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An Efficient Technique to Remove Gaussian Noise and Improve the Quality of Magnetic Resonance Image

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Abstract**:** ***Medical Resonance Imaging (MRI) is very useful in different medical applications for diagnosis the diseases in human body. But the main problem arising in MRI images is presence of various noises. These noises are affecting the originality of the MRI images and producing erroneous results. Here Brain MRI images are used for analysis of noise. Brain images are fractal in nature and especially those images are affected by various noises. In this paper we discussed about the Gaussian noise in brain MRI image. The effect of this noise is reduced by wavelet based thresholding techniques. They are namely Visu shrink, SURE shrink and Bayes shrink. These three methods are applied to the brain MRI images and obtained results are compared by PSNR(Peak signal to Noise ratio), MSE(Mean Square Error),Absolute error, Fractal dimension, IEF(Image Enhancement Factor),Normalized cross correlation and structural content.***

Index Terms**:** ***MRI Images, Gaussian Noise, Wavelet Thresholding, PSNR,MSE, NK, and IEF.***

I. INTRODUCTION

Many researchers are focusing the medical image processing for removal of noises. Because, the noise affected MRI images produced the erroneous result and misleading the user for false observation of diseases. Image restoration technique is used to deal larger part of image processing with or image denoising, denoising the noise affected images plays a major role to diagnose the diseases in a proper manner and to retain the image up to its quality[1-2]. One of the best method suggested many researcher by image denoising and this will helpful for the reduction of noises in MRI images. The different fields this technique applicable and tradeoff between the image features and noise reduction must be taken into account while denoising. Many soft computing techniques are recently used for removal of noises in MRI [3]. MRI (Magnetic Resonance imaging) is used for taking medical images. CT (Computed Tomography) and Ultrasound imaging techniques are also used in medical images. Among these MRI sounds better in giving high resolution images of the soft tissues in human body. Human brain is the soft and most complex organ of human body. An image of human brain consists of several complex patterns that are independent of scales. Thus brain image is a self similar structure and is fractal in nature [4-5]. Salt and pepper noise, Gaussian noise, speckle noise and fractional Brownian motion noise (fBm noise) are also affected the MRI images [6-7].

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II. PROPOSED TECHNIQUE

Now days, wavelet transform technique is most popular because of accuracy and classification of images. Here, DWT (Discrete Wavelet Transform) is used [8-9]. Using this technique can represent an image with high resolution. To remove the noise presented in brain MRI images Wavelet denoising technique is proposed in this paper. Also it preserves the image details without considering the frequency content of the image and so it suits well for medical images. In DWT the brain MRI image is considered to be consisting of small functions called wavelets [10]. The three wavelet techniques are explained below,

A. Visu Shrink

Here fixed threshold is applied and is given by the equation,

$$T_u = \sigma_n^2 \sqrt{2 \log N}.$$

Where N is the size of the image and the median absolute deviation of noise σn2 is given by,

$$\sigma_n^2 = \left[\frac{median(HH1(n,m))}{0.6745}\right]^2 \qquad (2)$$

Here n and m are the pixel indices of the sub band HH1 which is obtained by the first level of wavelet decomposition.

Visu shrink considers only the images of size N and the standard deviation of the noise. Visu shrink threshold value increases as the number of pixels in the image increase and as a result, the significant coefficients are killed. Visu shrink minimizes the overall error in the denoised image and produces overly smoothened estimation. This method does not work properly if there are discontinuities in the signal.

B. SURE Shrink

The combination of universal threshold and the Stein's unbiased risk estimator constitutes SURE shrink. Each sub-band is having separate threshold here. This is best suited to image with sharp discontinuities. This performs well in denoising the image and it has minimum value for mean square error. The threshold function is given by,

$$T_S = \min(T, \sigma_n^2 \sqrt{2 \log N}) \qquad (3)$$

Here T is the value that minimizes the Stein's unbiased risk estimator.

C. Bayes Shrink

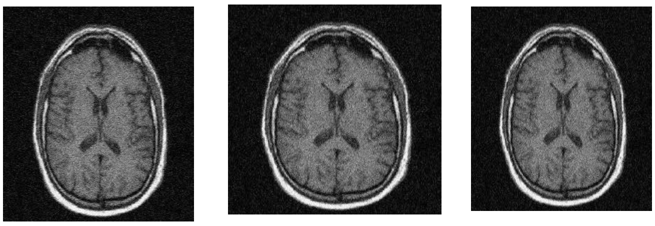
Bayes shrink models the wavelet coefficients with general gaussian distribution. This adapts to both signal and noise characteristics. The threshold is given by the relation,

$$T_B(\sigma_x) = \frac{\sigma_n^2}{\sigma_x} \qquad (4)$$

Here σx denotes the standard deviation of the image in each wavelet sub band.

III. Simulation Results and Discussions

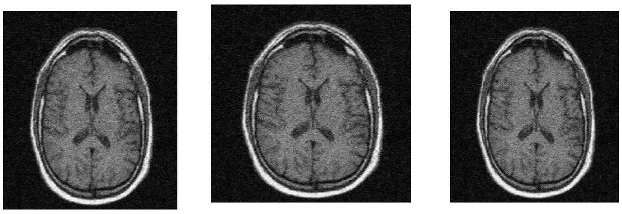
The wavelet based thresholding techniques are implemented by using MATLAB (R20111a) and the simulation results for Visu shrink are given in the Fig. 1. The Fig. 1(a) shows the original image. The Fig. 1(b) shows the noisy image. The Fig. 1(c) shows the denoised image. Here in the noisy image the value of the Hurst parameter is 0.11 (for a classical Brownian motion, the Hurst parameter h=0.13).



(a) (b) (c)

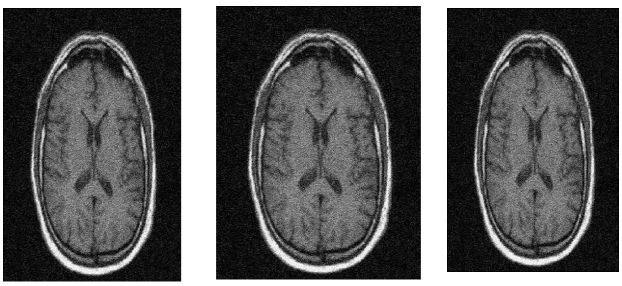
Fig.1. Simulation results for Visu shrink

The simulations results for SURE shrink are given in the Fig. 2. The Fig. 2.(a) shows the original image. The Fig. 2.(b) shows the noisy image. The Fig. 2.(c) shows the denoised image. Here also the noisy image takes the value of 0.11 for H.



(a) (b) (c)

Fig.2. Simulation results for SURE shrink



(a) (b) (c)

Fig. 3.Simulation results for Bayes

The simulation results for Bayes shrink are given in the Fig.3. The Fig.3. (a) shows the original image. The Fig.3.(b) shows the noisy image (with Hurst parameter of 0.11). The Fig.3.(c) shows the denoised image.

The performances of all the three thresholding techniques are listed in the following Table. 1.

Table 1: Comparison of wavelet thresholding techniques

S.No.	Performance Metrics	VISU Shrink	SURE Shrink	BAYES Shrink
1	MSE (Mean Square Error)	0.6465e+02	0.2525e+02	0.1854e-02
2	PSNR (Peak signal to Noise ratio)	30.9852	50.2565	80.0658
3	FD(Fractal Dimension)	1.9844	1.9526	1.9965
4	IEF(Image Enhancement Factor)	1.2365	1.4424	9.000
5	SSIM (Structural Similarity Index)	1.000	0.6556	1.000
6	NK(Normalized Cross correlation)	0.6554	0.9912	0.9932
7	AD(Average Difference)	236	165	46
8	SC (Structural Content)	1.0000	1.0000	1.0000
9	MD(Maximum Difference)	251	228	254
10	NAE(Normalized Absolute Error)	0.6545	0.0563	0.0053
11	Time Elapsed when attempt to denoise	1.2604 sec	8.1924 sec	1.0801 sec

The following figures (Fig. 4 to Fig. 8) show the comparison graph for all the performance metrics for various samples of brain MRI images.

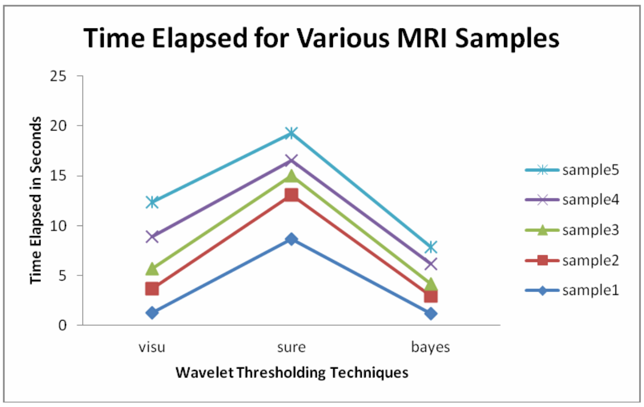


Fig.4. Chart for MSE

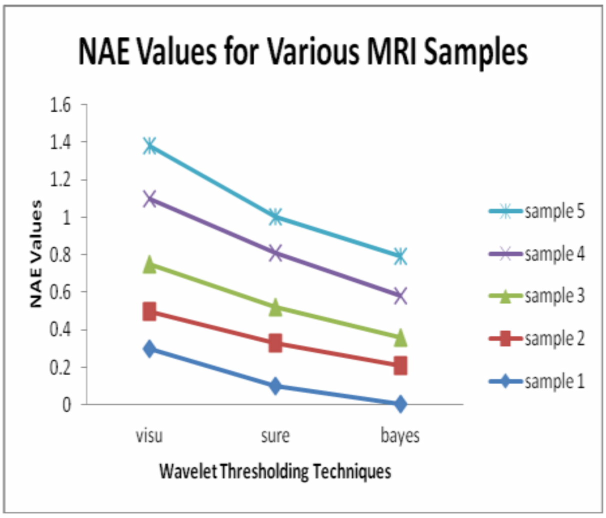


Fig.5. Chart for Normalized Absolute Error-NAE

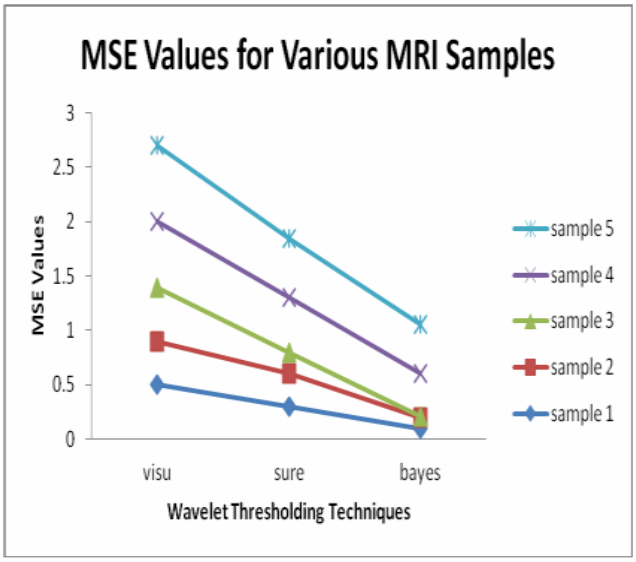


Fig.6. Chart for Cross Correlation-NK

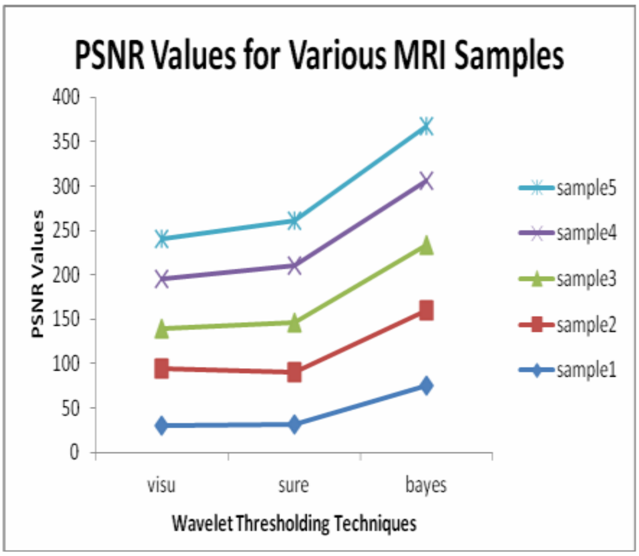


Fig.7. Chart for PSNR

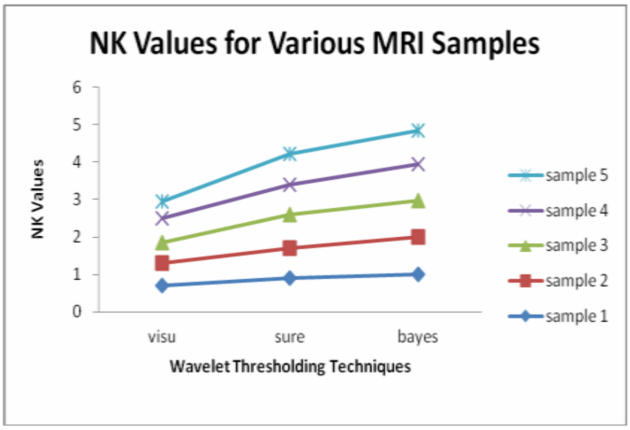


Fig.8. Chart for Time Elapsed to produce denoised image

IV. CONCLUSION

The inference from all these implementations are that Bayes shrink performs better in terms of all performance metrics. It has high PSNR ratio, lowest MSE and lower Normalized Absolute Error. In future this work may extend to analyze and implement by different filters for removing noise in MRI images. The conventional noise removal technique uses only the homomorphic filtering approach. The future scope also aims to propose a new type of filter that best suits to remove the noises and to test the performance of the filters using various evaluation metrics.

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