**Enhanced Reconstruction of Compressive Sensing MRI via Cross-Domain Stochastically Fully-Connected Random Field Model**

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**Introduction**: Acquisition time is an important concern for Magnetic Resonance Imaging (MRI). Reducing imaging time directly reduces patient discomfort and it reduces artifacts due to patient motion thus improving overall image quality. Recent developments in compressed sensing MRI show that different forms of MRI are inherently sparse in certain domains [1], which requires a high quality reconstruction of MR images acquired at sub-Nyquist sampling ratios [2]. Given measurement sparsity in compressive sensing MRI, advanced reconstruction algorithms such as the ones proposed in [1, 2, 3,4] are required to reconstruct high quality MR images. Existing reconstruction methods for compressive sensing MRI are limited in taking full advantage of information across the entire MR imaging data to improve the preservation of fine tissue details and contrast in the reconstructed MR images. In this study, we propose a Cross-Domain Stochastic Fully-Connected Conditional Random Field (CD-SFCRF)-based reconstruction method for compressive sensing MRI. This cross-domain method will utilize both spatial- and frequency-domain information within a SFCRF framework to improve the quality of reconstructed images via preserving fine tissue details and contrast.

**Materials and Methods:** In this work, we incorporate the SFCRF method proposed in [5] in a MRI setting. While the end goal remains to model the conditional probability of a state set $Y$ given measurements $X$, $P(Y|X)$, the CD-SFCRF models the Bayesian Inference problem as:

$$P(Y|X) = \frac{1}{Z(X)} \exp\big(-\psi(Y|X)\big) \quad (1)$$

$$\psi(Y|X) = \mathcal{F}\{\sum_{i=1}^{n} \psi_u(y_i, X)\} + \sum_{\varphi \epsilon C} \psi_p(y_\varphi, X) \quad (2)$$

where $Z(X)$ is the normalizing function and $\psi(.)$ is a cross domain combination of unary($\psi_u$) and pair-wise ($\psi_p$) potential functions in Equation (2), $\varphi$ is a clique structure in the set of $C$ (vertices in a graph) with regards to the random fields, and $\mathcal{F}$ is the Fourier operator. The unary optimization is performed in *k*-space, while the pair-wise optimization is performed in the spatial domain. This cross-domain approach allows the preservation of fine details and spatial characteristics in the reconstruction process. A Philips Achieva 3.0T machine was used to acquire MRI data of 10 patients and institutional research ethics board approval was obtained. The patients' age ranged from 58-80 years, with a median age of 69. This paper uses the T2-weighted MRI data with resolution of 0.49 mm x 0.49 mm to test the proposed method in comparison with the widely used total variation reconstruction method [1].

**Results and Discussion:** Peak signal-to-noise ratio (PSNR) analysis at different sub-sampling rates was performed on phantom MRI data collected from a multi-modality prostate training phantom from Computerized Imaging Reference Systems Inc (CIRCS Model 053), shown in figure1. Figure 2 shows the PSNR (dB) with respect to under-sampling ratio of radial MRI acquisitions (%). As it is seen, the proposed method produced a higher PSNR compared to other methods total variation [1] and L2 norm minimization [4] on the phantom data across all sampling ratios. Figure 3 shows the comparison between L2 norm minimization (A, D) [4], total variation (B, E) [1], and the proposed CD-SFCRF method at 30% under-sampling ratio (C, F) for two of the ten patient cases. The CD-SFCRF performed well in preserving original details while eliminating artifacts due to sub-Nyquist sampling. These results and comparisons demonstrate the potential of the CD-SFCRF as a viable sparse reconstruction model for compressive sensing MRI.

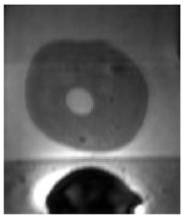

Figure 1: Prostate phantom MRI image.

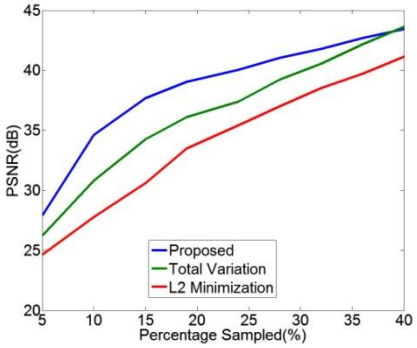


Figure 2: PSNR (dB) vs. Sub-sampling ratio of radial aquisitions (%).

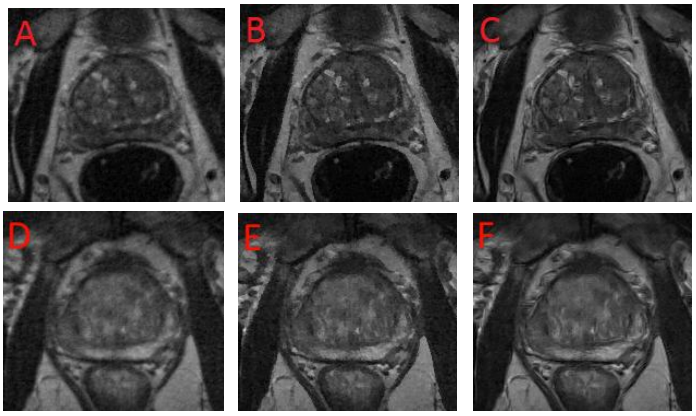


Figure 3: Comparison between L2 minimization (A, D), total variation (B, E), and CD-SFCRF (C, F) for two patient cases.

Reference:

[1] M. Lustig, *et al*. (2007) Magn. Reson. Med., vol. 58, no. 6, pp. 1182–1195.

[2] A. Wong, *et al*. (2010) IEEE Trans. Biomed. Eng., vol. 60, no. 3, pp. 743–752.

[3] K. Block, *et al*. (2007) Magn. Reson. Med., vol. 57, pp. 1086–1098.

[4] J.Trzasko. *et al.* (2009) IEEE Trans. Medical Imaging, vol. 28,no. 1,pp. 106-121.

[5] M. J. Shafiee, *et al*. (2013) IEEE Conference on Image Processing.