Motion-Guided Temporally-Constrained Compressed Sensing for Dynamic MRI

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Background:
Compressed sensing (CS) exploits data sparsity to accelerate MR image acquisition and uses a nonlinear algorithm to reconstruct images from k-space data sampled below the Nyquist rate[1]. An MR image series presents sparsity in the time domain (temporal sparsity) when its signal intensity changes smoothly over time[2], which occurs quite commonly with dynamic contrast-enhanced images, multi-TI images and several other types of acquisitions. However, object motion within the image series violates the temporal smoothness constraint and significantly degrades the quality of the CS-reconstructed images. To improve CS reconstruction quality in the presence of object motion, we propose a general motion-guided (MG) CS algorithm which uses motion tracking to guide the CS sparsity transform.

Theory:
To incorporate motion guidance into a temporally-constrained CS reconstruction model[3], the following optimization cost function was used:
$f(R,m)=\|F_u m - y\|_2^2 + \lambda\|\nabla_t Rm\|_1$, where m is the image with motion, R is the motion guidance operator, y is the measured k-space data, F_u is the under-sampled Fast Fourier Transform (FFT), ∇_t is the temporal gradient, λ is a weighting factor for the temporal smoothness term, and $\| \|_2$ and $\| \|_1$ are the l2 and l1 norms, respectively. The motion guidance operator, R, tracks the motion in the images and guides the sparsity transform ∇_t in the motion direction (rather than using a straight line in the temporal-spatial space), as illustrated in Fig 1. With this approach, we iteratively optimize unregistered images, m, and apply the constraint to these images after applying the motion guidance operator. Another approach could be to iteratively optimize registered images. However, this approach would require using the inverse transform of R in the fidelity term, which may not be feasible for some motion guidance operators. In the early iterations of the CS optimization, a global cross-correlation rigid registration method[4] was used. When spatial resolution is increasing during the later iterations, an affine registration or a regional B-spline non-rigid registration method was used to register finer details[5]. For each iteration i of the CS reconstruction algorithm, R_i is updated from previously estimated images m_{i-1}. The current image estimate m_i is then calculated by minimizing the cost function using R_i.

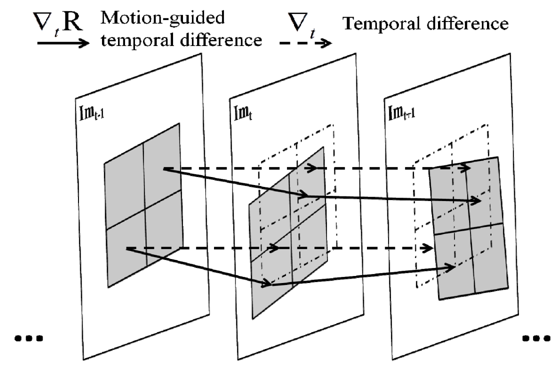

Fig 1. Motion guidance is required to compute the correct image temporal difference. Im_{t-1}, Im_t and Im_{t+1} are three consecutive dynamic images in time. When motion occurs between Im_{t-1}, Im_t and Im_{t+1}(from dashed frame to solid frame), the temporal difference from motion-corrected images (solid arrow) is correctly computed, while the temporal difference calculated from non-motion-corrected images (dashed arrow) is incorrect due to mis-registration.

Methods:
The proposed motion-guided CS reconstruction algorithm was tested on a series of cardiac first-pass contrast-enhanced perfusion images with substantial respiratory motion. Retrospective under-sampling was performed using a k_y-t pattern in which the center of k-space was sampled at the Nyquist rate and higher-spatial-frequency lines were randomly under-sampled, with an overall undersampling rate of 4. CS reconstruction was implemented in MATLAB (The Mathworks, Natick, Massachusetts). Images reconstructed with the motion-guided CS reconstruction algorithm were compared to images reconstructed using the same CS algorithm without motion correction.

Results:
Improved image quality was obtained by using the proposed motion guided CS algorithm, as illustrated in Fig 2. The images reconstructed using motion guided CS (4th column) more closely resemble the fully sampled images (1st column), preserving sharper edges and finer details than in images reconstructed without motion guidance (the 3rd column).

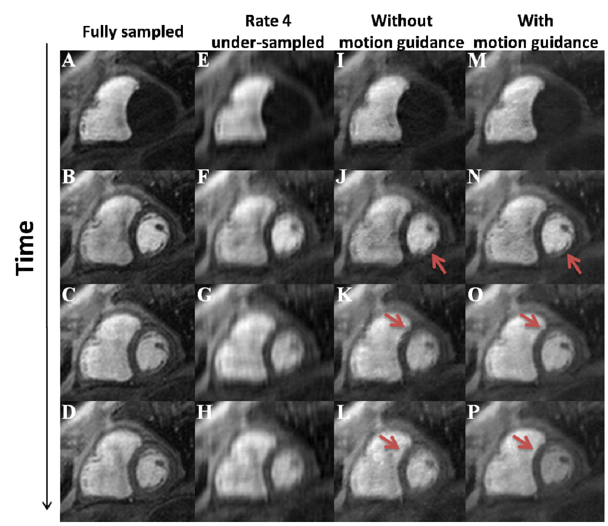

Fig 2. CS Reconstruction of a series of contrast-enhanced cardiac perfusion images. The first and second columns are the images reconstructed using FFT from fully sampled and rate 4 under-sampled k-t space respectively. The third and fourth columns are the CS-reconstructed images without (3rd column) and with motion correction (4th column). The red arrows highlighted areas that are blurred or obscured due to motion and are recovered by CS with motion correction.

Conclusion and Discussion:
We developed a motion-guided temporally-constrained CS reconstruction algorithm capable of accurately reconstructing images in the presence of physiologic motion. Improved image quality was observed using the proposed algorithm at an acceleration rate of 4 compared to non-motion guided reconstruction. Importantly, our method can be broadly generalized: the motion guidance operator R in the cost function is not limited to a particular registration method or model, and any algorithm that describes object movement, such as optical flow, could be used. Future work includes applying the algorithm to dynamic cine images, combining the algorithm with parallel imaging techniques, and performing a systematic evaluation of the algorithm on more datasets.

References: [1]Lustig et al. MRM 2007 58:1182-1195 [2]Adluru et al. MRM 2007 57:1027-1036 [3]Chen et al. ISMRM 2011 p6349 [4]Guizar-Sicairos et al. Opt. Lett. 2008 33:156-158 [5]Kroon. www.mathsworks.com 2011

Acknowledgements: This study was funded by NIH R01 EB 001763 and Siemens Medical Solutions. Thank N. Tustison for providing expertise in image registration methods.