Deep Learning for Brain MRI Image Restoration

Tram-Anh Nguyen
tnguy150@gmu.edu

Ulugbek Kamilov
kamilov@wustl.edu

August 2019

Abstract

Compressive sensing (CS) is a technique for signal reconstruction from undersampled measurements. Applying CS to MR imaging may speed up MRI scan times, reducing costs and mitigating noisy artifacts caused by movement. In this work, we evaluate a denoising neural network known as FFDNet, with the motivation of applying FFDNet to the plug-and-play (PnP) algorithms for image reconstruction. Relative to BM3D and TV denoising approaches, FFDNet was the most performant denoiser, as indicated by restorations with the highest average PSNR and SNR values.

1 Introduction

Data compression is widely used for transmitting and storing data in all forms, including audio recordings and natural images. Compressive sensing (CS) is a powerful sampling paradigm that allows us to reconstruct signals using significantly fewer samples than the number of samples we normally acquire to satisfy the Shannon-Nyquist theorem. Compressive sensing relies on two tenets: sparsity and incoherence. For an image (and more generally, a signal) to be reconstructed using CS, the image needs to have a concise representation in a transform domain (such that small coefficients in the transform domain may be set to zero without perceptual loss of information). Secondly, artifacts caused by undersampling should resemble noise in the transform domain. In other words, undersampling of the image needs to be done in semi-random fashion, so that artifacts may be removed using a denoiser [2].

Magnetic resonance imaging (MRI) dovetails with compressive sensing because most MR images have a suitable sparsifying transformation. MR imaging helps physicians image soft tissues and organs, diagnose diseases, and monitor patient treatments. MRI is non-invasive and requires no radiation, as opposed to other medical imaging modalities. On the other hand, MRI is time-consuming and susceptible to noise due to movement. Compressive sensing may help drive down the time and costs of an MRI scan, reducing noisy measurements [1] In particular, compressive sensing techniques may help image patients who have difficulty remaining still for the duration of an MRI scan, including young children and mentally ill patients.

Recovering MR images from undersampled k-space measurements requires a robust reconstruction algorithm. In 2018, Yu et al. developed an online variation and extension of PnP algorithms for large-scale image reconstruction. Similar to traditional PnP algorithms, these variations rely on a denoiser to remove artifacts for every iteration of image reconstruction [3]. In this study, we examine the effectiveness of FFDNet as a denoiser for brain MRI scans. Ultimately, our goal is to develop a robust denoiser to be used in the denoising step of the PnP iterative algorithms for MR image reconstruction.

2 Related Work

In 2013, Venkatakrishnan et al. developed the Plug-and-Play (PnP) framework that enables using denoisers as priors for image reconstruction. In doing so, the proximal operator in an iterative reconstruction algorithm is substituted by a denoiser, such as K-SVD and BM3D. A limitation of the PnP framework is its use batch processing; every iteration processes the full set of data [5]. To address this limitation, Yu et al. developed variants of PnP for processing very large datasets. Ready applications for these variants include 3D imaging applications, such as MR imaging, and imaging of dynamic items [3].

2.1 FFDNet as prior

Various denoisers have been employed as priors for the PnP framework, including BM3D and TV [5]. Deep-learning-based denoisers, such as the popular DnCNN [7] with residual learning, have also been tested.

Using DnCNN for its intermediate layers, FFDNet is capable of denoising 2D synthetic images with additive white gaussian noise (AWGN) from a wide range of noise levels. Additionally, FFDNet demonstrated faster performance compared to BM3D denoising. However, FFDNet fails to denoise authentic noisy images well [6]. Although FFDNet suffers from this shortcoming, we chose to evaluate this network because our goal was to denoise MR images artificially corrupted with AWGN. Real noisy MRI datasets are typically discarded as physicians cannot glean information from noisy scans.

In this study, we assessed the denoising performance of FFDNet relative to BM3D and TV denoising. FFDNet was chosen for its speed and ability to perform blind denoising of noise from a wide range noise levels. Unlike DnCNN, FFDNet uses a noise level map as input. In addition, FFDNet denoises downsampled sub-images rather than denoising the full-resolution input. Due to time constraints, the application of FFDNet in the PnP framework was observed but neither rigorously tested nor formally documented.

3 Methods

We evaluate the performance of FFDNet against two popular denoising algorithms: total variation (TV) and BM3D. To quantify denoising performance, we use peak signal-to-noise (PSNR) and signal-to-noise ratio (SNR) image quality metrics.

3.1 Experimental Settings

We used anonymized brain MRI images of 22 patients who were scanned at the Washington University School of Medicine in St. Louis. These 22 patients are healthy individuals with normal neurocognitive function. We designated this dataset as ground truth. Each brain scan consists of a 3D volumetric scan with 10 echoes, yielding 4D measurements. Our dataset was then divided into slices along the depth dimension. Grayscale and RGB images consist of 1 and 3 channels, respectively. In our study, each MRI slice has 10 associated echoes, which we effectively treat as a "10-channel" image.

FFDNet was originally designed to denoise 2D grayscale and RGB images. Modifications to the PyTorch implementation of FFDNet [4] were made to accommodate 10-channel image input. These changes are reflected in the project GitHub repository. Additional adjustments were made to ensure the code runs using Python 3.6 and Pytorch 1.2.

Our dataset consists of 256 x 192 x 72 x 10 scans with the first three dimensions representing the height, width, and depth dimensions. The last dimension represents the number of echoes (treated as the number of channels). The MRI dataset was divided into three separate sets for training (70%), validation (15%), and testing (15%). The batch size for training was 64 images, cropped into 44 x 44 patches.

The following two tables (Table 1 and Table 2) summarize the training configuration of our modified FFDNet. Table 2 displays the number of MRI slices used for each set.

Number of Conv Layers	12
Number of Feature Maps	96
Noise Level Range	[0, 75]
Training Patch Size	44 x 44
Epochs	70

Table 1: FFDNet training configuration

Set	Depth-wise Slices
Training	1100
Validation	236
Testing	236

Table 2: Division of brain MRI dataset for training FFDNet

In our study, additive white Gaussian noise (with $\sigma_1 = 15$ and $\sigma_2 = 50$)

was added to the ground truth images. These noisy images were then fed as input to FFDNet. For baseline comparison, total variation and BM3D denoising algorithms were applied to the same noisy images.

4 Results and Discussion

The following tables summarize the performance of FFDNet on our brain MRI dataset. On average, FFDNet outperformed both BM3D and TV when tasked with denoising images corrupted by AWGN with $\sigma_1 = 15$ and $\sigma_2 = 50$. Visual inspection of images denoised by FFDNet demonstrated that FFDNet preserves fine details better than BM3D and TV (as demonstrated in Figure 1 and Figure 2). Using FFDNet as a prior in the PnP framework yielded very poor MR image reconstructions, as the APGM reconstruction algorithm failed to converge.

Denoiser	Average PSNR	Average SNR
FFDNet	37.731	23.551
BM3D	36.067	21.888
TV	33.928	19.749

Table 3: Denoising results ($\sigma_1 = 15$)

Denoiser	Average PSNR	Average SNR
FFDNet	33.647	19.468
BM3D	30.494	16.315
TV	28.484	14.304

Table 4: Denoising results ($\sigma_2 = 50$)

5 Conclusions and Future Work

In this study, we assessed the denoising performance of FFDNet for brain MRI images corrupted with additive white Gaussian noise. Results on our brain MRI dataset show that FFDNet outperforms BM3D and TV denoising on average. FFDNet improves the quantitative and perceptual quality of noisy MRI scans as measured by PSNR and SNR image quality metrics.

Future work will focus on experimenting with additional CNN architectures (including 3D architectures) and applying the most performant denoiser to PnP algorithms.

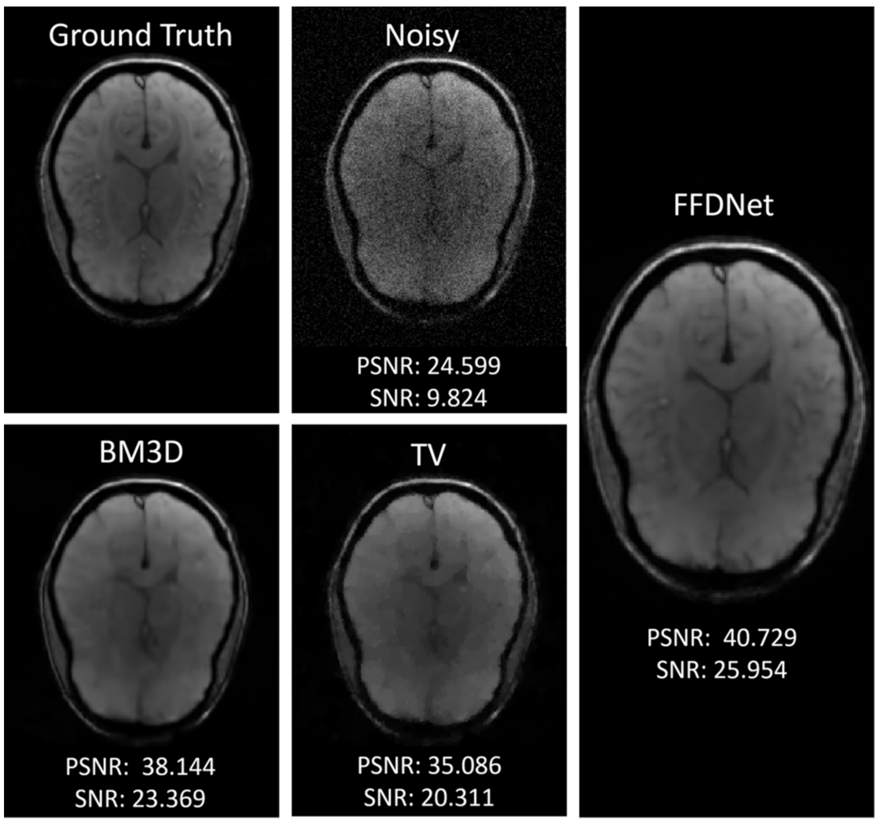

Figure 1: Example of restoration results using various denoisers ($\sigma_1 = 15$).

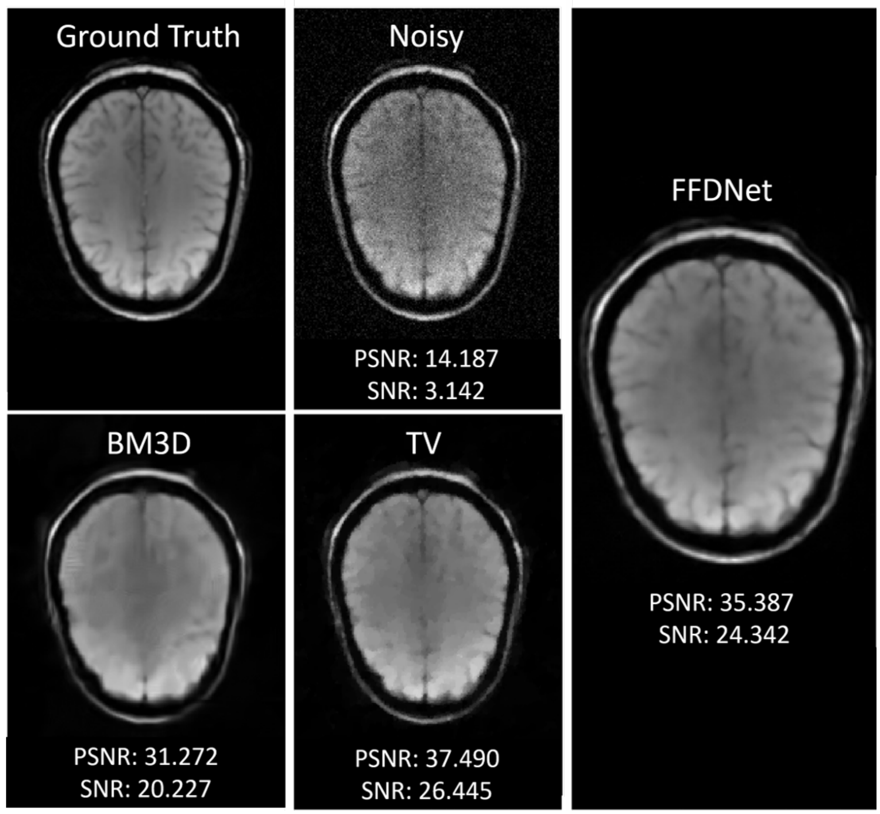

Figure 2: Example of restoration results using various denoisers ($\sigma_2 = 50$).

6 Acknowledgements

This work was supported by the National Science Foundation Grant No. 1852343. We would like to extend sincere gratitude and appreciation to members of the Computational Imaging Group at Washington University in St. Louis, notably Yu Sun, Guangxiao Song, and Weijie Gan, whose contributions to the code, kindness, and amazing generosity made this work possible.

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