A Sub-band Anisotropic Diffusion Technique for de-speckling of Ultrasound Images of Breast Cancer

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Abstract

Ultrasound imaging technique finds crucial application in clinical diagnosis of breast cancer. Presence of noise in ultrasound image due to different factor degrades the image quality and so the accuracy of diagnosis. Wavelet thresholding have been used from very beginning for de-noising of ultrasound image. Here in this paper, we propose an intervention of anisotropic diffusion techniques in wavelet thresholding. In wavelet thresholding the thresholding operation usually applied after various feature extraction step, but in this study, we proposed to use a combinational approach. The approach reduces computational complexity of previous techniques. The proposed technique provides a Peak Signal to Noise Ratio of 28.46 and Mean Square Error of about 92.5537. The technique was practiced over large dataset of breast cancer images.

Keywords: *Breast Cancer, Ultrasound Image, Wavelet thresholding, and Anisotropic Diffusion*

1 Introduction

One of the most common and deadly categories of cancer found in women is breast cancer [1]. The treatment of breast cancer totally depends upon the stage at which it is diagnosed. The tumor increases with stare and time so do the risk of its treatment [2], [3]. Ultrasound wave has been proved to be one of the most efficient tool for diagnosis of cancer. The technique involving ultrasound imaging is completely non-invasive and due to absence of any type of radiation it is safe. Its low-cost ability and harmless nature, frequent clinical diagnosis is possible. Even after having such great advantages the interference of noise is a huge disadvantage for clinical practice.

Convolving a mask of unique size and pattern with the image is elemental process for all filtering technique, but the name depends upon the purpose served by the mask. A filter is called linear if the mask performs a linear operation otherwise categorised as non-linear filter. Both type of filters has been used from very beginning for de-noising of image. Linear filters like Mean filter, Adaptive Mean [4] filter while Median filter [5] a non-linear filter, all are the most encountered filter in various studies. The Mean filter which involves averaging operation always yields in blurred image. Similarly, Median filter have some information loss associated with it. More spatial filters like Lee filter [6], Kuan filter [7] and Wiener filter [8] developed for de-noising of images. The most elemental dilemma of using spatial filter is the choice of filter size and most of them suffers from blurred output image.

Other than spatial filtering a different technique was introduced by David L. Donoho [9]–[11] which involves homomorphic transformation and wavelet decomposition of Input image. The coefficients of decomposed image are adjusted after comparing with an extracted threshold value [12]–[18]. The efficacy of this technique is based on the observation that small valued coefficients are noise component. One major drawback of the thresholding is that it nullifies every coefficient of detail sub-band lower than the threshold

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which may stand for some useful information. G. Andria *et. al.* [12]To overcome this demerit Anisotropic diffusion another best in class method coined by P. Perona and J. Malik [19]. The technique adapts directional smoothing approach using a differential equation. The technique not only remove speckle but also enhance the edge and boundaries.

Here in this study, we used a combination of wavelet decomposition and anisotropic diffusion. The Speckle Reduction Anisotropic Diffusion (SRAD) process is applied over the sub-bands of the noisy image. The proposed method is multi-scale because of the wavelet decomposition. Moreover, it does not involve any thresholding of coefficients so it does not end with loss in information. The computation of threshold value and noise variance estimation is no longer needed so more efficient compuationally. The smoothing is anisotropic so it also enhances the image boundaries or edges.

2 Methodology

The flow diagram of the complete methodology is provided in Fig 1. Since the speckle is a multiplicative noise which means for any image OI which is free of noise and NI be the noisy image with speckle noise NO, a simple mathematical relation can be expressed as per (1).

$$NI = NO * OI \qquad (1)$$

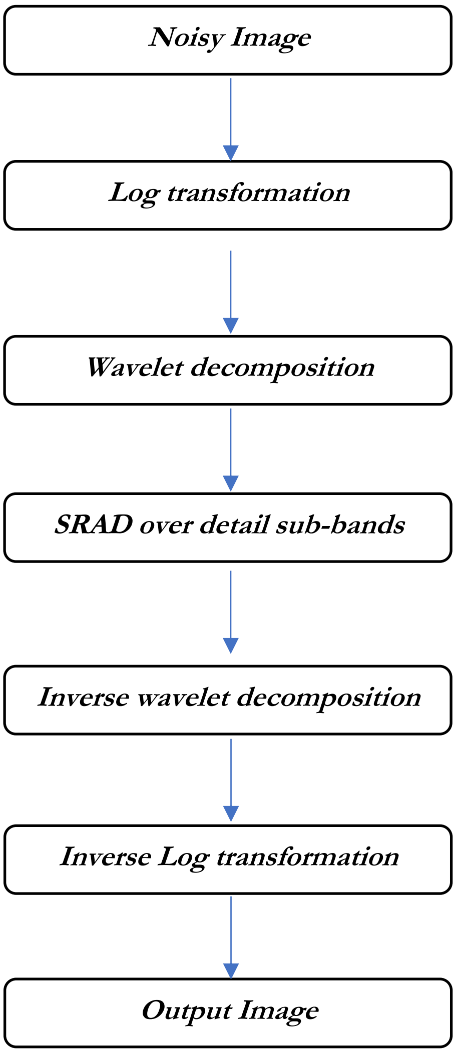

Fig 1. Flow diagram of proposed methodology

A logarithmic transformation is applied to the image to convert the multiplicative noise into additive noise. After this homomorphic transformation the image is decomposed with wavelet decomposition. The wavelet transformation decomposes the image into four parts (Fig 2.) namely A, H, V, and D. A is known as approximation sub-band and the rest of them are known as details sub-band. According to wavelet shrinkage theory the approximation sub-band holds most of the important information of the image, and the detailed sub-band which are low coefficients sub-band are said to be the one with most of the noise. So, we will apply SRAD only over the detailed sub-band.

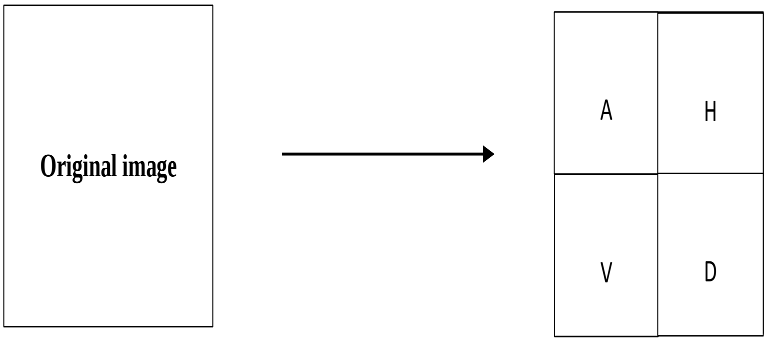

Fig 2. Decomposition of an image into four sub-bands (A, H, V, and D) after wavelet transformation

3 Results and Discussion

The complete process was tested for breast cancer images [20] and the Lena and Barbra images. MATLAB platform was used for the coding of the whole methodology. To observe the efficacy of the study noise were added to the images intentionally and then applied the algorithm. The output image was compared with the original image for the calculation of Mean Square Error as given in (2). The MSE tells us about the recovery of the image, higher value of MSE means very low grade recovery, and very small or negligible MSE means good recovery.

$$MSE = \sum (OI(x,y) - RI(x,y))^2 \qquad (2)$$

Here RI is the resultant image from the technique. Another parameter Peak Signal to Noise Ratio (PSNR) explored for verification of performance of the recovery procedure [21]. For L being the largest value of any pixel of the image, PSNR can be calculated as in (3).

$$PSNR = 10 \times log_{10}(\frac{L^2}{MSE}) \qquad (3)$$

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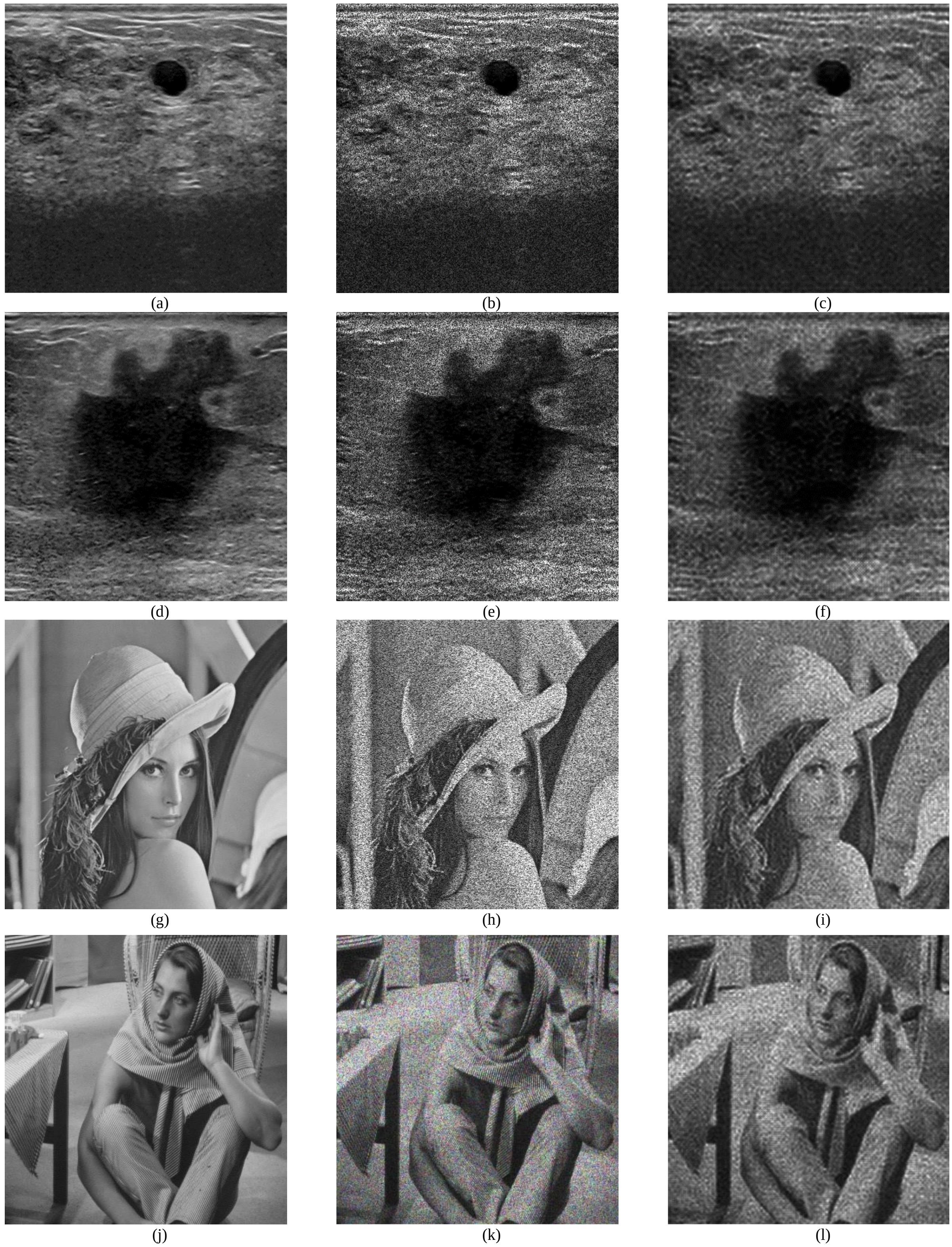

Fig 3. The (a), (d), (g), and (j) contains the original breast cancer image, Lean image, and Barbara image, while (b), (e), (h), and (k) has respective noisy version and the (c), (f), (i), and (l) contains the de-noised version.

Table 1 Performance parameters PSNR and MSE at three different noise variances.

IMAGES	BREAST			LENA			BARBARA		
NOISE VARAINCE	0.01	0.10	0.20	0.01	0.10	0.20	0.01	0.10	0.20
PSNR	28.4669	26.4727	23.9676	29.2371	24.2497	20.3660	23.5433	21.8219	19.5415
MSE	92.5537	146.4918	260.8081	77.5114	244.4050	597.7024	287.5772	427.4541	722.6518

Table 1 in the paper tabulates that the PSNR and MSE of the output image. The table presents the performance of the proposed method when applied on the breast cancer, Lena and Barbara images. Noise of three different variance (0.01, 0.10, and 0.20) was added to the image and the PSNR and MSE were noted in the table. It's clear from the table that the PSNR decreases with noise variance and the MSE increases, so it can be said that the performance degrades with increase in variance.

Fig 3 shows the recovery of the original image after the application of proposed methodology. The First column of the figure contains the original image which were next contaminated by speckle noise, and can be seen as in second column of Fig 3, the third column contains the output of the presented algorithm. It can easily be noticed that the speckle is reduced in the output image as well as the boundaries and the edges are also preserved in the output image. This can be seen all of the four images. The complete processing took 1.0625 second when implemented over MATLAB [22].

4 Conclusion

In this literature we build a unique architecture for the de-speckling of breast ultrasound image. The results support the ability of our technique for de-speckling application. The PSNR value for low variance noise is 28.4669and the MSE as low as 92.5534. The computational complexity of the proposed method is minimal which just take 1.06 second to process the image. Moreover, the thresholding step is omitted which requires estimation of noise variance and calculation of threshold values. As observed from Fig 3 the visual output is not so good when applied for non-medical images like Lena and Barbara. The efficacy of proposed technique can be improved with few advancements. With major improvements its application can further extend to high variance noise removal.

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