Plug-and-Play Denoising Priors in Magnetic Resonance Image Reconstruction

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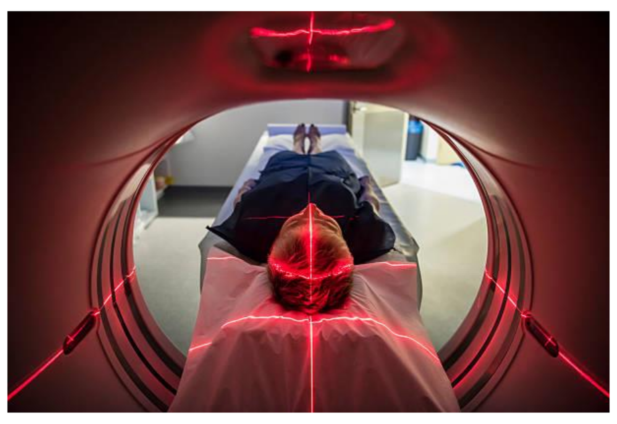
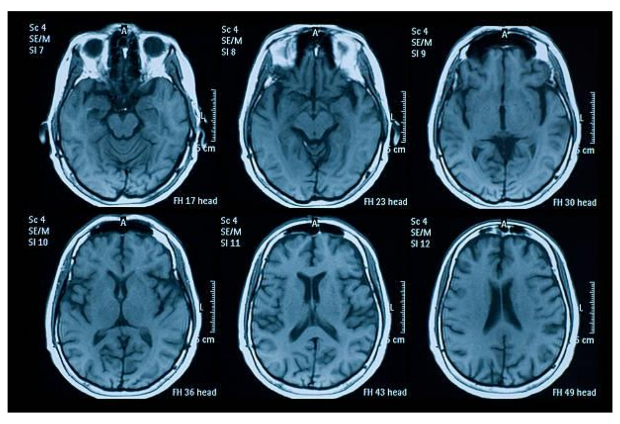
Introduction

- Magnetic Resonance Imaging (MRI) is an essential tool in neurology, oncology, and musculoskeletal medicine. However, long scan times remain a limitation for costs and patient discomfort resulting in motion artifacts.
- One strategy to reduce scan time is to limit information captured and reconstruct the image from an undersampled set of spatial frequencies in the k-space.
- This introduces an ill-posed problem in the reconstruction of high-resolution MR images from low-information measurements.





Related Work

- Serving as an authoritative dataset in MR image reconstruction, the NYU fastMRI Initiative database was used for training and testing in this project [1].
- The plug-and-play framework (PnP) for MR image reconstruction was introduced with convolutional denoisers as a regularization prior. DnCNN continues to act as a baseline in the PnP framework [2].
- Recent work has implements PnP reconstruction frameworks with multiple deep network priors [3].

References

[1] F. Knoll et al., “fastMRI: A Publicly Available Raw k-Space and DICOM Dataset of Knee Images for Accelerated MR Image Reconstruction Using Machine Learning,” Radiology: Artificial Intelligence, 2020.

[2] R. Ahmad et al., “Plug-and-Play Methods for Magnetic Resonance Imaging: Using Denoisers for Image Recovery,” IEEE Signal Processing Magazine, 2020.

[3] J. wang et al., “Deep plug-and-play MRI reconstruction based on multiple complementary priors,” Magnetic Resonance Imaging, 2025.

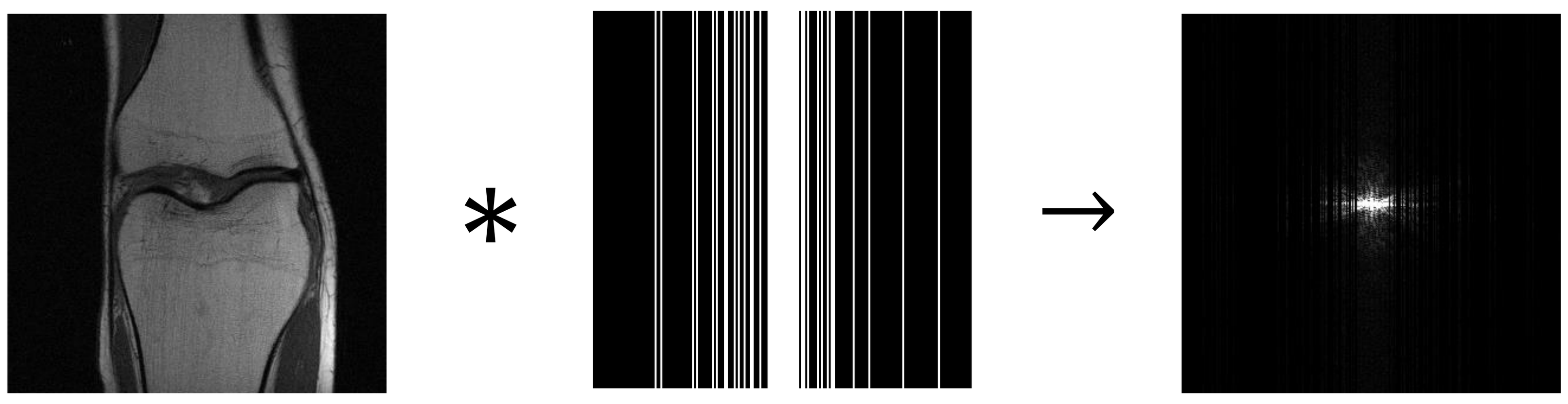
[4] K. Zhang, W. Zuo, Y. Chen, D. Meng, and L. Zhang, “Beyond a Gaussian Denoiser: Residual Learning of Deep CNN for Image Denoising,” IEEE Transactions on Image Processing, 2017.

[5] K. Zhang et al., “Practical Blind Image Denoising via Swin-Conv-UNet and Data Synthesis,” arXiv, 2022.

[6] J. Choi, S. Kim, Y. Jeong, Y. Gwon, and S. Yoon, “ILVR: Conditioning Method for Denoising Diffusion Probabilistic Models,” arXiv.org, 2021.

Methods

- Datasets were created by simulating undersampled images through applying Gaussian mask to fully sampled MR images in the Fourier domain.



Ground Truth | Undersample | Measurement

- Half Quadratic Splitting (HQS) Image Reconstruction Algorithm:

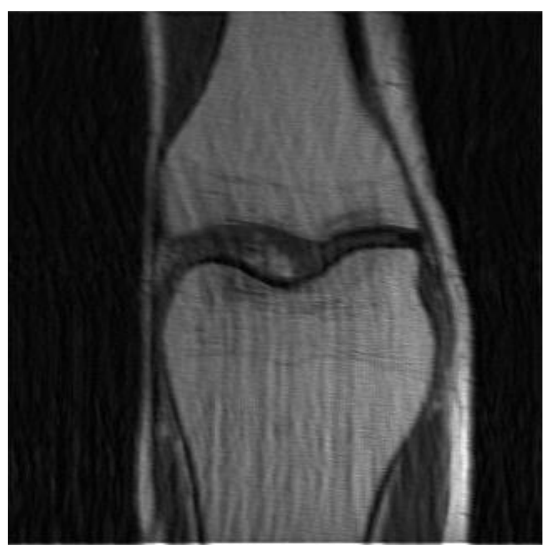
$$\underset{\{x\}}{\text{minimize}}\ \frac{1}{2}\|Ax-b\|_2^2+\lambda\Psi(z),\ \text{ subject to } x-z=0$$

alternates between updating x using the L2 data fidelity term and updating z using the denoising regularization term $\Psi(z)$.

- Denoiser priors used in regularization (PnP framework):
  - DnCNN – Series of convolutional layers with ReLU activation functions [4]
  - SCUNet – U-Net architecture incorporating local and non-local modeling through convolutional layers and Swin Transformer blocks [5]
  - DiffUNet – Well refined denoising diffusion probabilistic model [6]

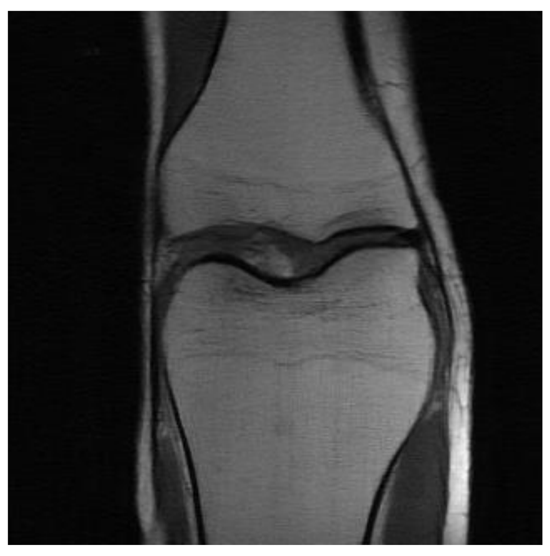
Results

Image Reconstructions:

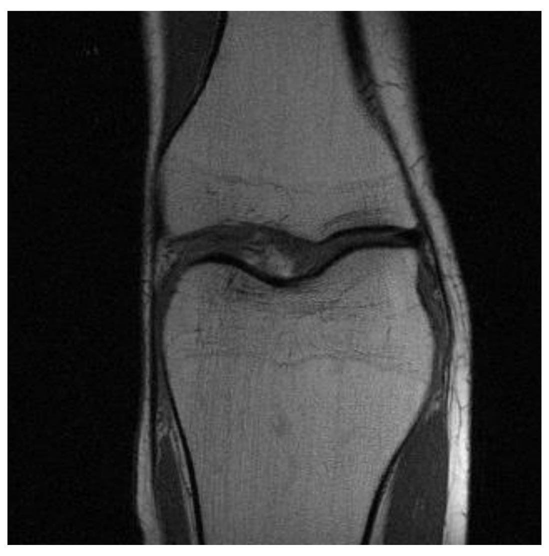


DnCNN

SCUNet



DiffUNet



Ground Truth

- Reconstructions with DnCNN and SCUNet denoiser priors produce artifacts in the form of patterned vertical lines.
- DiffUNet reconstructs ground truth image in more detail with no visible artifacts.
- All reconstructions were unable to reproduce high-frequency features of the ground truth image, demonstrating a need for additional training or model improvements.

Metrics:

Denoiser	PSNR	SSIM
DnCNN	24.6	0.518
SCUNet	26.8	0.533
DiffUNet	**29.1**	**0.711**

DiffUNet performs best in both Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM).

Limitations:

- Models were trained on small dataset (~1000 images of one anatomy type)
- Data was undersampled at an acceleration rate of 4, impacting performance
- Larger and more sophisticated versions of models may perform better