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Brain MR image denoising based on wavelet transform

Deepti Gupta* **and Musheer Ahmad**
Department of Applied Sciences & Humanities, Jamia Millia Islamia, New Delhi, India

Abstract
Images must be clear and noise free, in order to achieve better accuracy in classification results of brain tumor from magnetic resonance imaging (MRI). But in the process of collection of medical images, the picture gets noisy, inadvertently. Deletion of noise from images is known as wavelet shrinkage or thresholding. In this work, an ingenious and compatible method is proposed for the valuation of thresholding parameters, hinge on the information of wavelet coefficients. For the better illustration of the process brain MRI was introduced with Gaussian noise at the different level of variances and then denoised using Wavelet Transform with coding in MATLAB. The same procedure was repeated to denoise three brain MR Images with the brain tumor. Proposed method helps in embellished off the edge and texture details of the images. The image quality of brain MR images is assessed in terms of peak signal-to-noise ratio (PSNR). Experimental results represent that this method attain preferable denoised image with improved PSNR.

Keywords
Magnetic resonance imaging (MRI), Image denoising, Thresholding function, Peak signal to noise ratio (PSNR).

1.Introduction
Noise is a disturbance which occurs during acquisition and transmission of images from one medium to another. It may corrupt image and provide an erroneous repercussion during image processing. Image quality can generally be upgraded by removing noise and enhancing contrast. Preferably, at the time of removal of noise from images as many as possible significant features should be preserved. Medical images acquired from CT Scan, MRI and X-ray are the standard tool for diagnosis in the medical field. These images are often exaggerated by random noise and Gaussian noise. An existence of noise generates adverse visual quality and reduces the visibility of minimal contrast objects. Noise removal is vital in medical imaging applications to get hidden details of the data and enhance image quality. Medical images are normally contaminated with noise, which obstructs the medical finding related to these images. There is a widespread concern in the problem of denoising images in traditional devices from the traditional image processing area to the MRI images have been applied for denoising, However, the practice of noise inhibition must not considerably corrupt the valuable features in an image. In general, edges are significant features for medical images and hence the denoising must be balanced with edge preservation [1].

Wavelets are well accepted for medical image denoising and enhancement applications for their good localization properties both in space and frequency. Wavelets do not isolate the smoothness along the edges, and thus more suitable for reconstruction of sharp point singularities than lines or edges [2]. The wavelet transform is progressively applied in image denoising domain for their intrinsic worth furthermore, its functioning is easy, and its application performance is good, wavelet transform has been widely paid attention across the globe [3].

2.Related work
In general, the denoising methods are linear likewise Wiener filter, but one of the drawbacks of Wiener filter and Gaussian filter denoising is it consists image blur situation. In recent times, nonlinear systems are derived from wavelet transforms are more operable [4]. Elyasi et al. are the investigators of the initial denoising papers using wavelet [5]. In 2009 they have presented that the noise might be considerably diminished with persistence of edge sharpness by wavelet thresholding. Donoho and Johnstone have established various principal theoretical results namely wavelet shrinkage with higher convergence rate [6, 7]. One of the standard methods namely, Bayes shrink in which the threshold is acquired by means of the Bayesian method [8, 9]. Bayes Shrink method is a subband related it means that the thresholding is performed at each subband in

*Author for correspondence

the wavelet decomposition. It is studied as smoothness adaptive. Further efforts made in the domain of wavelet thresholding is reviewed in [10-13]. They proposed a new thresholding method using soft-thresholding. They demonstrated that their proposed method outperforms the traditional ones in terms of PSNR; thus, improving the denoised results significantly [14]. Simulation results are also given to show the efficacy of our proposed method.

Denoising by the methods of Wiener filter and Gaussian filter causes the edge blurred situation. Bilateral filtering [11] is the highest intensive nonlinear smoothing filter, in spite of the fact that it undergoes the gradient reversal effect, which employs an intricate computation based histogram approximation to figure out the weight. In recent times, Zhang et al. [9] create an augmented bilateral filter based structure which is competent of effectively get rid of the noise. It receives spatial information and grayscale similarity from images and attains denoising along with edge-preserving.

2.1Available threshold function for image denoising

Let us take an original image k_{ij} of size NxN and add the Gaussian noise m_{ij} to original image to make it noisy image n_{ij} , i.e.,

$$n_{ij} = k_{ij} + m_{ij} \quad (1)$$

Apply the wavelet transform to (1) to obtain the wavelet coefficientsF_{ij}. Convert the wavelet coefficients F_{ij} by applying the soft thresholding [7]. and then take inverse-wavelet transform to get the denoised image $\hat{f}$.

$$\hat{f} = \begin{cases} F_{ij} - t, & \text{if } F_{ij} \geq t \\ F_{ij} + t, & \text{if } F_{ij} \leq -t \\ 0, & \text{if } |F_{ij}| < t \end{cases} \quad (2)$$

Where t is the threshold value.

Donoho et al. [7] have discussed a simple but influential wavelet-based denoising pattern known as VisuShrink. The outcomes of VisuShrink are stable along with an alluring visual feature. Even though VisuShrink is liable to over-smooth the signal, but fail to retain details like sharp edges of the original signal that come out in the increased estimation error. VisuShrink uses the Universal threshold, S, which is proportional to the standard deviation of the noise, is defined as [6]:

$$S = \sigma\sqrt{2logN} \quad (3)$$

Where σ^2 is the noise variance defined as given in following equation.

$$\sigma^2 = [(median|\, n_{ij}|)/0.06745]^2 \quad (4)$$

Where $n_{ij} \in HH_1$ subband thresholding.
N: Number of a pixel for the test image.

3.Proposed denoising method

With this proposed technique we are obtaining denoised images afterward estimation of new thresholding function.

3.1Evaluation of proposed thresholding function

To get an improved value of the thresholding is our main task. An undersized threshold will outpace all the noisy coefficients [15]. So, noise remains in the denoised image. On the contrary, a wide threshold value label an extra number of coefficients as zero, which destroy some important details by converting the noisy signal into smooth and it may create blurs and artifact [16, 4]. Therefore, we try to explore optimum threshold technique. The proposed technique is adaptive to dissimilar sub-band characteristics by investigating the parameters of the wavelet coefficients as follows [17]:

$$A(p) = \sum_{i,j} F_{ij} \quad (5)$$

For p=0,1 and 2, the F_{ij} are the wavelet coefficients for horizontal, vertical and diagonal values respectively.

$$T = \frac{\sum_0^2 A(p)}{\hat{N}} \quad (6)$$

Where $\hat{N} = N/2^b$, here b= 1, 2,…,k and k denotes the number of decompositions.

Threshold Factor

$$Q = exp\{(S - T)/(S + T)\} \quad (7)$$

Now, we evaluate a new threshold value S_{new} as given in eq^n (8)

$$S_{new} = \sigma Q \quad (8)$$

With this new threshold parameter, we will get the denoised image from the noisy image.

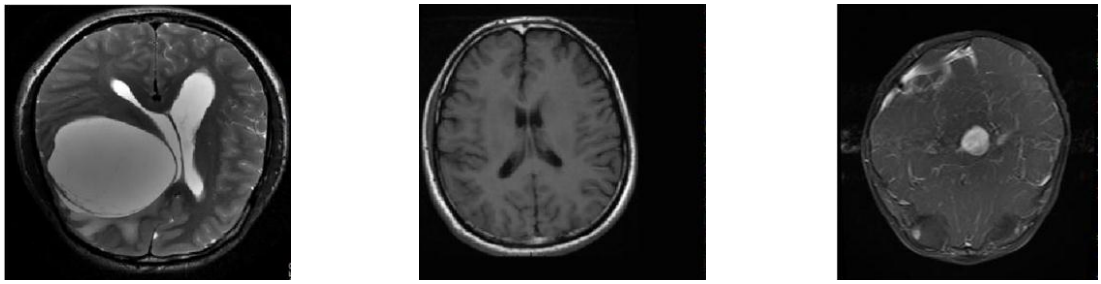
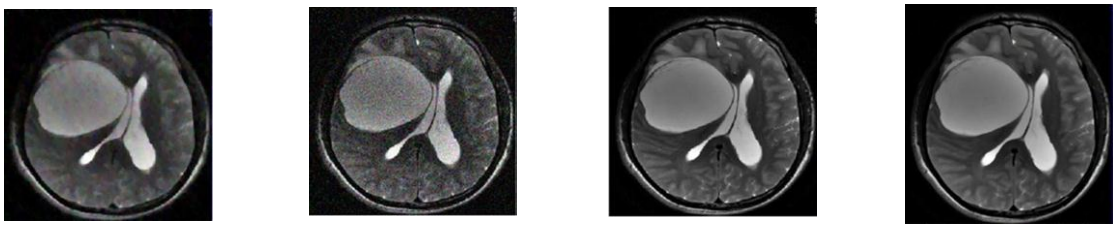


Image (1) Image (2) Image (3)

Figure 1 Brain tumor input images

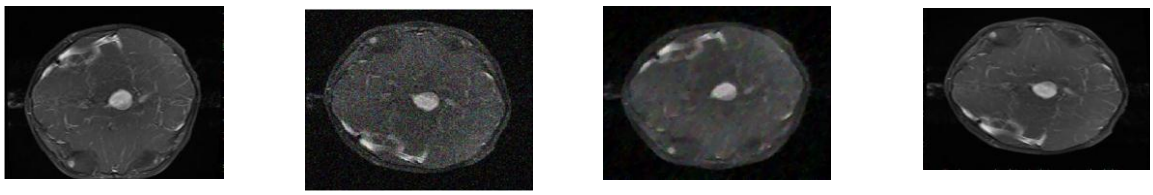


1(a) Original Image 1(b) Noisy image 1(c) denoised image (Conventional method) 1 (d) denoised image (Proposed method)

Figure 2 Processing through proposed method of image 1 of figure 1

2(a) Original Image 2(b) Noisy image 2(c) Denoised image (Conventional method) 2(d) Denoised image (Proposed method)

Figure 3 Processing through proposed method of image 2 of figure 1



3(a) Original Image 3(b) Noisy image 3(c) Denoised image (Conventional method) 3(d) Denoised image (Proposed method)

Figure 4 Processing through proposed method of image 3 of figure 1

3.2Steps to be performed for image denoising

- Apply the kth disintegrations on discrete wavelet transform (DWT) for an image n to transform into noisy wavelet coefficients F.
- Evaluate the noise variance σ^2 by equation 4.
- Assess S_{new} from equation 8 at every high sub band, and put on soft-threshold to the wavelet coefficients.
- Apply inverse discrete wavelet transform to obtain reconstructed image $\hat{f}$.

4.Results and discussion

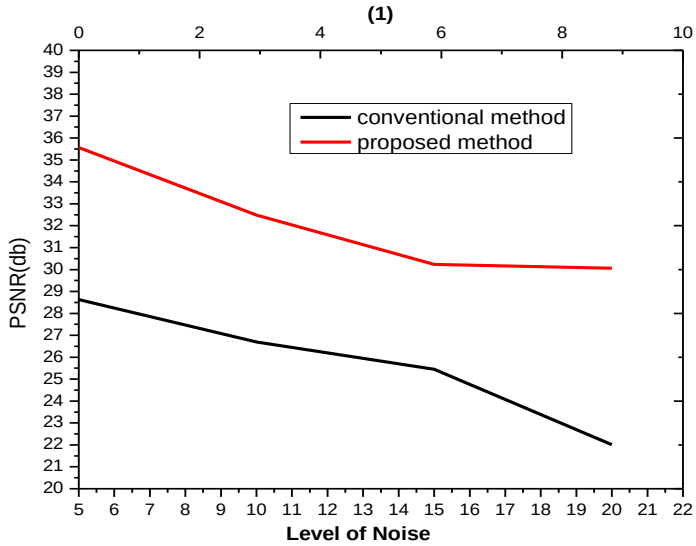
We have run a sequence of experiments using MATLAB R2013a. By taking brain tumor images as an input. Image 1 having a tumor on left side in the brain. Tumors present on both sides of brain in image

2 and right side of brain in image 3. Gaussian noise at different level of variance 5, 10, 15 and 20 has been added to all three images. It generates the noisy images displayed in *Figures 1(b), 2(b)* and *3(b*). The first image i.e. (a) presents the original one, and the second image i.e. (b) presents the noisy image with Gaussian noise level 20 as shown in *Figures 2-4*. The third ones (c) are the denoised images applying the conventional method [5] of denoising and the fourth image in a row i.e. (d) are the denoised images using our proposed method. It is manifest from these figures that the denoise images using our proposed method have superior visual quality as compared to the available conventional methods.

The quality of test images is measured in terms of PSNR. The experimental results of our proposed method are depicted in *Table 1*. These PSNRs specify that our proposed method is better to the existing method. As we increase the noise level, denoising effect of conventional method decreases, but the proposed method contributes better execution with high noise. From the results obtained in *Table 1* and *Figures 2-5* verify that, our method achieves better edge effects and eliminate noise well as compared with available methods.

Table 1 Results in terms of PSNR (in db) for brain tumor images

Image name	Noise level	Methods	
		Conventional	**Proposed**
(1)	5	28.63	35.56
	10	26.70	32.48
	15	25.45	30.23
	20	22.01	30.06
(2)	5	26.60	39.65
	10	25.94	35.13
	15	23.10	32.89
	20	21.45	31.18
(3)	5	28.15	36.65
	10	23.14	33.23
	15	22.69	32.09
	20	22.16	30.25



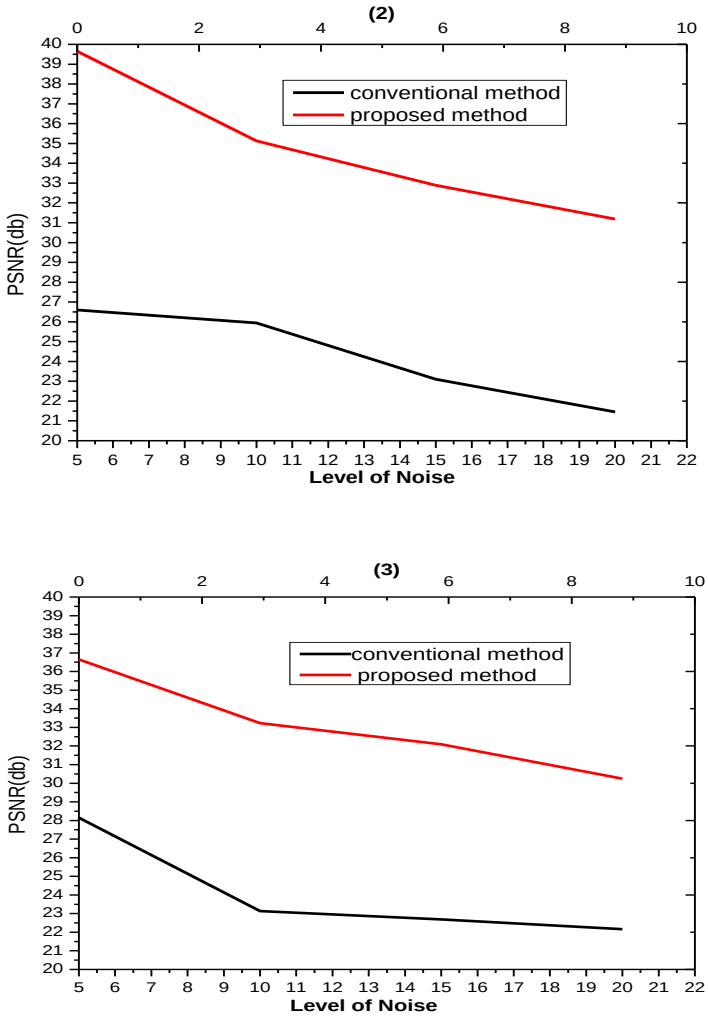


Figure 5 PSNR vs. noise levels of conventional and proposed methods with images (1), (2) and (3)

5.Conclusion

In this paper a new thresholding technique that decreases gaussian noise significantly from a noisy image has been introduced. In addition to that, it improves considerably the visual quality of the noisy image. In future to achieve higher PSNR and more clarity in images other techniques may be applied as suggested in [18]. Our approach can be improved in the direction of hybrid approaches for better denoising results [19].

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Conflicts of interest

The authors have no conflicts of interest to declare.

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Deepti Gupta has completed M.Sc. (Mathematics) from DBRAU Agra, Currently, she is pursuing Ph.D. in the field of Applications of support vector machine and wavelets in image processing from Jamia Millia Islamia, New Delhi, India.

Email:dg.gupta399@gmail.com

Prof Musheer Ahmad is working as Head of the Department of Applied Sciences & Humanities at Jamia Millia Islamia, New Delhi, India. He is Ph.D. and M.phil from Department of Mathematics, Aligarh Muslim University, India. His current research interests include Fuzzy algebra, Graph theory, Image Processing , Soft computing and Information Security.