Very Rapid 4D Compressed Sensing MR for Lung Imaging during Forced Expiration

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Introduction: Spirometry measurements are currently the standard of care for diagnosing pulmonary diseases such as cystic fibrosis, asthma, and chronic obstructive pulmonary disease[1]. While spirometry measurements can be made at high temporal resolution, they contain no spatial information and can therefore only detect global changes in lung function which become present at fairly advanced stages of disease. Early detection of localized changes is crucial for effective treatment but the temporal and spatial resolution requirements for imaging forced expiratory maneuvers used in tests of pulmonary mechanics are extremely demanding for conventional imaging systems (full 3D lung coverage with sub-100 millisecond temporal resolution)[2]. In this work, we demonstrate a rapid imaging and compressed sensing (CS) reconstruction method capable of capturing the spatio-temporal dynamics of the lungs during forced respiration.

Figure 1 – Experiment description from raw data

Methods: Data were acquired using a 3D radial gradient echo (VIBE) golden angle stack-of-stars[3] pulse sequence on a 3T Siemens scanner (TE=0.68ms, TR=2.1ms, flip angle=5°) with a 64×64×22 acquisition matrix to yield images with a spatial resolution of 7.5×7.5×10mm. The k-space stack has coronal orientation, and saturation bands were placed above and below the lungs. Multi-channel data were collected using 30 coils covering the chest and spine.
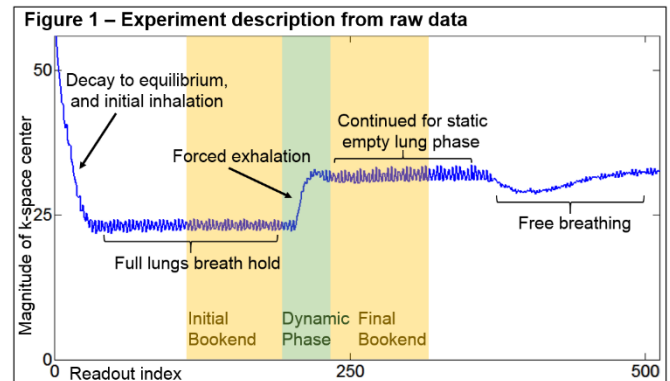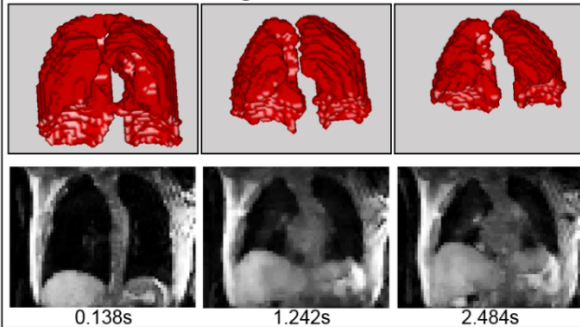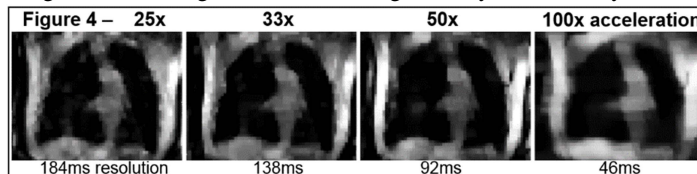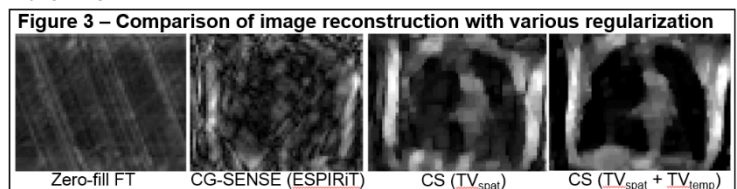
During the scan, a healthy volunteer was asked to inhale and maintain a breath hold, then forcefully exhale and continue with empty lungs for a brief period, then finish with free breathing. Data were acquired throughout the scan, and were later placed into temporal bins utilizing the golden angle view-ordering. Each phase of this forced expiration experiment is clear from the change of magnitude of the k-space origin in the raw data, as shown in Figure 1. The initial and final bins, called "bookends", contain fully sampled data corresponding to full and empty lungs respectively (100 views/slice). The data from the forced exhalation are placed in as many bins as determined by the resolution (as low as 1 view/slice).

Image reconstruction was performed by solving the CS optimization problem $\mathbf{argmin}_x \ \|\mathbf{F}(\mathbf{S}x)\text{-}d\|_2^2 + \alpha\mathbf{TV}_{temp}(x) + \beta\mathbf{TV}_{spat}(x) + \gamma\mathbf{TV}_{ref}(x)$. Here, x denotes the underlying dynamic image, and d the acquired multi-channel data. $\mathbf{S}$ denotes the coil sensitivities, and $\mathbf{F}$ denotes the undersampled non-uniform Fourier transform. TV

Figure 2 – Example of 4D CS reconstruction at 138ms resolution during exhalation

0.138s   1.242s   2.484s

denotes total variation, which is applied temporally ($\mathbf{TV}_{temp}$) as well as spatially ($\mathbf{TV}_{spat}$). $\mathbf{TV}_{ref}$ measures the residual sparsity between the fully resolved bookends and each of the images within the dynamic phase. $\mathbf{S}$ is generated by the ESPIRiT parallel imaging technique[4]. α, β, and γ are regularization weights. The optimization problem is solved by nonlinear conjugate gradient iterations[5].

Results and Discussion: Figure 2 shows an example of a 4D CS reconstruction with a 138ms temporal resolution. In this case, the dynamic phase was binned into 21 temporal points, each with only 3 views/slice. The bottom row shows the central slice of each 3D dataset at 3 different time points through the experiment. Since each readout is associated with only one temporal bin, there is no view sharing. The top row shows a 3D segmentation for data at each time point illustrating the lung compression through the experiment.

Figure 3 – Comparison of image reconstruction with various regularization

Zero-fill FT   CG-SENSE (ESPIRiT)   CS (TV_{spat})   CS ($TV_{spat} + TV_{temp}$)

Figure 3 illustrates the importance of CS (in particular the inclusion of $\mathbf{TV}_{temp}$) in the reconstruction. The images from left to right correspond to the zero-filled Fourier transform, the parallel imaging reconstruction without CS, the CS reconstruction with spatial regularization only, and the CS reconstruction with full spatio-temporal regularization. These images were each reconstructed from the same dataset. Note that when CS is used the image starts showing features of the lung anatomy, but it is only when temporal constraints are used that the lung anatomy is better delineated.

Figure 4 –   25x   33x   50x   100x acceleration

184ms resolution   138ms   92ms   46ms

Figure 4 shows that spatial undersampling can be pushed to further extremes in order to improve temporal resolution. The figure shows the central slice of the 3D image from a full lung frame for 4, 3, 2, and 1 view/slice/time (acceleration factors of 25, 33, 50, and 100 relative to static images satisfying the Nyquist criterion). Being able to reconstruct and image from such highly undersampled data relies on effective parallel imaging and sparse transformations. We can compensate for the small amount of data in each frame with information from the dataset as a whole. Here, this global information is utilized within parallel imaging and CS. The sensitivity maps are calibrated from the complete dataset, and then applied at each time point. $\mathbf{TV}_{temp}$ sparsity comes from the assumption that the difference between temporally-neighboring 3D images should be small for most voxels. The same assumption is used for $\mathbf{TV}_{spat}$ between adjacent voxels within each image. Additionally we have implemented $\mathbf{TV}_{ref}$ between the bookend frames, and each of the forced expiration frames. These artifact-free reference frames aid in spatially resolving the dynamic images.

Conclusion: This study has shown that 4D lung MR imaging can achieve a temporal resolution that sufficiently captures the dynamics of forced respiratory maneuvers. Unlike spirometry, MR can add spatial information for lung function analysis, and avoids the harmful radiation associated with CT. Dynamic lung MRI can present pulmonologists with additional biomechanical and physiological details.

References: [1]Gold. In: Textbook of Respiratory Medicine. 2000, 783-804. [2]Plathow et al. Investigative Radiology. 2005, 40:173-179. [3]Chandarana et al. ISMRM. 2012, 4206. [4]Uecker et al. Magn. Reson. Med. 2013, preprint. [5]Lustig et al. Magn. Reson. Med. 2007, 58(6):1182-1195.