Accelerated lung MRI using Low-Rank Decomposition: a prospective and simulation study

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Target audience: Researchers interested in low rank decomposition, lung MRI and compressed sensing reconstruction.

Purpose/Introduction: Respiratory motion has posed significant challenges in lung cancer radiotherapy. Effective management of the motion to reduce normal tissue dose and maintain tumor coverage requires the precise knowledge of internal anatomies before and during the treatment. For patients presented with lung cancer, dynamic 2D lung MRI is a safe and robust method to characterize internal organ motion. It has been shown that dynamic MRI (dMRI) of sagittal and coronal slices was better suited than 4D CT for characterization of the lung tumor motion over a long time period (>200 seconds) that produces sufficient data for robust motion statistical analysis[1,2]. The emergence of MRI-guided radiotherapy has further afforded the opportunity to visualize and adapt to moving anatomy during treatment, enhancing the role of MRI in the intrafractional tumor motion management[3]. Since the MR speed depends on the number of data points that can be sampled in a given time, under-sampling of the k-space is a practical approach to shorten imaging time and increase temporal resolution. Recently, various compressed sensing (CS) techniques[4-6]. have been utilized to accelerate imaging acquisition exploiting the intrinsic sparsity of the MR images. Although extensive research has been performed on the topic of compressed sensing MRI, its applications for the lung imaging and lung tumor tracking have not been reported. In the study, the combination of transform domain sparsity with rank deficiency is used to reconstruct spatial-temporal lung dynamic MRI data and its ability to track lung tumor motion is examined.

Materials and Methods: A preliminary prospective study was performed on a healthy volunteer using a Cartesian random under-sampling scheme with fully sampled low frequencies as shown in Fig.1(a). The real-time MRI was performed utilizing a prospectively under-sampled Cartesian balanced steady-state free precession (bSSFP) sequence (sagittal orientation) on a 1.5T Siemens Avanto MRI scanner (Siemens Medical Solutions, Erlangen, Germany) with a 6-channel body receive coil array and a spine coil with the scan parameters: TR/TE: 4.29/2.05 ms; FOV: 272 ×322 mm^2; flip angle = 60◦; slice thickness: 7 mm; matrix dimension: 310×368. The random under-sampling was set to 6x, 8x, and 12x. A k-space lines pairing technique was used in the prospective sequence to mitigate artifacts caused by field inhomogeneity, motion, and eddy currents due to SSFP balanced gradients within the TR 22. To further test the utility of CS reconstruction in tumor tracking of lung cancer patients, CS was simulated using fully sampled 2D dynamic lung MRI datasets acquired from 7 lung cancer patients. Data were acquired using the same scanner with the scan parameters: TR/TE: 3/1.04 ms; FOV: 300×360 mm2; flip angle = 52◦; slice thickness: 7 mm; matrix dimension: 160×192, GRAPPA 2 (24 reference lines) and partial Fourier of 6/8. For all our simulation study we used the same masking scheme as of prospective study.

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)

$$\arg\min_X \left\| F_u X - d \right\|^2 + \lambda_1 \varphi(X) + \lambda_2 \psi(X) \qquad (1)$$

where d is incoherently under-sampled k-space data, F_u is the undersampled Fourier transform, $\varphi(X) = (\|X\|_p)^p$ is the Schatten p norm, $\psi(X)$ is the total variation (TV) norm and λ_1, λ_2 are regularization parameters. The optimization problem of eqn. (1) was solved using a three-step alternating minimization scheme[6,7]. To determine the integrity of CS reconstructed image for image guided radiation therapy, the tumor motion trajectories were quantified based on the reconstructed and the original images using an in-house Matlab program[2]. The usefulness of the technique is determined by the cross correlation co-efficient between them.

Results: We were able to reconstruct the prospective data with various down-sampling ratios (6x−12x folds). As expected, direct reconstruction from under-sampled k-space data results in noisy images that degraded imaging details such as blood vessels. The resultant 2D dynamic lung MR images in the retrospective simulation study at various down-sampling ratios (5x−12x) shows very promising results.We were able to reconstruct the prospective data with various down-sampling ratios (6x−12x folds), Clean images were obtained up to 8x using k-t SLR. Higher undersampling ratio resulted in more prominent artifacts that may slightly increase tracking and registration errors. Fig. 1(b)-(e) shows a representative frame of the prospectively acquired 8x under-sampled dMRI using NUS and resultant k-t SLR reconstructed images. NUS image quality is unusable but the k-t SLR image has substantially reduced the incoherence artifacts and retained imaging details such as the blood vessels. k-t SLR reconstructed images showed good retention of the detail and very little increase in imaging artifacts even at the highest under-sampling fold of 12x. Fig. 2 shows the tumor tracking results for all 7 patients describing the automatically tracked tumor motion trajectories from the fully sampled reconstructed data, corresponding k-t SLR from under-sampled data at 10x. The tumor was accurately localized despite irregular breathing patterns. The estimated total tumor displacements from the fully sampled and reconstructed data were found to be well correlated with average correlation coefficient for 7 patients and all under-sampling ratios was found to be ≥0.85.

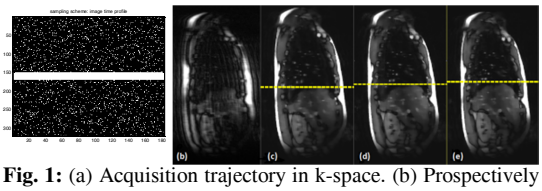

Fig. 1: (a) Acquisition trajectory in k-space. (b) Prospectively acquired 8x under-sampled dMRI using (a) NUS and (c-e) k-t SLR. k-t SLR results include 3 frames at end-of-inhalation, middle and end of exhalation, respectively. Yellow dotted lines denote the diaphragm apex positions.

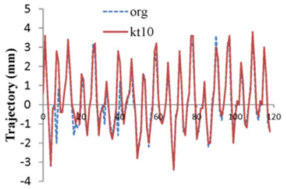

Fig. 2: Estimated tumor motion for the fully sampled data and reconstructed data at sampling ratio of 10%.

Discussion and Conclusion: Imaging reconstruction from under-sampled k-space data in MR has been extensively researched in areas such as cardiac and brain imaging but the applications on lung images have been rarely reported. The CS image quality is adequate for the tumor tracking as evident by the high cross-correlation coefficients of the motion trajectories tracked from the original images and the CS reconstructed images. The reconstruction method for accelerated undersampled MRI is compatible with dynamic 3D imaging. Additional acceleration is possible with the second encoding direction. Emerging MR guided radiotherapy systems provide the hardware capacity for continuous intrafractional motion monitoring but the potential is not fully realized without dynamic 3D imaging acquisition. We have used the lung tumor MR as a model system but similar applications are expected in other regions such as the upper abdomen where the organs move significantly with respiratory motion.

Implementation of the technique in radiotherapy is expected to markedly improve the accuracy of treatment by increasing the tumor control probability and reducing the normal tissue complication. Current computation time using the Matlab program does not allow real-time implementation, however, we expect substantial computational improvement with implementation of reconstruction algorithms such as parallel computing on GPU32. This study demonstrates the potential of increasing dynamic MR acquisition volumes for complete organ motion monitoring.

Acknowledgement: This research was supported by NIH R21CA161670 and R21CA144063.

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