Towards 3D Dynamic MRI of the Lung using Blind Compressed Sensing

Sajan Goud Lingala[1], Yasir Baqqal[1], John Newell[1], Dingxin Wang[2], Jessica C Sieren[1], Daniel Thedens[1], and Mathews Jacob[1]
[1]*University of Iowa, Iowa city, Iowa, United States,* [2]*Siemens Medical Solutions, Minneapolis, MN, United States*

Target audience: Researchers and clinicians interested in 3 dimensional dynamic MRI (3D-DMRI) of lung. The presented methods of blind compressed sensing and 3D radial imaging are also of interest to researchers involved in image reconstruction.

Purpose/Introduction: 3-D dynamic MRI of the lung is a promising tool to assess lung function and mechanics. Compared to multi-slice 2D-DMRI, 3-D acquisitions enables the accurate estimation of lung volumes and its variations. It has recently been shown that the vital capacities estimated from 3D acquisitions are more correlated with spirometric measurements compared to 2D-DMRI [1]. However, its full potential is not clinically realized due to restricted spatio-temporal resolutions and volume coverage. To obtain whole lung coverage, a 3D FLASH scheme with Cartesian undersampling, view-sharing and parallel imaging was realized in [1] to achieve an isotropic resolution of 3.75 mm^3 with 1 sec time resolution. However the reconstruction scheme was designed to image the dynamics of the lung during very slow, and controlled breathing conditions. More recently, [2] used a 128 channel coil array with Cartesian 3D-FLASH to image realistic breathing conditions.

In this work, we propose to employ a recently proposed blind compressed sensing (BCS) scheme [3] to overcome existing trade-offs with 3D-DMRI. The BCS scheme exploits the sparsity of the dynamic dataset in a dictionary of temporal bases that are estimated from the measurements. Since the bases are learnt from the data at hand, they are more representative of the temporal variations within the data, and are expected to provide sparser representations than compressed sensing (CS) schemes that utilize predetermined bases. In addition, it does not require any assumptions on the breathing conditions. Additionally, we propose to combine BCS with parallel imaging and golden angle (GA) radial sampling; the combination offers superior incoherence properties.

Methods: ***(a) Blind compressed sensing***: The BCS scheme models the spatio-temporal Casorati signal matrix ($\mathbf{\Gamma}_{MxN}$) as a product of a sparse coefficient matrix ($\mathbf{U}_{MxR}$) and a dictionary of temporal basis functions ($\mathbf{V}_{RxN}$); where M, N, R are respectively the number of pixels in each frame, the number of time frames, and the number of bases. The reconstruction is posed as an optimization problem by promoting l_1 norm sparsity on $\mathbf{U}$ and energy preserving Frobenius norm on $\mathbf{V}$ (to avoid scale ambiguity): $\min_{\mathbf{U},\mathbf{V}} \|A(\mathbf{UV}) - \mathbf{b}\|_2^2 + \lambda_1\|\mathbf{U}\|_1 + \lambda_2\|\mathbf{V}\|_F^2$; where $\mathbf{b}$ is the undersampled k-t data. $\boldsymbol{\lambda_1}$ and $\boldsymbol{\lambda_2}$ are regularization parameters. The operator A considers coil sensitivity encoding, and Fourier transform evaluation on radial trajectory. The coil maps are estimated from time averaged data using an eigen-decomposition method [4]. The optimization is solved by using an efficient majorize minimize algorithm by alternating between three well defined subproblems [3].

Experimental evaluation: ***(a) Retrospective undersampling of a 2D acquisition:*** To test the feasibility of the BCS scheme in accelerating typical DMRI lung data, we performed retrospective undersampling experiments on a 2D free breathing dataset. Data from one coronal slice was acquired on an anesthetized swine using a TrueFISP sequence (TR/TE = 138.62 /TE = 1.06 msec, phase encodes: 128, Image matrix size after interpolation: 256x256, FOV 320 mm2, GRAPPA factor: 3) on a 3 T Siemens Trio with the body matrix coil array. The 28 second acquisition resulted in 200 2D images with a temporal footprint of ~7images/sec. The reconstructed images were retrospectively undersampled using a golden angle radial k-t sampling pattern. Subsampling was performed by considering 40 to 10 spokes/frame. Image reconstructions with BCS, CS using Fourier bases, low rank (nuclear norm regularized), and view sharing were performed and compared.

(c) Prospective 3D undersampling with stack of spokes GA radial acquisition: A radial FLASH sequence with a 3D stack of spokes trajectory was used to image a healthy volunteer on a Siemens 3T Trio scanner with the body coil and spine coil arrays enabled. The sequence performs a radial readout in the read/phase (kx-ky) plane combined with a conventional 3D encoding step along the kz partition. The spacing between the spokes in each kx-ky plane is determined by golden angle of 111.25 degrees. 1000 radial spokes in each partition were continuously acquired for a total of 45 secs during normal breathing with (16 coronal partitions, TR/TE = 2.84ms/1.24ms, FOV: 380mmx380mm, Base matrix size: 160x160, 2.37x2.37x4mm3). The data was binned at a time resolution of 0.72 seconds by considering 16 spokes/frame resulting in total of 62 frames. This corresponded to an acceleration of R = 10 fold, defined as (R = Base matrix size./spokes). The BCS reconstruction was performed slice by slice after performing an inverse Fourier Transform along the kz dimension.

Results: From figure 1, we observe that the BCS scheme provided superior reconstructions compared to all the other methods. The view sharing method resulted in severe temporal blurring and artifacts due to normal breathing conditions. The CS scheme was found to be sensitive to motion artifacts, while the low rank reconstructions suffered from spatio-temporal blurring. The superior performance of BCS is attributed to the learned basis functions which capture underlying temporal dynamics (see example bases in fig.1). Feasible acceleration levels of upto 10 fold, (25 spokes/frame) where the mean square error was within 0.1 percent was achieved with the BCS scheme.

In figure 2, we show every fourth slice from the 16 slice reconstructed dataset. The BCS reconstructions depicted adequate image quality in all the dynamic frames with minimal artifacts. The intensity variations of a pixel on the diaphragm depict the dynamics during breathing.

Discussion: This work showed preliminary feasibilities that BCS scheme utilizing learned dictionaries could significantly accelerate 3D dynamic lung MRI. During normal breathing with a 10 fold acceleration factor, spatial resolutions and time resolutions of upto (2.37mm2, 0.72 sec) were achieved with a reasonable slice coverage (16 slices, 4 mm thickness). Further acceleration factors could be achieved by exploiting redundancies along the kz dimension, and undersampling the kz dimension. Future work includes systematic analysis under different breathing conditions (normal/deep/shallow) with comparisons against spirometry. Further analysis on multiple patient datasets with image quality evaluation using clinical scoring are required to fully evaluate the reconstructions.

References: [1] Plathow et al., Investigative Radiology 05 [2] Tokuda et al., ISMRM 2008 [3] Lingala et.al, IEEE TMI 2013, [4] Walsh et al, MRM 2000.

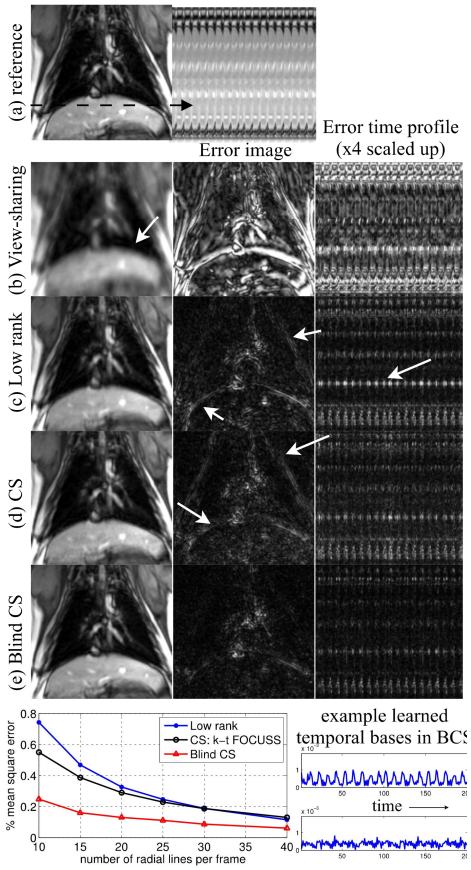

Figure 1: Comparisons on 2D data with retrospective undersampling: BCS depicted superior quality in terms of minimial temporal and motion blurring. This is attributed to the usage of learned bases that represent the temporal dynamics (see example BCS bases in the last row that depict patterns from breathing and cardiac pulsations).

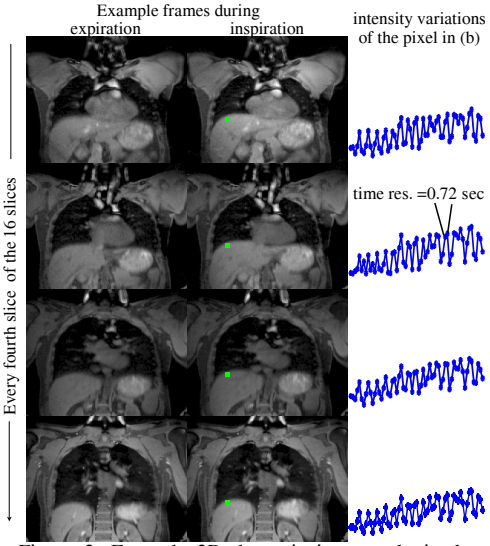

Figure 2: Example 3D dynamic images obtained with BCS using 16 spokes/frame with 16 slices, at spatial resolutions of 2.37x2.37x4mm3, and time resolution of 0.72sec.