Deep Learning for MRI Reconstruction Using a Novel Projection Based Cascaded Network

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Objectives

- Deep learning (DL) and convolutional networks (CNNs) are making strides in inverse problems of imaging.
- Magnetic resonance image (MRI) reconstruction is an important imaging inverse problem, where deep learning methodologies are starting to make impact.
- We develop a new CNN based deep structure for MRI reconstruction. We introduce a novel data consistency (DC) layer structure which calculates the projection onto the unobserved Fourier subspace.
- The newly developed cascaded deep network results in improved reconstruction performance when compared to some other recent deep network approaches.

Introduction

A recent stronghold for DL and CNNs are inverse problems in imaging. Recently, MRI reconstruction has been addressed by DL practitioners using a plethora of approaches. In the image domain methods, the zero-filled reconstruction image is taken to be the input of the network, and the ground-truth image is enforced as the desired output. After the initial usage of vanilla CNNs, more advanced networks such as encoder-decoder networks, U-Nets [1] and generative adversarial networks (GANs) have been employed in MRI reconstruction. A recent is the deep cascaded CNN (DC-CNN) network [2]. This network utilizes a series of separate CNNs interspersed with data consistency (DC) layers. The DC layer in a MRI reconstruction setting reenforces the actual acquired k-space data onto an intermediary reconstructed image.

MR Reconstruction Prior

The data acquisition forward model for MRI reconstruction can be given as follows [3].

$$\boldsymbol{y} = \boldsymbol{\mathcal{F}}_\Omega \hat{\boldsymbol{x}} + \boldsymbol{\eta} \quad (1)$$

Here, $\hat{\boldsymbol{x}} \in \mathbb{C}^N$ denotes the underlying original image in a vectorized form. The operator $\boldsymbol{\mathcal{F}}_\Omega : \mathbb{C}^N \to \mathbb{C}^M$, with $M < N$, designates the undersampled Fourier transform operator, with $\Omega \in \{1, 2, \ldots, N\}^M$ being the set of indices for the subsampled Fourier data stored in $\boldsymbol{y}$. Ω specifies the positions of the samples included in the acquired Fourier (k-space) data [4]. Hence, Ω also dictates the downsampling ratio M/N. $\boldsymbol{\eta} \in \mathbb{C}^M$ designates the additive noise.

A standard way of reconstructing $\hat{\boldsymbol{x}}$ is by straightforward backprojection $\boldsymbol{x}_{\text{zf}} = \boldsymbol{\mathcal{F}}_\Omega^H \boldsymbol{y}$, also called as zero-filling (ZF) reconstruction. Until recently model based reconstruction methods using iterative solutions to regularized variational formulations offered the best performance results for MRI reconstruction. Total variation (TV), wavelet transforms or self-similarity have been widely utilized as source of sparsity models for compressed sensing (CS) MRI reconstruction algorithms [4]. However, CS-MRI does have its own pitfalls. Firstly, the iterative solutions to the CS variational problems are computationally expensive and time-consuming. As another disadvantage, the iterative algorithms incorporate a plethora of coefficients which necessitate fine-tuning for different setups.

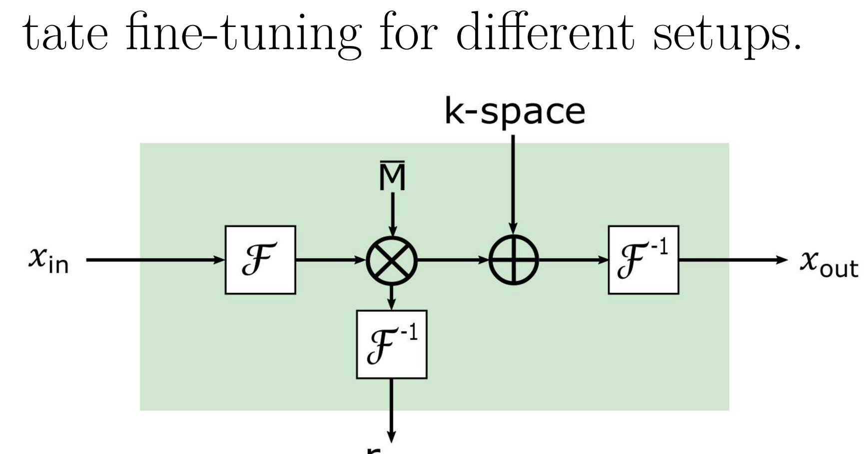

Figure 1:Novel UDC layer as utilized in the proposed algorithm.

Projected Deep Cascade CNN for MRI Reconstruction

Inverse problems in imaging form a recent stronghold for DL approaches. One recent and effective DL approach for MR reconstruction has been the deep cascaded CNN (DC-CNN) network developed in [2]. The DC-CNN includes a succession of individual CNN stages interlinked together by so-called DC layers. The DC layer acts as a block which reimposes the original k-space data onto the intermediary reconstructed image.

$$\boldsymbol{x}_{\text{out}} = \boldsymbol{\mathcal{F}}^{-1}\{\overline{\mathbf{M}} \circ (\boldsymbol{\mathcal{F}}\boldsymbol{x}_{\text{in}}) + \boldsymbol{y}\} \quad (2)$$

The regular DC layer as utilized in [2] and elsewhere has two inputs (input image $\boldsymbol{x}_{\text{in}}$ and k-domain data $\boldsymbol{y}$) and a single output (the rectified image $\boldsymbol{x}_{\text{out}}$). In this work we propose an updated DC layer (UDC). This novel UDC layer not only produces a rectified output image $\boldsymbol{x}_{\text{out}}$, but also outputs a residual or innovation image $\boldsymbol{r}_{\text{out}}$.

$$\boldsymbol{r}_{\text{out}} = \boldsymbol{\mathcal{F}}^{-1}\{\mathbf{M} \circ (\boldsymbol{\mathcal{F}}\boldsymbol{x}_{\text{in}})\} \quad (3)$$

The new secondary output $\boldsymbol{r}_{\text{out}}$ is a projection of the intermediary estimate $\boldsymbol{x}_{\text{in}}$ onto the Fourier subspace which corresponds to the nonobserved coefficients not included in Ω. We extract these projected images $\boldsymbol{r}_i$ from each UDC stage. These projection images are delivered via skip connections to a concatenation layer which is at the input of a final reconstruction CNN. These $\boldsymbol{r}_i$ projection images carry the innovation introduced by each CNN stage. The final CNN reprocesses the information in these projection images and the intermediary output of the first phase to form the final output image.

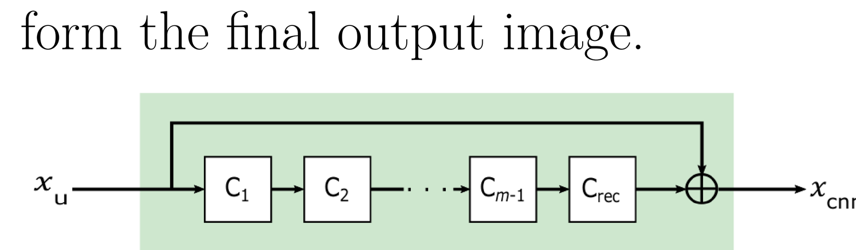

Figure 3:Inner structure of the CNN stages.

Results

Model	PSNR	SSIM	time (sec)
Zero-filled	25.53	0.589	0.013
CS-MRI [3]	26.86	0.723	1.80
PANO	27.95	0.781	70.80
U-Net [1]	33.73	0.908	0.019
DC-CNN [2]	34.74	0.921	0.028
PDC-CNN	**35.10**	**0.934**	0.038

Table 1:Performance and reconstruction time per image comparison.

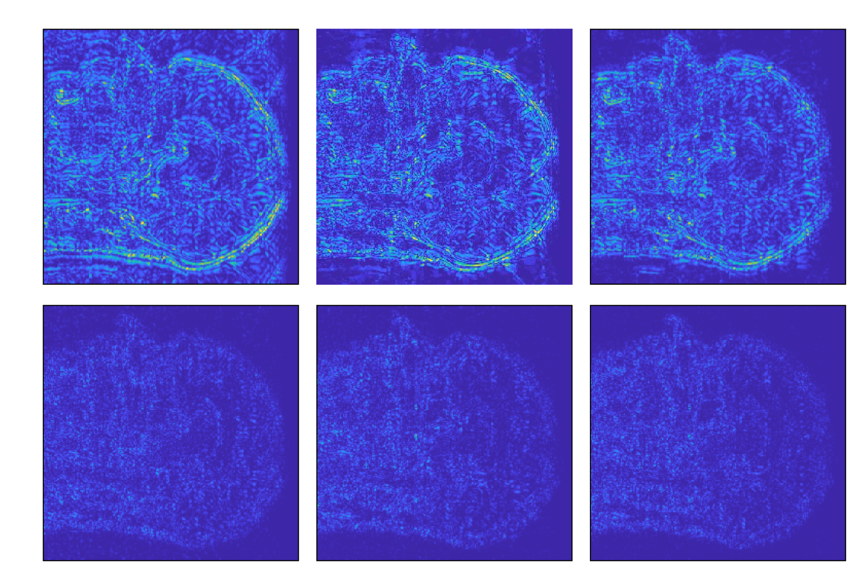

Figure 4:Sample error images. First row: ZF, CS-MRI [3], PANO. Second row: U-Net [1], DC-CNN [2], proposed PDC-CNN.

References

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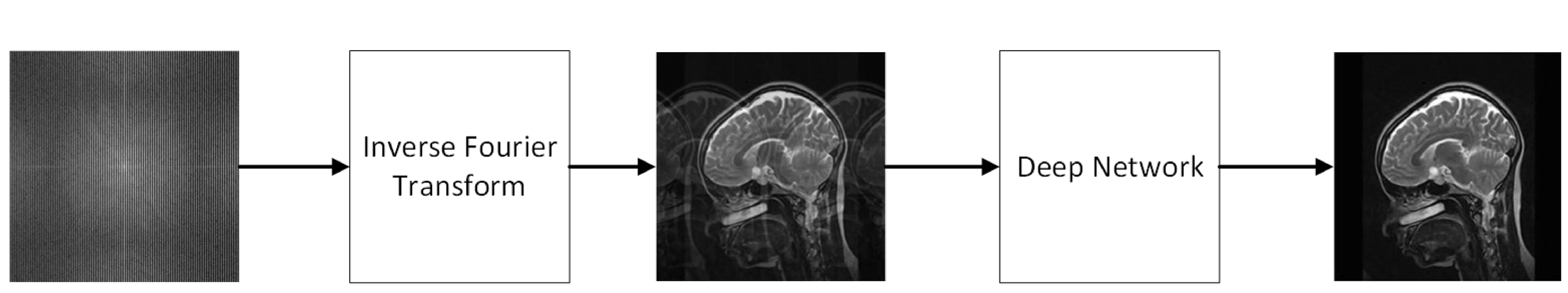

Figure 2:The deep learning based MRI reconstruction framework utilized for the newly developed approach.

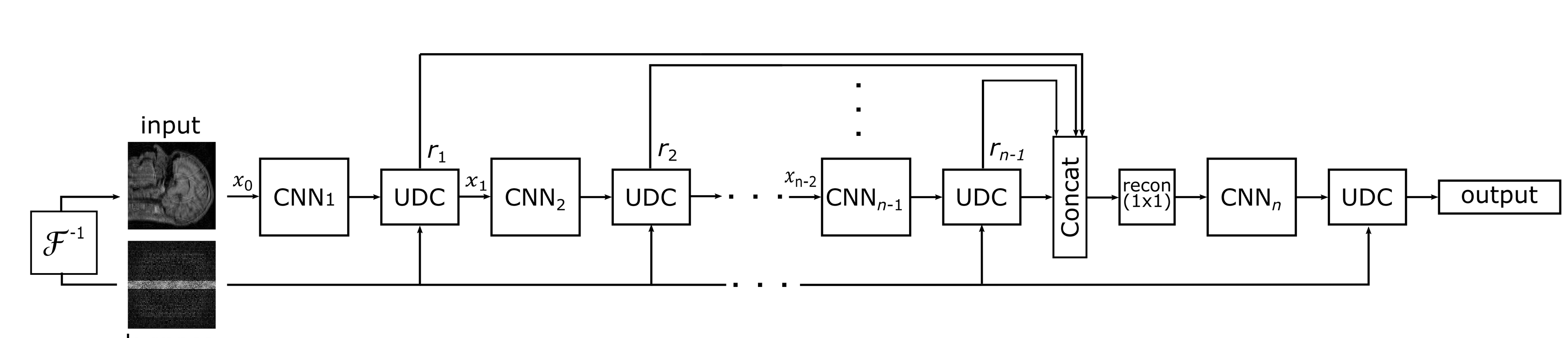

Figure 5:Structure for the newly proposed Projective Deep Cascaded CNN (PDC-CNN) framework for MRI reconstruction.