Enhanced Non Local Means Filter to Denoise MR Brain Images by Using Mean Absolute Deviation Error Measure

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Abstract
Now-a-days, Magnetic resonance (MR) images are using for diagnosing and treatment planning. Though, MR images are often contaminated by several kinds of noises such as Rician and Gaussian noises which are produced by the random thermal motion of electronic components. It diminishes the quality and trustworthiness of the images. This paper proposes an Enhanced Non Local Means Filter (ENLMF) to denoise Rician type of noise from MR images. Human brain is a complex structure that contains millions of neurons which makes acute changes in intensity of pixels. Therefore, the earlier model of NLMF might be improved to remove Rician noise from brain MR image. This study, implemented Dynamic window to enhance the noise removal process which utilizes Mean Absolute Deviation Error (MADE) to determine the window size. The method implemented in publically available noise introduced data set. The results also compared with the existing NLMF by visual and quantitative measures such as Peak Signal to Noise Ratio (PSNR) and Structured Similarity Index (SSIM) measure. The experimental results show that the proposed method provides 9% to 10% higher result than the existing NLMF.
Keywords - ***MR images, Brain MR image, noise, denoise, NLMF, PSNR, Mean absolute deviation error.***

I. INTRODUCTION

Magnetic Resonance (MR) scan can be used as an extremely accurate method of disease detection throughout the body. It provides sufficient and valuable information about soft tissues of the body to confirm a patient's diagnosis. Though, it produces noisy images cause of electrical and thermal problem that are modelled as Rician distribution [1] [2]. The noise reduces image contrast [3] and degrades images in both qualitative and quantitative senses. Hence, image quality step up is adequate process for further processing such as feature extraction and segmentation. In 2003, Fan et al. introduced bias correction for denoising [4], however it needs more in-depth knowledge about image acquisition process. Now-a-days, computerized denoising process becomes indispensable to get clear images.

Basically, denoising processess make use as linear, non-linear filters and wavelet thresholding techniques. In earlier days, median filter with various window scale acts as non linear filter. The linear filters make changes linearly in the neighbouring pixels. Non-linear filters and wavelet thresholding techniques restore the selected noisy pixels according to certain criteria. Recently, the non local means filters play vital role and achieved much impact in image processing. Buadas et al. Proposed a Non Local Means Filter (NLMF), that takes averages of similar pixels with in a window according to the Gaussian weights, Euclidean distance and self similarity of the pixels at certain distances [5]. The computational complexity was reduced by introducing optimization in block wise estimation and employed in 3D MRI images [6]. Several iterative methods based on NLMF are employed to remove speckle noise [7], Poisson noise [8], mixed noise [9] and salt and pepper noise removal [10]. Multiple filters such as median, wiener and NLMF were employed sequentially in order to remove the Gaussian noise from the MR images [11]. A noise sensitive switching NLMF was proposed to denoise images that estimates the noise level and switch on NLMF in the noisy block and switch off NLMF in the clean block [12]. Some corrections made in the weight calculation function that improves the performance of NLMF and called as improved NLMF [13]. Even though there is a drawback of NLMF is that demolishes the edges and fine structures when the noise level increases. Hence, Shreyashma Kumar proposed a non-local means filter and its method noise thresholding (NLFMNT) which combines both NLMF and wavelet thresholding technique to denoise the images without affecting its edges [14]. Rician nature of MRI data and spatial information are utilized to fix the patches in MRI images. Further, the smoothening parameter is adjusted by local noise estimator. It outperform of it than earlier NLMF in order to remove the Rician type of noises [15]. The NLMF method proved as superior non-linear filter, but it produces artifacts when cleaning Rician type of noises from MR images [16]. Perfect noise estimator requires for NLMF, generally Median Absolute Deviation (MAD) estimator [17] or signal to noise ratio (SNR) is used for Gaussian noises in wavelet domain.

Koay and Basser's made an analytic correction procedure based on Signal to Noise Ratio (SNR) [18]. Coupe et al. proposed a robust Rician noise estimator by using Koay's procedure and MAD estimator [19].

The proposed method fixes dynamic search window based on Mean Absolute Deviation Error (MADE) measure to ensure the type of region whether it is homogeneous or fine structure region. On account of the error value, the window size is changed dynamically. The process is discussed in the next section.

The remaining part of the paper organized as 3 sections. Section 2 discusses the proposed method and evaluation metrics, section 3 discusses materials used for experiment and results of existing and proposed method by visual and quantitative results and section 4 concludes the performance of the proposed method.

II. PROPOSED METHOD

A. NLM Filter

NLMF utilizes two windows, one window collects a patch of neighborhood pixels called patch comparison window another window is called search window which is larger than the patch window and collects similar pixel neighborhood from the patch window. NLM assign weights of each similar neighborhood pixels by using Euclidean distance.

Let the image U to be denoised, each pixel is replaced by using the following equation,

$$\mathrm{U(p)} = \frac{1}{\mathrm{C(P)}} \sum_{\mathrm{q} \in \mathrm{B(p,r)}} \mathrm{U(q)w(p,q)} \qquad (1)$$

$$\mathrm{C(p)} = \sum_{\mathrm{q} \in \mathrm{B(p,r)}} \mathrm{w(p,q)} \qquad (2)$$

where B(p,r) indicates a neighborhood centered at p with the radius r and size to be (2r+1)×(2r+1) pixels. w(p,q) represents the weight depends on squared Euclidean distance d2=d2(B(p,f), B(q,f)) of (2f+1)×(2f+1) patches centered respectively at p and q.

$$\mathrm{d}^2\big(\mathrm{B(p,f)}, \mathrm{B(q,f)}\big) = \frac{1}{(2\mathrm{f}+1)^2} \sum (\mathrm{U(p+j)} - \mathrm{U(q+j)})^2 \qquad (3)$$

The above equation represents that each pixel value is restored as an average of the most resembling pixels. The weight of each pixel in the window is calculated as follows

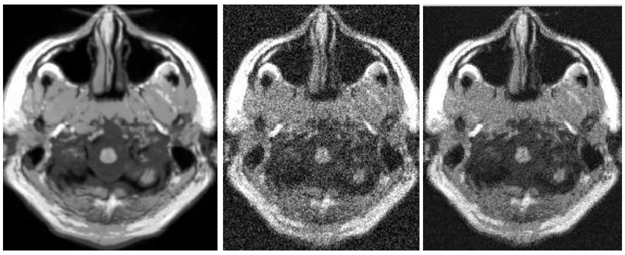
$$\mathrm{w(p,q)} = \mathrm{e}^{-\max\left(\frac{\mathrm{d}^2 - 2\sigma^2, 0, 0}{\mathrm{h}^2}\right)} \qquad (4)$$

where σ represents the standard deviation of the noise and h is filtering parameter that controls the decay in patch weight. The Euclidean distance between two patches are smaller than 2σ2 are set to 1. The larger distances decrease by the exponential kernel.

1. TABLE 1. NLMF PARAMETERS

σ	Patch window size (Γ)	Search window size(ζ)	h
0<σ≤15	3×3	21×21	0.40σ
15<σ≤30	5×5	21×21	0.40σ
30<σ≤45	7×7	35×35	0.35σ
45<σ≤75	9×9	35×35	0.35σ
75<σ≤100	11×11	35×35	0.30σ

The estimated noise σ can provide a starting point for setting the R. The layer h allows more smoothing between dissimilar patches. Buades et al. analysed the size of the patch (Γ) and search window size (ζ) corresponding to noise level σ. The large search window helps to obtain prominent results. Hence, Buades et al. Relate h and σ as h=kσ, the size of the patch increases when k decreases [5]. The search window and patch sizes are listed in Table 1. Initially, some comparisons made by setting the parameter values as given in Table1.



(a) (b) (c)

Fig. 1. Sample result of NLMF. (a) Clean image, (b) Noisy image and (c) Denoising result of NLMF. The NLMF parameter values are σ=24, comparison search window size=21×21 and patch window size = 5×5.

The results are given in Fig. 1. The clean, noisy and denoised images are given from Fig. 1(a)-(c). Here, The noise level σ=24 is estimated by using the Robust Rician noise estimator [19]. The ζ = 21×21 and Γ = 5×5. Even though, the denoised image contains some noises in brain region. The results ensure that the parameters given in Table 1 are not suitable for the

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Rician type of noises. Hence, several results were obtained by changing the search window sizes. The results are given in Fig. 2.

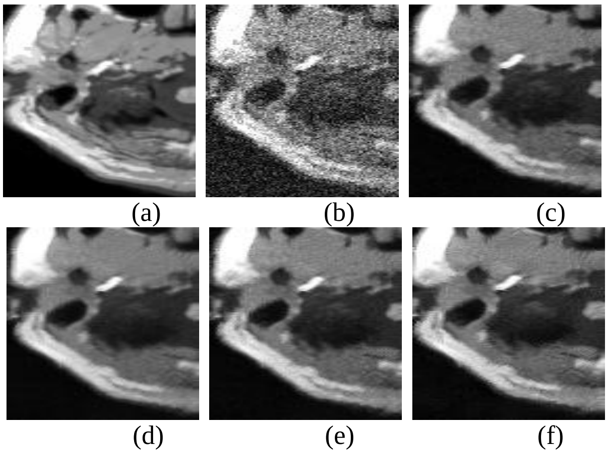

Fig. 2. Results of various comparisons patch and search window sizes. (a) clean image segment, (b) noisy image segment, (c)-(f) results of setting window sizes ζ=17×17 and Γ=3×3, ζ=11×11 and Γ=3×3, ζ=7×7 and Γ=3×3 and ζ=5×5 and Γ=3×3 respectively

Fig. 2(a) is the clean image segment, the image segments from Fig. 2(b)-(e) are the results of various window sizes. Fig. 2(e) is the results obtained by setting the window sizes such as ζ= 5×5 and Γ= 3×3. It clears the noise but made some edge like artefacts in homogeneous regions. Fig. 2(d) is the result of ζ=7×7 and Γ = 3×3 which gives some moderate results. Fig. 2(c) is the result of ζ=7×7 and Γ= 3×3 which gives some moderate results. Fig. 2(c) is the result of ζ=17×17 and Γ= 3×3, that retains the fine structure but unclear the noise in homogeneous region. The results conclude that the static window sizes fixed for

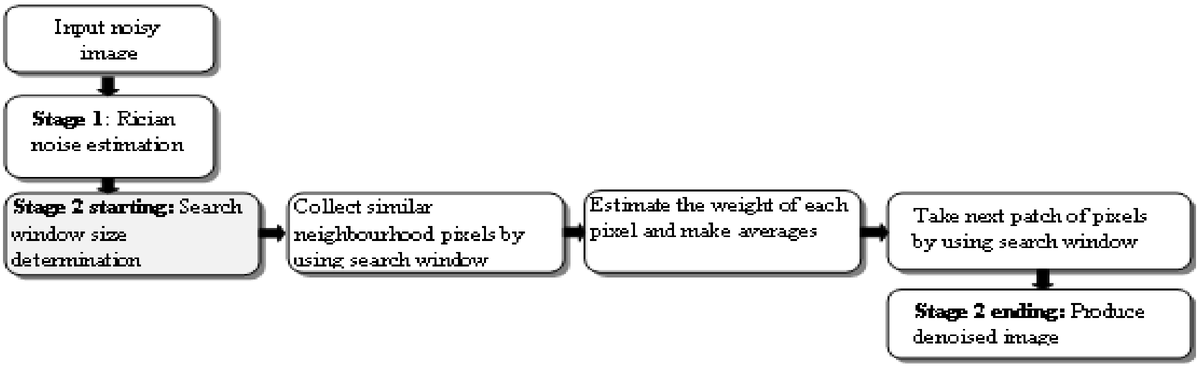

Fig. 3. Flow diagram of the proposed method

all brain image regions does not provide significant results. The keen observation motivates us to make some changes in window sizes. Hence, the proposed method concentrates on dynamic window sizes corresponding to the gray level deviation in the search window.

The proposed method solves the drawback of NLMF by employing dynamic window sizes. The flow diagram of the proposed method is given in Fig. 3. It is a three stage process, stage 1 estimates the noise level, stage 2 employed the proposed new approach for window size determination and employ the NLMF and stage 3 verify the performance of the proposed denoising method by employing Fuzzy C-means clustering.

B. Noise Estimation

In MRI images, an inverse discrete Fourier transform is used to decode the acquired MR signals, so the result value is in complex numbers; the magnitude image is computed on a pixel-by-pixel base as follows,

$$\mathbf{M_i} = \sqrt{\mathbf{R_i^2} + \mathbf{I_i^2}} \qquad (5)$$

At high SNR, the Rician distribution is well approximated by a Gaussian distribution. The object based Rician estimator is computed in [Coupe P, 2010] as follows,

$$\boldsymbol{\sigma} = \sqrt{\boldsymbol{\sigma}_\mathbf{n}^2/\boldsymbol{\varepsilon}(\boldsymbol{\theta})} \qquad (6)$$

The SNR of $\boldsymbol{\theta}$ is computed by using the mask extracted from wavelet domain by using K-means segmentation on noisy image.

$$\boldsymbol{\theta} = \frac{\boldsymbol{\mu}}{\boldsymbol{\sigma}_\mathbf{n}} \qquad (7)$$

$\boldsymbol{\mu}$ and $\boldsymbol{\sigma}_\mathbf{n}$ are mean and standard deviation respectively. The correction factor $\boldsymbol{\varepsilon}(\boldsymbol{\theta})$ is computed by Koay et al.

$$\boldsymbol{\varepsilon(\theta) = 2 + \theta^2 - \frac{\pi}{8} \times \exp\left(-\frac{\theta^2}{2}\right)\left((2+\theta^2)I_0\left(\frac{\theta^2}{4}\right) + \theta^2 I_1\left(\frac{\theta^2}{4}\right)\right)^2} \quad (8)$$

where $\mathbf{I_0}$ and $\mathbf{I_1}$ are zeroth and first order Bessel functions. The correction factor is iteratively applied until reach the stoping criteria $|\boldsymbol{\theta_t - \theta}| > 0$

The iterative correction scheme is

$$\theta_t = \sqrt{\varepsilon(\theta_{t-1})(1 - \frac{m_0}{\sigma}) - 2} \quad (9)$$

$\mathbf{m_0}$ is the mean signal of the object and $\boldsymbol{\sigma}$ is obtained from the MAD estimator. Result of last iteration is implemented in (6) to identify the standard deviation (σ) of noise.

C. Proposed Dynamic Window NLMF

A new approach, dynamic patch window size is analyzed with the help of MADE. Sample random distribution of noise pixel patch (17×17) in homogeneous and fine structure image region are analyzed by vision. The noise distributions on both image segments are almost equal. However, the region pixel gray levels are different, thus induce us to use mean based error measure MADE to define the window size. The 9% of Rician type of noise distributed on the given image, the estimated MADE from noise homogeneous and respective clean patches are 51 and 18 respectively. But MADE are 163 and 152 for fine structure patches obtained from noise and respective clean images. The promising results ensure that the MADE depends on the heterogeneity of the region. Hence, the proposed Dynamic window NLMF uses MADE. The proposed method is as follows, Initially, a random size of ζ is selected, then the size to be estimated by using MADE defined as follows,

$$\mathbf{MADE} = \sum_{i=1}^{N}\sum_{j=1}^{N}\frac{\mu_k - I_{i,j}}{\mu_k} \quad (10)$$

where μk represents the mean of the ζ at kth patch and N represents the maximum number of row and column of ζ

$$\textbf{size of } \boldsymbol{\zeta} = \begin{cases} \mathbf{2s+1, 2s+1}, & \mathbf{MADE > 100} \\ \mathbf{3s+1, 3s+1}, & \mathbf{otherwise} \end{cases} \quad (11)$$

where s is a constant between 3 to 5 that is recommended based on the experiments carried over more noisy MRI images. Then the similar neighbourhood pixels are detected from the selected pixel patch ζ. Further, Eqn. (1-5) are implemented for the selected patch. The ζ size estimation process repeated for each ζ selection.

C. Evaluation Metrics

Both qualitative and quantitative validations are considered for the performance evaluation. The qualitative evaluation is simply the visual inspection of the result. The quantitative evaluation measured in terms of peak signal to noise ratio (PSNR) and structured similarity index measure (SSIM). The PSNR calculation depends on mean squatted error (MSE) values and both are defined as,

$$PSNR = 10\log_{10}\left(\frac{255^2}{MSE}\right) \quad (12)$$

$$MSE = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}(f - f')^2 \quad (13)$$

where, f is the intensity value of original image, f' is the intensity value of denoised image, m and n represent number of rows and columns. The higher PSNR values ensure effective denoising work.

SSIM is used for measuring the similarity between two images; original and denoised image.

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \quad (14)$$

$$\mu_x = \sum_{i=1}^{N} w_i x_i \quad (15)$$

$$\sigma_x = \left(\sum_{i=1}^{N} w_i (x_i - \mu_x)^2\right)^{1/2} \quad (16)$$

$$\sigma_{xy} = \sum_{i=1}^{N} w_i (x_i - \mu_x)(y_i - \mu_y) \quad (17)$$

$$c_1 = (k_1 L)^2 \text{ and } c_2 = (k_2 L)^2 \quad (18)$$

where L is the range or pixel values (255 for 8 bit grayscale images) and k1<<1 is a small constant and also k2<<1.

III. Results and Discussion

A. Materials Used

One hundred and eighty T1 images (one volume) obtained from Internet Brain Segmentation Repository (IBSR) website developed by Centre for Morphometric Analysis (CMA) at Massachusetts General Hospital used for experiments. The three dimensional axial T1 weighted spoiled gradient echo MRI scans were performed on two different imaging systems. The machine type is 1.5 tesla Siemens Magnetom MR System (Iselin NJ) with the following parameters: TR = 18 ms, TE = 10 ms, flip angle = 30 degrees, slice thickness = 1mm, INU field is A type, Image type = Magnitude and the different percentage of (2% to 10%) noises introduced in bright tissues.

B. Discussion

Other real time clinical noisy datasets were collected from Indian MRI research and diagnostic center, Madurai, Tamil Nadu, India. The data sets were acquired in 0.3 tesla machine on 2013. The machine parameters were TE=120.0, ET=11, TR=3600.0, FOV=24x24cm and image size is 256x256.

The entire algorithm was coded in Matlab 2013 without using toolboxes.

Initially a three dimensional (3D) raw image is obtained from the IBSR web site. Some level of noise that was the percentage of its maximum intensity distributed based on Rician distribution randomly. The 3D were converted as 181, 2D slices. Then the experiments were carried over the noisy images. Some sample images and image segments are given in Fig. 4. The column 1 of Fig. 4 shows the clean images, the column 2 shows the noisy images, column 3 and column 4 show the denoised results of the proposed and existing NLMF. One fine structure image segment is given in row 1 of the Fig.4. The proposed method correctly retains the fine structure which is marked by a square. A homogeneous region segment of the clean and noisy images and denoised results of the proposed and existing methods are given in row 2 of Fig. 4. The existing method slightly blurs the homogeneous region but the proposed method significantly replaces the noisy pixels. The prominent results of the proposed method in denoising homogeneous and fine structure regions are given in Fig. 4 row 3.

2. TABLE 2. QUANTITATIVE DENOISING RESULTS

Noise Level	PSNR value of the Proposed Method	PSNR value of the Existing Method
3	35.2614	32.1263
4	33.8976	31.4137
5	30.2337	29.2597
6	28.9275	27.8145
7	27.3156	26.2632
8	25.1247	24.9220
9	25.0163	23.9653
10	24.5341	23.0421
11	23.3591	22.0994
12	20.6823	19.3866
13	19.0418	18.6437
14	18.4965	17.8489
15	17.9382	17.2092
Clinical Images	25.1035	24.5883

Table 2 shows the average PSNR values of 181 IBSR image slices and clinical images. The proposed method makes higher PSNR values for different noise levels which imply that the proposed method outperform the existing method. The significant performance also proved in clinical images also.

The SSIM of the proposed and existing methods are given in bar chart Fig.5. The x-axis represents the noise level and y-axis represents the SSIM value. The proposed method accounts high SSIM from noise level 4% the higher SSIM is achieved in mid slices.

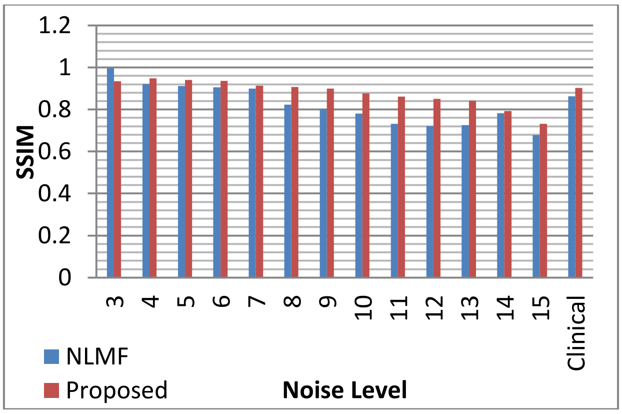

Figure 5. Flow chart of SSIM

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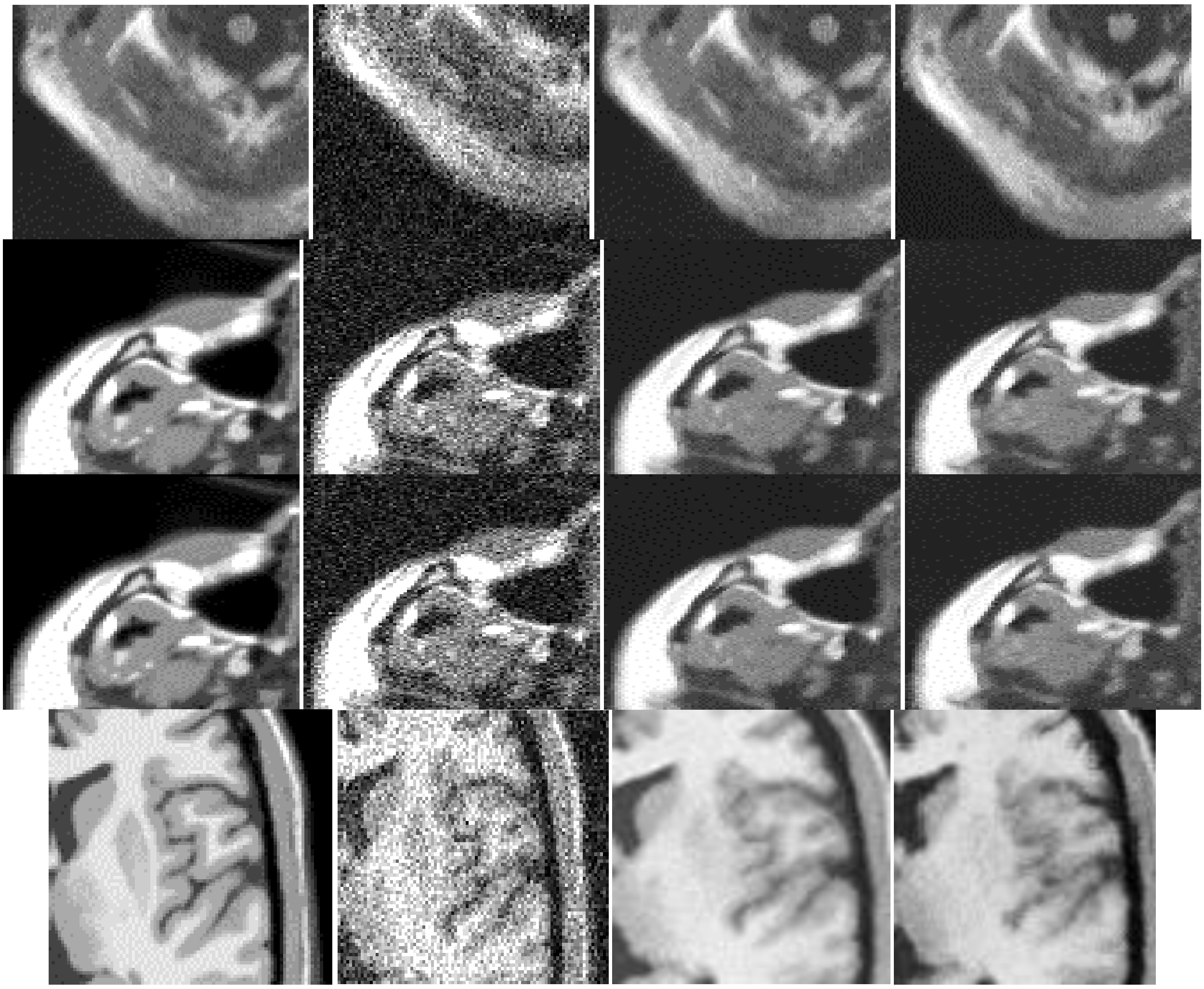

Figure 4. Output of the proposed method

The visual and quantitative results of the proposed method and existing NLMF ensure that the proposed method outperforms the existing.

IV. Conclusion

Dynamic window based NLMF method proposed for denoising the brain MRI images. Each and every parameter of NLMF is fixed based on the experiments carried over various levels of noise applied images. The experiment results proved the outperformance of the proposed method. Moreover, the proposed Dynamic window NLMF preserves the details of the fine structures. Hence, the proposed method is highly supportable to the physicians in diagnosing process.

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