Compressed Sensing MRI with Joint Image-Level and Patch-Level Priors

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Introduction

Problem: MRI is a promising medical imaging technique but it is limited in slow imaging speed. To overcome this disadvantage, compressed sensing (CS) theory is used to accelerate MR Imaging by capturing few k-space data for reconstruction.

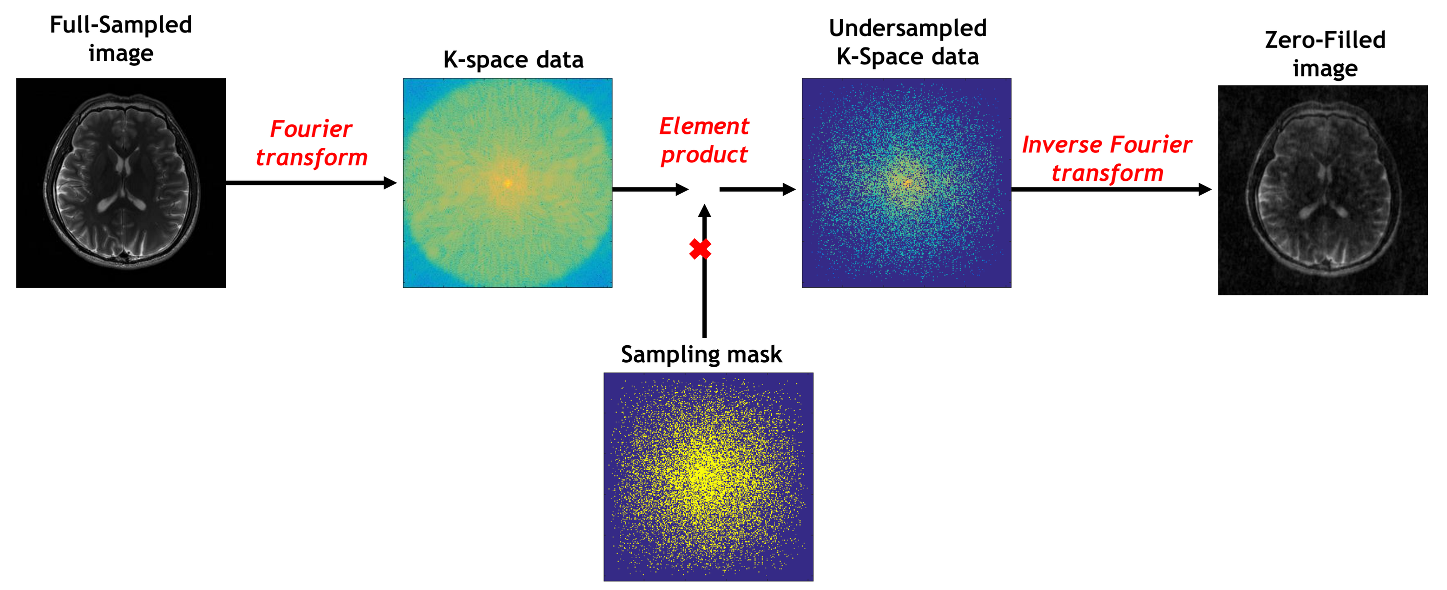

Fig. 1: MRI reconstruction using undersampling k-space data.

Contributions: We develop a novel compressed sensing magnetic resonance imaging algorithm with joint image and patch priors, and our contributions are below:

1. Joint image-level and patch-level priors are adopted to make use of image global and local sparse nature for promoting MR image structures and suppressing artifacts or noise. Total variation (TV) is efficiently adopted for global sparse prior, and expected patch log likelihood (EPLL) is effectively used for local sparse prior.
2. An efficient optimization scheme is proposed to address the proposed cost function by iteratively alternating l1 norm approximation, latent patch reconstruction, and ideal image reconstruction.

Proposed Method

Model Construction:

$$L(\mathbf{x}) = \arg\min_{\mathbf{x}} \frac{\lambda}{2}\|\mathcal{F}_u\mathbf{x} - \mathbf{Y}\|_2^2 + v\|\mathbf{x}\|_{\mathbf{TV}} - \mathbf{EPLL}_p(\mathbf{x})$$

1. $\|\mathcal{F}_u\mathbf{x} - \mathbf{Y}\|_2^2$ is data fidelity which uses the l2 norm to ensure the consistency of the reconstruction and the measured data.
2. $\|\mathbf{x}\|_{\mathbf{TV}}$ denotes anisotropic TV adopted to represent image global sparse prior, which employs l1 norm to enforce piece-wise continuous on image gradient.
3. $\mathbf{EPLL}_p(\mathbf{x}) = \sum_j \log p(\mathbf{R}_j\mathbf{x})$ is EPLL which denotes image local sparse prior and employs a finite Gaussian mixture model (GMM) over the pixels of image patches since many image priors can be seen as special cases of GMM.

Optimization Algorithm:

We reformulate our objective function by bringing in an auxiliary variable to approximate TV, and introducing a set of auxiliary variables to approach EPLL, and we divide it into three subproblems which can be iteratively addressed until convergence.

1. Update for l1 Norm Approximation.
2. Update for Latent Patch Reconstruction.
3. Update for Ideal Image Reconstruction.

Experiments

Table 1: PSNR/SSIM of different reconstruction methods on real-valued shoulder with different sampling percentage.

Mask	Sampling ratio	SparseMRI	DLMRI	PBDW	RecPF	**Proposed**
Cartesian	10	26.34 / 0.824	28.52 / 0.846	27.81 / 0.839	29.55 / 0.863	**30.21 / 0.905**
	20	30.22 / 0.873	32.04 / 0.894	31.35 / 0.881	33.32 / 0.909	**34.53 / 0.924**
	25	32.03 / 0.902	32.35 / 0.917	32.36 / 0.898	35.21 / 0.930	**36.85 / 0.949**
	30	33.49 / 0.921	34.36 / 0.939	35.49 / 0.948	37.71 / 0.950	**38.80 / 0.961**
	35	33.87 / 0.925	35.30 / 0.942	36.58 / 0.950	37.91 / 0.951	**39.06 / 0.969**
Random	10	27.98 / 0.906	29.99 / 0.911	34.15 / 0.951	35.84 / 0.953	**37.27 / 0.962**
	20	25.69 / 0.896	27.09 / 0.908	34.87 / 0.955	37.29 / 0.965	**38.68 / 0.974**
	25	40.15 / 0.970	40.42 / 0.965	42.06 / 0.977	43.23 / 0.979	**44.47 / 0.987**
	30	43.76 / 0.979	42.73 / 0.976	43.30 / 0.981	45.41 / 0.985	**46.40 / 0.991**
	35	44.92 / 0.983	42.44 / 0.981	43.93 / 0.987	46.96 / 0.988	**47.86 / 0.996**
Radial	10	28.32 / 0.785	31.96 / 0.858	31.81 / 0.873	32.82 / 0.875	**33.02 / 0.897**
	20	35.60 / 0.910	37.20 / 0.924	37.79 / 0.934	37.91 / 0.936	**38.53 / 0.941**
	25	38.66 / 0.944	38.37 / 0.942	38.78 / 0.949	40.02 / 0.954	**42.41 / 0.968**
	30	41.18 / 0.964	36.55 / 0.955	39.07 / 0.963	42.03 / 0.968	**43.67 / 0.987**
	35	43.00 / 0.974	35.65 / 0.964	39.31 / 0.969	43.85 / 0.977	**45.85 / 0.989**

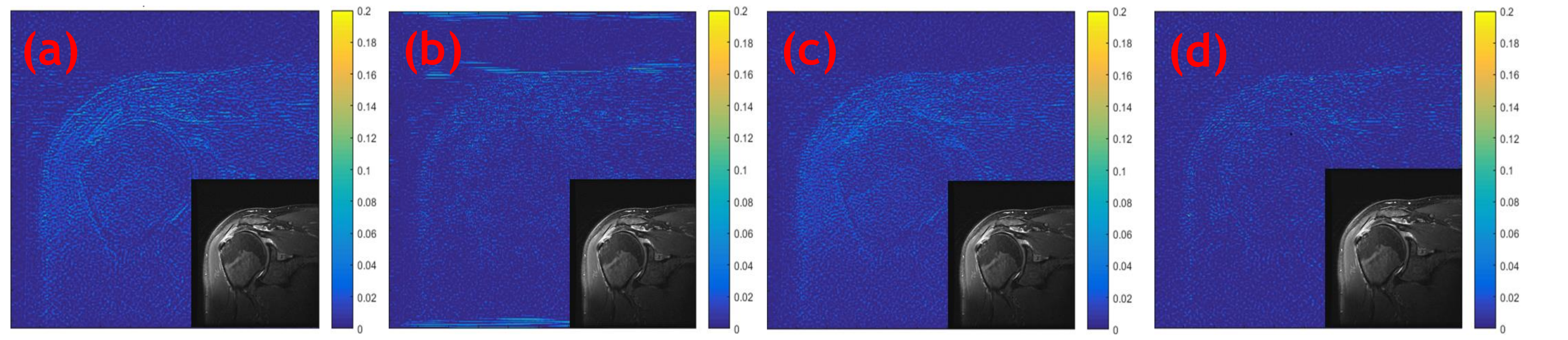

Fig. 2: Real-valued shoulder reconstructions and their absolute errors with 25% radial undersampling. (a) DLMRI(38.37/0.942), (b) PBDW(38.78/0.949), (c) RecPF(40.02/0.954), (d) Proposed (42.41/0.968).

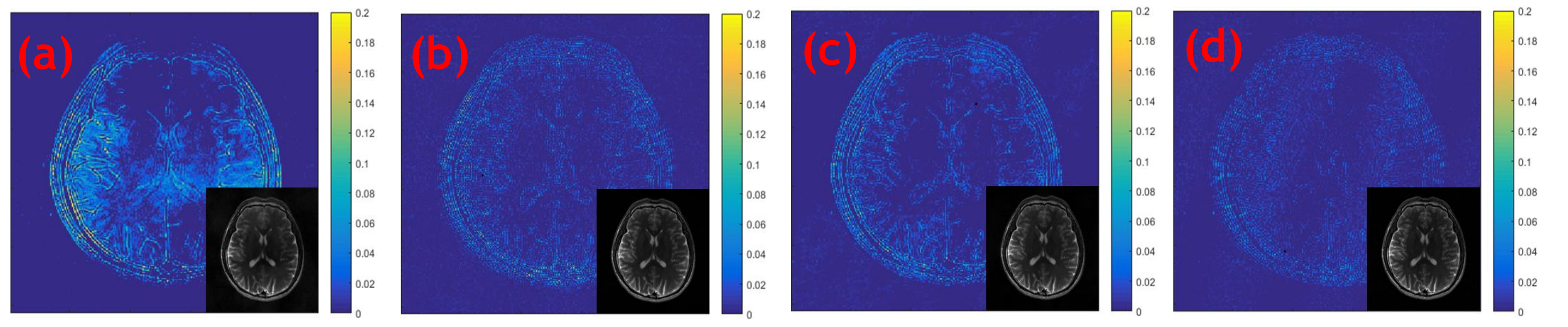

Fig. 3: Complex-valued brain reconstructions and their absolute errors with 50% random undersampling. (a) DLMRI(28.67/0.671), (b) PBDW(34.85/0.922), (c) RecPF(36.29/0.961), (d) Proposed (38.09/0.989).

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