# Ultra-fast dynamic MRI for lung tumor tracking based on compressed sensing

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**Target audience:** Researchers interested in Compressed Sensing Reconstruction and Lung MRI.

**Purpose/Introduction:** Despite its intrinsically low SNR in the lung, magnetic resonance imaging (MRI) is increasingly being used in lung cancer radiation therapy for treatment guidance purposes, which required determination of motion of lung and pulmonary tumors (1-3). In particular, for patients presenting with lung cancer, dynamic 2D lung MRI is a safe and reliable method to characterize tumor motion. It has been shown that dynamic MRI in the sagittal and coronal orientations more accurately characterize the lung tumor motion over a longer time period for more robust statistical analysis (1, 2) than 4D CT. The emergence of MRI-guided radiotherapy has afforded the opportunity to visualize and adapt to moving anatomy during treatment. High spatial and temporal resolution MRI has the potential to simultaneously describe the lung and lung tumor motion quantitatively. Though an acquisition speed of 4-8 2D frame/second can be achieved for 2D dynamic imaging, the speed is inadequate for 3D anatomy monitoring. Since the bottleneck of MR speed is the number of data points that can be sampled in a given time, under-sampling the k-space is the alternative strategy to shorten imaging time and increase temporal resolution. Compressed Sensing (CS) has been shown a viable technique to accelerate MR acquisition (4, 5) while preserving imaging integrity. In the study, we demonstrate its utility to reconstruct heavily down-sampled 2D dynamic lung MRI. The main aim of the present study is to exploit the spatial-temporal coherence of the patient anatomy and substantially decrease the amount of data samples that is needed to accurately track the lung tumor motion.

**Materials and Methods:** CS was simulated using fully sampled 2D dynamic lung MRI datasets acquired from nine lung cancer patients. The MRI protocol was approved by the Institution Review Board of the university. All data were acquired on a 1.5T Siemens Avanto MRI scanner (Siemens Medical Solutions, Erlangen, Germany) with TrueFISP (TFI) (7 images/second, sagittal and coronal orientation) using an 18-channel body receive coil. Scan parameters included: TR/TE: 155.35/1.04 ms; FOV: 300 ×360 mm; flip angle = 52˚; slice thickness: 7 mm; matrix: 160×192; slab thickness: 7 mm, phase sharing = 120.

Non-uniform under-sampling was imposed on the fully sampled data in the k-space using a golden angle radial undersampling scheme as shown in Fig. 1(b). The data was reconstructed using the k-t SLR (6) method based on low rank and sparsity penalties. To exploit the correlations between the temporal profiles of the voxels, the spatio-temporal signal were rearranged in a matrix X where the rows correspond to the voxels, while the columns represent the temporal samples. Recovery of X was posed as a spectrally regularized problem (eqn. 1)

$$\arg\min_{\Gamma} \left\| F_u X - Y \right\|^2 + \lambda_1 \varphi(X) + \lambda_2 \psi(X) \qquad (1)$$

where Y is incoherently (randomly) under-sampled k-space data, $F_u$ is the undersampled Fourier transform, $\varphi(X) = (\|X\|_p)^p$ is the Schatten p functional, $\psi(X)$ is the total variation (TV) norm and $\lambda_1$, $\lambda_2$ are regularization parameters. For p = 1, the spectral penalty term simplifies to the nuclear norm which is the sum of singular values of X. The optimization problem of eqn. (1) was solved using a three-step alternating minimization scheme (7). We quantified the performance of the CS reconstruction on 2D Lung dynamic MRI using the root mean square error (RMSE) between the reconstructions and the original data. More importantly, to determine the integrity of CS reconstructed image for image guided radiation therapy, the tumor motion trajectories were automatically quantified based on the reconstructed and the original images using an in-house Matlab program . The usefulness of the technique is determined by the cross correlation co-efficient between them.

**Results**: We were able to reconstruct the data with various down-sampling ratios (4x–20x folds). The resultant 2D dynamic lung MRI from the four sampling ratios 20%, 15% , 10%, 5% are shown in Fig. 1. Fig. 1(a) shows a representative frame from the fully sampled 2D dynamic MRI dataset of a lung cancer patient. Fig. 1(c) shows the images obtained by under-sampling the same dataset at the four sampling ratios. CS reconstructions by using the k-t algorithm of the same *k*-space data are shown in Fig. 1(d). Fig. 1(e) shows the difference between the original and reconstructed data at the corresponding sampling ratios. The overall quality and resolution of the reconstructed image is close to the fully sampled dataset indicating a successful implementation of CS in reconstructing thee 2D dynamic lung MRI data. Even at very low sampling ratio of 5% we were able to get useable images for lung tumor tracking with little additional error. The RMSE of the CS reconstruction of the under-sampled datasets calculated with respect to the fully sampled data, are shown in Fig. 2. It can be visually evaluated and from the low RMSE values that the CS reconstruction successfully cleans up the incoherent aliasing produced by the NUS. Fig. 3 shows the estimated tumor motion along the x and y co-ordinates for the fully sampled data set from a lung cancer patient and reconstructed data from corresponding under sampled data at sampling ratio of 10%. The correlation co-efficient for the estimated tumor motion from the fully sampled and reconstructed data along the two directions for all the datasets was found to be >0.8.

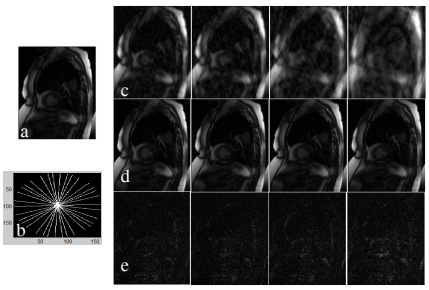


**Fig. 1:** (a) mid-coronal slice extracted from the fully sampled 3D lung MRI volume of a cancer subject. (b) golden angle radial under-sampling scheme at sampling ratio 10% (20 radial line) (c) under-sampling images at sampling ratios of 20%, 15% , 10%, 5% for the sampling scheme 1(b). (d) Corresponding recovered images, (e) difference between the original (a) and CS reconstructed data (c).

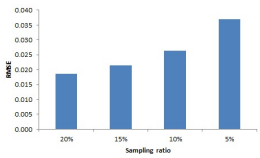


**Fig. 2:** Mean RMSE value of the 9 data sets over sampling ratio 20%, 15%, 10%, 5%.

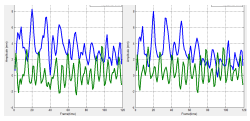

**Fig. 3:** Estimated tumor motion along the x and y co-ordinates for (a) the fully sampled data (b) reconstructed data at sampled data at sampling ratio of 10%. Correlation coefficient along x-co-redinate: 0.89, along y co-ordinate: 0.90.

**Discussion and Conclusion:** Because of the intrinsic coherent of the anatomy of the same patient, very little new information is needed to update each new imaging frame. The application of k-t SLR to accelerate 2D dynamic lung MRI has been demonstrated on nine lung cancer data sets with up to 20 fold acceleration while maintaining low reconstruction error as indicated by computed RMSE values. It can also be noticed that fine details of the image have been faithfully reproduced even at 20x. The CA image quality is adequate for the tumor tracking as shown by the high cross-correlation coefficients of the motion trajectories tracked from the original images and the CS reconstructed images. The results have important implications in radiotherapy where real time internal anatomy tracking is lacking. The accuracy and robustness of treating tumors subject to significant intrafractional motion, such as the lung tumor, is questionable without such tracking methods. Emerging MR guided radiotherapy systems have afforded the hardware potential for continuous intrafractional motion monitoring but existing dynamic MRI sequences cannot provide adequate 3D imaging speed for real time imaging of the lung. We have demonstrated that by exploiting the spatial-temporal coherence of human anatomy, the number of k-space samples can be drastically reduced without noticeably degrading the imaging quality and tumor tracking accuracy. Implementation of the technique in radiotherapy is therefore expected to markedly improve the accuracy of treatment by increasing the tumor control probability and reducing the normal tissue complication.

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**References:** 1. Donoho. IEEE Trans Info Theory. 52, 1289-1306 (2006). 2. Lustig, M., D. Donoho, et al. Magn Reson Med. 58, 1182-95 (2007). 3. Cai, J, Read PW, et al. Phys Med Biol. 52, 365-73 (2007). 4. Cai, J, Read PW, et al. Int J Radiat Oncol Biol Phys. 72, 1228-35 (2008). 5.Cervino LI, Du J, et al. Phys Med Biol. 56, 3773-85 (2011). 6. Goud S, et.al, ISBI (2010). 7. Alfonso M, et.al, IEEE-TIP (2010).