Accelerated myocardial perfusion MRI using motion compensated compressed sensing (MC-CS)

Sajan Goud Lingala[1], Edward DiBella[2], and Mathews Jacob[1]
[1]The University of Iowa, Iowa city, IA, United States, [2]University of Utah, Salt lake city, UT, United States

Introduction: High spatiotemporal resolution, slice coverage, and signal to noise ratio are necessary to accurately quantify first pass myocardial perfusion MRI data. Compressed sensing (CS) schemes that exploit sparse representations in transform domains such as temporal Fourier domain [1] and temporal total variation domain [2] have been proposed to recover myocardial perfusion data from undersampled data. However, one challenge is the sensitivity of these methods to inter-frame motion, which decreases the sparsity of the representation; these methods suffer from temporal blurring at high accelerations. One approach to overcome this challenge is to estimate the motion and compensate for it during reconstruction. Otazo et al. in [3] partially corrected for the motion using a rigid deformation model, where all the frames from a preliminary CS reconstruction were mapped to a single fully sampled reference image to estimate the motion. However, registering image frames to a single reference image may be suboptimal as image contrast varies significantly across time-frames [4]. In this work, we propose a novel framework to jointly estimate motion and dynamic images from undersampled data. The proposed scheme does not require any training data or customized navigators to estimate the motion. Instead of using a single reference image as in [3], the proposed scheme uses an implicit motion compensated dynamic dataset with perfusion contrast, which is used as the reference. In addition, it utilizes a more flexible non-rigid deformation model.

Methods: The joint estimation of the dynamic images $f(\mathbf{x},t)$ and the motion parameters $\theta(\mathbf{x},t)$ from undersampled data $\mathbf{b}(\mathbf{k},t)$ is posed as the total variation penalized minimization criterion:

$$\min_{f,\theta} \underbrace{\left\|A(f)-b\right\|_2^2 + \lambda\, TV(\tau_\theta(f))}_{C(f,\theta)}; \qquad (1)$$

The regularization penalty is essentially the temporal TV norm of the motion compensated dataset $\tau_\theta(f)$; here, τ_θ is the spatial warping operator. A is the Fourier sampling operator and λ is the regularization parameter. We simplify (1) as a constrained optimization problem by introducing a motion compensated auxiliary dataset $\tau_\theta(f)=g$. By using a quadratic penalty to enforce the constraint, we simplify (1) as :

$$\min_{f,g,\theta} \left\|A(f)-b\right\|_2^2 + \lambda\, TV(g) + \lambda\beta\left\|\tau_\theta(f)-g\right\|^2; \qquad (2)$$

While this form appears more complex than (1), it results in considerable simplification. We rely on an alternating minimization strategy to update the variables, thus obtaining an iterative algorithm with three simple steps:

(a) Quadratic regularization scheme to update *f*,
(b) Total variation shrinkage to derive *g* by smoothing the warped dataset, and
(c) Deformable registration algorithm to determine θ by comparing *f* and *g*.

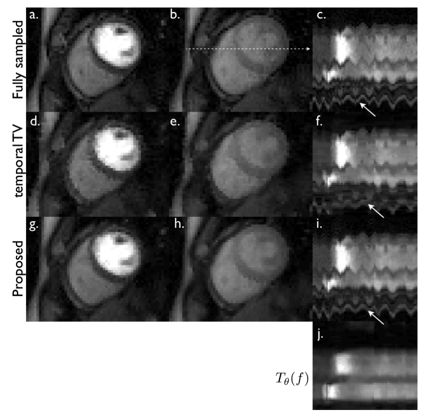

Fig.1 Simulation results: Few spatial frames and the image time profile are shown for the fully sampled data (top row), temporal TV constrained reconstruction (second row), and the proposed method (third row). The TV reconstruction lost significant temporal detail due to motion blurring. The proposed motion estimation compensation reconstruction scheme was able to correct for these artifacts, and obtained robust reconstructions with high spatio-temporal fidelity. The warped time series using the estimated motion maps is also shown in (j).

The first step is obtained by fixing *g* and τ_θ in (2). We solve $\min_f \left\|A(f)-b\right\|_2^2 + \lambda\beta\left\|f-g_1\right\|^2$ using the conjugate gradient optimization scheme. Here, $g_1=\tau_\theta^{-1}(g)$. The second step is specified by $\min_g TV(g)+\beta\left\|f_1-g\right\|^2$. Here, $\tau_\theta f = f_1$. This sub-problem is solved using total variation shrinkage, resulting in temporal smoothing of $\tau_\theta f$. Finally, we solve for the deformation parameters by solving $\theta=\arg\min_\theta\left\|\tau_\theta(f)-g\right\|^2$ using a deformable registration algorithm. We initialize the scheme with $g=0$ and $\tau_\theta=I$. We start with a small value of β and progressively increase it to enforce the constraint.

Reconstruction examples

Simulation: In figure 1, we considered a simulated experiment, where we retrospectively undersampled a fully sampled myocardial perfusion data set. This data was acquired with a saturation recovery FLASH sequence (TR/TE=2.5/1ms) on a Cartesian grid (N_{PE} x N_{FE} = 190 x 90; time resolution: 1sec). The data contained motion primarily due to breathing and inconsistent gating. Some integer shifts were added to amplify motion (see fig.1, c). A golden ratio radial trajectory with 20 rays was considered for undersampling. From figure 1, we observe the temporal TV constrained reconstruction to suffer from considerable loss in temporal detail due to motion related artifact. The proposed scheme compensated for these artifacts, and provided robust reconstructions with high spatio-temporal fidelity. Also shown in fig 1(j) is the warped dynamic image time series using the motion estimates from the proposed scheme.

Invivo experiment: Patient data was acquired during free breathing stress perfusion using a radial FLASH saturation recovery sequence (TR/TE = 2.5/1.3 ms; 5 slices, 72 radial rays uniformly spaced in each frame with uniform rotations across frames, 256 read out points, 4 coils). In figure 2, we considered reconstructing a subset of this data. Specifically we performed a single coil single slice reconstruction using 21 radial rays. As demonstrated in fig. 2, we find that the proposed scheme corrects for the motion blur observed with temporal TV, especially in image frames with significant motion.

Discussion: We have proposed a novel motion compensated compressed sensing reconstruction scheme for myocardial perfusion MRI. Our preliminary results show that proposed scheme is able to considerably reduce motion related artifacts in temporally constrained reconstruction. Extensions to multicoil imaging could further improve the performance, similar to those in [1].

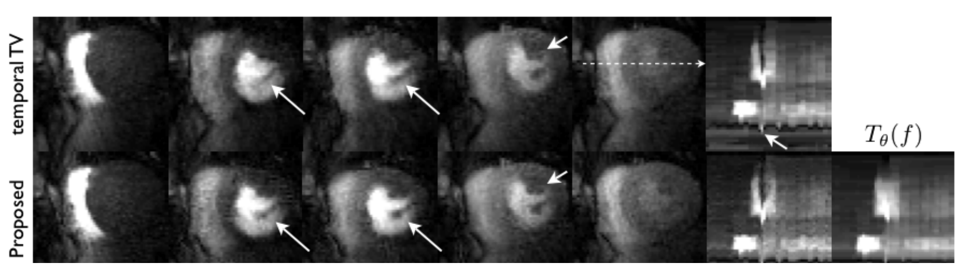

Fig.2 Invivo experiment results: Undersampled reconstruction using data from 21 radial rays/frame and single coil from a stress perfusion exam is considered. Few spatial frames and the image time profile are shown for the temporal TV constrained reconstruction (first row), and the proposed method (second row). The TV reconstruction had temporal blurring especially evident in frames with high motion (see arrows in top row). In contrast, the proposed scheme had crisper images with better temporal fidelity (see arrows in bottom row). Also shown in the bottom row is the warped time series using the estimated motion maps.

References

[1] Otazo et al , MRM 2010, [2] Adluru etal MRM 2009, [3] Otazo et al ISMRM 2011, [4] Adluru etal MRM 2006.