Pre-Processing Techniques and Noise Distribution Learning in Magnetic Resonance Imaging

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02 December 2025

Project Background

- Alzheimer’s disease (AD), defined by amyloid plaques and tau tangles in the brain can be diagnosed with biomarkers obtained from PET scans or CSF proteomics. However, such methods are expensive and invasive, leading to most AD diagnoses being made based on cognitive tests and evidence of atrophy in the medial temporal lobe structures, such as the hippocampus and amygdala.
- Machine and deep learning with architectures such as convolutional neural networks (CNNs) have seen great success in diagnosing AD from structural MRI [1]. Some studies even outperform methods currently used in practice for classifying hard to detect subgroups (atypical AD).
- However, MRI scans rely heavily on pre-processing and “accurate detection of AD using MRI is contingent on the signal-to-noise ratio (SNR) of the scan data, which is directly connected to instrument-related parameters such as magnetic field strength” [2].

This Work

- In this project, we first investigate and implement common pre-processing techniques in medical image analysis with fMRIPrep: such as intensity non-uniformity (INU) correction, skull-stripping, spatial normalization, and brain tissue segmentation [3]. We use this output as the reference image for modeling the noise and calculating SNR.
- Next, Rician noise, a common form of noise in MR images [5] will be added to the images to test the visual effects of noise on the images and on the SNR. This type of noise can easily be generated by the magnitude of a bivariate normal distribution $\sqrt{(real + noise)^2 + (imaginary + noise)^2}$ with $\mu = 0;\ \sigma_{\mathbb{R}} = \sigma_i$.
- The Rician distribution of a noisy MRI magnitude image has the following PDF:

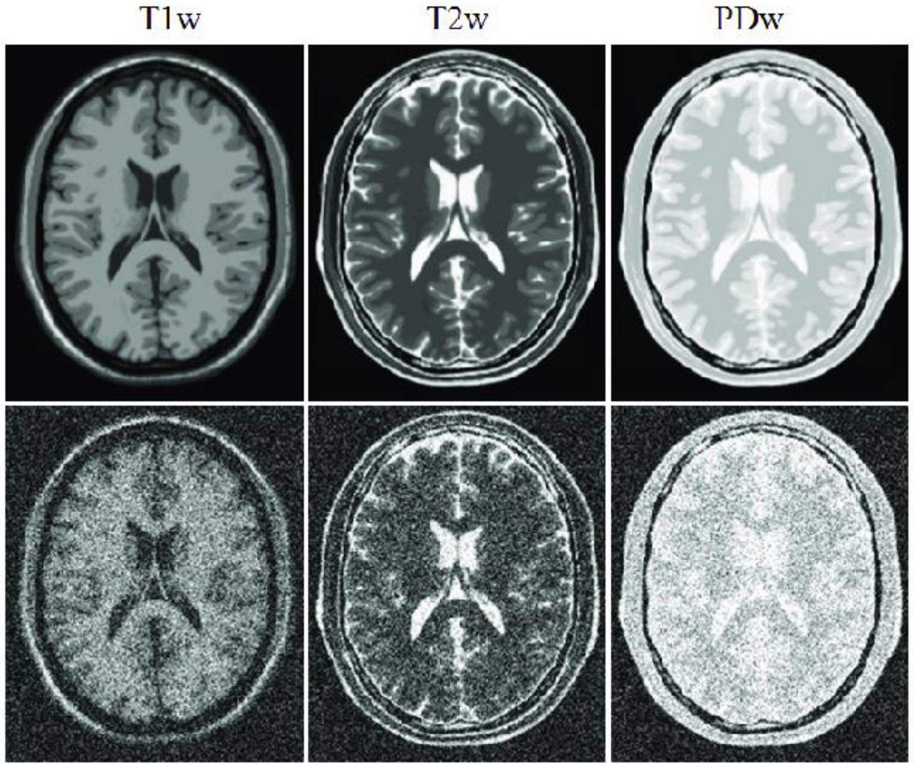
$$p_M(M) = \frac{M}{\sigma^2} \exp\left(-\left(\frac{M^2 + A^2}{2\sigma^2}\right)\right) I_0\left(\frac{A * M}{\sigma^2}\right)$$

Where M is the measured pixel intensity, A is the image pixel intensity without noise, and I_0 is the modified zeroth order Bessel function [5, 6].

- Finally, we apply non-local means filtering to denoise the MR images and plot the residual distribution of the noise at increasing σ on the whole image and brain tissue only.

Rician Noise in MR Images

- The signal is measured through a quadrature detector, reading in both real and imaginary signals in k-space (Fourier space) [8].
- We assume the noise in both signals is Gaussian with zero mean and the distributions are uncorrelated, due to the complex Fourier transform applied to the k-space being linear and orthogonal preserving the Gaussian characteristics [8].
- Magnitude images are created by calculating the magnitude pixel by pixel from the real and imaginary images [8].
- This nonlinear mapping to create the magnitude image causes the noise distribution to no longer be Gaussian. This is called Rician noise [8].



First row: Original images; Second row: Noisy image with Rician noise at 15% [7].

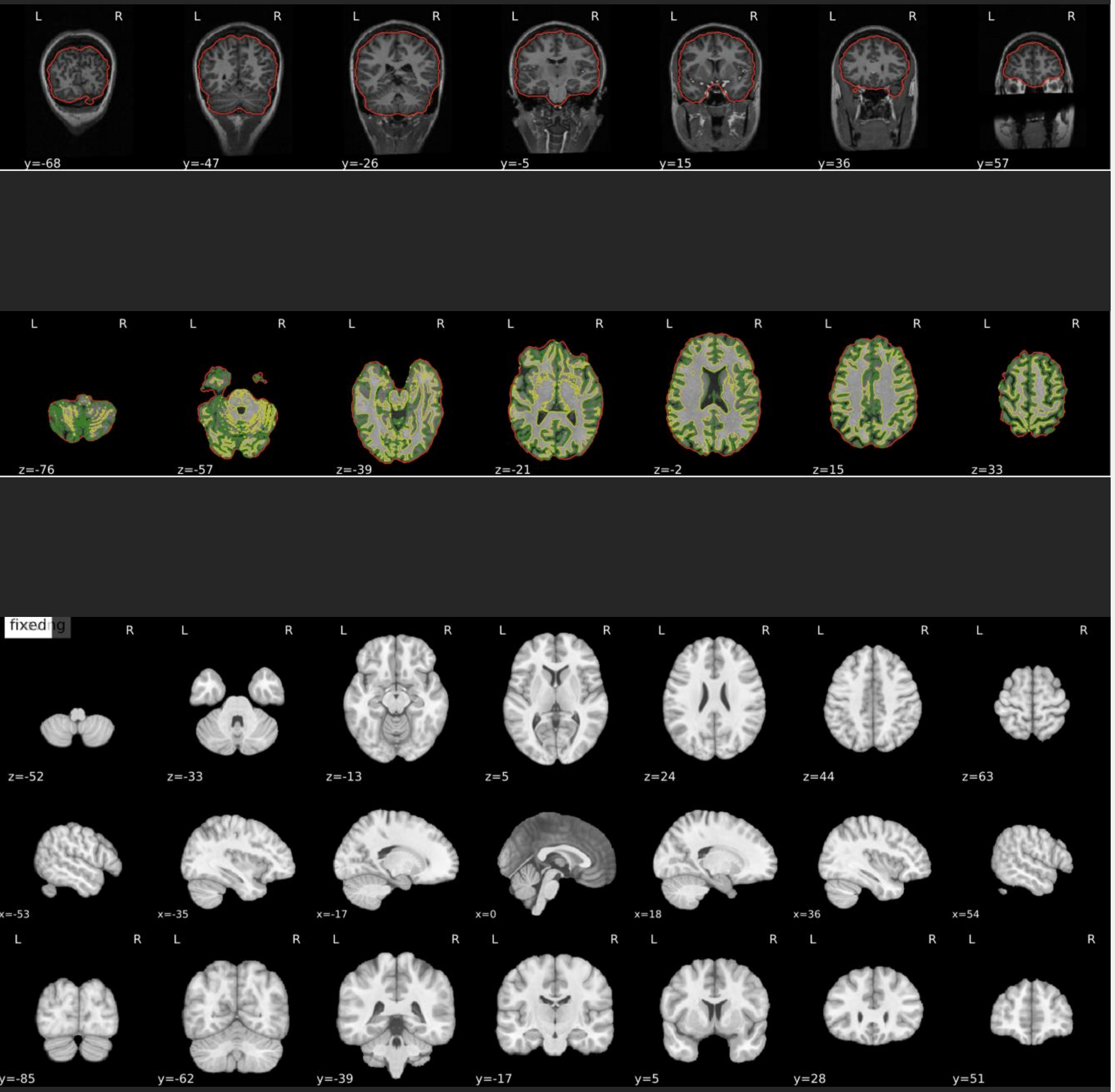
Pre-processing in MR Images

- **Intensity Non-Uniformity (INU) Correction:** Signal intensity measured from homogeneous tissue is rarely uniform and varies across the image. This nonuniformity is usually attributed to “poor radio frequency (RF) coil uniformity, gradient-driven eddy currents, and patient anatomy both inside and outside the field of view” [9].
- To correct this issue, the intensity histogram of the image is repeatedly sharpened by deconvolving by a Gaussian (assumed Gaussian can model bias), then smoothed with a B-spline [10].

- **Skull-Stripping:** Eliminates non-brain tissues from MR images using template-based registration to OASIS [11]. Essential step before performing normalization to template images and for de-identification of subjects [12].

- **Spatial Normalization:** Registration to a common reference space allows to establish a one-to-one correspondence between the brains of different individuals [13].

- **Brain Tissue Segmentation:** Segments a 3D image into different tissue types (Grey/White matter, CSF) [14].

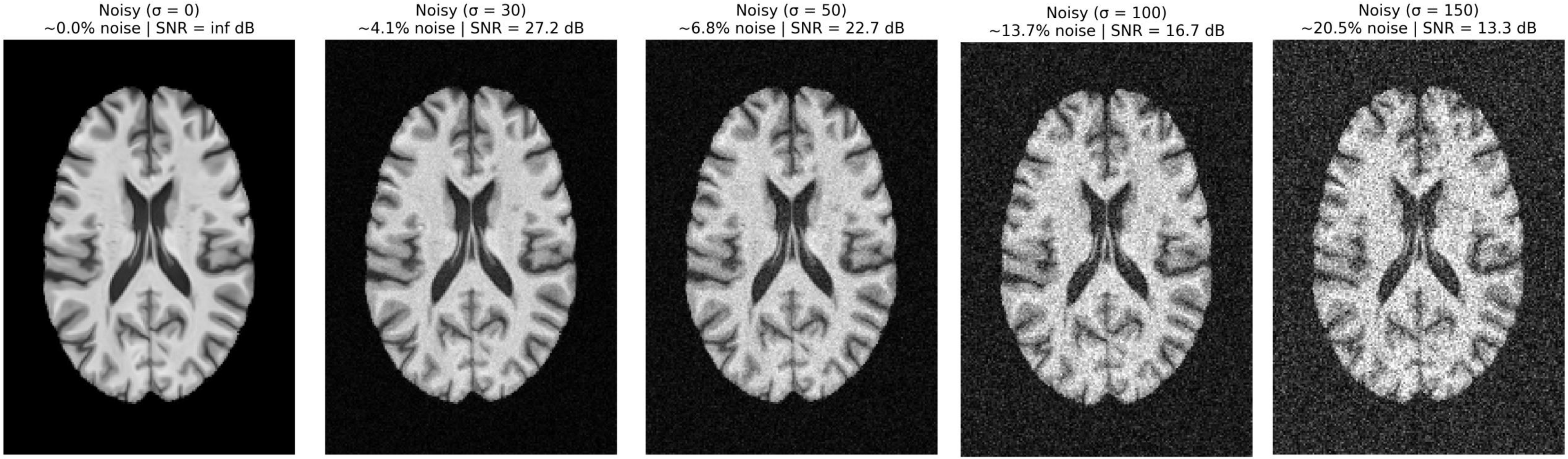


* Images from fMRIPrep documentation https://fmriprep.org/en/latest/workflows.html

Built Dataset

- 257 patients with AD from the ADNI database.
- 293 cognitively normal patients from the ADNI database.
- Pre-processing steps from top to bottom:
  - Brain extraction
  - Tissue segmentation
  - Spatial normalization to MNI space

Additive Rician Noise Results



Non-Local Means Denoising

- Unlike local meaning filters, non-local (NL) mean filtering takes the mean of all pixels in the image, taking advantage of the natural redundancy of information in images [15].
- The restored intensity $NL(v)(i)$ of the voxel i is a weighted average of all voxel intensities in the image I.

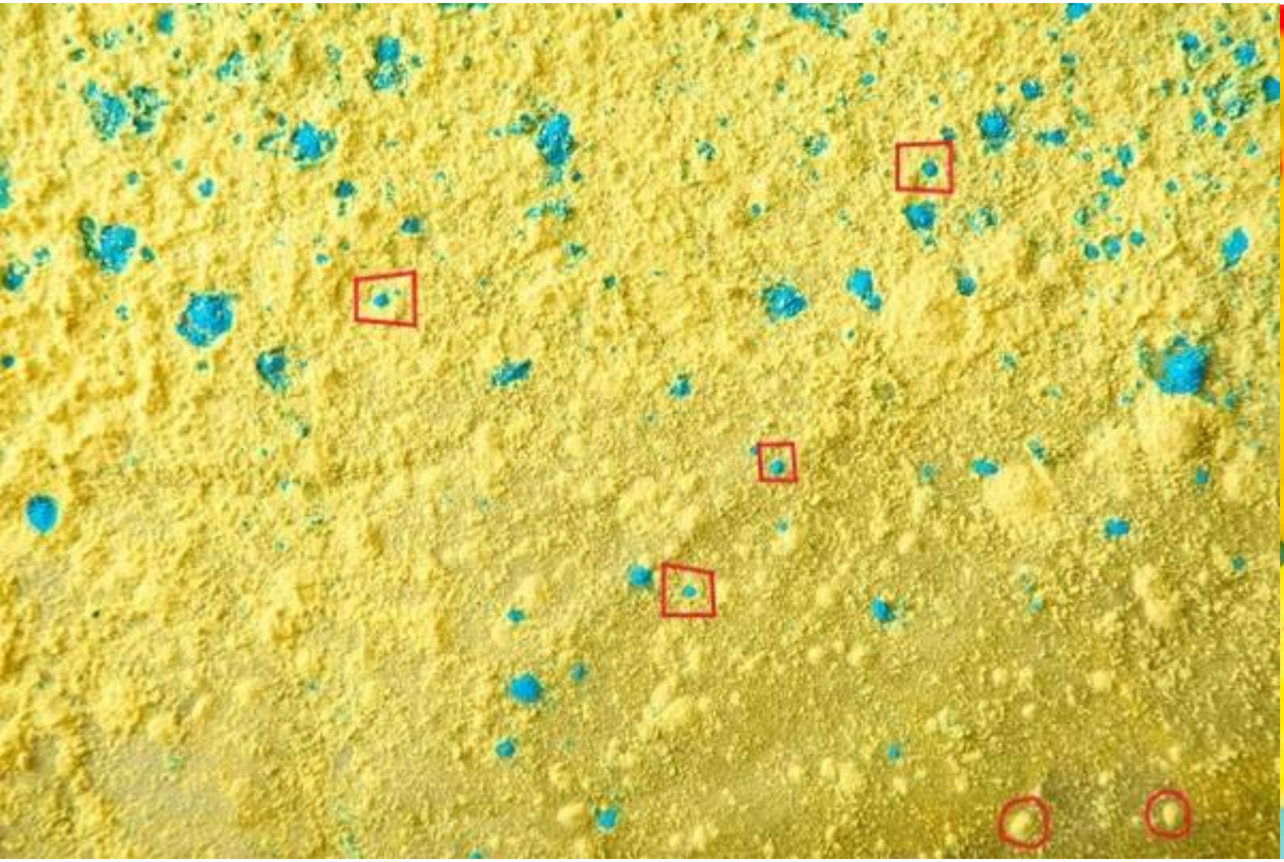
$$NL(v)(i) = \sum_{j \in I} w(i,j)v(j)$$

Where v is the intensity function and $w(i,j)$ is the weight assigned to $v(j)$ in the restoration of voxel i [15].

For averaging M samples, $\bar{p}(x,y) = \frac{M^2 s^2(x,y)}{ME\{N^2(x,y)\}}$: signal increases with the square of M, noise linearly

- The central idea of using NL means filtering is that similar pixels are not guaranteed to be close in space [16]. Therefore, it is better to search a large portion of the image for pixels resembling the one we want to denoise [16].
- Parameters:
  - h: Cut-off distance in gray levels (recommended to use σ)
  - Patch size: Size of patches used for denoising
  - Patch distance: Maximum distance to search for patches

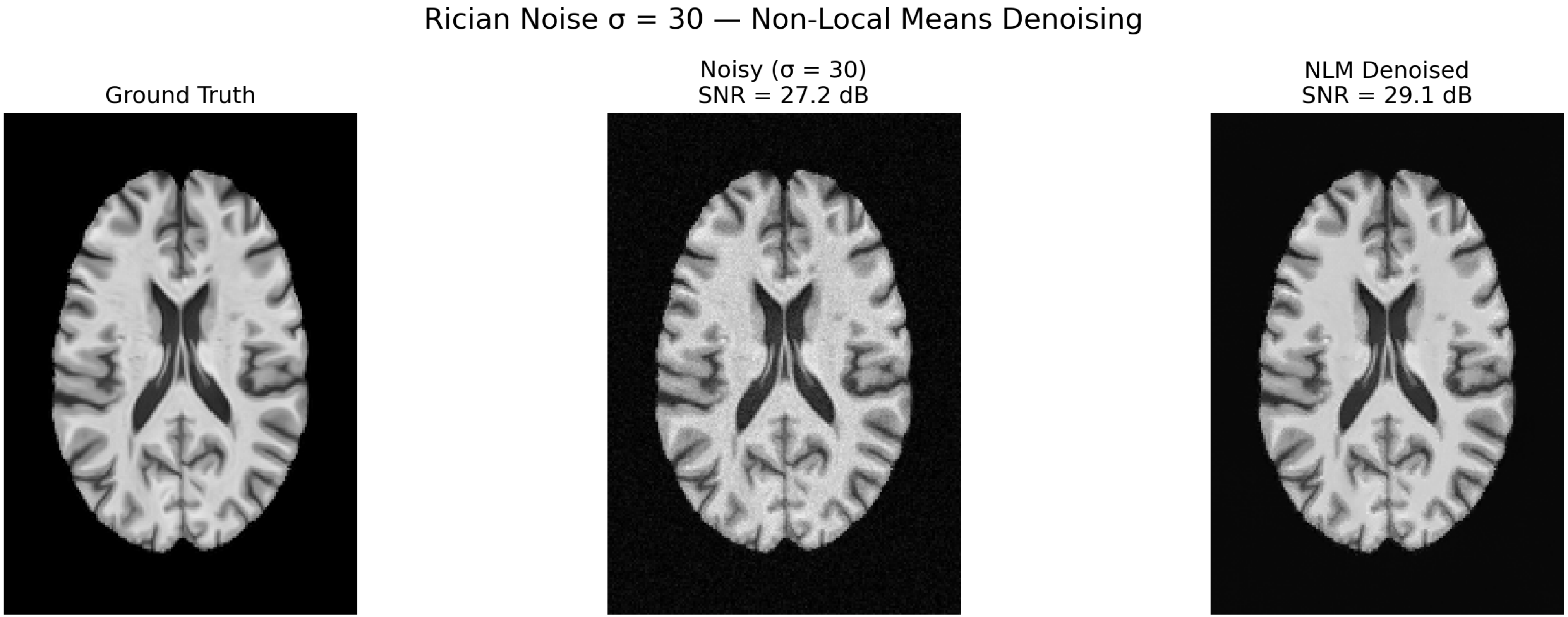
Non-Local Means Denoising Examples



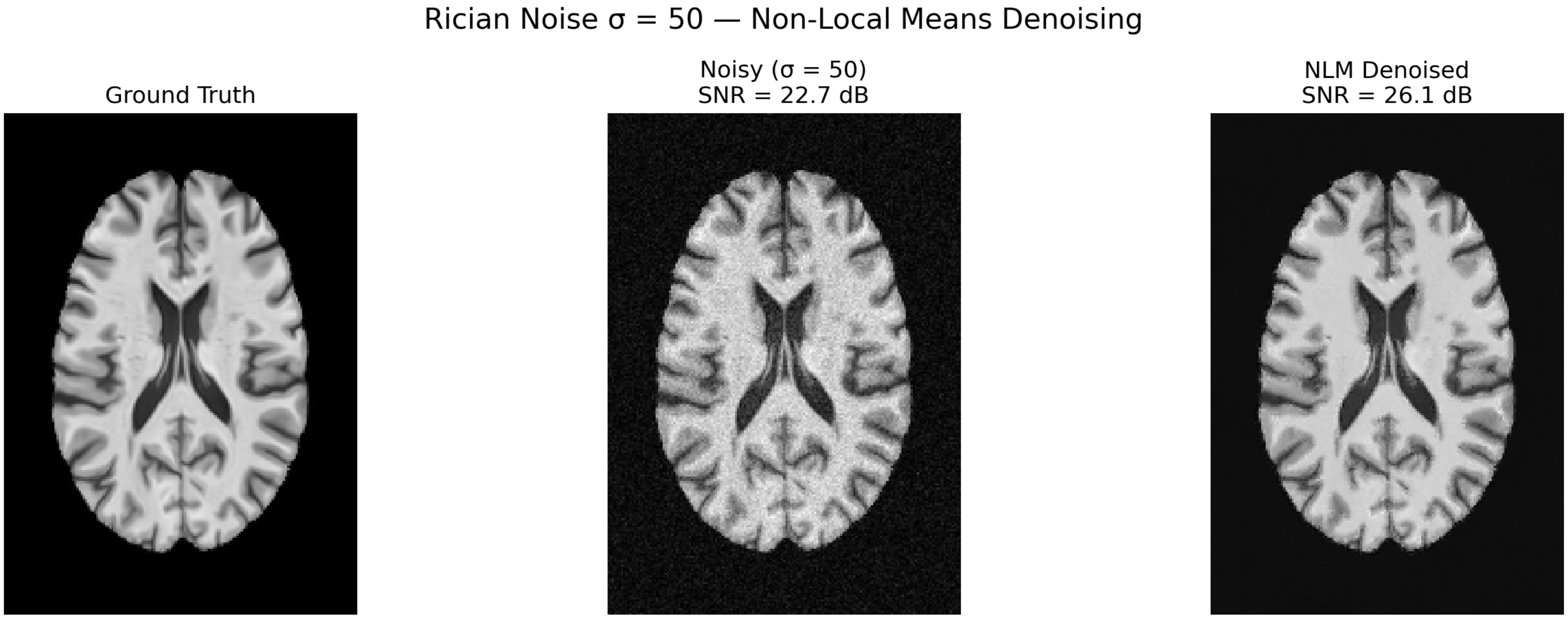
Patches have low MSE

$$MSE = \frac{1}{MN}\sum_{n=1}^{M}\sum_{m=1}^{N}[p_0(n,m) - p_1(n,m)]^2$$

Denoising Results 1/5

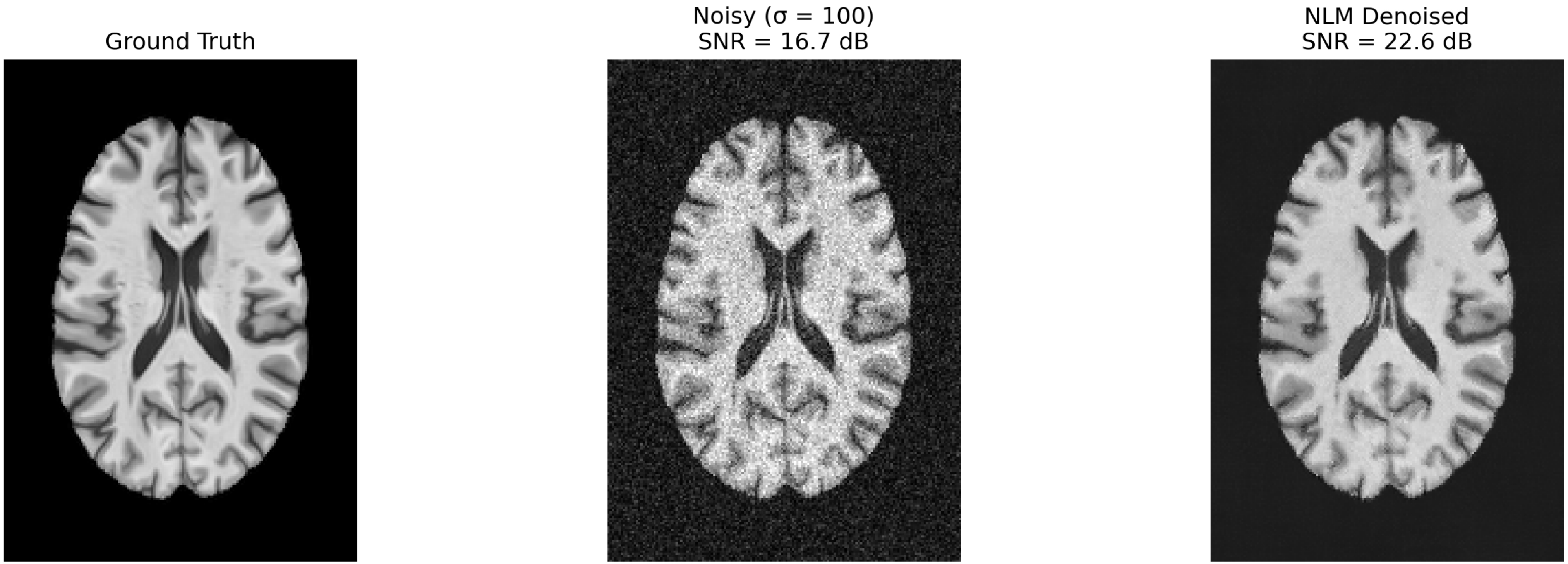


Denoising Results 2/5

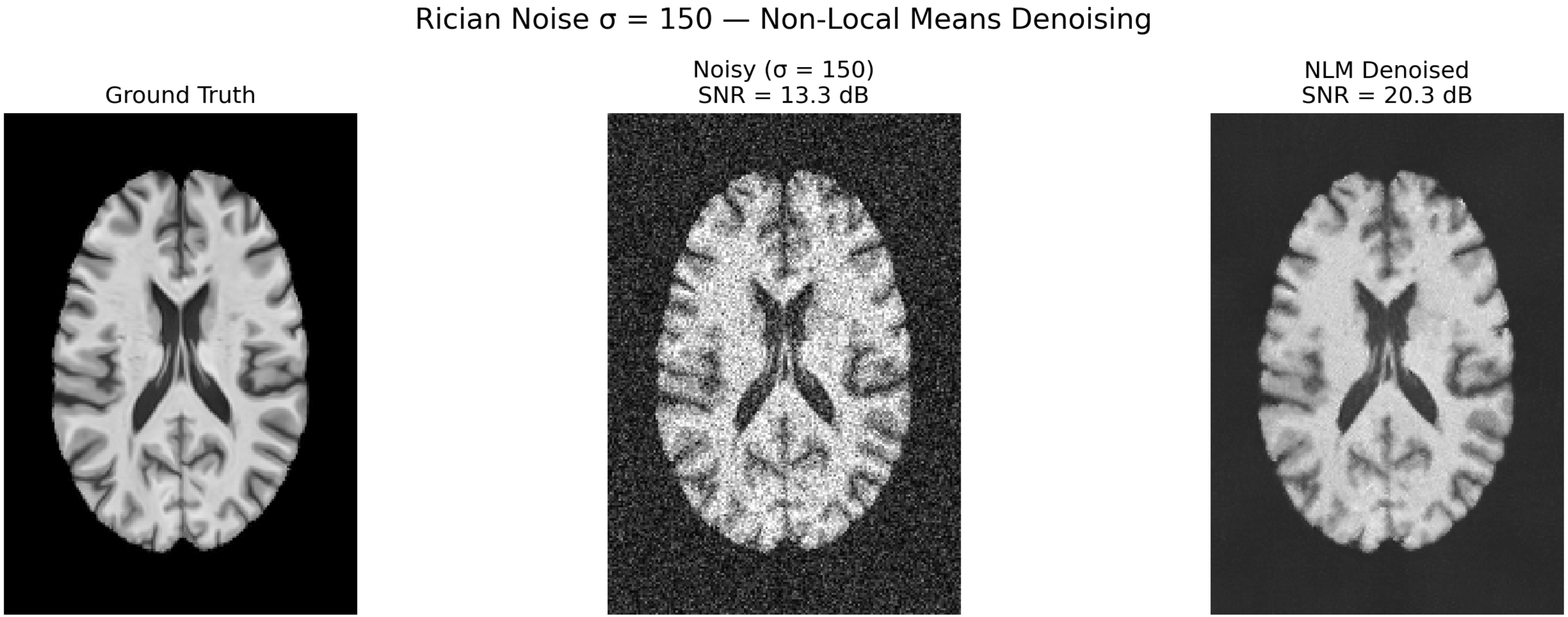


Denoising Results 3/5

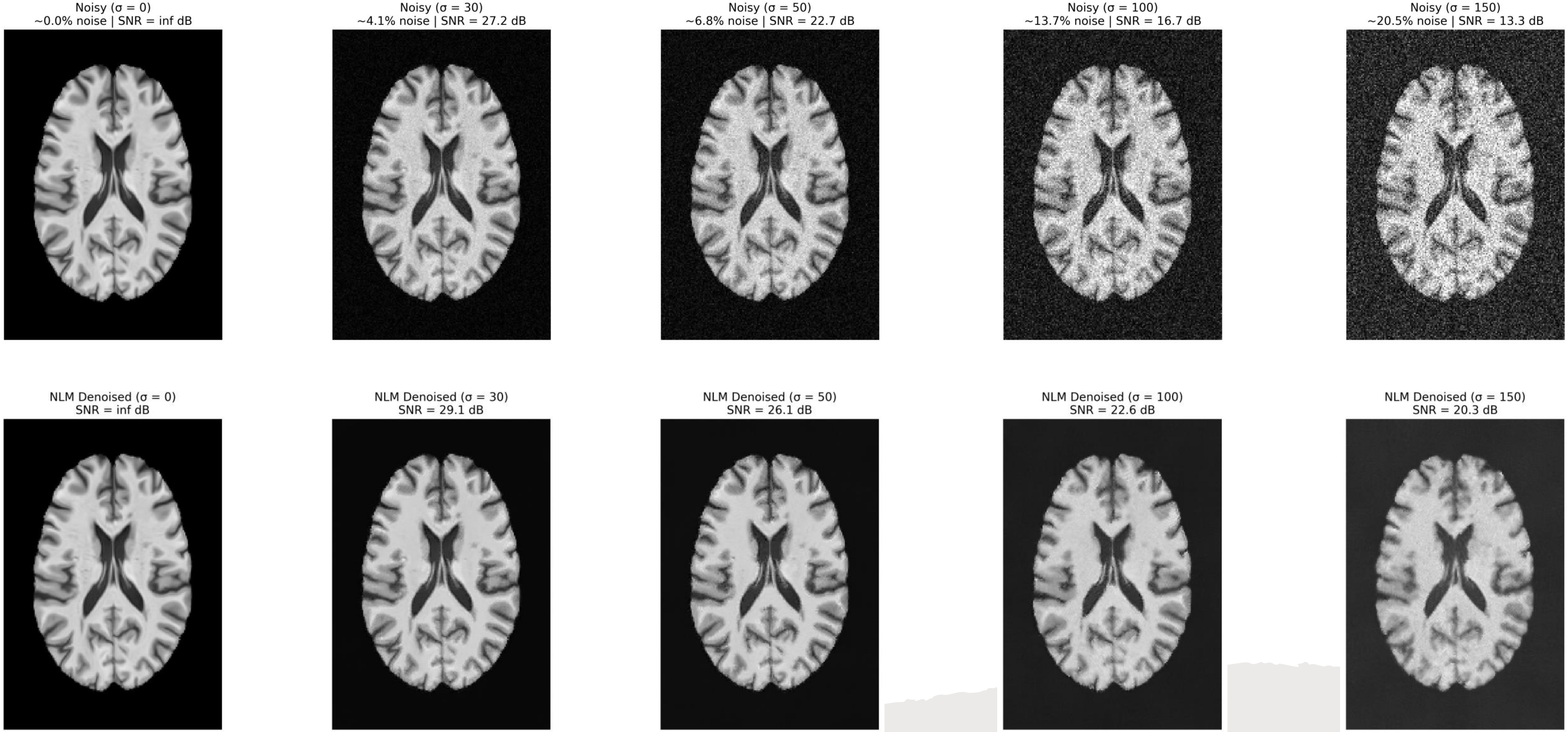
Rician Noise σ = 100 — Non-Local Means Denoising



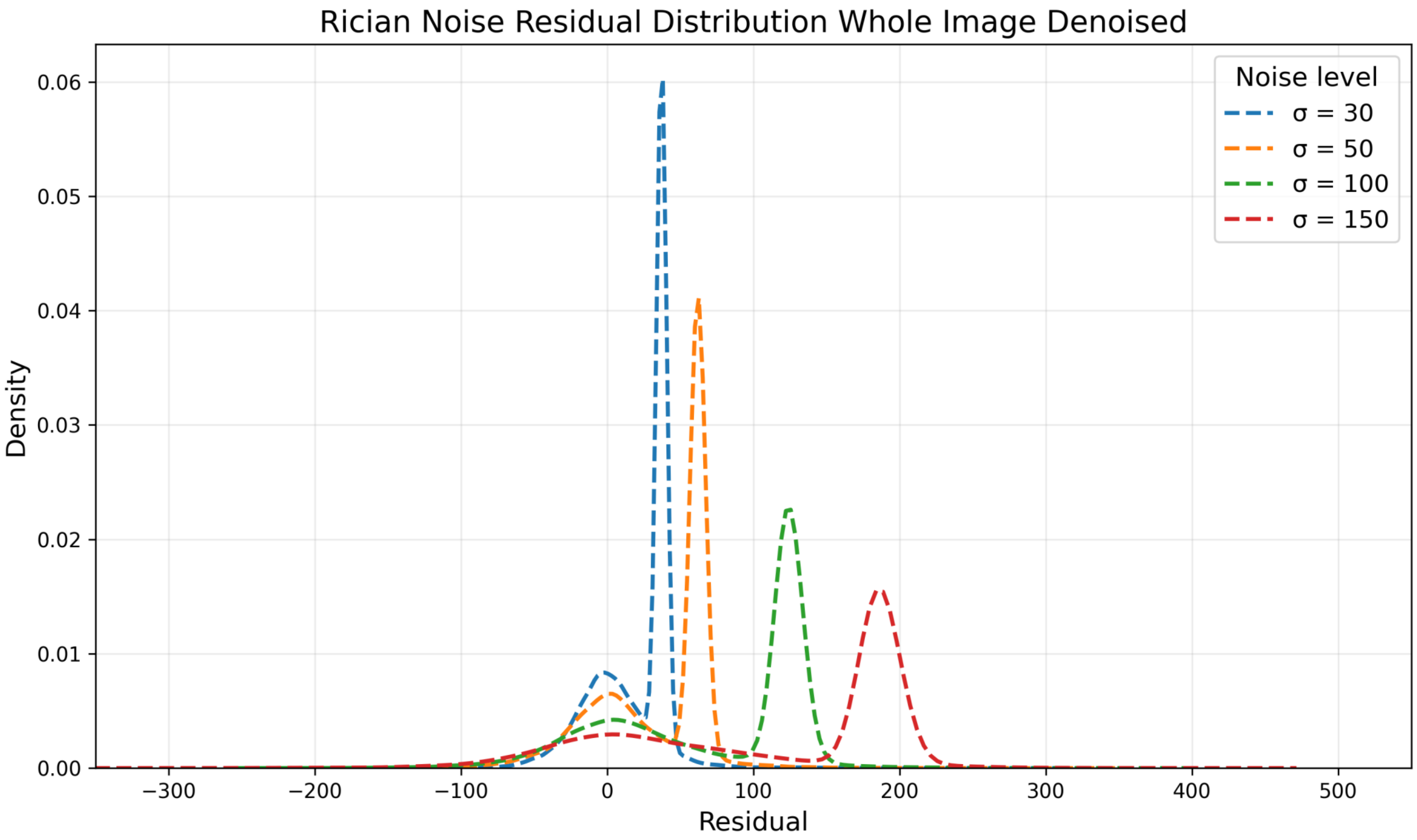
Denoising Results 4/5



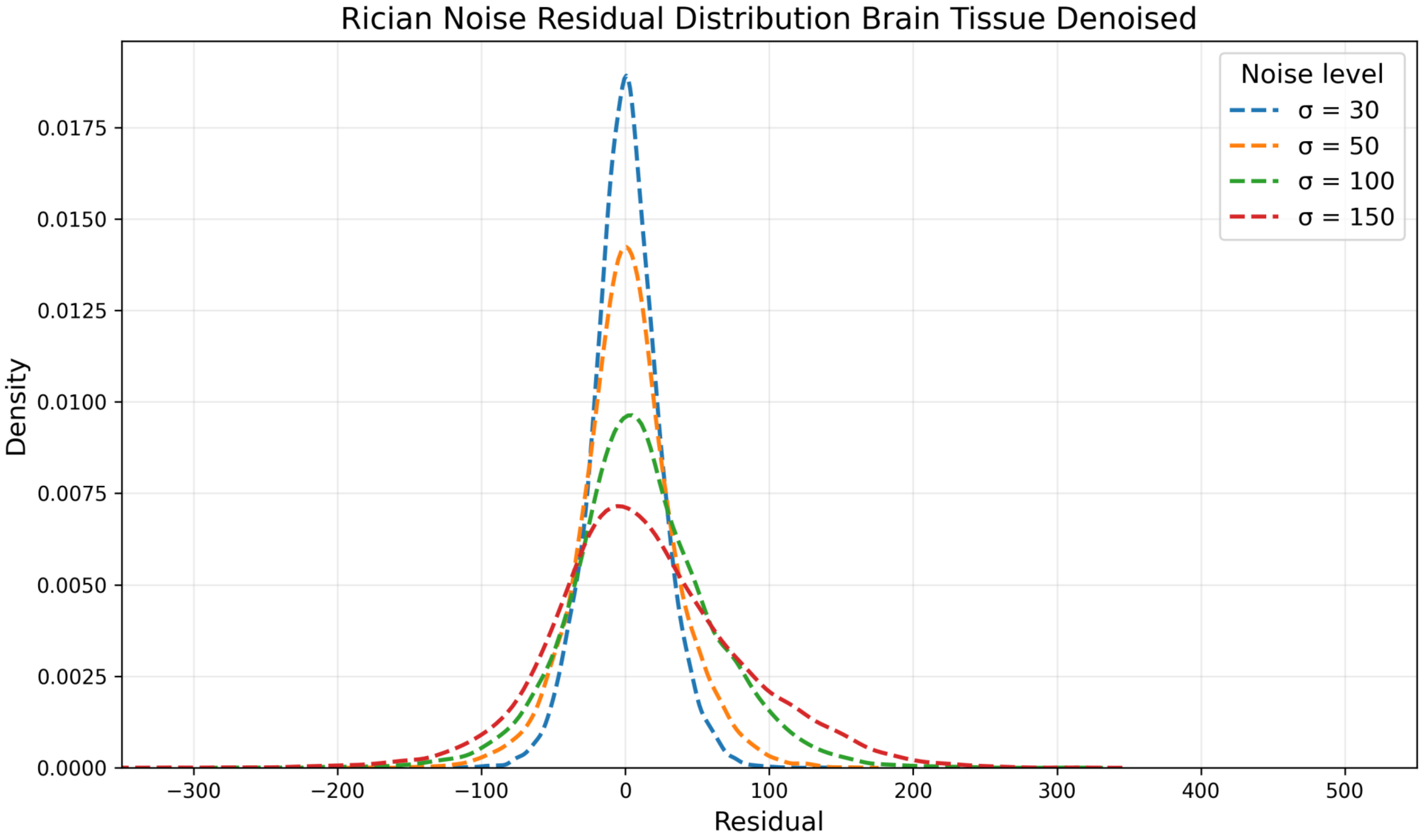
Denoising Results 5/5



Rician Noise Distribution Results 1/2

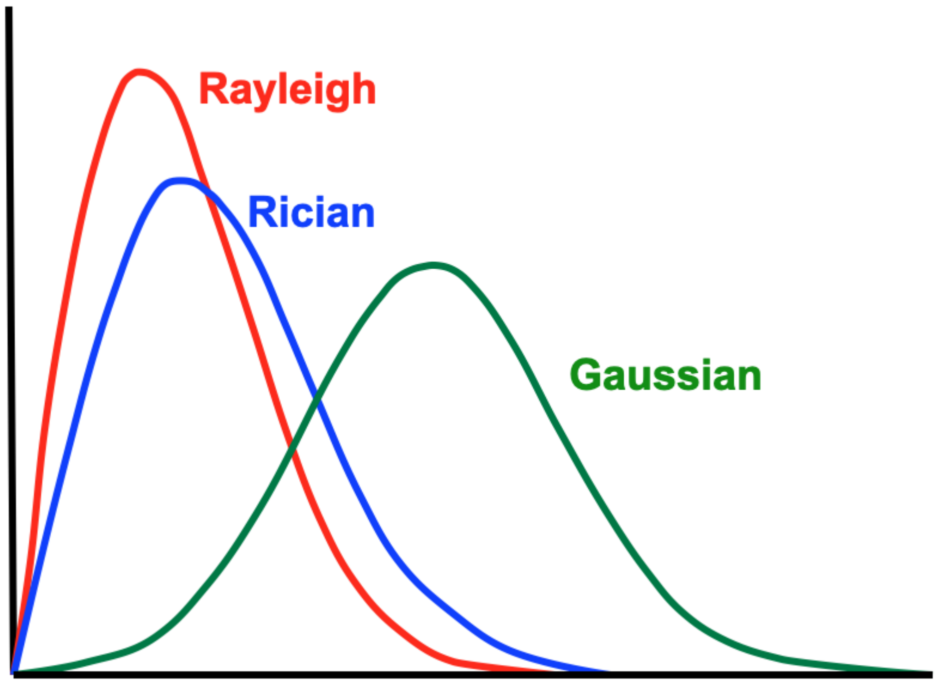


Rician Noise Distribution Results 2/2



Results Discussion

- The residual plot is a visual representation of the error in the denoised image compared to the ground truth image (pre-processed 2D slide).
- With a good denoising filter, you can expect the residual to show the true noise distribution with lower scale.
- Residual figure has peak around 0 for tissue signal, and large peaks of over-estimation of signal for air.
- $\sigma = 150$ most closely models Rician, noise approximates Gaussian as SNR increases (σ decreases). Expected from [5].



[17]

Conclusion

- Built a dataset with pre-processing techniques: intensity non-uniformity (INU) correction, skull-stripping, spatial normalization, and brain tissue segmentation to serve as the reference images for residual noise plotting and SNR calculation.
- Added Rician noise to degrade the 2D magnitude MRI slices and denoised with NL means filtering.
- Plotted residual to show error in denoised image against ground truth, following the distribution of noise.
- Experimentally supported that the Rician distribution approximates the Gaussian distribution for high SNR.

	$\sigma = 30$	$\sigma = 50$	$\sigma = 100$	$\sigma = 150$
Noisy SNR	27.2 dB	22.8 dB	16.8 dB	13.3 dB
Denoised SNR	29.1 dB	26.1 dB	22.6 dB	19.9 dB
% Increase	6.7%	13.5%	29.4%	39.8%

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