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Noise Removal of MRI Images with Different Similarities using Advance NLM Filtering

Abhishek Sharma, Vijayshri Chaurasia

Abstract*: In modern world, medical imaging has versatile application worldwide. It is very popular in the field of research and innovation. Medical image processing include the study of internal body structure like organs, tissues, etc., which provides much clear information of inner body structure using the digitalized data of human organs and help doctors to detect disease. Magnetic Resonance Imaging (MRI) is most effective and safe method for internal structure diagnosis. MRI images are generally magnitude images and they are follows by Rician distribution. In last few decades, many denoising techniques have been proposed like wavelet based techniques, Maximum likelihood (ML), bilateral filtering etc. But all those algorithms have some shortcomings and limitations. The purpose of our study is to propose a simple but effective advance Non-Local Means filtering approach for MRI denoising. Different distance matrix calculations have been introduced like Euclidean distance, Minkowski distance, Manhattan distance etc. These all are tested and identified best similarity measurement which preserves the image edges information and other information more effectively. The analysis is done on both the quality and quantity basis such as Peak Signal to Noise Ratio (PSNR) which shows the efficiency of noise removal technique and Mean Square Error (MSE) which represents the average of difference between pixels value of original image and denoised images.

***Keywords* : Magnetic Resonance Imaging, NLM filter, PSNR, Rician Noise.**

I. INTRODUCTION

Medical Image Processing becomes most interesting field in research area. With the advancement of different sensors, it has wide area of applications in remote sensing military surveillance, and computer vision. In medical field, it is called Biomedical Image Processing. It has wide area of research and intense application in the field of medical science. Medical imaging provides information about different internal tissues, organs and other structures. Digital processing helps to gather better information about the diseases and help in diagnosis very effectively.

Magnetic resonance imaging (MRI) is most efficient and harmless method which provides detailed description of the internal structure of the body. During the acquisition or post acquisition, MRI images are generally affected by noise and reduce the visual quality of image [1]. MRI data is affected by Gaussian noise. There are several methods have been introduced like transform domain filtering i.e. wavelet transform [3][4], curvelet transform [5], statistical domain filtering i.e. Linear Minimum Mean Square Error (LMMSE) [7], maximum likelihood [6] and many other filtering like linear and nonlinear filters.. Non local means filter [8] [9] is very efficient non-linear filter which is enhancement of the Yaroslavsky filter [10]. It is based on weights of similarity between pixels and taking the weighted average of all pixels. NLM were suffering with high computational complexity and has been modified to reduce the computational complexity like fast NLM [11] and Non local maximum likelihood (NLML) [12]. Further description of paper is presented as follows: Noise model introduced in section 2, literature survey of different Non Local methods are discussed in section 3. Section 4 includes proposed methodology for improvement, 5th section will cover the experiments results and discussion and 6th section will be conclusion.

II. RICIAN NOISE MODEL

The MRI is complex image. It is represented by Gaussian distribution [2][6]. The magnitude image is generally considered for its representation. Its noise distribution is represented by Rician noise or Rician distribution [8].

$$p_M(M) = \frac{M}{\sigma^2} e^{-\frac{A^2+M^2}{2\sigma^2}} I_0\left(\frac{A.M}{\sigma^2}\right) \tag{1}$$

Here A = intensity of original image pixel
M = denoised pixel value.
I_0 = Modified zeroth order Bessel function of the first kind
σ= standard deviation (SD) of the introduced noise distribution

$$\frac{A}{\sigma} = \begin{cases} \frac{A}{\sigma} = 0 & \text{Rayleigh distribution} \\ 1 \le \frac{A}{\sigma} \le 3 & \text{Rician distribution} \\ \frac{A}{\sigma} \ge 3 & \text{Gaussian distribution} \end{cases} \tag{2}$$

III. PROPOSED METHODOLOGY

Our aim is to reduce the noise effect as minimum as possible and improve the PSNR of denoised image by improving the similarity measurement and calculating denoised value with the help of neighbourhood patches information.

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* Correspondence Author
Abhishek Sharma*, Electronics and Communication Department, MANIT, Bhopal, India. Email: abhishektit09@gmail.com.
Dr. Vijayshri Chaurasia, Electronics and Communication Department, MANIT, Bhopal, India. Email: vchaurasia@manit.ac.in.

The Non-local Means filtration method is used for calculating the new value of targeted pixel. The standard NLM filter [9] is based on the formula

$$NLM\left(Y(p)\right) = \sum_{\forall q \in Y} W(p,q)\, Y(q) \qquad (3)$$

Where $W(p,q)$ is weight of pixels and it is

$$0 \leq W(p,q) \leq 1$$

$$\sum_{\forall q \in Y} W(p,q) \; = 1$$

p = targeted pixel to be filtered
q = other neighbourhood pixels in the image
The complete process of proposed methodology described in in figure 1.

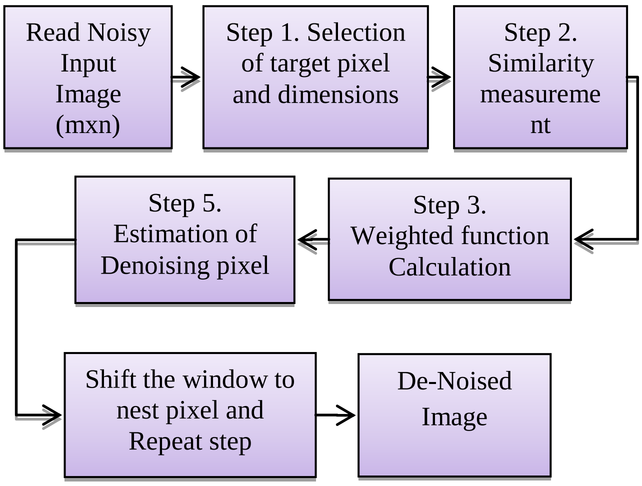

Figure 1. Stepwise Process of Proposed Algorithm

First we observed the noisy image (I) is of size MxN and perform the padding operation. We used mirror reflection padding technique to reshape the size of noisy image.

$$M_p = M + 2P \qquad (4a)$$

$$N_p = N + 2P \qquad (4b)$$

Where $P = \left(\frac{X-1}{2}\right)$; X= search window size.
Padding is used to de-noise the border pixels. The reference window of optimum size with targeted central pixel is selected inside the search window. Weight of each distance function is used to measure similarity. These weighted values are used to filter the targeted pixel and filtering is done using NLM.

A. *Selection of target pixel and dimensions:-*

The whole image is divided in subsections of predefined size called search window. Inside the search window, a small size window called reference window is selected with central targeted pixel.

B. *Similarity measurement:-*

1. Manhattan distance [14] –

It is calculated by moving through horizontal and vertical path between two points. It takes the algebraic sum of all horizontal and vertical components to measure distance. If (x_1, y_1) and (x_2, y_2) are two points, where x and y is vertical and horizontal axis, then Manhattan distance (d) will be

$$d = \sum_{i=1}^{n} [|x_i - y_i|] \qquad (5a)$$

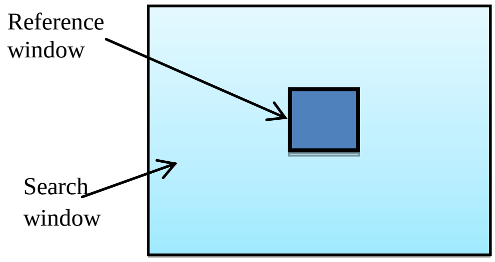

Figure 2. Window selection

2. Euclidean distance [14]-

It is calculate square of absolute difference between points of two different matrix vectors and then compute square root of resultant to find distance. Mathematically

$$d = \sqrt{\sum_{i=1}^{n} [|x_i - y_i|^2]} \qquad (5b)$$

3. Minkowski distance [13]-

It is calculated by taking cubic of difference between two matrices and then cubic root of sum of resultant matrix will distance between those two matrix vectors. Mathematically,

$$d = \sqrt[3]{\sum_{i=1}^{n} [|x_i - y_i|^3]} \qquad (5c)$$

4. Sum of squared absolute Difference (SSAD) [13]-

It calculates sum of squared difference between the points of two matrixes. It can also use in transform domain.it is represented mathematically as

$$d = \sum_{i=1}^{n} [|x_i - y_i|^2] \qquad (5d)$$

Hence the similarity between R and B need to be calculated using different distance function.

C. *Weighted function Calculation:-*

Based on the different distance function calculated in previous subsection, the weight of each distance will be calculated as

$$Weight = e^{\frac{-distance}{h^2}} \qquad (6)$$

Here h = decay parameter, which controls the degree smoothing of filter. Higher value of weight shows greater similarity between patches.

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D. *Estimation of Denoising pixel:-*

Each distance function will produce different weight and then final estimated value of central pixel will be calculated by taking average of all weighted pixel within the search window using equation (3). This is the denoised value of targeted pixel. Finally denoised image can be achieved by replacing all noisy pixels by denoised pixel value.

IV. RESULT AND DISCUSSION

The experiment has been conducted on image database form brainweb dataset and real time medical image database. The algorithm is tested with Mathworks™ Matlab® environment on processor Intel core i-5, 2.7 GHz, 8 GB RAM and windows 10 operating system. The test images were subjected to noise environment with different noise density (σ=5, 10, 15, 20, 25, 30). The experiment results has been observed and analyzed to shows the effectiveness of algorithm and evaluation parameters are PSNR and MSE [15]. The parameters for proposed algorithm are selected for optimal results. The radius of reference window set to f = 2 for window size $(2f+1)$ and search window size are selected as 25×25. Figure 3 shows the reference window and search window.

The PSNR of denoised image is calculated as

$$PSNR = 10\log\left[\frac{255^2}{\frac{1}{XY}\sum_{i=0}^{X-1}\sum_{j=0}^{Y-1}\left(I(i,j) - \hat{I}(i,j)\right)^2}\right] \quad (7)$$

And Mean Square error defined as

$$MSE = \frac{1}{XY}\sum_{i=0}^{X-1}\sum_{j=0}^{Y-1}\left(I(i,j) - \hat{I}(i,j)\right)^2 \quad (8)$$

Here $I(i,j)$= Real Test Image, $\hat{I}(i,j)$ = Denoised image.
$X \times Y$ = rows and columns of images.
The algorithm is tested on brain T1 image (slice 50). The Noise has been introduces artificially to original test images shown in figure 3. Denoised images with proposed method for various noise percentage shown in figure 4. The denoised images with different filter are shown in figure 5. Proposed algorithm showing clearer denoised images as compare to various denoising methods. The applied proposed method also tested for different distance functions like Manhattan distance, Euclidean distance, Minkowski distance and SSAD shown in table 2. These results show SSAD is most effective to MR images for similarity measurements.. It is clear by the PSNR values of denoised image by NLM with SSAD produces optimum results. Figure 6 shows the comparison graph of Mean Square Error of different denoising algorithms.

In this way the output error probability is very less as compare to other state of are methods. The optimum search window is selected for a best result is 25.

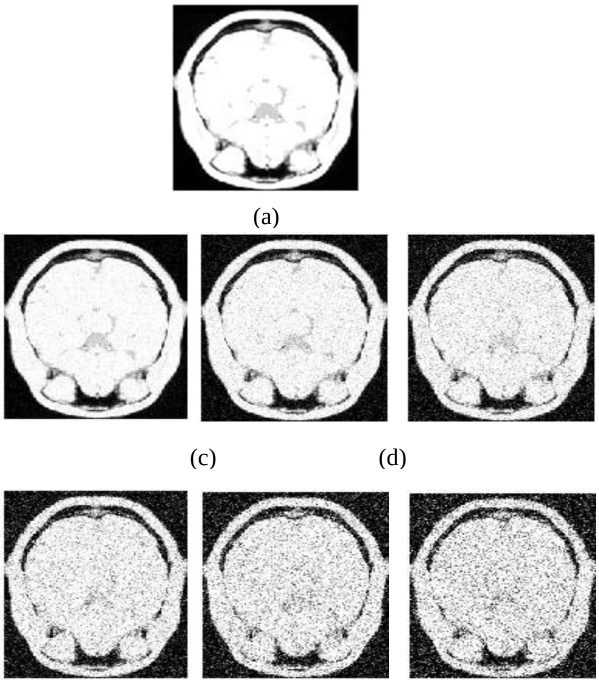


Figure 3: (a) Original MRI Image, (b) Noisy image $\sigma = 5$ (c) Noisy image $\sigma = 10$ (d) Noisy image $\sigma = 15$ (b) Noisy image $\sigma = 20$ (c) Noisy image $\sigma = 25$ (d) Noisy image$\sigma = 30$.

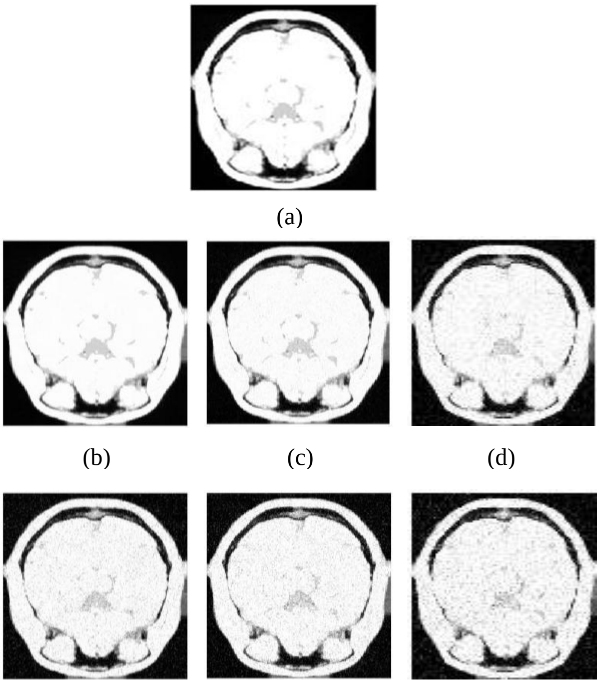
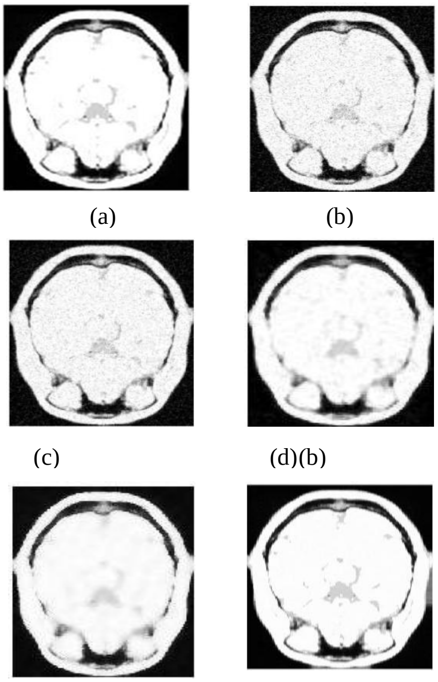


Figure 4: (a) Original MRI Image, (b) De-noised image $\sigma = 5$ (c) De-noised image $\sigma = 10$ (d) De-noised image $\sigma = 15$ (b) De-noised image $\sigma = 20$ (c) De-noised image $\sigma = 25$ (d) De-noised image$\sigma = 30$.



(a) (b) (c) (d)(b)

Figure 5: (a) Original MRI Image, (b) Noisy image $\sigma = 10$ (c) De-noised by Gaussian (d De-noised by Median (e) De-noised by Bilateral (g) De-noised by Proposed method

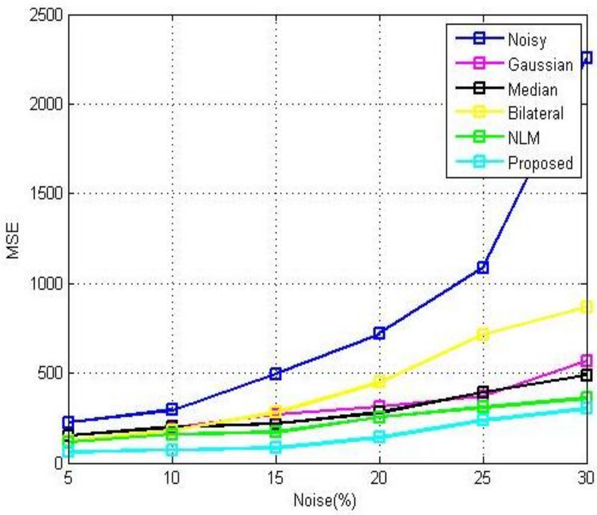


Figure 6. Graph representation of MSE (Mean Square error) of different denoising algorithms

V. CONCLUSION

The Denoising algorithm should be such that it does not change or effect image information and fine details. This algorithm represents advance NLM filtering method with better similarity calculation. This algorithm is simple and very effective to reduce the noise. The proposed method produces better quality denoised image than previous existing filters. This method produces better PSNR for high density noisy images, especially for the images affected by Rician noise. The method has been tested using different distance functions and SSAD was found best for similarity measurement. Other than quantitative measures, the quality measurement shows the visual quality of denoised image as compared to Median filter, bilateral filter, Gaussian filters and standard NLM. With the higher noise density, PSNR values of proposed technique are not decreasing much unlike previous filters. This method is most suitable and effective for higher noise density environment. The only limitation of this algorithm is computational burden which is expected to reduce by efficient code engineering.

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Table- I: Peak Signal to Noise Ratio (PSNR) in dB for different De-nosing algorithms

Sr. no.	Techniques	Noise Density (σ)					
		5	10	15	20	25	30
1.	Noisy	24.59	23.47	21.18	19.56	17.76	14.6
2.	Gaussian	26.29	25.21	23.84	23.16	22.42	20.59
3.	Median	26.31	25.12	24.74	23.64	22.18	21.24
4.	Bilateral	27.33	25.59	23.67	21.63	19.6	18.74
5.	NLM	27.55	26.16	25.86	24.08	23.24	22.58
6.	Proposed Algorithm	**30.24**	**28.64**	**27.93**	**26.6**	**24.43**	**23.32**

Table- II: Peak Signal to Noise Ratio (PSNR) comparison in dB for different distance functions

Sr. no.	Techniques	Noise Density (σ)					
		5	10	15	20	25	30
1.	Manhattan distance	20.42	19.75	17.82	16.45	15.63	13.72
2.	Euclidean distance	26.17	24.68	23.61	22.9	20.98	18.36
3.	Minkowski distance	22.94	19.86	18.99	17.64	16.52	14.85
4.	Sum of squared absolute Difference (SSAD)	**30.24**	**29.64**	**28.93**	**26.6**	**24.43**	**23.32**

AUTHORS PROFILE

Abhishek Sharma pursuing PhD. From MANIT Bhopal. He did B.E. in Electronics and Communication from Technocrtas Institute of Technology, Bhopal (M.P.) India. He did M.Tech in Microelectronics & VLSI Design from Technocrtas Institute of Technology, Bhopal (M.P.) India. Presently He is working as Assistant Professor in Electronics and Communication department of Sagar Institute of Research & Technology, Bhopal (M.P.) india. He has published 06 Research publications of international repute. His area of interest is Image Processing.

Dr. Vijayshri Chaurasia did B.E. in Electronics and Communication from Pt. Ravi Shanker University Raipur (C.G.) India. She did M.Tech in Digital Communication from Maulana Azad National Institute of Technology Bhopal (M.P.) India. She did Ph.D.in Electronics and Communication from MANIT Bhopal. Presently she is working as Assistant Professor in Electronics and Communication department of MANIT Bhopal. She has published around more than 60 Research publication of International repute. Her area of interest is Image Processing and Image Analysis and pattern recognition. She is a member of professional bodies IEEE, ISTE and IETE.

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