A frame work for non-rigid motion corrected compressed sensing for highly accelerated MRI

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Introduction: Compressed Sensing (CS) has been demonstrated to reconstruct sparse MR images of adequate quality from highly undersampled data [1], resulting in reduced scan times. In MRI, extensive motion during the acquisition (e.g. respiratory motion in cardiac scans) can cause inconsistencies in the k-space data, introducing blurring and ghosting like motion artefacts in the reconstructed images [2]. Motion correction is needed for these applications in CS MRI, not just to correct the motion related artefacts, but also to retain the sparsity level in sparse representation (such as x-f space in dynamic MRI) [3]. Recently, motion correction methods have been combined with CS to partially correct for effects of motion [4]. However, these approaches have been shown to correct for translational deformations only. In this work, we propose a novel Motion Corrected-Compressed Sensing (MC-CS) technique that incorporates a generalized motion correction formulation directly into the CS reconstruction. This technique can correct for any arbitrary non-rigid motion in the images reconstructed from CS undersampled data. The usefulness of this approach is demonstrated both in simulations and in-vivo free-breathing 2D CINE MRI, using a golden radial acquisition [5]. Results show that using this approach, a cardiac cycle free from respiratory motion, can be reconstructed with the same quality compared to that for the breath-held data. To our knowledge, the proposed approach is the first combination of CS and motion correction, where the motion information is directly incorporated into CS reconstruction.

Theory: Considering a free breathing CINE acquisition with N cardiac phases and T respiratory positions, the motion corrupted undersampled k-space data ($\mathbf{y_n}$) for each cardiac phase n=1,2,...,N corresponds to: $\mathbf{y_n} = \Sigma_t\, \mathbf{A_{t,n}}\, \mathbf{F^s}\, \mathbf{U_{t,n}}\, \mathbf{x_n}$ **(Eq 1),** where $\mathbf{x}_n$ is the motion-corrected image for cardiac phase 'n', $\mathbf{U_{t,n}}$ is the matrix describing the non rigid motion at respiratory position 't' (t=1,2,..,T) for cardiac phase 'n', $\mathbf{F^s}$ is the 2D spatial Fourier transform, $\mathbf{A_{t,n}}$ is the sampling pattern at the respiratory position 't' for the cardiac phase n, all $\mathbf{A_{t,n}}$'s for a specific cardiac phase 'n' are assumed to be mutually exclusive, $\mathbf{\Sigma}$ is the summation operator.

The proposed Motion Corrected-Compressed sensing (MC-CS) formulation is given as: $\min_x \| \mathbf{F^t}\, \mathbf{x} \|_1$ s.t. $\mathbf{y_n} = \Sigma_t\, \mathbf{A_{t,n}}\, \mathbf{F^s}\, \mathbf{U_{t,n}}\, \mathbf{x_n}$ **(Eq 2)**, where $\mathbf{F^t}$ is the Fourier transform along the temporal dimension, $\mathbf{x} = [\, \mathbf{x}_1\, \mathbf{x}_2 \ldots \mathbf{x}_N]^T$ and $\|.\|_1$ denotes the l_1 norm. Using the motion information embedded in $\mathbf{U_{t,n}}$, the above formulation finds the sparsest solution in the x-y-f space. In the min l_1-norm based reconstruction, instead of performing the inversion of operator $\mathbf{g_n} = \Sigma_t\, \mathbf{A_{t,n} F^s}\, \mathbf{U_{t,n}}$, the adjoint operator $\mathbf{g_n}^* = \Sigma_t\, \mathbf{U_{t,n}}^* \mathbf{F^s}^* \mathbf{A_{t,n}}^*$ can be used as is depicted in [2] with conjugate gradient method.

Method: An ECG gated golden angle radial acquisition is performed to ensure the k-space sample locations for any specific cardiac phase and respiratory position are mutually exclusive in subsequent R-R intervals allowing flexibility in the reconstruction. Data from different cardiac cycles is retrospectively combined to reconstruct N different cardiac phases (Fig. 1). The proposed method can be divided into four steps (a-d):
a) The acquired data is binned according to the respiratory signal that yields binned data $\mathbf{y_{ms,t}}$ for each respiratory position 't' *b)* A preliminary CS reconstruction of all cardiac phases at each respiratory position't' is done using k-t Sparse method (with x-y-f as sparse representation) [6]. *c)* Each cardiac phase within different respiratory positions is registered to a reference position in the breathing cycle (e.g. end-expiration) using an efficient non-rigid registration algorithm [7] to yield motion parameters. *d)* Using the motion matrices $\mathbf{U_{t,n}}$'s constructed from motion parameters, the MC-CS reconstruction is done using the formulation in Eq (2).

Experiment: *a) Simulation:* Golden radial motion corrupted data was simulated from cardiac gated breath-held CINE data acquired on Philips 1.5T (b-SSFP, TR/TE=3/1.46 msec, matrix size: 256x154, 50 cardiac phases, FOV: 400x320 mm^2, scan time=25sec). Two non-rigid transformations corresponding to different radial and angular deformations were generated for two respiratory positions. The reference respiratory position was considered to be the end- expiration at which the breath-held data were obtained. To simulate CS undersampling, the number of profiles in each respiratory position was reduced by a factor of 15. For comparison, a CS reconstruction without motion correction (CS+no MC) was also performed. The acquired fully sampled breath-held images were considered as being the ground truth.

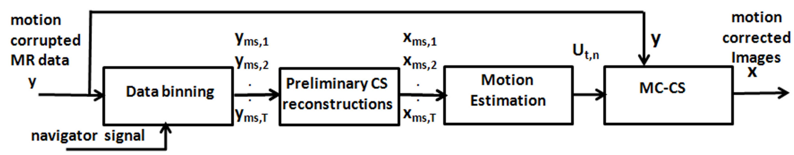

Fig 1: *Block diagram of proposed Motion Corrected-Compressed Sensing (MC-CS) framework*

b) In-vivo Experiment: An ECG-gated free breathing golden radial acquisition was performed on Philips 1.5T in two volunteers (b-SSFP, TR/TE=4/1.46 msec, matrix size =160x160, FOV: 300x300 mm^2, 200 radial profiles per cardiac cycle, scan time=36 sec). The respiratory signal was estimated from the data itself using an image based navigator [8]. The acquired data were binned into three regularly spaced respiratory positions (bin width: 3mm) with regard to the displacement of diaphragm at the lung-liver interface, with the bin near end-expiration being the reference. Twenty cardiac phases were retrospectively reconstructed.

Results and Discussion: *a) Simulation:* One of the example set of motion fields (in horizontal and vertical directions) that was used to generate non-rigid spatial transformations is shown in Fig 2 (top row). The CS reconstruction results without and with motion correction are also shown in Fig.2 together with the fully sampled reconstruction. The cardiac frames and profiles corresponding to temporal variation of pixel intensities (along the white dotted line across ventricles) are shown. Strong blurring artefacts are evident in the CS+ no MC reconstruction. MC-CS corrected for non-rigid motion and achieved similar image quality as for breath-held images.
b) In-vivo Experiment: The reconstructed cardiac frames and temporal profiles without and with motion correction are shown in Fig. 3. MC-CS method corrected for blurring artefacts and resulted in higher spatial and temporal quality of the reconstructed images.

Because, the data in each respiratory position has to be sufficient in order to reconstruct the major anatomy of the heart for motion estimation, the proposed approach requires slightly longer scan time than that for breath-hold acquisition, but it allows self-gated free-breathing acquisition in a short scan time (36 sec). In the future, we will combine all steps of the proposed method into one coupled problem, using an approach similar to GRICS [9].

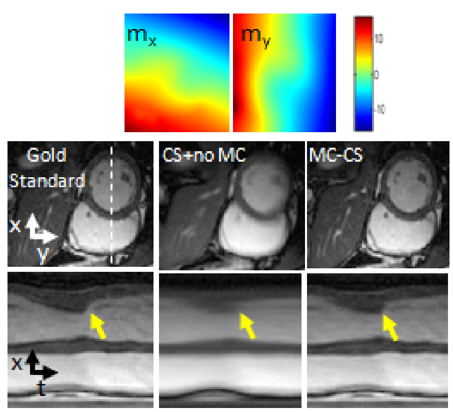

Fig 2: Simulation results: first row: *One of the example set of motion fields (**m_x** and **m_y**) that was used to generate non-rigid spatial transformations,* ***second row:*** *reconstructed cardiac frames obtained from CS reconstruction without and with motion correction,* ***third row:*** *reconstructed profiles corresponding to the temporal variation of pixel intensities along white dotted line. MC-CS corrected for non-rigid motion and achieved image quality similar to the breath-held images.*

Conclusion: A novel reconstruction method was presented which benefits from high acceleration available with CS, and correction for any arbitrary non-rigid motion in the CS reconstruction.

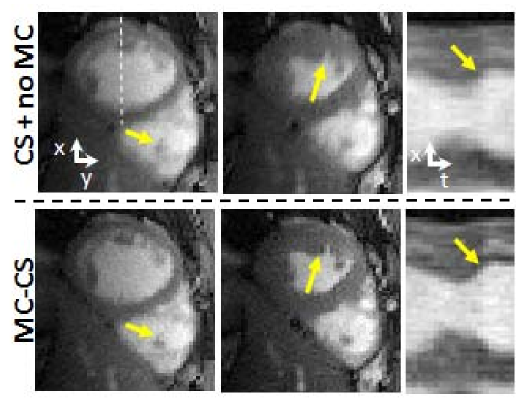

Fig 3: ***In-vivo experiment results: upper row:*** *reconstructed cardiac frames and temporal profiles for CS reconstruction with no motion correction. Frames at both diastole and systole are shown.* ***lower row:*** *cardiac frames and temporal profiles reconstructed with MC-CS method. The arrows indicate regions where the MC-CS method is able to correct for blurring artefacts in the CS reconstruction*

References:[1] Lustig et al, MRM, 2008 [2] Batchelor et al, MRM 2005 [3] Jung et al, Phy Med Bio, 2007 [4] Otazo et al, ISMRM 2011 [5] Winkelmann et al, IEEE TMI, 2007 [6] Lustig el al, ISMRM, 2007 [7] Buerger et al, Med Im Anal, 2011 [8] Kellman et al, MRM, 2008 [9] Odille et al, MRM, 2008