HYBRID DEEP NEURAL NETWORKS FOR PARALLEL MR IMAGE RECONSTRUCTION

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ABSTRACT

Two popular frameworks for reconstruction of undersampled MR acquisitions are compressive-sensing/parallel-imaging (CS-PI) and deep neural networks (DNNs). CS-PI assumes sparsity in fixed transform domains and suffers from sub-optimal hyperparameter selection. Meanwhile, DNNs can be difficult to train in a multi-coil setting due to increased model complexity. To mitigate the limitations of CS-PI and DNN, we propose a hybrid architecture that couples population-driven priors obtained via DNNs with subject-driven priors obtained via PI.

***Index Terms*—** MR Image Reconstruction, Deep Neural Networks, Parallel Imaging, Compressive Sensing

1. INTRODUCTION

Two mainstream frameworks for reconstruction of undersampled MR acquisitions are CS-PI [1] and DNNs [2]. CS-PI weighs sparsity priors in fixed transform domains against subject-driven priors based on a physical signal model [1]. Reliance on fixed sparsifying domains and sub-optimal hyperparameter selection can limit reconstruction performance in CS-PI. DNNs, on the other hand, perform an end-to-end recovery of undersampled acquisitions via population-driven priors learned using large datasets [2]. However, training DNNs in a multi-coil setup can prove hard due to increased model complexity, especially when the training data are limited. To address the limitations of both frameworks, we propose a hybrid architecture (Hybrid-DNN) that complementarily merges subject-driven priors in PI with population-driven priors in DNNs.

2. METHODS AND RESULTS

Hybrid-DNN was implemented by performing alternating projections for data-consistency (DC), calibration-consistency (CC) obtained using SPIRiT [1], and network-consistency (NC) blocks via a cascade of 5 subnetworks (Fig. 1). Evaluations were performed on multi-coil T_1- and T_2-weighted complex brain images of (6,1,3) subjects used for (training, validation, test). Retrospective undersampling was performed via variable-density Poisson-disc sampling for acceleration factors R=(4,8). To examine sensitivity of Hybrid-DNN to the

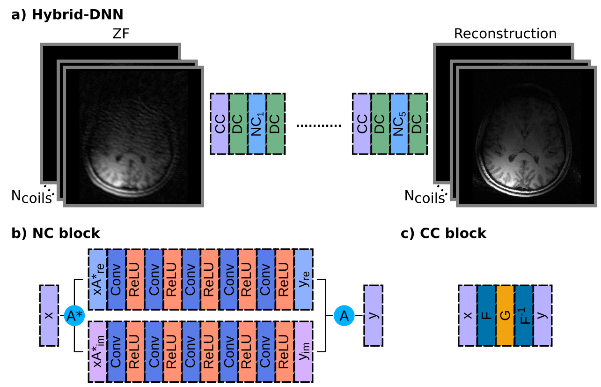

Fig. 1. (a) Hybrid DNN, (b) NC block reconstructs real and imaginary parts of coil-combined images, and (c) CC block performs kernel interpolation in the Fourier domain.

Tikhonov parameter (λ) used in estimation of SPIRiT interpolation kernel and number of training subjects (N), networks were trained for λ in [10^{-3}-10^{-1}] and N in [1,6]. Hybrid-DNN was compared against L1-SPIRiT [1] and DNN [2]. On average across the test subjects, Hybrid-DNN achieves (1.62,1.81) dB higher PSNR in (T_1, T_2)-weighted image recovery compared to the second-highest performing method. Compared to L1-SPIRiT, Hybrid-DNN yields consistently higher PSNR values across λ. Furthermore, Hybrid-DNN outperforms L1-SPIRiT even at N=1. In contrast, the standard DNN requires N=3 in T_1- and N=6 in T_2-recovery to reach the performance of L1-SPIRiT.

Hybrid-DNN simultaneously enhances the immunity of the DNN model to limited training data, and reduces the sensitivity of the PI model to hyperparameter selection.

3. REFERENCES

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