme to recover dynamic images from undersampled Cartesian k-t measurements that were acquired using a real time free breathing sequence. This data was acquired using a SSFP sequence on Siemens 3T scanner with 12 coil elements total (body and spine coil arrays). The relevant parameters include FOV:320mm2, Image matrix 128x128, TR=1.37 ms, TE:2.7 m, BW:1184 Hz/pixel, and flip angle=40 degrees [3] In this paper, we only used a single coil for the recovery. We compare the proposed reconstruction against the classical total variation recovery of the same dataset. The parameters of all the algorithms were tuned for optimal performance.

Results – The results of the retrospective downsampling experiments are shown in Fig. 1, where we compare the proposed algorithm (second column) against the ME-MC algorithm (third column). We observe that the proposed scheme is capable of providing comparable or even better image quality than the more complex ME-MC scheme; the the run time of the proposed algorithm was considerably shorter than the ME-MC scheme. The retrospective experiments are shown in Fig. 2. The comparison against classical total variation regularization shows that the proposed non-local regularization scheme is capable of provide considerably less blurred images. We are currently extending the proposed algorithm to multi channel recovery, which is expected to further improve performance.



2nd experiment: We used Cartesian undersampled real CINE datasets recovered from 18 lines. The NL shrinkage reconstructions show better depiction of myocardial borders and papillary muscles and preserve crispness in comparison to the TV reconstruction.

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

IV. References 1. Z.Yang, M.Jacob, Nonlocal regularization of inverse problems: a unified variational framework", IEEE TIP, vol.22(8), pp 3192-203, 2013.

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