Deep Plug-and-Play Prior for Parallel MRI Reconstruction

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1 Synopsis

Fast data acquisition in Magnetic Resonance Imaging (MRI) is vastly in demand and scan time directly depends on the number of acquired k-space samples. Conventional MRI reconstruction methods for fast MRI acquisition mostly relied on different regularizers which represent analytical models of sparsity. However, recent data-driven methods based on deep learning has resulted in promising improvements in image reconstruction algorithms. In this paper, we propose a deep plug-and-play prior framework for parallel MRI reconstruction problems which utilize a deep neural network (DNN) as an advanced denoiser within an iterative method. We demonstrate that a deep plug-and-play prior framework for parallel MRI reconstruction with a regularization that adapts to the data itself results in excellent reconstruction accuracy and outperforms the clinical gold standard GRAPPA method.

2 Introduction

Many approaches for reducing MRI experiments scan time works by acquiring a fraction of the measurement required for a high-quality image. The plug-and-play prior framework is proposed by Venkatakrishnan et al. [1] with an idea to utilize the denoiser without any regularization objective as proximal operator in an iterative method for image reconstruction. The method has been used in different imaging inverse problem applications [2, 3, 4, 5]. In [2], authors used the plug-and-play framework for bright field electron tomography. In [3], plug-and-play alternating direction method of multipliers (ADMM) has been used for image restoration applications. In [4], the authors developed the fast-iterative shrinkage/thresholding algorithm (FISTA) variant of plug-and-play prior for model-based nonlinear inverse scattering and proved that the framework is applicable beyond linear inverse problems. In [5], the authors introduced a scalable version of plug-and-play framework based on iterative shrinkage/thresholding algorithm (ISTA) which utilized a subset of measurement at every iteration in order to parallelize the algorithm. In all the mentioned papers, a fixed denoiser has been used as the proximal operator which its accuracy can't be ideal in different scenarios for different application. However, in this paper we present a learning-based plug-and-play prior framework for parallel MRI reconstruction which extends the framework to its data-adaptive variant and provides an end-to-end reconstruction scheme.

3 Methods

The discretized version of MR imaging model given by

$$\mathrm{d} = \mathrm{Ex} + \mathrm{n}. \tag{1}$$

where x is the samples of unknown MR image, and d is the undersampled k-space data. $\mathrm{E} = \mathrm{PFS}$ is an encoding matrix, and F is a Fourier matrix. P is a mask representing k-space undersampling pattern and $\mathrm{S} = [\mathrm{S}_1 ... \mathrm{S}_L]$, S_l is a matrix representing the sensitivity map of the l_{th} coil, $1 \leq l \leq L$, and L is the total number of coils. Assuming that the interchannel noise covariance has been whitened, the reconstruction relies on the regularized least-square approach:

$$\widehat{\mathrm{x}} = \underset{\mathrm{x}}{argmin}\ \|\mathrm{d} - \mathrm{Ex}\|_2^2 + \beta \mathrm{R}(\mathrm{x}) \tag{2}$$

where R is a regularization functional that promotes sparsity in the solution and $\beta > 0$ controls the intensity of the regularization.

Our iterative deep plug-and-play prior framework for solving the Equation (1) is provided in Figure 1. DNN architecture is Unet-type convolutional network [6] and Loss minimization was performed using ADAM [7] optimizer. Zero-filled reconstruction is used as an initialization to the algorithm. For least-square cases, we have

$$prox(\mathrm{d}, \mathrm{S}, \widetilde{\mathrm{x}}; \lambda) = \underset{\mathrm{z}}{argmin}\ \frac{1}{2}\|\mathrm{z} - \widetilde{\mathrm{x}}\|_2^2 + \frac{\lambda}{2}\|\mathrm{PFSz} - \mathrm{d}\|_2^2 \tag{3}$$

Since the deep network frameworks work on real-valued parameters, inputs, and outputs, in our method complex data are divided into real and imaginary parts and considered as two-channel input and output.

4 Results

In our experiments, we have tested our method with two different datasets. First dataset has been acquired (3D MPRAGE) on six volunteers with a total of 450 brain images used as the training set. For the second dataset, we have used one of the knee datasets (Coronal fat-saturated proton-density (PD)) presented by [8] which includes a total of 200 images (from central slices) from 10 patients as the training set. 10 images from different patients for each dataset have used for testing purposes. The sensitivity maps were computed from a block of size 24x24 for both brain and knee datasets using ESPIRiT [9] method. Full k-space data reconstructed with the adaptive combine method [10] was used as our gold standard for comparison. Figure 2 display the impact of acceleration factor R=2x2 for zero-filled reconstruction, the clinical gold standard GRAPPA, and our proposed method on 3D MPRAGE brain images. We observed that the proposed method reconstructs artifact-free images, which have better quality than GRAPPA reconstruction, and GRAPPA result shows noise amplification compared to our result (PSNR of ours is 52.93 compared to PSNR of 43.91 for GRAPPA). Figure 3 shows the impact of acceleration factor R=4 for zero-filled reconstruction, GRAPPA, and our proposed method on fat-saturated PD knee data. Similar to Figure 2, GRAPPA result for knee data in Figure 3 shows noise amplification compared to our result (PSNR of ours is 40.48 compared to PSNR of 29.39 for GRAPPA). PSNR and SSIM quantitative variations on two test datasets are depicted in Table 1.

5 Conclusion

This paper proposes a deep plug-and-play prior framework and demonstrates the effectiveness of learning-based plug-and-play prior framework for parallel MRI reconstruction and the experimental results on two MRI datasets show that our proposed method outperforms the clinical gold standard GRAPPA method.

	Brain Dataset		Knee Dataset	
Method	PSNR	SSIM	PSNR	SSIM
Proposed	53.3±0.91	0.99±0.0015	39.87±1.08	0.93±0.0086
GRAPPA	44.8±0.69	0.97±0.0023	28.43±0.97	0.6±0.045

Table 1: PSNR and SSIM variations on the two test datasets

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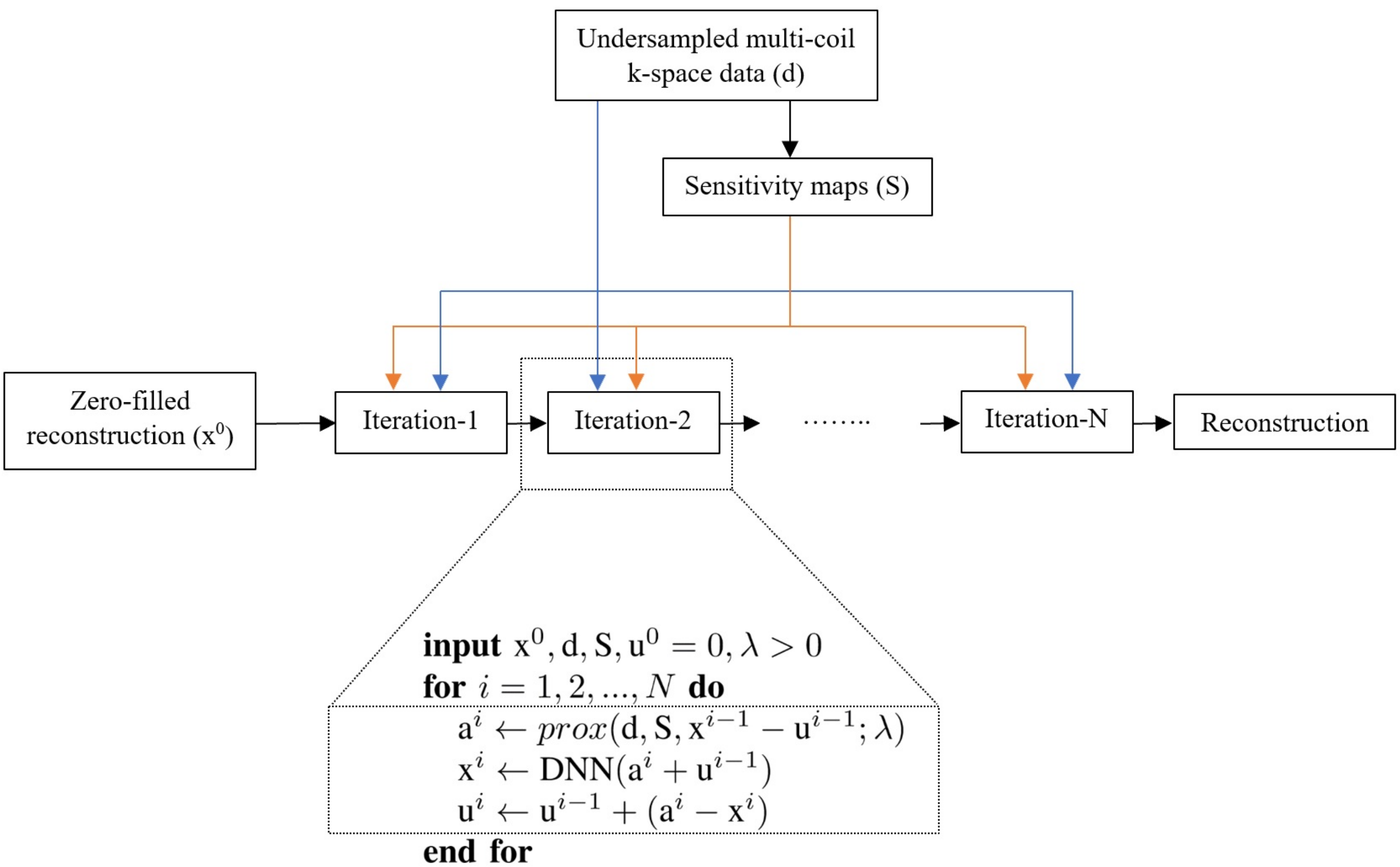

Figure 1: Proposed deep plug-and-play prior framework.

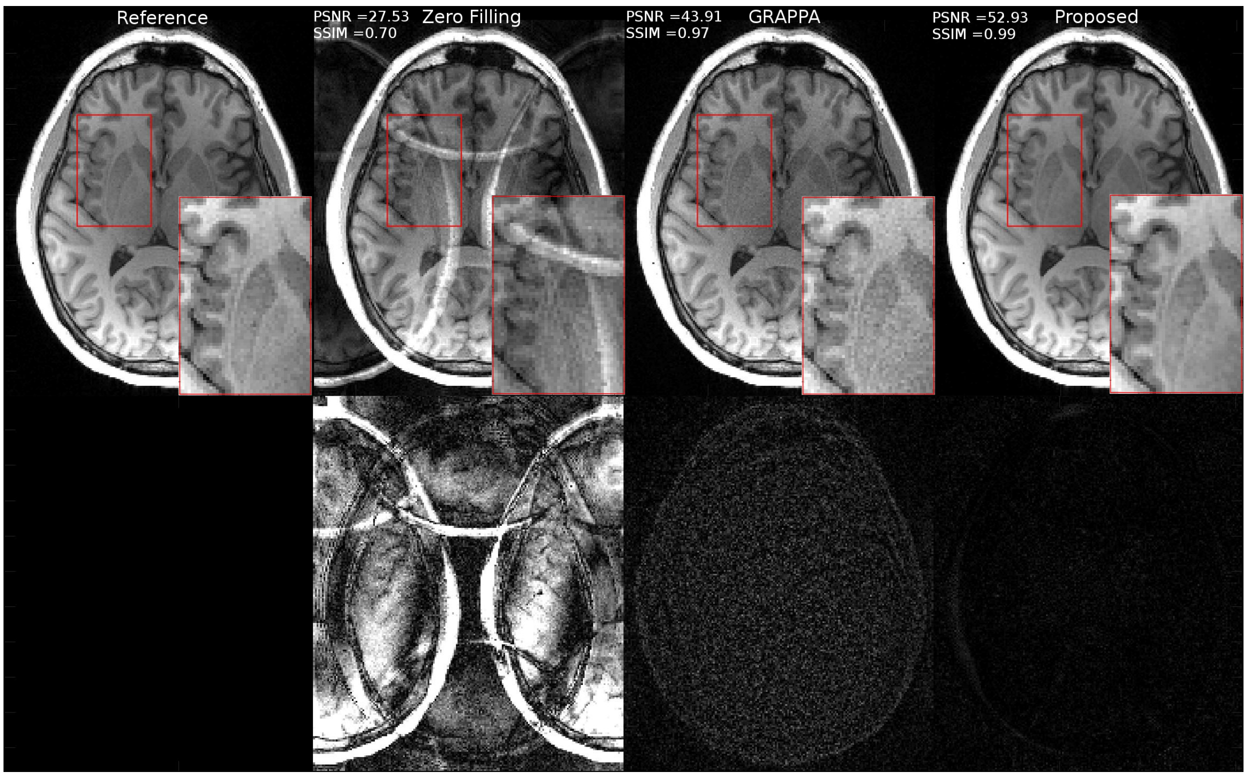

Figure 2: First row (left to right): Gold standard reconstruction result using fully sampled data, zero-filled reconstruction, GRAPPA reconstruction result with undersampling factor of 2x2, and our reconstruction result with undersampling factor of 2x2 for 3D MPRAGE data. Second row, includes error maps correspond to each reconstruction results for comparison.

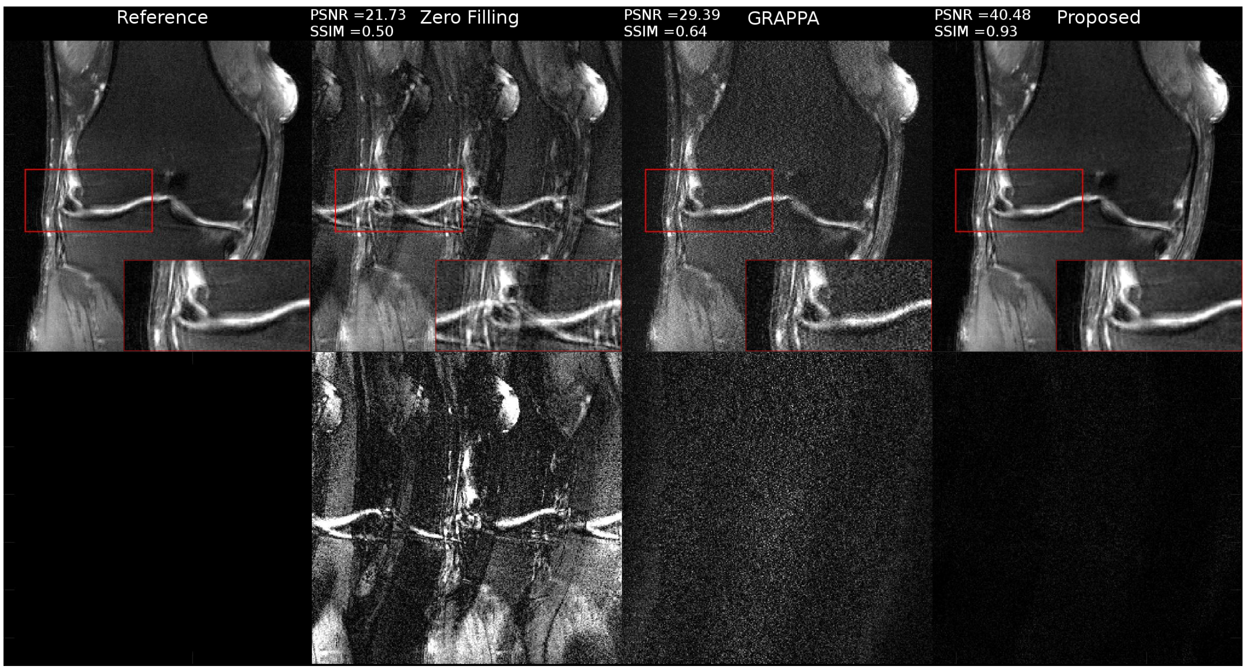

Figure 3: First row (left to right): Gold standard reconstruction result using fully sampled data, zero-filled reconstruction, GRAPPA reconstruction result with undersampling factor of 4, and our reconstruction result with undersampling factor of 4 for 2D coronal knee data. Second row, includes error maps correspond to each reconstruction results for comparison.

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