ENHANCEMENT METHOD FOR MULTISCALE IMAGE RESTORATION IN ULTRASOUND MEDICAL IMAGING

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ABSTRACT : *In diagnosis of diseases Ultrasonic devices are frequently used by healthcare professionals. The main problem during diagnosis is the distortion of visual signals obtained which is due to the consequence of the coherent of nature of the wave transmitted. These distortions are termed as 'Speckle Noise'. The present study focuses on proposing a technique to reduce speckle noise from ultrasonic devices. This technique uses a SRAD filter with wavelet based BayesShrink technique. The proposed filter is compared with traditional filters and existing filters using anisotropic diffusion. Experimental results prove that the proposed method is efficient in reaching convergence quickly and producing quality de-noised images.*

Keywords — Anisotropic Diffusion, Bayesshrink, Speckle De-Noising, SRAD Filter, Wavelet Based.

I. INTRODUCTION

Medical digital images have become an essential part in the healthcare industry for diagnosis of diseases. These images are produced by various medical imaging devices like x-ray, CT / MRI scanners and electron microscope all of which produce high resolution images. Medical images are usually corrupted by Noise during their acquisition and transmission, and noisy images often lead to incorrect diagnosis. The main objective of Image De-noising techniques is to remove such noises while retaining as much as possible the important signal features. Ultrasonic imaging is a widely used medical-imaging procedure because it is economical, comparatively safe, transferable and adaptable [1].

One of the major problems of ultrasound images is that they suffer from a special kind of noise called 'speckle'. Speckle is a complex phenomenon and it significantly degrades image quality. Speckle appears interference of back-scattered wave from many microscopic diffused reflection which passing through internal organs and makes it more difficult for the observer to discriminate fine detail of the images in diagnostic examinations.

This paper is an effort made to produce a speckle noise removal using various filtering technique. This paper is organized as below. The second section gives an overview to the noise under discussion, while Section 3 discusses the wavelet based denoising uses for ultrasound. Section 4 presents results of experimented images and comparison of parameters.

II. SPECKLE NOISE

The most critical part of developing a method for - recovering a signal from its noisy environment seems to be choosing a reasonable statistical (or analytic) description of the physical phenomena underlying the data-formation process. The availability of an accurate and reliable model of speckle noise formation is a prerequisite for development of a valuable de-speckling algorithm. In ultrasound imaging, however, the unified definition of such a model still remains arguable. Yet, there exist a number of possible formulae whose probability was verified via their practical use. A possi.ble generalized model of the speckle imaging is

$$g(n, m) = f(n, m)u(n, m) + \xi(n, m) \quad (1)$$

Where g, f, u and ξ stand for the observed image, original image, multiplicative component and additive component of the speckle noise basically. Here (n, m) denotes the axial and lateral indices of the image samples or, alternatively, the angular and range indices for images. When applied to ultrasound images, only the multiplicative component of the noise is to be considered; and thus, the model can be considerably simplified by disregarding the additive term, so that the simplified version of (1) becomes g(n, m) = f(n, m)u(n, m) (2)

Speckle has a negative impact on ultrasound imaging. Presence of speckle noise prevents Automatic Target Recognition (ATR) and texture analysis algorithm to perform efficiently and gives the image a grainy appearance. Several adaptive filters have been implemented for speckle noise removal and some examples include Lee filter, Frost filter, Kaun Filter and SRAD Filter. most of these proposed local adaptive speckle filters are able to reduce speckle while preserving the data. However, all these uses a lossy approach, as all these filters rely on local statistical data related to the filtered pixel. This data depends on the occurrence of the filter window over an area. The achievement of both speckle reduction and preservation of edge data is only possible when the filter window is uniform. If the filter window happens to cover an edge, the value of the filtered pixel will be replaced by the statistical data from both sides of the edge that is from two different intensity distributions. An alternative approach is to use wavelet transform Page Layout

III. WAVELET BASED THRESHOLDING

we show several adaptive filters for speckle noise removal and some examples include Lee filter [09], Frost filter [13], Kaun Filter [12] and SRAD [15] Filter. Most of these proposed local adaptive speckle filters are able to reduce speckle while preserving the data. However, all these uses a lossy approach, as all these filters rely on local statistical data related to the filtered pixel. This data depends on the occurrence of the filter window over an area. The achievement of both speckle reduction and preservation of edge data is only possible when the filter window is uniform. If the filter window happens to cover an edge, the value of the filtered pixel will be replaced by the statistical data from both sides of the edge that is from two different intensity distributions.

Wavelet filtering exploits the decomposition of the image into the wavelet basis and zeroes out the wavelet coefficients to de-speckle the image. Wavelet analysis is particularly useful for the analysis of transient, non stationary or time-varying signals. Wavelets can be used to analyse signals in different spatial resolutions. Their advantage is in their ability to analyse a signal with accuracy in both the time and frequency domains. This is not the case when applying traditional Fourier analysis, where there is significant accuracy in the frequency domain, but less accuracy in the temporal domain. In other words, increasing accuracy in one domain implies a decrease in precision in the other domain. Wavelets are also known for their capacity to identify singularities associated with fine variations of the signal to be evaluated [08]. For denoising, we need to identify the specific image scales where most of the image energy lies ([07],[08]).

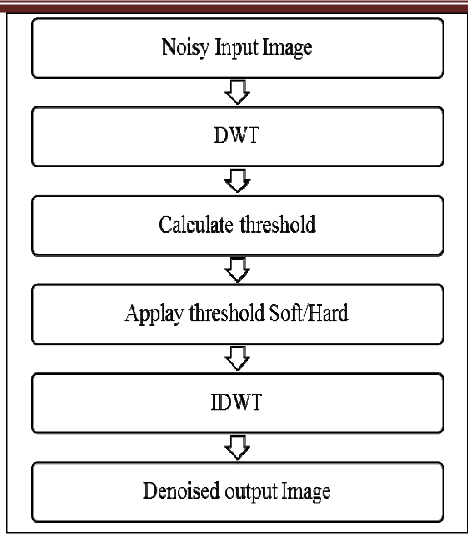


Fig.1 Flow of Wavelet based De-noising Process

The Figure.1 shows wavelet based denoising method for speckle reduction implemented in this study is described as follows.

Compute the discrete wavelet transform (DWT).

For each sub band: Compute a threshold. Apply the threshold on the wavelet coefficients of each band.

Compute the inverse DWT to reconstruct the despeckled image.

IV. SPECKLE-REDUCING ANISOTROPIC DIFFUSION (SRAD) FILTERING

The essence of speckle-reducing anisotropic diffusion is the replacement of the gradient-based edge detector cd(|∇gl) in an original anisotropic diffusion PDE with the instantaneous coefficient of variation that is suitable for speckle filtering csrad(|∇gl) The speckle-reducing anisotropic diffusion filter uses two seemingly different methods, namely, the Lee [09] and Frost diffusion filters [13]. A more general updated function for the output image by extending the PDE versions of the despeckle filter is [15].

$$f_{i,j} = g_{i,j} + \frac{1}{n_s}\left(C_{srad}\left|\nabla_g\right| \nabla_{g_{i,j}}\right) \quad (3)$$

The diffusion coefficient for the speckle anisotropic diffusion csrad(|∇gl) is derived [15] as

$$C^2_{srad}\left(\left|\nabla_g\right|\right) = \frac{\frac{1}{2}\left|\nabla g_{i,j}\right|^2 + \frac{1}{16}\left(\nabla^2 g_{i,j}\right)^2}{\left[\nabla_{i,j} + \frac{1}{4}\nabla^2 g_{i,j}\right]^2} \quad (4)$$

It is required that csrad(|∇gl) > 0. The above instantaneous coefficient of variation combines a normalized gradient magnitude operator and a normalized Laplacian operator to act like an edge detector for speckle images. A high relative gradient magnitude and a low relative Laplacian indicate an edge. The filter utilizes speckle-reducing anisotropic diffusion after Eq. (3) with the diffusion coefficient csrad(|∇gl) in Eq. (4).

V. PERFORMANCE PARAMETER & SOFTWARE

The selection of the denoising technique is application dependent and therefore, it is necessary to learn and compare denoising techniques to select the technique that is application for the application of interest. Here I took one Liver Ultrasound.tif image for experiments and apply some special noise then it applied for the denoising techniques based three different shrinking techniques (VisuShrink, SureShrink and BayesShrink) in MATLAB 7.8.0(2009) . The models proposed are given in Table 1.

For the evaluation we calculate the MSE, SNR, COC and PSNR.PSNR is a quality measurement between the original and a denoised image. The higher the PSNR, the better is the quality of the compressed or reconstructed image. To compute PSNR, the block first calculates the Mean Squared Error (MSE) and then the PSNR.

1) Mean Squared Error (MSE)

The MSE calculates the difference between the original image and filtered image. MSE can be represented in mathematically by

$$MSE = \frac{\sum_{MN}[I_1(m,n) - I_2(m,n)]^2}{M * N}$$

(5)

Here M and N, m and n are number of rows and columns in the input and output image respectively.

2) Signal To Noise Ratio (SNR)

The signal to noise ratio measure the noise per image. It can be represented by

$$SNR = \frac{\sum_{M,N}\left[I_1^2(m,n) - I_2^2(m,n)\right]^2}{\sum_{M,N}\left[I_1(m,n) - I_2(m,n)\right]^2} \quad (6)$$

It measures the signal to noise ratio between the original and processed images in an *M X N* window.

3) Peak Signal to Noise Ratio (PSNR)

The PSNR is a quality measurement between the original and a denoised image. The higher the PSNR, the better is the quality of the compressed or reconstructed image.

$$PSNR = 10\log_{10}\left[\frac{R^2}{MSE}\right]$$

(7)

R is the maximum possible pixel value of the image. When the pixels are represented using 8 bits per sample, this is 255.

Correlation indicates the strength and direction of linear relationship between two signals.

4) Correlation coefficient (COC):

Correlation indicates the strength and direction of linear relationship between two signals.

$$COC = \frac{\sum_{M,N}(I_1(m,n) - \bar{I_1})(I_2(m,n) - \bar{I_2})}{\sqrt{\sum_{M,N}(I_1(m,n) - \bar{I_1})}\sqrt{\sum_{M,N}(I_2(m,n) - \bar{I_2})}}$$

(8)

Where I1, I2 is the image to find correlation, Ī1=mean of I1 and Ī2=mean of I2.

Value of COC lie between +1 to -1.

"0" indicates no linear relationship.

"+1" indicates a perfect positive linear relationship.

"-1" indicates a perfect negative linear relationship.

for all the other cases, including the degree of linear dependence between the two signals. The closer the coefficient is to either -1 or +1, the stronger the correlation between the signals.

VI. METHODOLOGY

Many methods have been developed to reach the our objectives, The speckle noise reduction techniques use traditional filters like lee, kuan, frost, median, and wavelet filters.

Anisotropic diffusion filter is another denoising technique which is equally gaining popularity. Anisotropic diffusion was initially introduced by and has been improved by several manners. Problems faced by the initial Anisotropic diffusion filter and its variants are;

They cause blocky effects in images

They destroy structural and spatial neighborhood information and

They are slow in reaching a convergence stage.

The Rajan Hybrid Model (RHM) improved this method by using a combination of anisotropic diffusion and a relaxed median filter to remove the noise. The RHM was successful in removing the noise and had less blocking effects. The drawback still faced is the slow convergence to remove the noise. The reason behind this is that the convergence time for denoising is directionally proportional to the image noise level. In the case of anisotropic diffusion, as iteration continues, the noise level in image decreases (till it reaches the convergence point), but in a slow manner. But in the case of Bayesian shrinkage, it just cut the frequencies above the threshold in a single step. Decrease in convergence time has a direct impact on image quality. This model of using BayesShrink with Anisotropic filter was proposed and they named their denoising model as WEAD. Even though this work reduced the blocking artifacts and fast convergence, improvements are still needed. Here we proposes a novel method that improves the RHM and WEAD model, In this study, the PDE used by Speckle Reducing Anisotropic Diffusion (SRAD) is fed to BayesShrink technique to obtain a denoised image.

VII. PROPOSED ALGORITHM DEVELOPMENT

The block diagram of proposed modal is shown in figure 2.

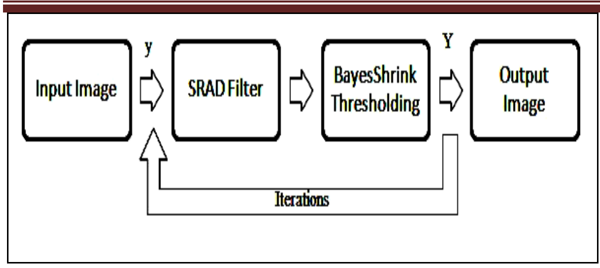


Fig.2 Block diagram of the proposed de-noising Algorithm.

In the proposed model the Bayesian Shrinkage of the non-linearly diffused signal is taken. The equation can be written as

$$I_n = B_s\,(I'_{n-1}) \qquad (9)$$

Where Bs is the Bayesian shrink and In-1 is Speckle Reduction Anisotropic diffusion at (n-1)th time. Numerically can be written as

$$I_n = B_s\,(I_{n-1} + \Delta td_n) \qquad (10)$$

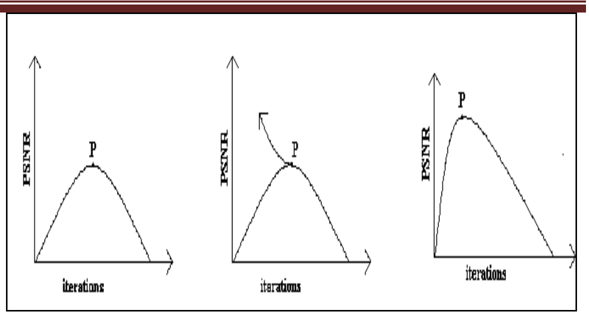
Where Bs can be calculated by finding Tb as mentioned in e after taking wavelet transform of In-1

The intention to develop this method is to decrease the convergence time of the SRAD filter. It is understood that the convergence time for denoising is directionally proportional to the image noise level. In the case of SRAD filter, as iteration continues, the noise level in image decreases (till it reaches the convergence point), but in a slow manner. But in the case of Bayesian shrinkage, it just cut the frequencies above the threshold and that in a single step. An iterative Bayesian Shrinkage will not incur any change in the detail coefficients from the first one. Now consider the proposed algorithm, here the threshold for Bayesian shrinkage is recalculated each time after SRAD filter, and as a result of two successive noise reduction step, it approaches the convergence point much faster than SRAD filter.

The block diagram of proposed modal is shown in figure 3. the iteration process continues till the input signal y is converted to Y.

The iteration process will continue till the input signal y is converged to Y. As the convergence time decreases, image blurring can be restricted and as a result image quality increases. The whole process is illustrated in Figure 2.

Figure 3(a) shows the convergence of the image processed by SRAD filter. The convergence point is at P. Suppose at P we will get the better image, with the assumption that the input image is a noisy one. If this convergence point P can be shifted towards y-axis, its movement will be as shown in Figure 3 (b). Now if we pull the point P towards y-axis, it will move in a left-top fashion. Here the Bayesian shrinkage is the catalyst, which pulls the convergence point P of the SRAD towards a better place.



(A) (B) (C)

Figure 3. Working of Proposed modal

In figure 3 (a) shows the convergence of a noisy image (convergence at P). If this P can be shifted towards left, image quality can be increased and time complexity can be reduced. Illustrated in (b). (c) Shows the signal processed by Proposed modal. It can be seen that the convergence point is shifted to left and moved upwards.

VIII. ULTRASOUND OF FOCAL HEPATIC LESIONS

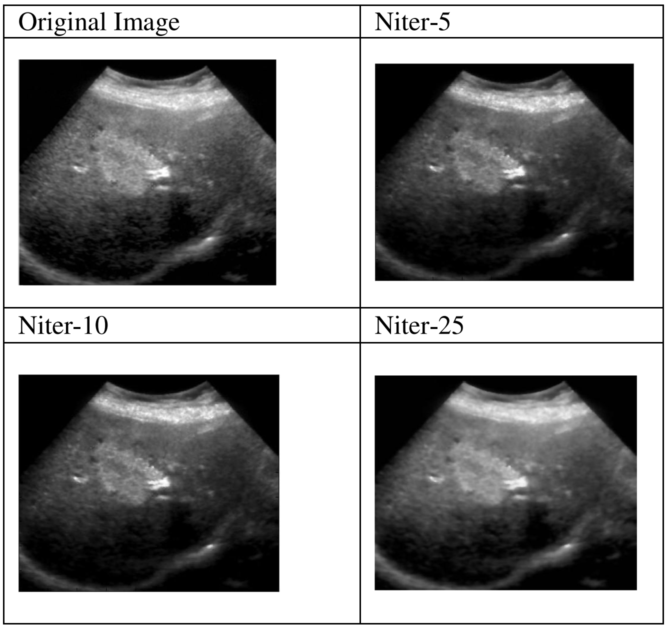


Fig.4 Proposed Method Outputs of Focal Hepatic Lesions

Results of Prostate Focal Hepatic Lesions

Table.1 Performance Parameter Of Focal Hepatic Lesions

Niter	MSE	SNR	PSNR	COC
Niter-4	18.90	78.60	35.33	0.9971
Niter-10	12.56	80.38	37.10	0.9981
Niter-25	22.76	77.96	34.52	0.9965

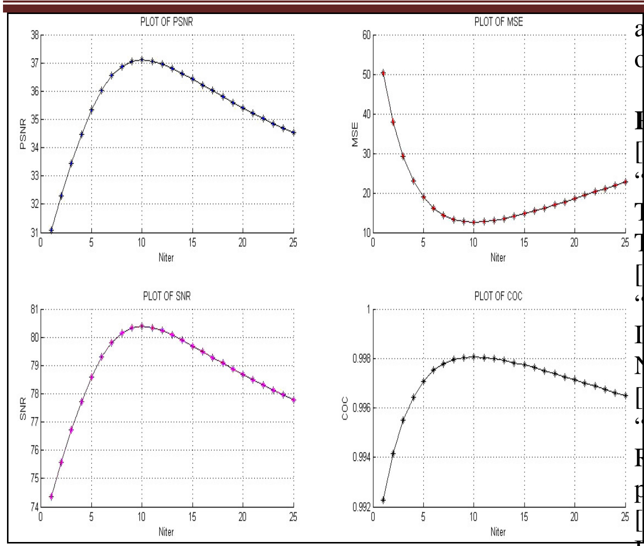


Fig.5 Results of PSNR, MSE, SNR, and COC of Focal Hepatic Lesions

IX. CONCLUSIONS

In this paper for restoration of medical ultrasound imaging from the experimental and mathematical results on different techniques for restoration of medical ultrasound images it can be concluded that partial domain filtering methods such as mean filter, median filter, lee filter and frost filter remove noise but important diagnostic details are lost. Wavelet based bayesshrink thresholding perform better then visushrink thresholding and sureshrink thresholding. Wavelet based threshold shrink techniques gives better results but they fail to perform well near edges. PDE based srad filter gives better denoising and with edge prevention but it require more iteration to reach convergence.

The proposed algorithm produces images which are cleaner and smoother and at the same time kept significant details, resulting in a clearer an appealing vision. Moreover, the proposed method is fast at reaching the convergence, which has a direct impact on noise reduction and preserve image edges. Experimental results on quality parameters PSNR, SNR, MSE and COC prove that proposed method perform better form all other methods for remove speckle.

X. FUTURE SCOPES

Ultrasound imaging is a widely used by healthcare professionals because of safe, noninvasive nature, low cost. For correct diagnose of diesis it is important that the ultrasound images are clear and more informative.

Proposed algorithm gives grates results for ultrasound imaging this proposed method can be used for the pre-process of image segmentation, image enhancement and other image processing. It improves the performance of post-process of medical image processing. By the use of proposed algorithm with other image processing method we can easily find lessens, characterize tissues, size and type of abnormality in ultrasound images with great quality of information.

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