Accelerated 3D lung MRI using compressed sensing

MRI has been increasingly used in lung cancer radiation therapy for lung and tumor motion characterization and treatment guidance. 2D dynamic MRI is a powerful tool to study the lung motion in sagittal and coronal orientations but the dimensional restriction has limited its ability from deriving 3D deformation vector field of the lung and lung tumor. Temporal resolution of 3D MRI is insufficient to resolve the real time respiratory motion. In this study we show that application of Compressed Sensing (CS) [1, 2] can be used to accelerate the 3D lung MRI scan. We show that the under-sampled datasets can successfully be reconstructed, preserving the important features of the lung.

Method and Materials: The entire process of compressed sensing consists of three steps: encoding, sensing, and decoding. In the first step, a data matrix $m$ is encoded into a smaller vector, $y$ using a linear transformation. In the second step, $y$ is acquired and the third step is to recover $m$ from $y$.

The proposed CS method was tested on retrospective 3D lung MRI data. Simulation was done using a fully sampled Trufi 3D sequence performed on a 3T Trio-Tim MRI scanner (Siemens Medical Solution, Erlangen, Germany) in a lung cancer patient (the small disperse lung tumor was nearly indiscernible in both MRI and CT) during expiration and inspiration. Scan parameters included: TR/TE: 31.56/1.14 ms; FOV: 400 ×400 mm; flip angle: 41°; slice thickness: 2.6 mm; matrix: 224× 224; phase sharing: 120, no. of slice = 80. As $k_z$ was the readout direction, the under-sampling was simulated in the $k_x$-$k_y$ plane.

$k$-space sampling scheme: $k$-space was non-uniformly under-sampled along the phase direction. We chose to sample more points near the center, fewer points near the bottom left and bottom right corners. Because of the symmetry of the 2D Fourier transform, we mask the upper half space. Following these guidelines, we randomly created sampling matrices. Fig. 1(a) highlights the positions of the selected frequencies (in one of the several experiments) in the k-space. We found that this kind of selection allowed us to recover MR images from a fewer of samples than a unbiased random selection as shown in Fig. 1(b).

Reconstruction: The data was reconstructed using the Split Bregman method for L1 regularized problems [3] which solves the unconstrained optimization problem,

$$
\min_m \| \nabla m \|_1 + \lambda \| F_y m - y \|_2
$$

iteratively by splitting the L1 and L2 components. Here, $V$ is the gradient operator, $m$ is the reconstructed data, $\| x \|_n$ is the $l_n$ norm, $\lambda$ is a regularization parameter, $F_y$ is the under-sampled Fourier transform, and $y$ is the under-sampled data. Equation (1) removes the artifacts due to the non-uniform under-sampling by minimizing the total variation (TV) while maintaining fidelity with the sampled measurements. The degree of the influence of TV regularizer was controlled by the choice of the regularization parameter $\lambda$.

The data corresponding to the 3D lung MRI were randomly under-sampled in y-z space with different reduction factors. To investigate the effects of noise on the reconstructions, Gaussian noise with standard deviation, $\sigma = 0.01$ was added to the noiseless model dataset in all the simulations.

Results and Discussion: We were able to reconstruct the data sub-sampled with different reduction factors (2x–4x4 folds). Figure 2(a) shows images from a mid-sagittal slice extracted from 3D volume in the retrospective sub-sampling experiment. Figure 2(b) is the image obtained by under-sampling the same 3D volume with the sampling matrix shown in Fig 1(a) at sampling ratio of 13.05%. CS reconstructions by using the Split Bregman algorithm of the same $k$-space data are shown in Fig 2(c). The overall quality and resolution of the reconstructed image is comparable to the fully sampled dataset, indicating a successful implementation of CS in reconstructing the phase encoding dimensions in the 3D MRI sequence. Even at very low sampling ratio of 13.05% we were able to get acceptable results.
Also, we found that the under-sampling strategy of randomly sampling more densely towards the center of k-space and less points from the corners allowed us to recover lung MR images from fewer samples than completely random selection of k-space data. In the current, Matlab™ implementation we were able to reconstruct a 224×224×80 volume CS in ~56 seconds on a computer with a quad-core CPU clocked at 2.4 GHz and 16 GB memory.

Conclusions: A CS theory based reconstruction method has been introduced for 3D lung MRI. The proposed method significantly reduces under-sampling artifacts and can speed up the scan significantly. Also, introduction of Wavelet Transform as another regularization term in the minimization formulation can ensure accurate reconstruction of smooth images at higher acceleration ratio. Optimization of the sampling density and the reconstruction algorithms to better utilize the sparsity of the lung MRI images will increase acceleration ratio and decrease imaging acquisition time for real time whole lung imaging.

**Fig. 1:** (a) The positions of samplings (highlighted in white) with sampling ratio 13.05%. (b) Random under-sampling mask at sampling ratio 21.6%.

**Fig. 2:** (a) is the original lung image. (b) is the under-sampled image at sampling ratio 13.05%. (c) is the recovered image.