Prior Data Assisted Compressed Sensing - A Novel Strategy for Real Time Dynamic MRI

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Introduction: Compressed Sensing[1] (CS) can potentially improve real time MR guided interventions by significantly increasing imaging frame rates. One such application is the real time tracking of moving lung tumours during radiation delivery in hybrid Radiotherapy/MR imaging devices[2,3]. In such a treatment scheme[4], dynamic MR imaging is performed near real time, from which the location of the moving tumour will be determined automatically, and the radiation treatment beam will be adjusted to-the new tumour position. The benefits of this type of treatment are maximized when images are acquired and reconstructed rapidly. Spatial-temporal (k-t)[5,6] CS methods can increase the acceleration potential of conventional CS, but they require significant longer reconstruction times due to the increase in computation complexity. In this work, we propose a novel spatial-temporal CS imaging strategy for real time MRI - Prior Data Assisted Compressed Sensing (PDACS), which aims to improve the reconstruction quality of conventional CS without significantly increasing reconstruction times.

Methods: PDACS Algorithm. In 2D-PDACS, undersampling is performed using a predefined 2D random pattern with sampled lines (k_s) that is applied to all dynamic images. Unlike conventional CS, PDACS requires 2D prior data in the unsampled regions (k_{us}) to assist in reconstruction. For best results, the prior data $\bar{\mathbf{D}}$ should be acquired and averaged over at least one breathing cycle (~5s), which can be used to support ~1 minute of reconstruction before it needs to be re-acquired. The PDACS algorithm minimizes the objective function: $\boldsymbol{arg\,min}_{\tilde{\rho}} \left(\left\| \mathcal{F}_{2D}\{\tilde{\boldsymbol{\rho}}(x,y)\}|_{k_s} - \mathbf{D}(k_s) \right\|_2^2 + \lambda_1 \|\boldsymbol{\Psi}_{2D}\tilde{\boldsymbol{\rho}}(x,y)\|_1 + \lambda_2 \left\| \mathcal{F}_{2D}\{\tilde{\boldsymbol{\rho}}(x,y)\}|_{k_{us}} - \bar{\mathbf{D}}(k_{us}) \right\|_2^2 \right)$

Where $\tilde{\boldsymbol{\rho}}(x,y)$ is the 2D image domain solution, $\mathcal{F}_{2D}$ is a 2D Fourier transform, $\mathbf{D}$ is the acquired k-space matrix with data at locations k_s, $\boldsymbol{\Psi}_{2D}$ is a 2D finite difference operation, and λ_1 governs the relative weight of the sparsifying term. PDACS requires a consistency term with a weaker constraint (λ_2<1) that constrains the unacquired k-space locations, $k_{us}$to the prior data averaged 2D k-space matrix, $\bar{\mathbf{D}}$. In this work, PDACS is demonstrated by retrospectively removing k-space lines from a fully acquired set. Unlike other k-T methods[5,6], PDACS require no 3D sparsifying operations in its iterative steps, which allows 2D images (128x128) to be reconstructed at approximately 0.3s using a split-bregman[7] algorithm (Intel i7-4770. 3.4GHz CPU), similar to that of conventional 2D CS.

In vivo Data Acquisition: Three patients with non small cell lung cancer (NSCLC) tumour are imaged in a 3T Philips MRI unit using a fully sampled dynamic bSSFP sequence (FOV: 40x40cm, voxel size, 3.1 x 3.1 x 20mm, TE = 1.1ms. TR = 2.2ms, 275ms imaging time) under free breathing for approximately 3 minutes (650 images). The maximum extent of motion of the three patients are measured to be: SI: 26, 3, 32 mm; AP: 5, 3, 10 mm.

Reconstruction Performance Evaluation: The benefits of PDACS over conventional CS is demonstrated by performing a retrospective study on the fully sampled images by systematically removing k-space data. As one set of prior data (~5s, 20 dynamics) is used to support the reconstruction of the following 200 undersampled images (~1 minute), image 1-20 is treated as prior data to support reconstruction of images 21-220, image 221-240 is used as prior data to support images 241-440, and images 441-460 is treated as prior data to support images 461-650. Of the 650 images acquired 590 images are treated as undersampled images. To further improve statistics, we generated three different random sampling patterns for each fraction of k-space sampling. In these patterns, 16 central k-space lines are fully sampled, while the remaining k-space lines are pseudo-randomly sampled. A Monte Carlo[1] method, governed by a decreasing probability distribution function, effectively reduced the number of k-space lines to 50, 40, 30, 25, 20 and 15% of original size (2, 2.5, 3.3, 4, 5, 6.7x acceleration). For quantitative assessments, we evaluated the image artifact power, $AP = \sum_i (\tilde{\boldsymbol{\rho}}_{us} - \tilde{\boldsymbol{\rho}}_{full})^2 / \sum_i \tilde{\boldsymbol{\rho}}_{full}^2$ to assess overall reconstruction quality. We also applied an automatic contouring algorithm on the fully sampled images to generate a standard set of contours. We then applied the same contouring algorithm on the CS/PDACS reconstructed images. CS/PDACS contours are compared against the standard by assessing localization error (contour centroid deviation) as well as the overall contour agreement using the Dice Coefficient Metric: $DC = 2 \times Area(ROI_{Full} \cap ROI_{US}) / (Area(ROI_{Full}) + Area(ROI_{US}))$.

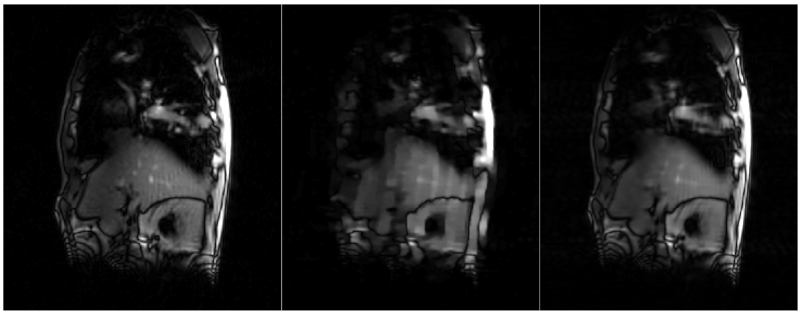

Figure 1: From left to right: Fully sampled, 5x accelerated 2D CS, 5x accelerated PDACS reconstructed image of patient 1 displayed at the same window and level. At 5x acceleration, PDACS is able to reconstruct the image with a higher degree of fidelity.

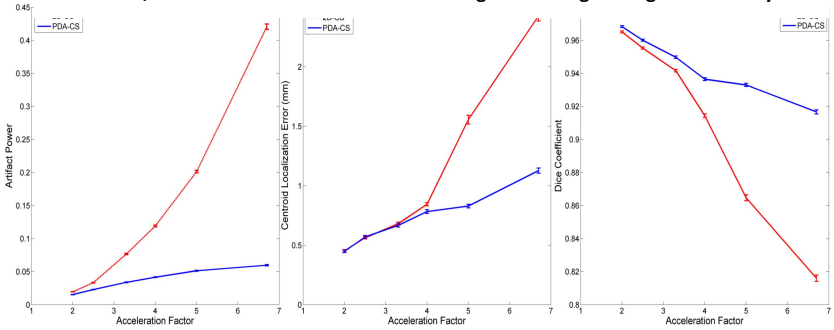

Figure 2: From left to right: Artifact Power, Centroid Localization Error and Dice's Coefficient metrics comparing the conventional CS to PDACS. Error bars indicate 95% CI

Results and Discussions: A representative image comparing the CS and PDACS is shown in Figure 1. Quantitative metrics comparing the two techniques for the aggregate data from the three patients are shown in Figure 2. PDACS is particularly beneficial at higher accelerations (>4x). In the maximum speed up factor 6.7x explored in this work, the PDACS method reduced the average artifact power from 0.42 to 0.06, mean localization error is reduced from 2.4mm to 1.1mm, and mean Dice Coefficient improves from 0.82 to 0.92.

Conclusions: Our results shows that PDACS is a promising imaging strategy for real time interventional MRI in the lung. PDACS reconstruction can be performed in a reasonable amount of time (0.3s). For the tracking of moving lung tumours, PDACS, applied to the bSSFP sequence, allows for a near 7 fold increase in imaging speed while only generating an average localization error of 1.1 mm. The ability to accurately localize moving tumours with highly accelerated MRI suggests that real time, 3D MR localization of lung tumours for radiation therapy guidance may be feasible using this technique.

References: [1] Lustig M *et al.*, Magn Reson Med 58:1182 (2007); [2] Fallone G *et al.*, Med Phys, 36:2084 (2009); [3] Raaymakers BW *et al.*, Phys Med Bio 54:N229 (2009); [4] Yun *et al.*, Med Phys 39:1481 (2012); [5] Jung *et al*, Magn Reson Med 61:103 (2009); [6] Lingala *et al.*, IEEE Trans Med Imaging 30:1042 (2011); [7] Goldstein *et al.*, SIAM J Imaging Sci 2:323 (2009).