Fractional Brownian motion Noise Removal in Breast Cancer Magnetic Resonance Images

N.Rajeswaran, C.Gokilavani, T.Samraj Lawrence, P.Ramkumar

Abstract**:** ***In Medical Image Processing, high resolution images are very much essential to analyze the different features of the image for better diagnosis of the disease. Now days, more and more women are getting affected by breast cancer. Magnetic Resonance Imaging is the most popular technique used to diagnose the breast cancer images, whose resolution in turn is affected by the fractional Brownian motion (fBm) noise, Gaussian noise and Salt and Pepper noise. In this paper, wavelet based thresholding techniques namely Visu shrink, SURE shrink and Bayes shrink are implemented to denoise the breast cancer images affected by fBm noise.***

Index Terms: fBm noise, Medical image Processing, Magnetic Resonance Imaging, wavelet thresholding.

I. INTRODUCTION

In medical image processing, noise tends to reduce the visibility of the image and obscures the information needed for accurate treatment. Since the larger part of image processing deals with Image restoration or image denoising, denoising the 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]. Image denoising attempts to remove the various types of noises present in an image and restores the original image back while preserving the important features needed for proper diagnosis and to track the progress of the disease. However, the tradeoff between the image features and noise reduction must be taken into account while denoising. Recently fuzzy logic has been used for noise removal [3]. Medical images are taken by means of MRI (Magnetic Resonance imaging), CT (Computed Tomography) and Ultrasound imaging. Among these, MRI sounds better in giving high resolution images of the soft tissues in human body such as the brain and breasts. The images of these organs consist of several complex patterns that are independent of scales. Further, the breast cancer image is fractal in nature [4]. Hence, in this paper, the fractional Brownian motion noise is eliminated by using the wavelet based thresholding techniques namely Visu shrink, SURE shrink and Bayes shrink methods.

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II. GENERATION OF FBM NOISE

Based on the concept of bisection and interpolation [5], Ilkka Norros proposed the simulation of fractional Brownian motion with conditional random midpoint displacement algorithm [6]. This is also called as diamond square algorithm. This produces fractals in images. Here the entire trace of the fractional Brownian motion is generated before it is used for the purpose for which it is specified for. Fractional Brownian motion has been used in various fields such as hydrology, imaging landscapes and much more [7]. The properties of a normalized fBm are:

- Normalized fBm is a stochastic process(Zt) with Hurst parameter, H(0,1)
- Zt has stationary increments
- Zt is Gaussian
- Zt has continuous sample paths

A. Algorithm of fBM Noise

Ordinary Brownian motion is the special case of Normalized fBm with the parameter H=1/2. This algorithm consists of following steps,

Step 1: Take the given image.

Step 2: Assign height values to each corner of the image.

Step 3: Divide the image into four sub-images and assign height values to them such that their height is the mean values of the corners of the image taken in step 1.

Step 4: When computing the middle height, add small error value depending on the image size taken in step 1 and some constants that controls the fractal's roughness.

Step 5: Continue the iteration and sub-divide the sub-images further.

Step 6: When no noticeable difference is seen, stop the iteration and render the pixel with mean height values.

Thus the fractals are produces by the above RMD procedure and are shown below.

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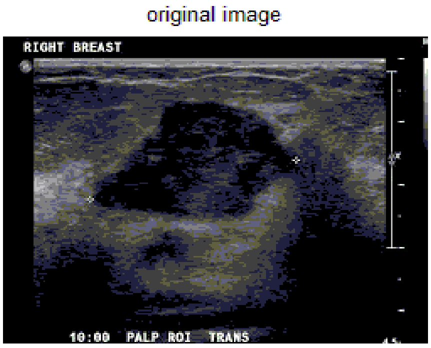

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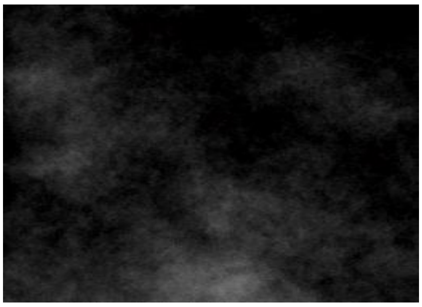

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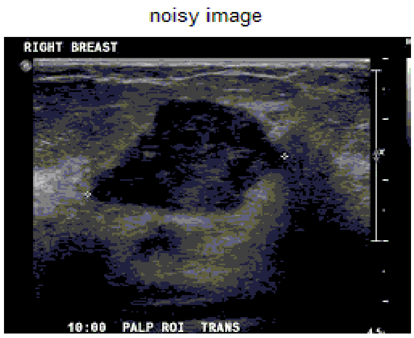

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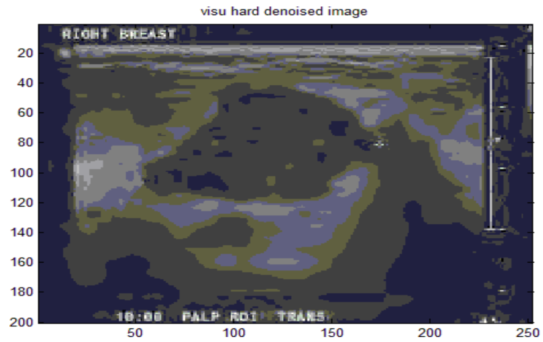
Fig.1(a),(b),(c). Simulation results of fractional Brownian motion noise

Fig.1 shows the MATLAB simulation results for the generation of fractional Brownian motion noise for an Breast cancer image of size 512x512. Fig.1 (a) shows the original Breast cancer image. Fig.1 (b) shows the pattern of fractional Brownian motion. Fig.1 (c) shows the Breast cancer image corrupted with fBm noise.

III. RESULTS AND DISCUSSIONS

The wavelet based thresholding techniques are implemented by using MATLAB and the simulation results for Visu shrink are given in the Fig. 2. The Fig. 2.(a) shows the original image, Fig. 2.(b) shows the noisy image and the Fig. 2.(c) shows the denoised image. Here in the noisy image, the value of the Hurst parameter is 0.3 (for a classical Brownian motion, the Hurst parameter h=0.5).



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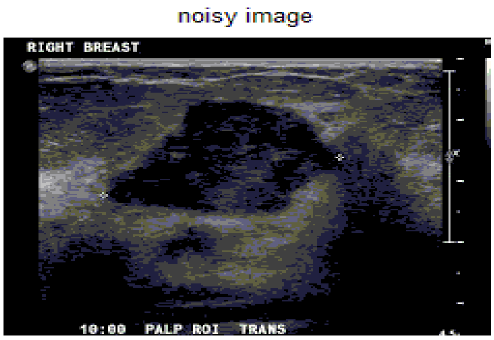

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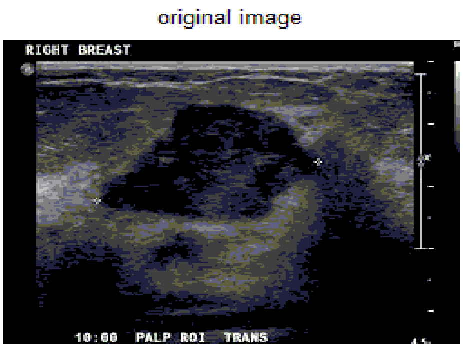

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Fig. 2(a),(b), (c). Simulation results for Visu shrink

The simulations results for SURE shrink are given in the Fig. 3. The Fig. 3.(a) shows the original image, Fig. 3.(b) shows the noisy image and Fig. 3.(c) shows the denoised image. Here also the noisy image takes the value of 0.3 for H.

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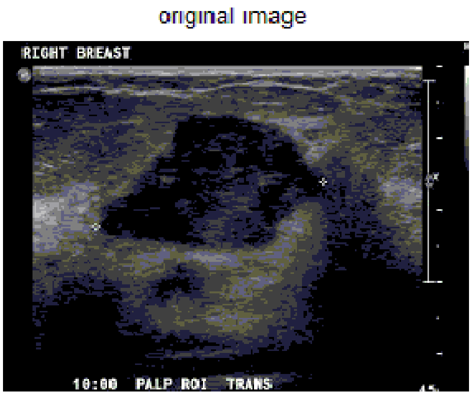

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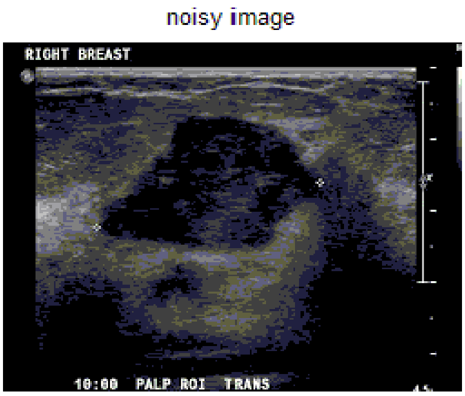

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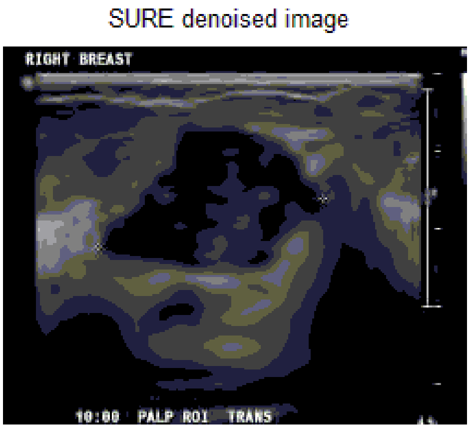

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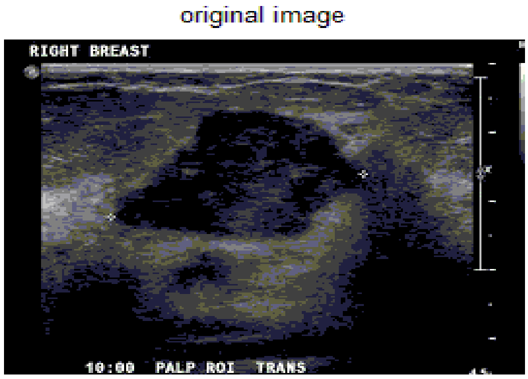
Fig 3.(a),(b) and (c). Simulation results for SURE shrink

The simulation results for Bayes shrink are given in the Figure. 4. The Fig.4. (a) shows the original image, Fig. 4.(b) shows the noisy image (with Hurst parameter of 0.3) and Fig.4.(c) shows the denoised image.



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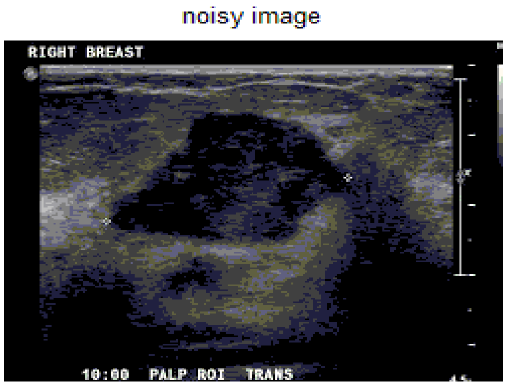

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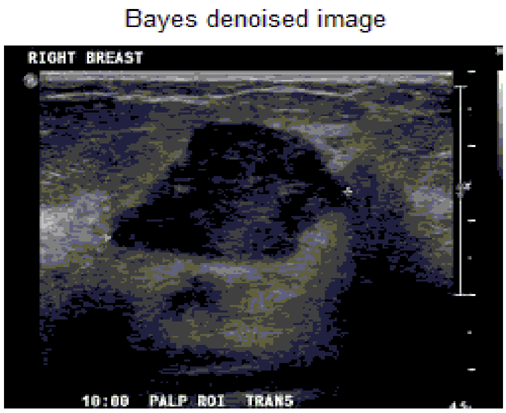

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Fig 4.(a)(b) and (c). Simulation results for Bayes shrink

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

Table 1: Comparison of wavelet thresholding techniques

S.NO	PERFORMANCE METRICS	VISU SHRINK	SURE SHRINK	BAYES SHRINK
1	MSE (Mean Square Error)	865.45	665.45	2.1544
2	PSNR (Peak signal to Noise ratio)	56.9841	76.5454	78.5645
3	FD(Fractal Dimension)	1.9645	1.9751	1.9884
4	IEF(Image Enhancement Factor)	0.6844	0.7554	0.9987
5	SSIM (Structural Similarity Index)	0.7454	0.7865	1.000
6	NK(Normalized Cross Correlation)	0.8502	0.9265	0.9965
7	AD(Average Difference)	210	165	154
8	SC (Structural Content)	0.9265	0.9756	1.000
9	MD(Maximum Difference)	214	155	221
10	NAE(Normalized Absolute Error)	0.8652	0.0218	0.0010
11	Time Elapsed when attempt to denoise	5.6545sec	4.6954sec	1.4545sec

From the above table, it is evident that the Bayes shrink method is performing more efficiently in denoising the images and thereby improving the resolution of the MRI images (Shown in Figures from 5 to 9). It has high Peak Signal to Noise Ratio, lowest Mean Square Error and lower Normalized Absolute Error.

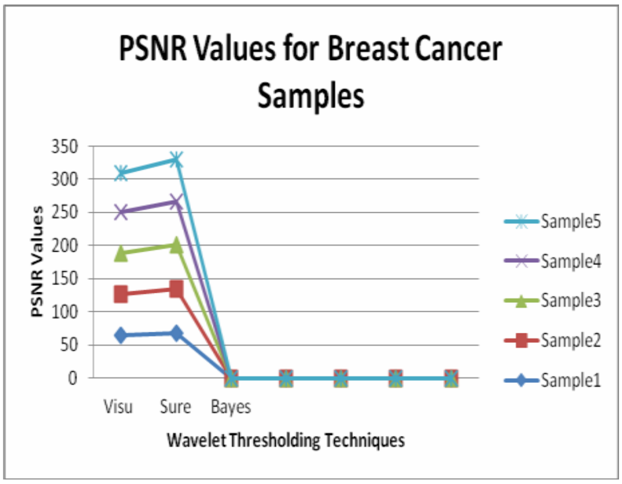

Fig 5. Chart for Peak Signal to Noise Ratio-PSNR

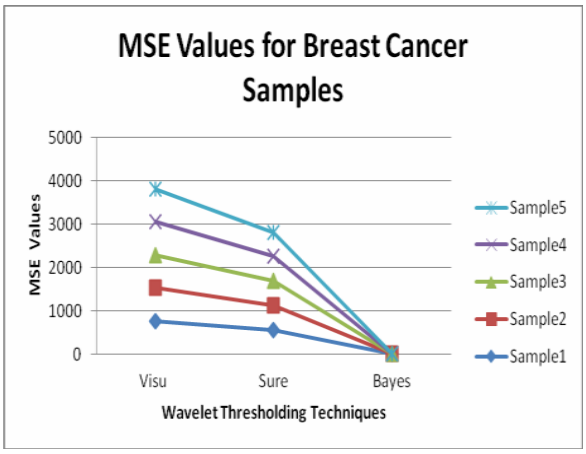

Fig 6. Chart for Mean Square Error-MSE

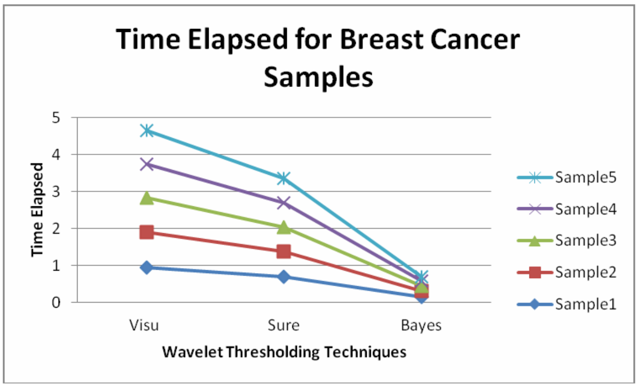

Fig 7. Chart For Normalized Absolute Error

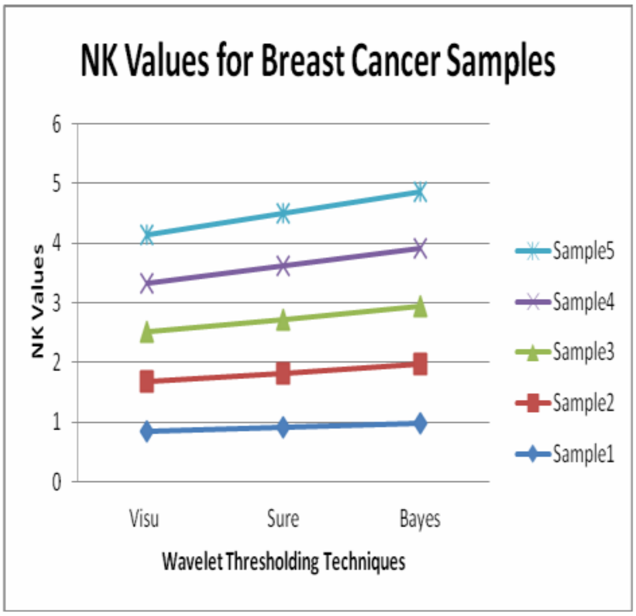

Fig 8. Chart for Normalized Absolute Error-NAE

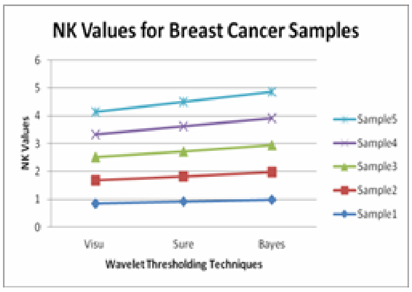

Fig 9. Chart for Normalized Cross Correlation-NK

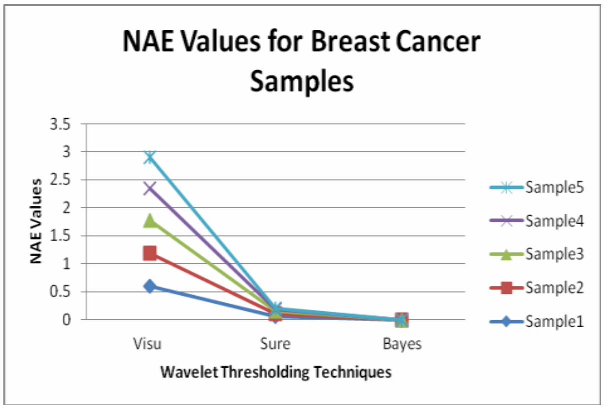

Fig 10. Chart for Time Elapsed to produce denoised image

IV. CONCLUSION

In this paper, wavelet based thresholding techniques namely Visu shrink, SURE shrink and Bayes shrink are implemented to denoise the breast cancer images affected by fBm noise. The inference from all these implementations are that Bayes shrink performs better in terms of all performance metrics. The future scope of this work includes analyzing and implementing various filters for removing all forms of noise.

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