github.com/mikgroup/mdd_mri

Untrained Modified Deep Decoder for Joint Denoising and Parallel Imaging Reconstruction

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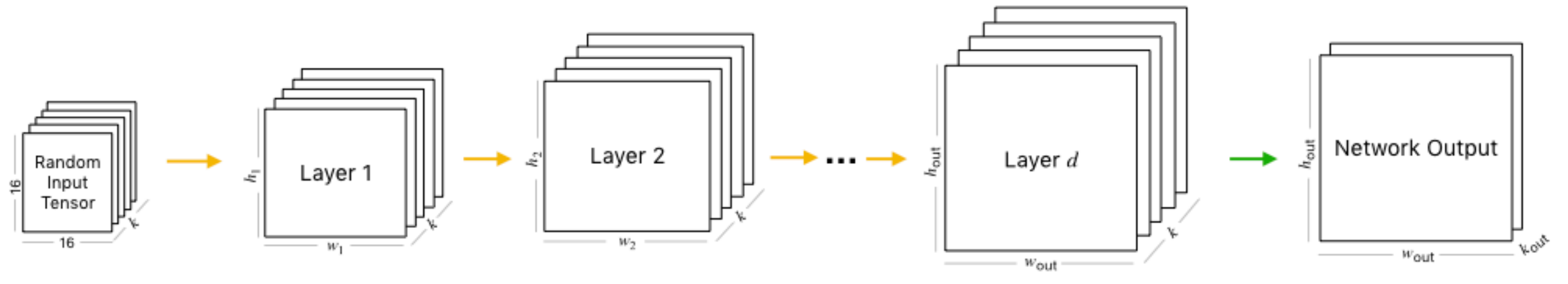
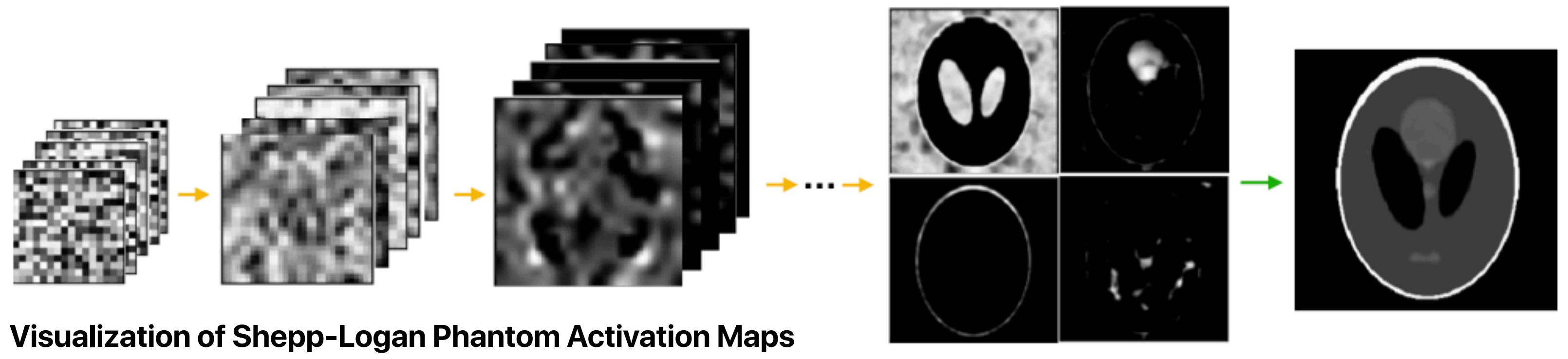


General mDD



Visualization of Shepp-Logan Phantom Activation Maps

→ linear comb., upsampling, ReLU, CN
→ linear comb.

Synopsis

We propose
- An untrained deep learning decoder model (mDD) for
  - image denoising
  - parallel imaging reconstruction
- That exploits multiple channel output to
  - jointly denoise images from adjacent slices
  - reconstruct subsampled multi-coil data without pre-determined coil sensitivity profiles

The untrained model
- Provides a possible alternative to conventional sparsity-based image priors
- Is particularly attractive in scenarios where access to training data is limited

Introduction

Trained reconstruction methods have had success in MR image denoising and reconstruction [1,2] but their success depends on access to large training datasets and ground truth data.

In the clinical context, the small amount of available training data and the lack of ground-truth data may make training-based techniques difficult to apply in practice.

Previous works have noted that the network itself can serve as a prior biased toward "natural" images [3]. In this work, we modify one such network, the Deep Decoder [4,5] (DD), and investigate its use to perform two different tasks without training: multi-slice denoising and parallel imaging reconstruction.

Model Architecture

The mDD architecture (shown above) is a generative decoder model $G_w(z)$ that starts with a fixed, randomly-generated tensor z, and generates k_{out} output images through pixel-wise linear combinations of channels, ReLUs, channel normalizations, and bilinear interpolation upsampling.

Methods

This modified DD (mDD) is used to solve inverse problems by solving, for an observation y and a given forward model A:

$$\min_w f(w) = ||AG_w(z) - y||_2^2$$

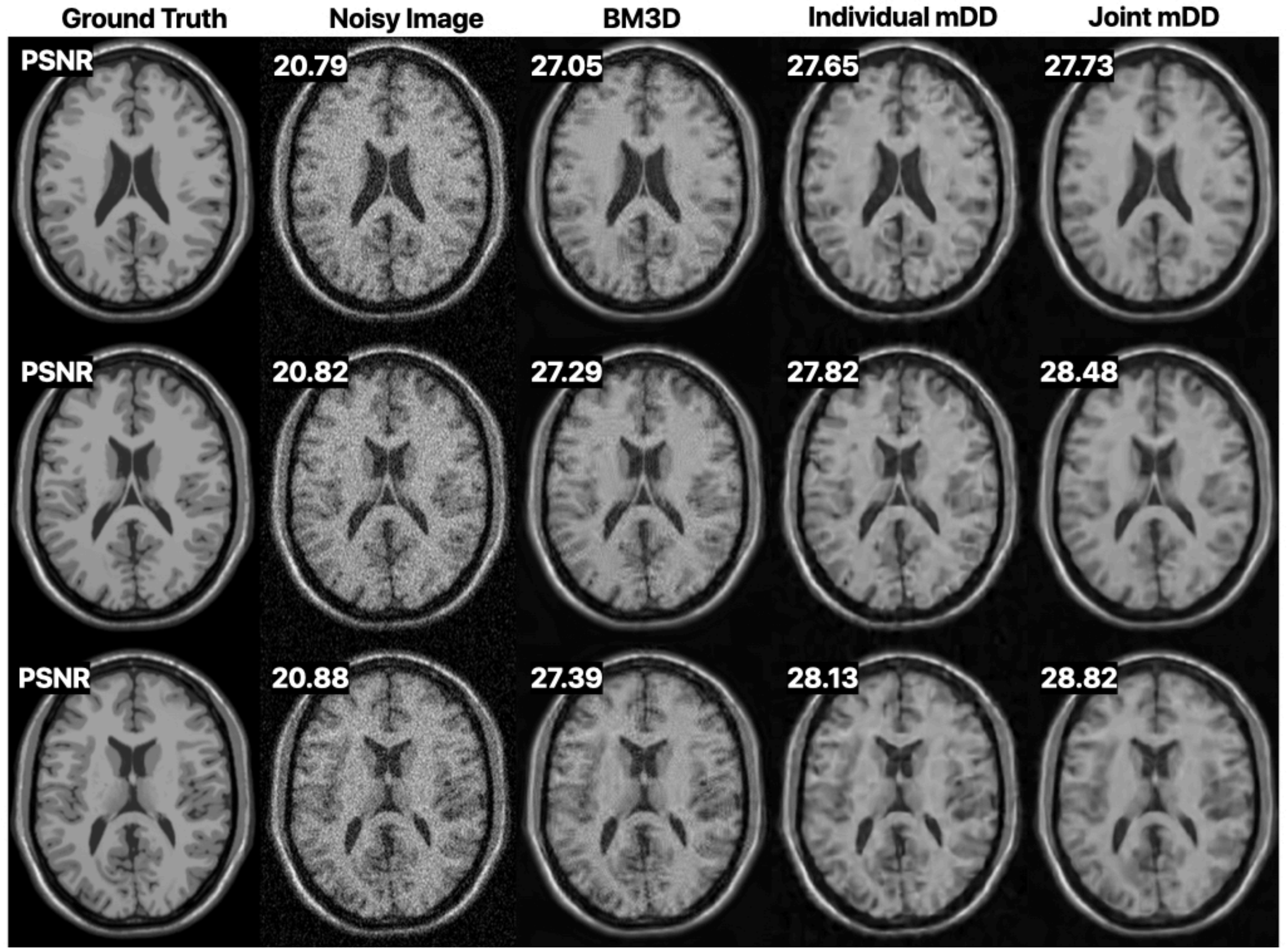
For denoising, we set $A = I$, and identify the network output channels with the set of slices to be jointly denoised.

For multi-coil image reconstruction, we set $A = P_k\mathcal{F}$ (Masked FFT), and identify the network output channels with the individual coil data (so no sensitivity maps are necessary).

For reference, we used single-slice mDD and BM3D [7] to compare denoising, and parallel imaging / compressed sensing (CS) to compare reconstruction [8].

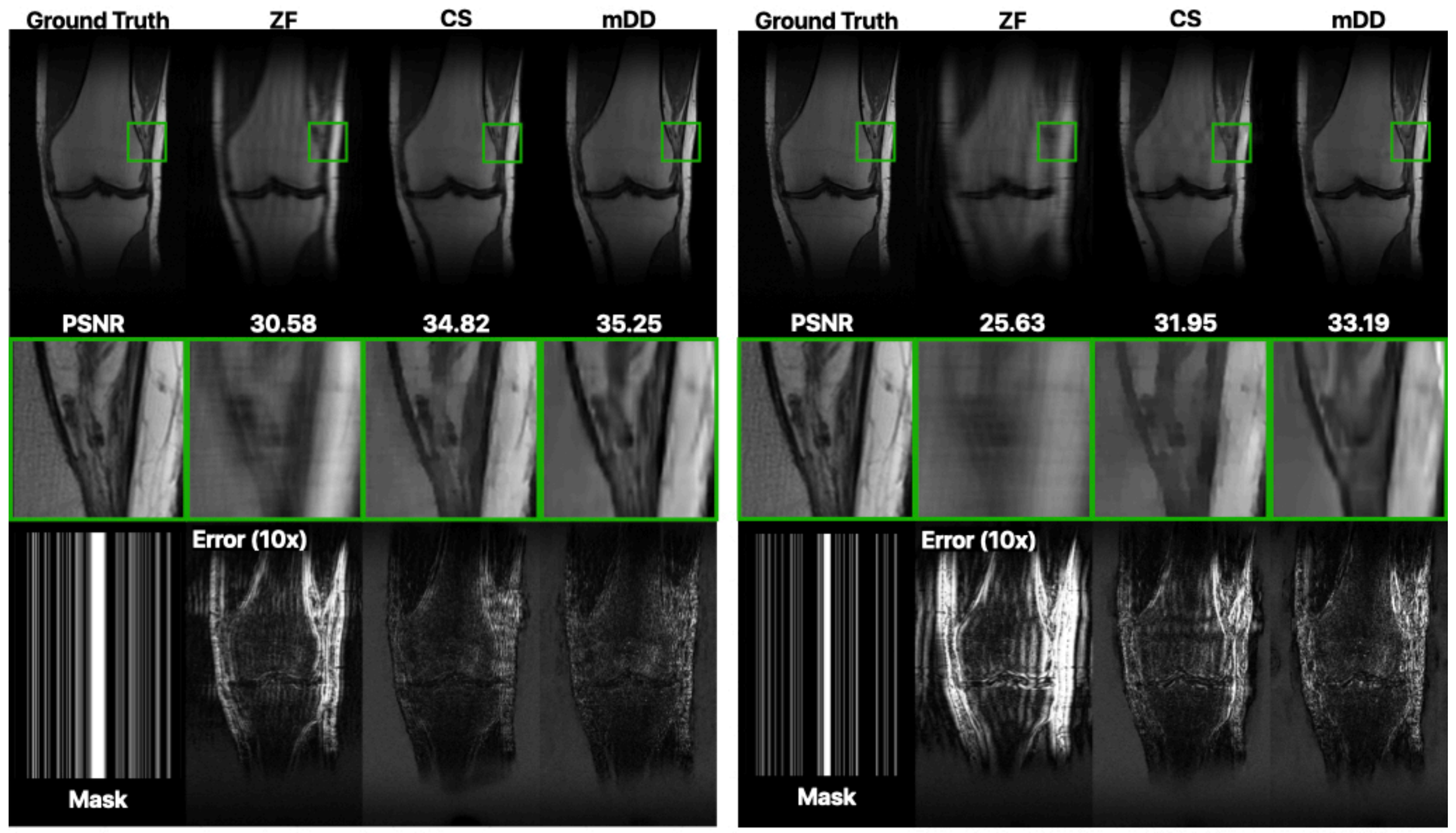
Results

Denoising



Denoising of 10 adjacent slices (3 displayed) of a synthetic data set [9] using BM3D, single-slice denoising mDD, and joint denoising mDD (where all slices are denoised simultaneously).

Parallel Imaging Reconstruction



4x Acceleration 8x Acceleration

Parallel imaging reconstruction of acquired 15 channel knee data [10]. K-space data is subsampled according to masks shown. The reconstructions are Zero Filled IFFT (ZF), Compressed Sensing (CS), and mDD. Center row is a zoomed-in region and bottom row shows error maps

Conclusion

Our results show that joint denoising preserves structure better and reduces the artifact level compared to slightly blocky BM3D and the blurrier, individually-optimized mDD.

For parallel imaging, the mDD generates images with a reduced level of aliasing artifacts. We hypothesize that the network output is biased toward smooth, unaliased images.

The results show that the Modified Deep Decoder architecture allows a concise representation of MR images. The flexibility of this generative image model was successfully leveraged to jointly denoise adjacent slices in 3D MR images and to reconstruct multi-coil data without explicit estimation of coil sensitivities.

This untrained method is particularly attractive in scenarios when access to training data is limited and provides a possible alternative to conventional sparsity-based image priors.

References

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