Total Variation Denoised Dynamic Reconstruction Applied to Pulmonary Perfusion Imaging in the Rat

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Introduction: Dynamic contrast enhanced (DCE) MRI in the rodent lung [1] is challenging due to the twin requirements of high spatial and temporal resolution, motion and the low signal-to-noise ratio (SNR) available. We have developed an interleaved radial acquisition to improve the SNR and make the acquisition less susceptible to motion. Gridding reconstruction of under sampled, noisy data results in low SNR, while *k*-space filtering techniques blur the edges and fine structures. Image denoising/restoration techniques have been well developed in the literature of post-processing, among which total variation (TV) based denoising is one of the most powerful methods for medical images [2]. Recently, Candes et al. [3] suggested the use of L1 norm minimization to recover a near-optimal image from an incomplete and noisy measurement. In this work, we integrate the TV norm regularizer with the non-uniform inverse FFT (NU-IFFT) [4] for interleaved radial imaging to iteratively reconstruct high SNR and high spatio-temporal resolution images.

(1)

Methods: We describe the design of the reconstruction algorithm, followed by the *in vivo* example in pulmonary perfusion imaging in the rodent.

1. TV-denoised reconstruction algorithm for radial MR

We consider the discretized noisy MR signal (s) model along the radial trajectory as:

s = AI + e

where A is the Fourier projection matrix that maps the underlying image I into the k-space samples on the trajectory, and e is the measurement noise. With a TV norm regularizer, the image is the solution of the following optimization problem:

$$\hat{I} = \operatorname*{arg\,min}_{\forall I} g(I) = \operatorname*{arg\,min}_{\forall I} \mu \|I\|_{TV} + \|AI - s\|_d^2 \tag{2}$$

where $\| \cdot \|_{TV}$ takes the L1 norm of the derivative of the image, *d* is a *k*-space weighting vector, and μ is the regularization parameter to adjust the relative penalties on the TV norm and the data fidelity. Note that the cost function *g*(*I*) in (2) consists of components from both image-space denoising and *k*-space matching. μ can be tuned to favor high SNR or fidelity to the measurements based on the specific interest of an application. The *k*-space weighting is purposely included to enhance high-resolution information as well as to accelerate the convergence. For the radial trajectory, a modified Ram-Lak function along each ray is used for this weighting. Equation (2) is solved iteratively by the nonlinear conjugate gradient (CG) method, and the efficiency of the solver is improved by the NU-IFFT technique that avoids the gridding of non-Cartesian samples [4].

2. Interleaved radial sampling and dynamic reconstruction

in vivo scans were performed on female Fischer 344 rats on a 2T scanner for a separate study [1]. All animal procedures were approved by the Duke Institutional Animal Care and Use Committee. The images were acquired using an interleaved radial sequence that samples the DCE curve (for 6.4 s) with a temporal resolution of 400 ms and a TR of 4 ms. Each of the 4 individual time-points in the sequence acquires a different set of *k*-space lines. This was repeated over 4 injections, resulting in the acquisition of 6400



(c) (d) **Fig. 1**: Computer phantom images reconstructed from noisy radial measurements. (a) original phantom, (b) gridding method, (c) gridding method with Fermi filter, and (d) TV-denoised reconstruction

unique *k*-space lines. The TV-denoised reconstruction was first applied to reconstruct a prior image from all the 6400 rays. The image had a very high SNR due to rich signal averaging as well as further denoising. The 6400 rays were then sorted into 16 time-points where each 400-ray dataset covered the entire *k*-space sparsely. The reconstruction was then applied to the 16 dynamic time-points individually with the prior image as the first iteration. The prior image is used to provide the structural information carried by the entire acquisition; however the presence or absence and the contrast of a particular structure during the different time-points are dependent on the local data fidelity term.

Results: To demonstrate the denoising performance of the proposed method, a computer phantom was constructed with sharp edges and high-resolution fine structures. Noisy measurements (SNR = 28dB) along an under-sampled (400 rays) radial trajectory were simulated with additive Gaussian noise. The images were reconstructed using the proposed method and the results were compared to the ones obtained by the direct gridding and gridding combined with *k*-space Fermi filter. Figure 1(b) shows that both image contrast and resolution are significantly degraded due to the low SNR if the gridding method is applied directly on the noisy measurements. Using a simple Fermi filter in (c) improves image SNR and contrast at the cost of resolution. In comparison, the proposed TV denoised reconstruction (d) is able to preserve the edges and fine structures, to a certain extent, while effectively increasing SNR. The proposed method was used to reconstruct the dynamic time-points of the perfusion study, first without the prior image, and then with. For each time point, only the corresponding sub-dataset was used in the data fidelity term to ensure temporal resolution. With the current implementation on a PC, the entire reconstruction process takes approximately 10 minutes to reconstruct all the 16 dynamic images. Figure 2 shows the image frame at time-point 8. Even without incorporating the prior image, the TV-denoised reconstruction (b) has visible SNR (10.4 dB higher) and contrast improvements over the gridding reconstruction (a), while preserving fine blood vessel structures. Guided by the prior image, the reconstruction (c) converged faster and the solutions had even better SNR [12.5 dB higher than (a)]. Figure 3 shows dynamic contrast endinced (DCE) perfusion curves in the pulmonary vein and the descending aorta. The dynamic trend correlates well with the results presented in [1].

Discussion and Conclusion: TV-denoising has been integrated into the radial MR reconstruction scheme to effectively enhance the image SNR in the pulmonary perfusion study of a rodent model. With the TV regularizer, the reconstructed image is the solution of an optimization problem that could be solved efficiently with modified NU-IFFT algorithm. A simulation study using a computer generated phantom demonstrated SNR improvement with the proposed method, while preserving the spatial resolution. The method has been successfully applied to DCE MRI that acquired data in an interleaved radial pattern. The prior image reconstructed from all the interleaves was incorporated to guide the reconstructions at individual time-points. Since the reconstruction effectively denoises the dynamic images, one does not have to trade off temporal resolution for spatial SNR during the scan. Further work is under way to take advantage of the strong temporal correlation available in the DCE MRI, which will potentially enable a more aggressive spatial under-sampling to achieve higher temporal resolution.

References:

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Acknowledgements: This work was supported by NIH/NCI R21 CA114680 (QHL), and NCRR/NCI P41 RR005959 and R24 CA092656 (GAJ).



Fig. 2: Post-injection rat lung images at time-point 8. (a) gridding reconstruction, (b) proposed method, no prior image (c) proposed method, with prior image.



Fig. 3: DCE curves of different parts in the cardio-vascular circuit.