Effect of using Genetic Algorithm to denoise MRI Images corrupted with Rician Noise

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Abstract— **It is well known that Genetic Algorithm (GA) uses large number of solutions, instead of a single solution for searching. This brings an important part to the robustness of genetic algorithms. It improves the chance of reaching the global optimum and nearly unbiased optimization techniques for sampling a large solution space. GA adapted in image processing because of this unbiased stochastic sampling. In this paper GA is proposed for removal of Rician Noise. This kind of noise mainly occurs in low signal to noise (SNR) regions. True low signal is corrupted due to presence of Rician noise and measurement gets hampered in low SNR regions. Noise in magnetic resonance (MR) magnitude image maintains Rician distribution. It is a signal dependent Noise. To overcome this problem real and imaginary data in the image field are rectified, before construction of the magnitude image. The noise-reduction filtering (or denoising) is accomplished by Genetic Algorithm. A fresh genetic operator is used that combines crossover and adaptive mutation to improve the convergence rate and solution quality of GA. The proposed technique effectively reduces the standard deviation and significantly lowers the rectified noise.**

Keywords- Genetic Algorithm, Mean square error, MR images, Rician Noise

I. INTRODUCTION

Noise frequently occurs in various imaging modalities. A signal is said to be corrupted with Rician noise if the probability density function (PDF) of the noisy signal has a Rice Distribution named after the scientist Stephen O. Rice. The image vividness in magnetic resonance magnitude images in the presence of noise is depicted mainly by a Rician distribution. When signal intensities become low (SNR < 2) it has been biased due to the noise [1]**.** The noise in magnitude MR images is signal-dependent (Rician), but most de-noising algorithms accept additive Gaussian (white) noise. However, the Rician distribution only looks Gaussian at high SNR [2-3].

Rician noise particularly creates hazards in high resolution, low signal-to-noise ratio (SNR) regions where it not only causes random variation, but also inserts a signal-dependent bias to the data that minimizes image contrast [4]. It mainly occurs in Magnetic Resonance Image (MRI), where SNR plays vital role for the clinical as well as research purpose [5].

There are various works that has been done for removal of Rician noise. Some paper reports wavelet domain filter that effectively removes Rician noise present in MR image [1],[4],[6]-[8]. Jan Aelterman, Bart Goossens, Aleksandra Pizurica and Wilfried Philips introduced a method where noise is removed from the squared magnitude image and denoising itself. It performed on the square root of this image in the wavelet domain [6].

In this paper, Genetic Algorithm optimization technique is proposed for removal of Rician Noise. It is well known that recently Genetic Algorithms (GAs) have been considered as a powerful and robust tool for the removal of noise in image processing [9]. Genetic procedures including reproduction, crossover, and mutation are applied to increase the signal-to-noise ratio and minimize the overall computational complexity, by using mean square error (MSE) as the cost function. GA is advantageous compared to other optimization algorithm because it is robust in nature, can reach optimum value with fewer number of iterations and easy to understand as it involves less mathematics [10]. The expected outcome of this research is to reduce the noise from contaminated MR images by significantly obtaining lower values of MSE.

II. RICIAN NOISE

Magnetic Resonance Imaging (MRI) has evolved significantly over the last few decades. It is generally well accepted to model noise on magnitude MR images as white and Rician distributed. Rician noise provides a bias into MRI measurements that has a strong affect on the shapes and predilections of tensors in diffusion tensor magnetic resonance images. Lower values of signal-to-noise ratio (SNR) is observed in Magnetic resonance imaging (MRI) obtained with high temporal (EPI) and/or spatial (micro-imaging, angiography) resolution [8]. Rician noise is mainly creating disturbance at high resolution, low signal-to-noise ratio (SNR) areas where it not only generates random variation, but also introduces a signal-dependent bias to the data that lowers image contrast. These noises affect the character and versions of medical image data in changing degrees, based on the parameters and type of image acquisition and the area of anatomy being scanned.

Rician noise is dependent on the data itself, and hence it is not additive. Therefore to "add" Rician noise to data, it is necessary to make the data Rician distributed. This type of noise is especially baffling at low signal-to-noise ratio (SNR) regions. Magnetic Resonance magnitude images are found by taking the square-root of the sum of the square of the two nondependent Gaussian random variables (pure and imaginary images) pixel by pixel [1], [11-12]. Next this nonlinear transformation, MR magnitude data can be acquired to be Rician distributed. For an MR magnitude image defined on a discrete grid L.

I = {mi *i ε* I}, the probability distribution function (PDF) of I is

$$P(mi \mid A) = \frac{m}{\sigma^2} e^{(m_i^2+A^2)/2\sigma^2} IO\left(\frac{A.M}{\sigma^2}\right) \quad (1)$$

In the above equation I0 is the zeroth-order modified Bessel function of the first kind, A is the pure signal amplitude, and is the standard deviation of the Gaussian noise in the original and artificial images. SNR is defined here as A/σ. When SNR is high, the Rician distribution approaches a Gaussian, when SNR approaches 0, the Rician distribution becomes Rayleigh distributed and the PDF becomes:

$$P(mi) = \frac{mi}{\sigma^2} e^{-m_i^2/2\sigma^2} \quad (2)$$

III. OPERATION OF GENETIC ALGORITHM

It is known that the idea of evolution was familiarized by Charles Darwin in the early 1900s, but, it required next 80 years before John Holland used it to the purpose of optimization process and produced the basic GA template what we are using now-a- days [13]. This algorithm has now become an important search heuristic because of its robustness. It mimics the process of natural evolution and its fundamental construction is planned to support a wide variety of optimization problems without the need of supplemental data. The proposed method makes use of genetic algorithm to act as a filter in order to reduce Rician Noise by optimizing the mean square error taken as a cost function.

Fitness function for evaluation is used for GA rather than derivatives. Because of this it can be used to any kind of continuous or discrete optimization problem. Optimization is obtained using natural exchange of genetic material between parents. Offspring's are created from parent genes. Reproduction creates offspring and has combination of features inherited from each parent. The fitness of offspring's is then measured and only the fittest offspring are granted to breed. Artificially, genetic material is replaced by strings of bits and natural selection substituted by fitness function. Mating of parents is represented by cross-over and mutation operations. The flowchart of GA is shown in Fig.1. GA is a parallel optimization technique that relies on the basics of evolution for optimizing a group of solutions at once. GA is based on some important function, such as selection, crossover & mutation.

The proposed method uses select rank strategies of selecting the better one. After that uniform cross over is used as a cross over operator, where cross over point is randomly generated. The next operation performed is mutation which is truncate replacement procedure.

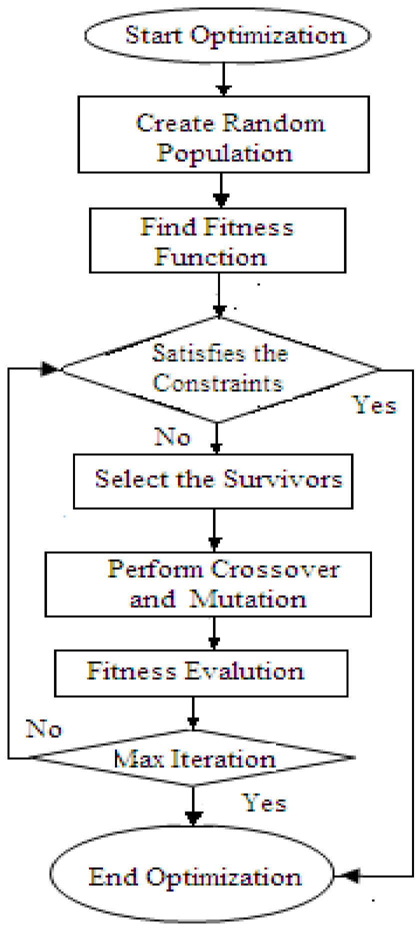


Fig.1 Flow Chart of Genetic Algorithm

Rician noise generates random variation in the data and has an influence on the MR images that reduces image contrast. GA is used to enhance image contrast and remove unwanted artifacts [14]. The GA based filtering procedure keeps key image element and characteristics, reduces random noise fluctuation and eliminates the bias introduced by Rician noise. In this paper, simulated Rician noise introduced in the test image slice and then noise is filtered out using GA based optimization.

IV. METHODOLOGY

In the proposed method shown in Fig.2, first a test image (particular slice of the brain) has been taken and its magnitude response is obtained. Next the following parameters are initialized, viz. the population size, number of elements (size of the image), number of generations, number of attempts, and minimum fitness value. Then artificially generated Rician Noise is added to the test image and Rician noise contaminated image is obtained. After that the magnitude response and corresponding error in magnitude between test and Noisy image is computed. A fitness parameter is created depending on this error.

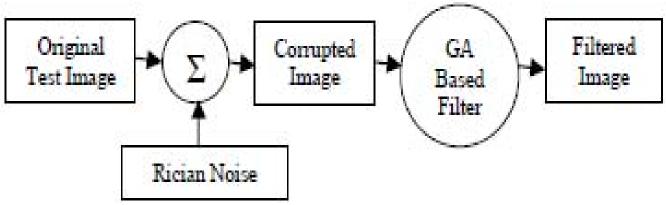


Fig.2 Block Diagram of Design Flow

The function performed next is selection of image having better fitness value and arrange all the images of a generation based on this fitness function. After that crossover is to be done, where best parents are chosen from selected module. For this a uniform cross over is done between parents. The number of parents that has to be chosen for reproduction depends on crossover probability. Crossover generates offspring for next generation. During mutation less fit elements are replaced by these offspring, or newly generated image. The whole process generates a new generation having better image compared to previous generation. The whole population of next generation goes to fitness evolution. The process occurs continuously as long as maximum iteration is achieved or fitness value is equal to or less than tolerable value. The output of whole process is the best image whose magnitude response is closer to test image. Error reduces as the number of generation increases, up to a certain value of generation after that it becomes almost constant.

The fitness function of GA should be based on both the magnitude response of image undergoing evolution and desired magnitude response. A frequency weighted square error technique is proposed for this .The fitness function used in proposed technique is given by [13]

$$F(x_n) = 1/Y\sum_{y=1}^{Y} K_n[\,|I\_d| - |Im\_r|]^2 Q_y \tag{3}$$

where $F(x_n)$ is square magnitude error of desired $|I\_d|$ and designed image Im_r. The error is scaled by K_n chosen to minimize the error between I_d and Im_r. Here Y is the total number of frequency bins. The square error value are weighted by multiplying them with a weighted vector Q where Q_y is an element of Q.

V. RESULTS

Most existing MRI denoising methods for removal of Rician Noise is based on Wavelet domain filtering [2], [4] and [7]. However, the main disadvantages of these methods are shift sensitivity, poor directionality and computational complexity for obtaining the desired result. But the expected results can be obtained by using GA which does not demand for complex mathematics and give near perfect result. This is depicted by the result obtained using the proposed method which makes use of GA for removing the unwanted Rician noise.

The test image considered for the research is a slice of brain, shown in Fig. 3. To this original test image, simulated Rician noises of different noise levels were added. The resulting corrupted images were subjected to the proposed GA based filter developed for the purpose of removing the Rician noise.

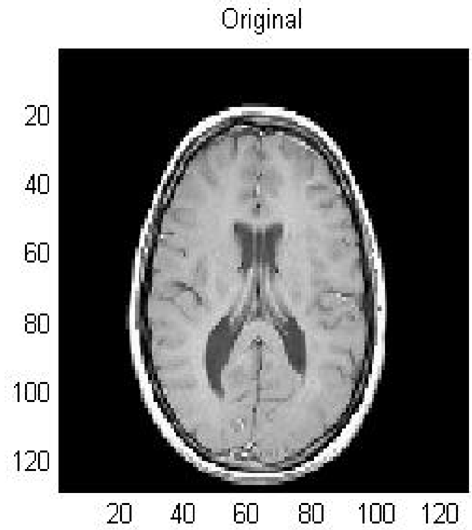


Fig.3 Original Test Image

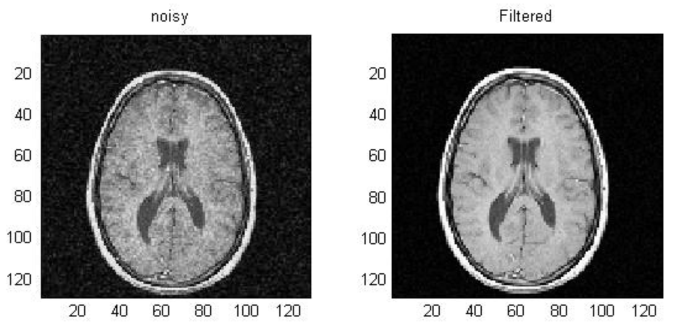
The research was carried out by considering two different approaches: First the noise level was kept at a constant value and the GA based filter was tested for different number of generations ranging from N =100 to 5000. In the second approach the number of generations was kept constant at a particular value and the noise level was increased gradually to find the impact on the developed filter. In the later case, three different values of N were taken under consideration viz. N= 100, N=500 and N=5000.

The results obtained using the first approach is shown in Fig.4 (a) through (d). The summary of the mean square errors calculated for the noisy and denoised image using the developed filter is given in Table I below.

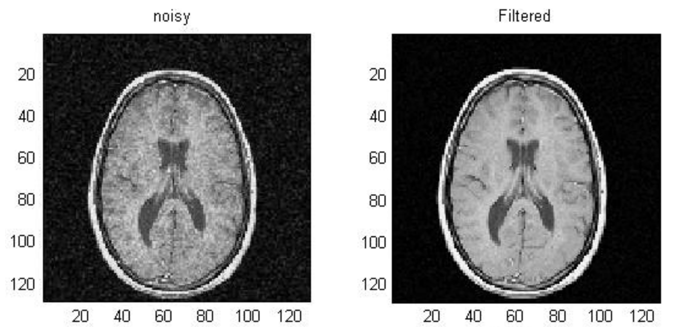
TABLE I. MEAN SQUARE ERROR FOR NOISY & FILTERD IMAGE ASSUMING NOISE LEVEL = 5

No. of Generations (N)	Mean Square Error (Noisy)	Mean Square Error (Filtered)
100	39.2705	33.3914
200	39.1363	33.7917
300	38.7186	33.0487
500	38.6990	33.0190
1000	39.1797	32.9739
2000	38.7037	33.0736
5000	39.1761	33.4812

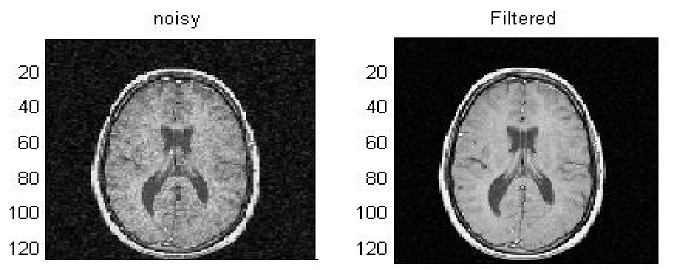
It is thus observed that the mean square error is substantially high for the image corrupted with Rician noise. After subjecting this corrupted image to the GA based filter, there is a considerable reduction in the mean square error. This effect is illustrated in Fig.5.



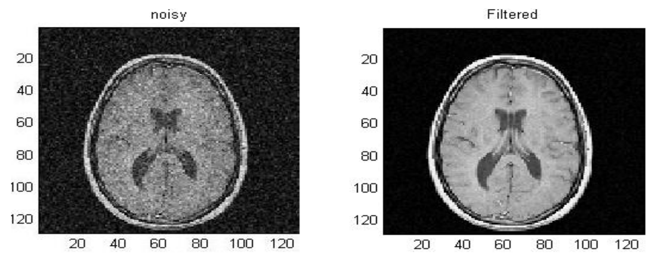
(a)



(b)



(c)



(d)

Fig.4 Noisy and Filterd images with fixed noise level = 5 and different number of geneartions (a) N=300 (b) N=500 (c) N=1000 (d) N=2000

For validating the results, the proposed filter was then tested by keeping the number of generations fixed and gradually increasing the noise level from 1 to 10. Similar trends of decrease were obtained in the MSE values after the filtering was performed.

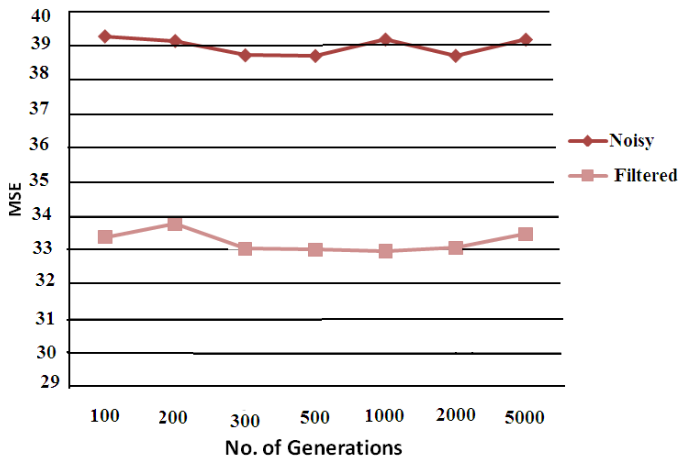


Fig.5 Variation of MSE with number of generations in Noisy and Filtered test image using proposed method for fixed Noise Level =5.

The results obtained for three different values of N are summarized in Tables II to IV. The corresponding images are shown in Fig. 6. The graphical representation of the obtained results is given in Fig.7 through 9.

TABLE II. MEAN SQUARE ERROR FOR NOISY AND FILTERD IMAGE FOR 100 GENERATIONS

Noise Level	Mean Square Error (Noisy)	Mean Square Error (Filtered)
1	1.5637	1.3175
2	6.2829	5.3246
3	14.1831	11.9835
4	24.8826	20.9806
5	39.3662	33.6546
6	57.2035	48.5525
7	76.9379	65.0732
8	100.3745	86.4755
9	126.9523	107.5770
10	156.8933	128.8745

TABLE III. MEAN SQUARE ERROR FOR NOISY AND FILTERD IMAGE FOR 500 GENERATIONS

Noise Level	Mean Square Error (Noisy)	Mean Square Error (Filtered)
1	1.5727	1.3516
2	6.2211	5.2645
3	14.1266	12.2513
4	24.7417	21.3650
5	39.8296	34.0084
6	57.0014	47.3019
7	77.1089	64.9113
8	99.6667	83.3335
9	127.3319	108.6410
10	156.7350	131.7424

TABLE IV. MEAN SQUARE ERROR FOR NOISY & FILTERD IMAGE FOR 5000 GENERATIONS

Noise Level	Mean Square Error (Noisy)	Mean Square Error (Filtered)
1	1.5622	1.3638
2	6.2829	5.3246
3	14.1039	11.9005
4	23.9826	20.8806
5	38.7341	33.3696
6	57.4535	47.5625
7	75.9379	64.0792
8	100.3785	86.3755
9	125.9513	106.5370
10	155.5404	130.0359

From the obtained results it can be seen that the MSE is high at higher values of noise level. Also, there is a reduction in the obtained values of MSE for the filtered image and this reduction increases as the noise level is increased keeping the number of generations at a constant value.

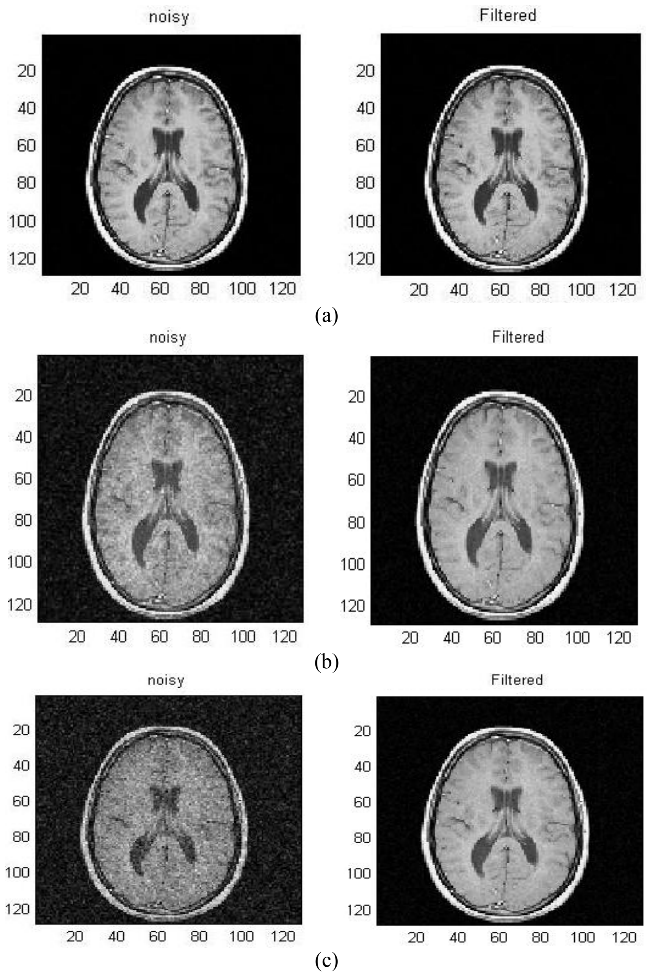


Fig.6 Noisy and Filterd images with (a) noise level = 1 & N=100 (b) noise level = 5 & N=500 (c) noise level = 10 & N=5000

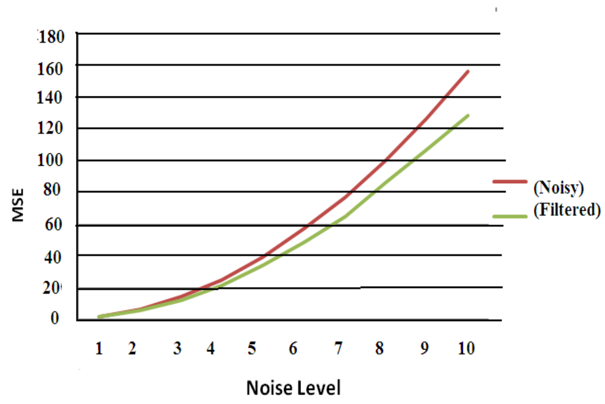


Fig.7 Variation of MSE with different Noise Levels in Noisy and Filtered test image for100 generations

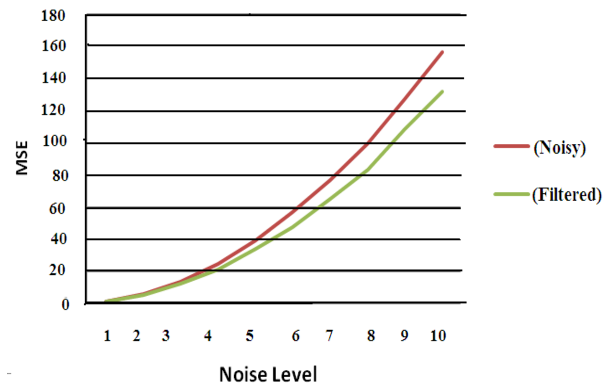


Fig 8. Variation of MSE with different Noise Levels in Noisy and Filtered test image for500 generations

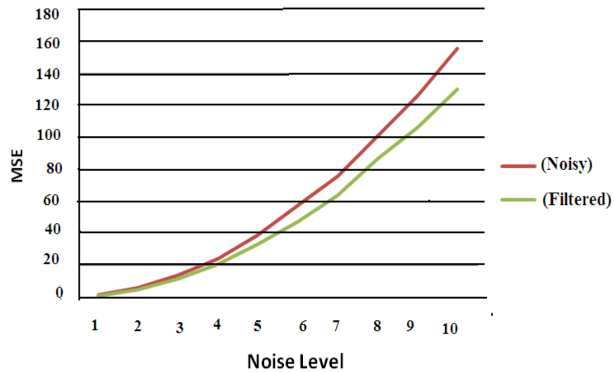


Fig.9 Variation of MSE with different Noise Levels in Noisy and Filtered test image for 5000 generations

CONCLUSION

A new approach to denoise Rician noise has been presented in this paper which makes use of the Genetic Algorithm to optimize the mean square error. Although there are various evolutionary optimization algorithms which can be applied for image enhancement but out of them GA is assumed to achieve better results, faster processing times and easy implementation with satisfactory performance. The GA based filter proposed in this paper has provided high levels of noise reduction which is evident both from the visual inspection as well as quantitative analysis of the performance matrix considered in the research.

The visual inspection of the filtered image obtained shows a considerable decrease of the unwanted artifacts and improvement of image contrast. From the analysis of the mean square error computed from the noisy and filtered images it has been shown that the Rician noise has been removed to a large extent. The MSE is observed to decrease substantially as the number of generations has been increased and after a certain stage N=500 the amount of decrease is found to be constant i.e. irrespective of increasing the value of N there was no change in MSE. Also, at higher values of noise level the proposed technique has shown to yield grater noise reduction. Thus the GA based filter developed can be considered as the most suitable denoising approach for Rician noise as it works best at lower values of SNR.

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