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# RICIAN NOISE REMOVAL IN MRI SCANS USING IMPROVED HYBRID MEDIAN FILTERING TECHNIQUE

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**Abstract**

In this article, we proposed a new filtering technique to remove the Rician noise from magnetic resonance imaging (MRI) scans. During the acquisition process, MRI images are produced with a Rician noise, which reduces the quality of the image and making difficult in clinical to diagnose. To avoid thisissue, we proposed a Rician noise removing technique using the adaptive nonlocal median filtering method. In this hybrid method, initially, the input image is preprocessed by a nonlocal median filter. Then the image is processed by the adaptive median filter in which the search window size is adaptively fixed as 3×3, 5×5, 7×7, and 9×9 based on the noise. This approach classifies pixels as noise by comparing every pixel within its neighbor pixels by adjusting the window size. A pixel that is completely different from the majority of its neighbors is tagged as noise. Then these noise elements are replaced by the median pixel value of the finalized window of the neighbors. It gives better quality than the existingmethods in a higher noise ratio. Observational results are brought out on the brain web dataset and evaluated by image quality metrics such as peak-signal noise ratio(PSNR) and normalized absolute error(NAE). This proposed technique removes noise as well as preserves the details of the MRI images.

**Keywords:** Rician noise, Median filter, Noise removal, Nonlocal median filter, Adaptive median filter.

## 1 | INTRODUCTION

Magnetic Resonance Imaging (MRI) is the maximum broadly used imaging approach for clinical prognosis and treatment [1]. MRI produces a very clean and detailed image of human organs like the brain, breast, abdominal, heart, lumbar. An MRI test isn't the same as a CT scan or an X-ray in that it doesn't use radiation to produce pix. An MRI test combines images to create a 3-D photograph of yourinternal systems, so it is more powerful than other scans at detecting abnormalities in small structures of the brain, including the pituitary gland and mind stem. During the manner of taking an MRI, there are special types of noise that passed off in MRI photos, which encompass Gaussian, Impulse and Rician. Noise means, the depth values of pixels inside the picture display specific values in preference to authentic pixel values i.e. noise is the undesirable outcomes produced inside the medical photos. MRI is primarily based on the principles of tomographic imaging techniques. MRI provides grater diagnostic statics than any of the prevailing imaging strategies; it does now not involve the use of ionizing radiation hence, unfastened from related harmful results acknowledged with different imaging techniques. The raw information obtained for the duration of MRI scanning are complex values that constitute the Fourier remodel of a magnetization distribution of a volume of tissue. MRI imaging equation specific as a two- dimensional entity given as

$$(s_x, s_y) = f[L(x, y)] \tag{1}$$

Where the spatial information encoding scheme represented by f. A data consistent L can be obtained from the inverse transform when f is invertible such that

$$(x, y)f^{-1}\ M(s_x, s_y) \tag{2}$$

The desired image intensity function L (x, y) can be written as

$$L = [T_1, T_2, T^*, \rho, R]_2 \tag{3}$$

Where, f is the function of relaxation times, T1, T2, and T2 ∗; spin density, ρ and diffusion coefficients R.

Generally, T1 and T2 are two independent processes and happen simultaneously. T1is called spin-lattice relaxation because the power from this technique is launched to the encircling tissue (lattice). T1 happens along the z-component axis and its value is always greater than the spin relaxation T2. The relationship between protons and their immediate surroundings (molecules) is described by thespin relaxation T2 and it happens along the x-y plane.

Therefore, the Inverse Fourier transform is used to reconstruct the MRI image from raw data and these data converts into the frequency, magnitude, and phase component. The measurement of signal components in two types of channels is a real channel and another one imaginary channel. These channels are commonly affected by the additive white Gaussian noise and it is also a complex-valued data. Since the magnitude or phase image computation is a non-linear operation, so the MRI data probability density function (PDF) may be changed. In the spatial domain, magnitude records are modeled as rician distribution and it also referred to as rician noise. Rician noise is dependent on the signal. If the magnitude image has a low intensity, then the Rician distribution tendency to a Rayleigh distribution and in high-intensity regions tends to a Gaussian distribution [2]

$$P(M|A,\sigma_n) = \frac{M}{\sigma_n^2} e^{-\frac{M^2+A^2}{2\sigma_n^2}} I_0\left(\frac{AM}{\sigma_n^2}\right) u(M) \tag{4}$$

where $I_0(\cdot)$ is the modified zeroth-order Bessel function of the first kind, $\sigma_n^2$ is the noise variance, A is the noiseless signal level, M is the MR magnitude variable and u(·) is the Heaviside step function. In high SNR , high intensity (bright) regions of the magnitude image, the Rician distribution tends to a Gaussian distribution with mean $\sqrt{A^2 + \sigma_n^2}$ and variance $\sigma_n^2$ are given as,

$$P_M(M|A,\sigma_n) \approx \frac{1}{\sqrt{2\pi\sigma_n^2}} e^{-\frac{\left(M-\sqrt{A^2+\sigma_n^2}\right)^2}{2\sigma_n^2}} u(M) \tag{5}$$

In the image background, where SNR is zero due to the lack of water proton density in the air, the Rician PDF simplifies to a Rayleigh distribution with PDF given as,

$$P(M|A,\sigma_n) = \frac{M}{\sigma_n^2} e^{-\frac{M^2+A^2}{2\sigma_n^2}} u(M) \tag{6}$$

Between low and high it is neither Rayleigh nor Gaussian as shown in Figure 1.

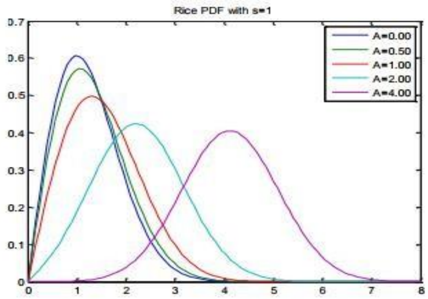


**FIGURE1:RicianDistribution[@wikipedia.org]**

This noise signal can be removed from the original signals. The reconstruction of a signal froma noisy one is known as denoising. It is removing unwanted noise to restore the original image. There are two types of denoising processes in MRI, the first one is the reduction of noise based on the acquisition and another one based on the post-acquisition. The technique for enhancing the SNR during the image acquisition is either increasing the time of acquisition and reducing spatial resolution. However, the acquisition time is limited because of patient consolation and device throughput. Therefore, in an acquisition-based method, there is a practical restriction at the SNR of the obtained MRI data. Hence, the post-acquisition based image denoising is a non-expensive and effective alternative [2]. The motive of a post-processing MRI denoising algorithm is reducing the strength of noise and maintaining the original details of the MRI images. Some of the denoising techniques and their merits and demerits are discussed in following section.

The noise present inside the images will reduce the contrast of the image and creates problems within the diagnostic phase. So denoising is incredibly necessary to get rid of the noise from these images. Noise removal is a challenging task in the medical area. So there is a necessity to develop an efficient method to get rid of the noise in the MRI images. In the MRI process, the time of acquisition islimited. So the MRI images usually have the low signals to noise ratio (SNR) value. The features of the MRI images are commonly degraded with numerous artifacts and noises which are competently modeledas Rician noise. Denoising method that removes noise and preserves the image details. MRI denoising focuses on the many types of research to produce images with good spatial resolution and high SNR. Several filtering techniques were developed inside the past decades to address the denoising problem inMR images. In that series of techniques here we proposed a new methodology to remove a rician noise in MRI images with high picture quality in high noise ratio level called as Adaptive nonlocal median filtering. In the following section, we discussed the details of our proposed work.

## 2 | LITERATURE REVIEW

In image denoising work there are so many numbers of literature are available. Most of all methods are developed to remove impulse noise and they are tested only on standard images and naturalimages. Rarely few methods are developed to remove rician noise in MRI images. so that here we developed this improved median filtering technique. Buades et al [2] they proposed the nonlocal means (NLM) filter for denoising digital images. This filter makes use of the similarity between the pixels in the entire image whereas the other filters make use of the similarity of the neighborhood pixels. Yan Jin et.al [3] developed an improved nonlocal means(NLM) method to remove noise from the standard images, and they achieved 32.5 of PSNR value for the 10% of noise level. They proved that their methodis better than normal nonlocal means method. UrguErkan et.al [4] developed a method to remove salt and pepper noise from an image using different applied median filter technique. They used standard images for testing and evaluation and they achieved 26.04 PSNR value of 90% noise level.

Ci wang et.al [5] made an adaptive nonlocal means filtering techniques to remove a quantization noise from images using the concept of image deblocking. Theyused a standard image for testing and evaluation process and also they calculated the PSNR value for compressing images with JPEG format with quality score(QS) 20,25 and 30. For QS 30 they achieved 31.43 as a PSNR value.Theyused visual informationfidelity (VIF) evaluation score as the evaluation score. Rajiv Verma et.al [6] introduced a nonlocal means algorithm with adaptive isotropic window size for denoising the images. They used gray level difference (GLD) images for evaluation of removing additive white Gaussian noise with standard deviation of 30 to 60 and finally achieved 23.08 of PSNR value for 60%noise level. They compared their method with a nonlocal means algorithms and achieved a good result.

Saritha et.al [7] discussed the filters that are available for denoising the MRI images and also analyze the performance metrics and analytical relationship between PSNR and SSIM. They implemented spatially adaptive nonlocal means algorithm to remove a Gaussian from a MRI brain images. They compared their method with some existing method like nonlocal means(NLM),PCA-NLM,Bilateral filter with $\sigma$ level10,15,20,25 and achieved 37.2451 as PSNR value. Ruitta et.al [8] developed a new improved adaptive median filter algorithm to remove the salt and pepper noise from the images. Theycompared their method with standard median filter techniques for 10 to 80% of noisy level and achieved PSNR 28.9 of 80% of noise level for depth image captured from Kinect. Raghuram et.al [9] proposed a median filter method to remove impulse noise from the image-based modified decision-based algorithm and for the evaluation they used the standard images. They compared their method with existing methods like MF, WMF, AMF, and DBMF with noise level 10 to 70% and achieved 36.88 PSNR value of 70% noise level.

Roji et.al [10], introduced a two-stage quaternion vector median filter to remove impulse noise from medical images. They used different standard images and medical images to evaluate the results. For medical images, they used the medpix database with 10 to

70% noise ratio and achieved 28.37 PSNR value of 70% noise level. Jyohei et.al [11] proposed an improved nonlocal median filter (NL- median) for effective removal of random-valued impulse noise superimposed on natural gray-scale images by using a weighted similarity. They used standard images for result and evaluation with the noise level7% and achieved low level MSE value compared than VMF, RSVM, NLVMF and PRP methods. An improved nonlocal means approaches for denoising the MRI images are proposed by Nikita et.al [12]. They used various MRI brain images for experimental results with a noise ratio as 6,9,13,20 and 25 with original NLM method and achieved 36.28 as PSNR of 25% sigma level.

Kunal N.et al [13] proposed the Nonlocal Euclidean Median for Removal of large noise levels using irrelatively reweighted least-squares they used synthetic and natural images for evaluation. Nagarajan et.al [14] removed Rician noise in MRI images by using a block difference- based filtering method. Theypartitionedthe noisy and normal images into blocks then find the block difference between both images and then based on this block difference denoising process was done by them. Finally combined all denoised blocks to reconstruct the images. Theyused a Brain web data set images for testing and evaluation with a noise ratio 3% to 30% and achieved 30.16 PSNR value for 30% of noise level. Theycompared their method with existing methods like IBLF, nonlocal means, iterative bilateralfilter. Cheng et.al [15]develops an adaptive neighbor pixel median filtering technique to remove impulse noise from images. Here the method performed based on neighbor pixels and the three adaptivewindows. They used standard images for the testing and evaluation.

## 5 | PROPOSED METHODOLOGY

Based on the literature, Adaptive Nonlocal median filter has been proposed to remove Rician noise from MR brain images obtained from Brain web data. The flowchart of the proposed method is shown in Figure2.

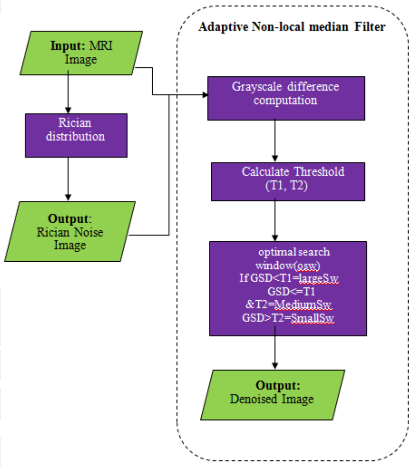


**FIGURE 2: Flowchart of Adaptive nonlocal Median Filtering**

Median filtering is based on basic statistical operation of finding the median. It is a simple noise reduction method that reduces the noise by computing the local distribution of data and eliminates noise. It has low computational complexity. For each pixel within the image, calculate the median value in a surrounding neighborhood of the pixel. Replace the pixel with the median value. However, the median filter affects all image pixels regardless of noise content, so that in images with the high noise level, it blurs the image substantially. So it only performs well on the low noise level. The Nonlocal median filter and its derivatives use an adaptive window size. because fixed window size removes the noise at a low level. The processing of the Nonlocal media filter is as follows. Figure 3 shows the processing between pixels.

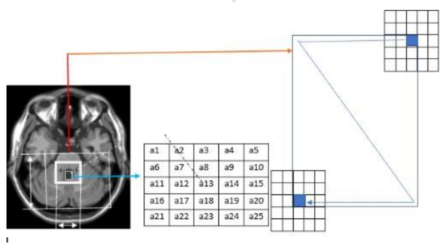

**FIGURE 3: Nonlocal median processing**

Based on the Non-local-means filter and adaptive nonlocal means filter we proposed an Adaptive nonlocal median method to remove a rician noise from MRI brain images. Adaptive Nonlocalmedian filter (ANLMF) is a hybrid filter technique.

Step 1: Input image from Brain web image data.

Step 2: produce the Rician noise in the original MRI brain image using

$$N(i,j) = \sqrt{(OI(i,j) + level * rand(m,n))^2 + (level * ran(m,n))^2} \quad (7)$$

Where NI (i.j) is noisy image and OI (i, j) is the original image, level refers to the noise levelset to the image. (m,n) denotes the size of input image.

Step3: Estimate the noise with use of $\sigma = \sigma^2_L * \varphi$ here $\sigma^2_L$ denotes the local estimation variance and $\varphi$ denotes the correction factors that are computed with the aid of skewness. Step4:Input: noisy image $x = x_i$ and parameters p, sw, w

Step5: Output: Denoised image $\hat{x} = (\hat{x}_i)$.

Extract patch $p_i$ of size w × w at every pixel i.For each pixel i do

Set $w_{ij} = \exp\left(-\frac{\|p_i - p_j\|_2^2}{h}\right)$ for every $j \in s(i)$.

Find patch p that minimize $\sum_{j \in sw(i)} w_{ij} \left|\left|p - p_j\right|\right|$.

Assign $\hat{x}_i$ the value of the center pixel in p.

Step 6: For this process we setting the window size as s= {3,5,7,9} for the preprocessed nonlocal median values and find the size of filtering window adaptively by.

$$sw = s_i|\sigma - level_i| = min_{dis} \quad (8)$$

Where $\sigma$ describe the noise estimation of the image calculated in step 3, sw describes window size and level denotes noise level of image set. Based on this parameters minimum distance is calculated by using lesser distance

$$min_{dis} = \min_{s \in s} \{|\sigma - level_i|\} \quad (9)$$

This approach classifies pixels as noise by comparing every pixel within the image to its close neighbor pixels. The size of the neighbour element is adjustable. A pixel that is completely different from majority of its neighbours is tagged as noise. Then these noise elements are replaced by the approach of the median pixel value of the pixels within the neighbour. In the adapting part it checks the median computation result, and if the median is distorted too much by noise, it defines the median over a larger region to overcome the noises. The algorithm continues adapting until noise is removed. The result of the method is discussed in the following section.

## 6 | QUALITY MATRICS

The performances of different filters are evaluated using different performance metrics such as PSNR, RMSE, SNR, and NAE, NCC Different perceptual quality assessments are clearly explained fortwo-dimensional images with different evaluation metrics.

### PSNR

**Peak signal-to-noise ratio i**s an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale. PSNR is most easily defined via the mean squared error (*MSE*). This MSE metric is used to check or measure the images which are tested by the image enhancement algorithms. When the MSE value is increased then the degradation of image also increased, if MSE value is decreasedthen the images will be perfect [16].

$$PSNR = 10\log_{10}\left(\frac{MAX^2}{MSE}\right) \quad (10)$$

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2 \quad (11)$$

where $MAX_I$ is the maximum possible pixel value of the image. When the pixels are represented using 8 bits per sample, MAX is 255[7].

### NAE

Normalized absolute error is the total absolute error normalized by the error simply predictingthe average of the actual values. This quality measure can be expressed as follows.

$$NAE = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}(|A_{ij} - B_{ij}|)}{\sum_{i=1}^{m}\sum_{j=1}^{n}(A_{ij})} \quad (12)$$

A higher NAE value shows that the image is poor quality and low value shows that the image is high quality.

## 7| Results and Discussion

The proposed denoising technique has been applied to the brain's web simulated data. These volumes with 1%, 3%, 6%, 9%,12%, 15% and 18% up to 100% of rician noise and are used to evaluate the performance of the proposed ANLMF with other existing methods Nonlocal mean filter(NLM), Nonlocal median filter(NLMED), Average weighted median filter(AWMF), Hybrid median filter(HMF), Differential applied median filter(DAMF), Mean filter (Average filter), Non adaptive fuzzy switching median filter(NAFSM) results are shown from figure 4 to figure 6, Table 1 and Table 2.

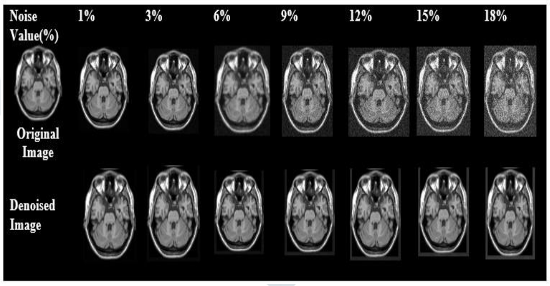


**FIGURE 4: Rician Noise Applied and Removed Images Original Image with various Noise level are in row1 and Results of Proposed Method are in row2.**

Rician noise is applied to the original image taken from brain web dataset with different level, in figure 4 column1 show the original brain image and row1 shows the rician noise applied image from noise level 1 to 18 percent. Row2 shows the result of proposed method.

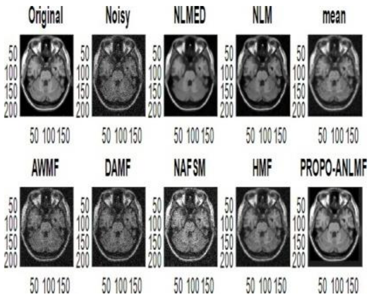


**FIGURE 5: Comparison of the proposed work with existing methods for 10% noise level**

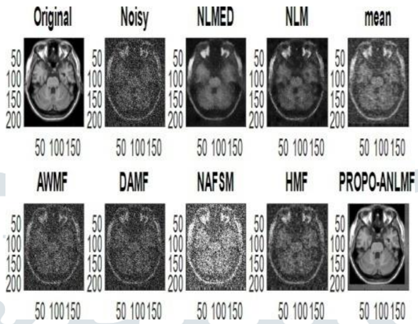


**FIGURE 6: Comparison of the proposed work with existing methods for 30% noise level.TABLE 1: PSNR value of proposed method with existing methods for Brain web image**

| Methods | 1% | 3% | 6% | 9% | 12% | 15% | 18% |
|---|---|---|---|---|---|---|---|
| **Median** | 37.581 | 35.6051 | 33.3435 | 29.7475 | 20.6365 | 18.693971 | 17.102674 |
| **Avgfilter** | 27.3935 | 27.3856 | 25.2889 | 22.4823 | 20.441538 | 18.687876 | 17.145521 |
| **NLM** | 38.2201 | 38.2221 | 29.0027 | 24.5953 | 21.017753 | 18.960766 | 17.303221 |
| **DAMF** | 39.4352 | 30.3981 | 26.5555 | 22.3938 | 17.575082 | 15.638318 | 14.065347 |
| **AWMF** | 34.5828 | 29.5363 | 26.1805 | 22.0385 | 17.909692 | 16.030854 | 14.503821 |
| **NAFMF** | 39.1906 | 29.668872 | 23.586561 | 20.094190 | 17.575082 | 15.638318 | 14.065347 |
| **HMF** | 33.6897 | 30.098260 | 25.699704 | 22.764539 | 20.438819 | 18.522876 | 16.976684 |
| **NLMEDF** | 40.178576 | 31.910917 | 26.326565 | 23.002405 | 20.484120 | 18.582796 | 17.025285 |
| **proposed-ANLMF** | 25.672210 | 25.459154 | 24.810987 | 23.865235 | **22.881881** | **21.764904** | **20.720171** |

In this article we compared all existing methods for apply Rician noise because of they tested by impulse noise and Gaussian noise only. Basically MRI images affected by Gaussian, Speckle, Poisson and Rician noise [17] so here we tested with Rician noise and achieved more quality image than other methods which are analyzed by NAE, PSNR metrics.

**TABLE 2: NAE value of proposed method with existing methods for Brain web images**

| Methods | 1% | 3% | 6% | 9% | 12% | 15% | 18% |
|---|---|---|---|---|---|---|---|
| **Median** | 0.0374 | 0.0734 | 0.1295 | 0.1850 | 0.246164 | 0.307704 | 0.371681 |
| **Avgfilter** | 0.0892 | 0.111736 | 0.153552 | 0.199564 | 0.251907 | 0.309750 | 0.372611 |
| **NLM** | 0.0302 | 0.062953 | 0.116955 | 0.171942 | 0.230646 | 0.295131 | 0.360439 |
| **DAMF** | 0.0292 | 0.087630 | 0.176675 | 0.264031 | 0.353032 | 0.441194 | 0.527776 |
| **AWMF** | 0.0318 | 0.088788 | 0.174889 | 0.257618 | 0.342337 | 0.425458 | 0.506289 |
| **NAFMF** | 0.0292 | 0.087630 | 0.176675 | 0.264031 | 0.353032 | 0.441194 | 0.527776 |
| **HMF** | 0.0394 | 0.079015 | 0.138143 | 0.194391 | 0.254372 | 1.054604 | 0.380749 |
| **NLMED** | 0.026634 | 0.067509 | 0.127461 | 0.186712 | 0.249187 | 0.310107 | 0.373382 |
| **Proposed-ANLMF** | 0.092945 | 0.102263 | 0.116151 | 0.130882 | **0.144472** | **0.160210** | **0.175407** |

Drawback of our proposed method is time complexity, elapsed time is 1070.82 seconds and it depends upon the level of noise occurred in the image. In future we are modifying our proposed methodto preserve edges and reduce the time complexity.

## Conclusion

In this paper, we have developed a adaptive nonlocal median filtering approach. The experiments were done with Brain web data and the results were compared with existing methods using the metrics PSNR, NAE. The results show that the proposed approach yields better consequences than a number of existing techniques with a high noise ratio.

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