Non-Learning based Deep Parallel MRI Reconstruction (NLDpMRI)

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Problem and Motivations

- 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.

Current Issues:

- The clinical gold standard GRAPPA method [1] generates noisy reconstruction in highly accelerated data acquisition.
- Deep learning-based MRI reconstruction approaches [2,3,4,5] need to learn from massive datasets through the training processes and can't handle k-space data with different undersampling patterns, and different number of coils. Their networks must be trained from scratch every time with new training datasets, acquired under new configurations.

Proposed Solution:

- In this work, we developed the generalized deep neural network-based method without any training data involved using convolutional neural network for parallel MRI reconstruction. Our method can be categorize among the unsupervised energy-based methods [6,7].
- Our method only needs the single undersampled multi-coil k-space data for reconstruction.
- Two deep loss functions including non-regularized and regularized are proposed for parallel MRI reconstruction.

NLDpMRI: Main Idea

Our proposed method (NLDpMRI) includes U-net [8] convolutional network with deep loss function. In our reconstruction process, we optimize the loss function over the network parameters.

The following equations are the proposed non-regularized and regularized deep loss functions:

$$\hat{\theta} = \underset{\theta}{\text{argmin}}\ \|PFS_l x_\theta - d_u\|_2^2$$

$$\hat{\theta} = \underset{\theta}{\text{argmin}}\ \|PFS_l x_\theta - d_u\|_2^2 + \lambda\|\theta\|_2$$

θ represents the network parameters

x_θ is the network output with parameters θ

$x_{\hat{\theta}}$ is the MR image to be reconstructed

d_u is the undersampled k-space data

P is a k-space undersampling pattern mask

F is the Fourier transform operator

S_l represents coil sensitivity maps

l is the total number of coils

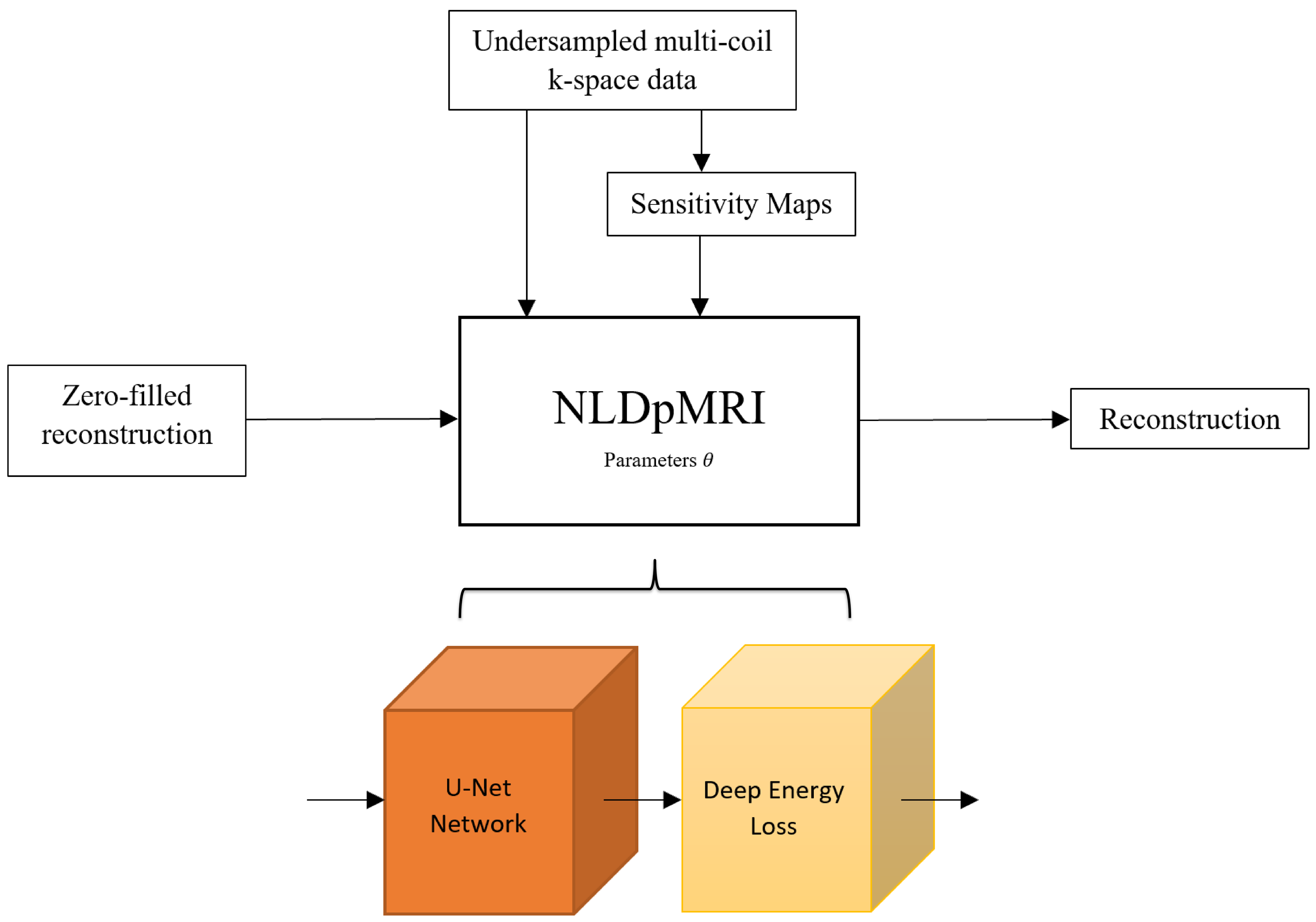

FIG 1. NLDpMRI Framework

NLDpMRI Reconstruction

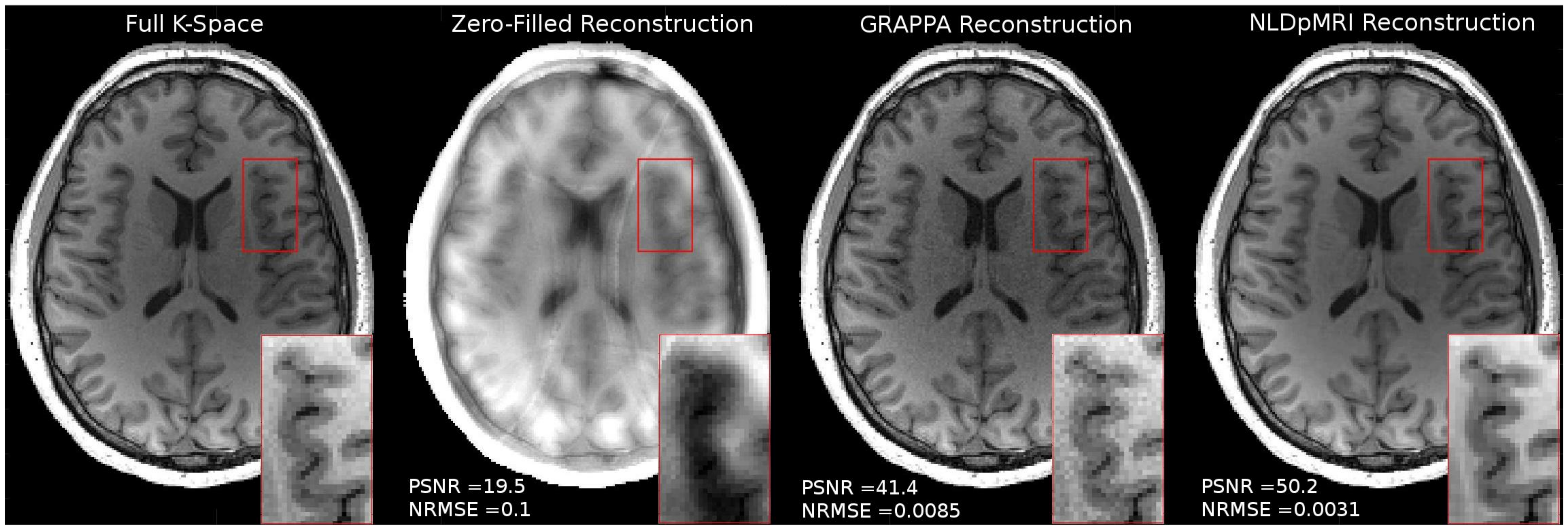

FIG 2. Left to right: Gold standard reconstruction result using full k-space data, zero-filled reconstruction result, GRAPPA reconstruction result, and non-regularized NLDpMRI reconstruction result all with undersampling factor of 2x2. NLDpMRI results in better quality image compared to GRAPPA.

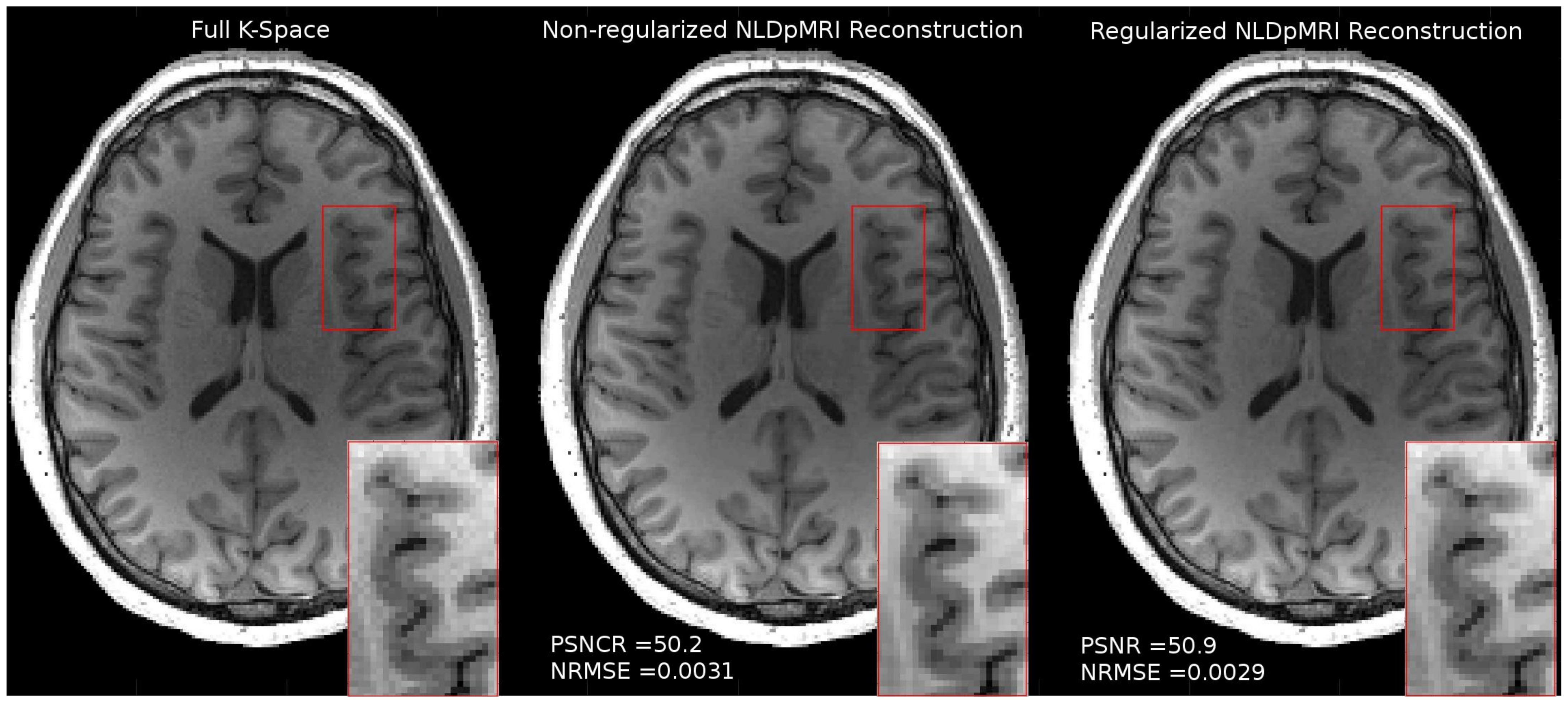

FIG 3. Left to right: Gold standard reconstruction result using full k-space data, non-regularized NLDpMRI reconstruction result, and regularized NLDpMRI reconstruction result all with undersampling factor of 2x2.

Conclusion

- We propose a generalized method to solve MRI parallel image reconstruction problem using deep neural networks without any training data involved.
- The proposed approach eliminates the need to collect massive datasets for training purposes, any form of normalization, and transfer learning techniques.
- Experimental results on real MRI acquisitions show that our proposed method outperforms the clinical gold standard GRAPPA method [1].

References

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