Hybrid Methodology for Speckle Noise Reduction in Medical Ultrasound Images with Coherence Enhancement

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Abstract- **Ultrasound imaging is associate degree incontestable important tool for designation, it provides in non-invasive manner the inner structure of the body to observe eventually diseases or abnormalities tissues. sadly, the presence of speckle noise in these images affects edges and fine details that limit the distinction resolution and create diagnostic harder. During this paper, we have a tendency to propose a denoising approach which mixes exponent transformation and a nonnative suggests that filter. and also the non-local mean (NLM) filter is used to filter extra noise by applying the redundancy info in wheezy images. A hybrid denoising methodology is planned in thought of the characteristics of each the native statistics of speckle noise and also the NLM filter. Since speckle noise is increasing and nonwhite method, the exponent transformation may be a cheap option to convert signal dependent or pure increasing noise to associate degree additive one. The key plan from mistreatment diffusion tensor is to adapt the flow diffusion towards the native orientation by applying eolotropic diffusion on the coherent structure direction of attention-grabbing options within the image. For example the effective performance of our rule, we have a tendency to gift some experimental results on synthetically and real ultrasound images**

Index terms- **Ultrasound image, Denoising, Speckle noise, Non-local means**

I.INTRODUCTION

Ultrasound has been used to image the human body for over 60 years and is among the most widely used imaging technologies in medicine. Ultrasound is advantageous over existent non-invasive imaging techniques, such as CT, MRI, and PET, in that it is portable, inexpensive, free of radiation risk, and acquires images in real time. This imaging technology is widely used to visualize internal body structures, including tendons, muscles, joints, vessels, and internal organs for potential pathology or lesions. Ultrasound is also widely used to examine pregnant women.

An inherent characteristic of ultrasound imaging is the presence of speckle noise. Speckle is a random deterministic interference pattern that degrades the edges and fine details in an image. This phenomenon complicates the detection of small and low-contrast lesions. It also reduces the accuracy of ultrasound image-processing tasks such as feature extraction, segmentation, registration, and classification. To obtain reliable analysis and diagonal results, speckle reduction is a necessary preprocessing step in ultrasound image processing. Moreover, as the denoising technique can remove the speckle noise that may interfere the similarity measurement determination, it is also benefited for the 3D reconstruction procedures for accurately recovering the ultrasound volume data. Therefore, the main objective of the current study is to remove speckle noise on ultrasound images.

Speckle noise can be removed by compounding, post-processing, or both. The compounding method minimizes noises when images are acquired using many transducers. Similar regions of images acquired by each transducer are combined to form a final image with improved quality. The post-processing method mainly includes the following two classes: (i) a spatial domain that is applied directly to the original image and (ii) a transform domain that is initially transformed into the frequency domain by fast Fourier transformation and is followed by denoising in the frequency domain. Many methods have recently been developed to eliminate speckle noise from medical ultrasound images in the spatial domain. These methods usually assume that this

noise is modeled as multiplicative. Therefore, specific filters must be designed to reduce it. The most commonly used filters include the median, Lee , Frost, and Kuan filters. These filters are based on the multiplicative speckle model and on local statistics .
The median filter is a nonlinear filter that effectively removes impulsive noise. It also reduces speckle. This filter applies median intensity in a selected region as the output pixel value of the center position of the region. Lee filters are based on minimum mean-square error (MMSE). The smoothing degree of Lee filter is inversely proportional to the variance over a local region. If the variance is high, usually near the edge, then the smoothing process is not performed. Otherwise, smoothing is conducted. Frost filter is an adaptive and exponentially weighted averaging filter. The weights are computed based on the ratio of the local standard deviation to the local mean of the degraded image. The pixel of interest is replaced by a weighted averaging value within the moving window. The weighting factors decrease with distance from the pixel of interest and increase when the variance within the window increases. Once the transformation of the multiplicative noise model into a signal-dependent additive noise model is combined with the minimum square error criterion, Kuan filter can generate the linear MMSE for an image that is corrupted with uncorrelated, image-dependent noise. The form of Kuan filter is similar to that of Lee filter, but it uses a different weighting value. Based on the Lee and Frost filters, an adaptive speckle reduction filter is designed by classifying the pixels [14]. Although these methods reduce speckle noise effectively, they also erase weak and diffused edges.
To preserve edges in images, the anisotropic diffusion (AD) filter is applied to suppress speckle noise. This filter is effective for images corrupted by additive noise. The nonlinear coherent diffusion filter log-transforms multiplicative speckle noises in ultrasonic images into additive Gaussian noises. The speckle reducing AD (SRAD) filter processes images directly to preserve useful information. This filter is based on a partial differential equation and on the MMSE, which can be related directly to Lee and Frost filters. The oriented SRAD filter improves on the denoising results of the SRAD filter using the local directional variance of image intensity. These methods are iterative and can preserve the edges in images while reducing noise. However, many fine structures are removed during iterations. The squeeze box filter (SBF) was developed to enhance the contrast in B-mode ultrasound images with respect to decreasing pixel variations in homogeneous regions while maintaining or improving the differences in the mean values of distinct regions. The smoothing parameter determines the amount of smoothing and is derived from a few functions of the local statistics. This filter not only generates high signal-to-noise ratio (SNR) value but also effectively preserves edges. Wavelet denoising methods are also used to reduce speckle. Moreover, fixed and soft thresholds are used to limit speckle noise. Artifacts are produced by these methods.

II. RELATED WORK

There are many speckle reduction filters available, some give better visual interpretations while others have good noise reduction or smoothing capabilities. Some of the best known speckle reduction filters are Median, Lee, Kuan, Standard Frost, Enhanced Frost, Weiner, Gamma MAP and SRAD filters. Some of these filters have unique speckle reduction approach that performs Spatial filtering in a square-moving window known as kernel. The filtering is based on the statistical relationship between the centre pixel and its surrounding pixels. The typical size of filter window can range from 3-by-3 to 33-by-33, but the size of window should be odd. If the size of the filter window is too large, important details will be lost due to over smoothing. On the other hand, if the size of window is too small, speckle reduction may not yield good results. Generally a 3-by-3 or 7-by-7 window is used giving good results [3].
The Wiener Filter [5], also called as Least Mean Square filter, is given by the following expression: H(u,v) shows the degradation function and H(u,v)* shows its conjugate complex. G(u,v) is the degraded image. Function Sf(u,v) and Sn(u,v) are power spectra of original image and the noise. Wiener Filter assumes noise and power spectra of object a priori.
Lee Filter [6] is depending on multiplicative speckle model and it may use local statistics to effectively preserve edges. This filter is based on the approach that if the variance over an area is low or constant, then smoothing will not be performed, otherwise smoothing will be performed if variance is high (near edges).

Kuan Filter [7] is a temporary linear minimum square error filter depending on duplicative order it does not make approximation on the noise variance within the filter window like Lee Filter it models the multiplicative model of speckle noise into an additive linear form. Banks, Bamberger and smith developed a two dimensional filter bank which can perform the maximum elimination together with an optimized reconstruction. In fact, directional filter bank [5] is able to receive high frequencies of input image. It is worth to mention that, high frequencies of images have data related to directions. The image is decomposed using contourlet transform to produce contourlet coefficients. For each part of noisy image pixel, the mean of the noise is obtained. Then we compare this value to predefined threshold value.

III. NOISE MODEL

Medical images are often contaminated by impulsive, additive or multiplicative noise due to a number of non-idealities in the imaging process. The noise usually corrupts medical images by replacing some of the pixels of the original image with new pixels having luminance values near or equal to the minimum or maximum of the allowable dynamic luminance range. The identification of type of noise in the medical image is carried out in two stages. In the first stage, a criterion is used to detect the presence of the impulsive noise. If the result of this criterion is negative, the image is then submitted to second stage of another criterion in order to identify either the additive or the multiplicative nature of the noise.

A. Model of Speckle Noise

An inbuilt characteristic of ultrasound imaging is the presence of speckle noise. Speckle noise is a random and deterministic in an image. Speckle has negative impact on ultrasound imaging, Base reduction in contrast resolution may be responsible for the poor effective resolution of ultrasound as compared to MRI (Magnetic Resonance Images). In case of medical literatures, speckle noise is also known as texture, generalized model of the speckle. Where, is the observed image, is the multiplicative component of the noise is to be considered and additive component of the noise is to be ignored. Given the stochastic nature of speckle noise, we must describe this noise pattern statically to draw general conclusions about imaging systems. The statistics used here to delineate ultrasound speckle are drawn from the literature of the laser optics [7]. Each of the diffuse scatters in the isochronous volume contributes a component to the echo signal in a sum known as a random walk in the complex plane. If each step in this walk is considered an independent random variable, over many such walks we can apply the Central Limit Theorem to their sum. Thus, in fully developed speckle, this composite radio-frequency echo signal from diffuse scatters alone has a zero mean, two –dimensional Gaussian probability density function (PDF) in the complex plane.

B. Noise in Ultrasound Images

Ultrasound imaging system is most widely used diagnostic tool for modern medicine. It is used to do the visualization of muscles, inner organs of the human body, size, structure and injuries. For example, Obstetric solography is used during pregnancy. In an ultrasound imaging speckle noise shows its presence while doing the visualization process.

C. Medical Ultrasound Speckle Pattern

Creation of speckle pattern based the number of scatters per resolution or scatter number density. For the spatially distribution and the characteristics of the imaging system can be divided into three classes: In the first category, fully formed speckle pattern occurs when many random distributed scattering exists within the resolution cell of the imaging system. Blood cells are the example of this class. The second category of tissue scatters is no randomly distributed with long-range order.

IV. METHODOLOGY

Noise reduction filters have an ideal operating condition. Each one performs best only in a particular set of circumstances. All the algorithms have their strengths and weaknesses. The final aim of all the methods is reduction of noise. The basic idea is to design a methodology which incorporates the advantages of algorithms but not their weaknesses. At each stage, an attempt is made is to fix a part of the unwanted alterations to the image while the reduction of noise is achieved. This methodology, organized in the form of steps with the reasoning behind it, is explained below:

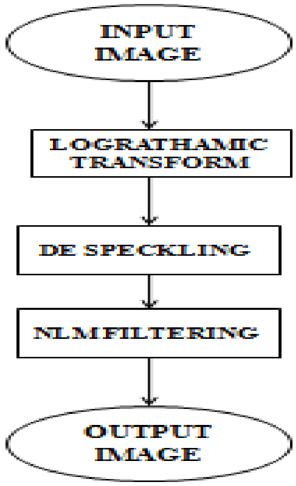

Fig 1: Proposed Workflow

A. Gaussian filter

If the noisy image and the ground truth image are compared, all the pixel locations of speckle noise have been observed with peaks in intensity values. The main idea of using a Gaussian filter here is to remove noise at the same time spread out the intensity peaks due to noise. The edges in the image have significant information and also are characterized by a sudden change in intensity values. Hence, the application of Gaussian filter does reduce the noise, but at the same time it does blur out the edges as well resulting in loss of fine details. This behavior can be observed if there is any text in the image.

B. Median Filtering

Here too first the noisy image is filtered using a Median filter. This operation is to make sure that there are no sudden variations in intensity values but just small bumps. Noise reduction through median values assumes additive noise so directly this cannot be used as speckle is multiplicative noise. Here, the biorthogonal wavelet filter set is used. Empirically, it has been observed that it has performed best when compared to others and this has been attributed to it having different wavelet for decomposition and reconstruction. A soft threshold has been used as it provides smoother results as compared to a hard threshold. The signal has been divided into three levels with threshold being kept uniform across all the levels and across all the details, i.e. horizontal vertical and diagonal. Higher the levels, smoother the image will be, and this might result in fine details being lost. Which may hamper disease identification and localization in Ultrasound images and if the level is less noise will not be removed. Although not medically validated, three levels of decomposition were used. The threshold is selected based on preserving the diagonal details at the first level, and the same threshold is extended for all the remaining levels. The same threshold is kept for all levels as the method needs to work for all images and hence it is not possible to custom design the threshold value for all levels. Importance is given to diagonal details. The retinal layer information is mainly represented by vertical details. However, horizontal details have value when the abnormality is within the layers of the retina.

C. Add noise Filter

Along with noise, the edge information is also represented by high-frequency components when the image is described in the frequency domain. Hence, the output of a low pass filter is a blurred image. Add noise filter has excellent performance while restoring a blurred image. But for add noise filtering, Point Spread Function (PSF) of the noise is to be known. Here in this case as the PSF is not known, it is approximated to be Gaussian to obtain the result.

D. Local Means filter:

This filter is beneficial in reducing speckle noise. It is useful in Synthetic-Aperture Radar (SAR) images with speckle noise. One of the disadvantages of the Lee filter is that pixels with low intensities remain unfiltered and this poses a big problem as the Ultrasound image which is the final target of the method developed do have a lot of darker regions. This again signifies the importance of using a Gaussian filter before the Lee filter. Thus, we obtain the effectiveness of the Local Means filter at the same time and try to circumvent its disadvantage. Now, Mean could also be used to the solve the problem regarding low intensity as shown in the literature but this is not used here because the pixels under consideration are given equal importance.

E. Combination of logarithmic transformation With Non Local Mean Filter

The proposed method consists of four steps as summarized in figure 1. The first step is necessary when the degraded image is very low contrast. This can be accomplished by using the histogram equalization which allows areas of lower local contrast to gain a higher contrast. Since speckle noise is multiplicative, the logarithmic transformation is a reasonable choice to convert it to an additive one. By neglecting additive Gaussian noise, we have:

$$f(x,y) = \eta_s f_0(x,y)$$

Where: f(x, y): noisy image, f0(x, y): noiseless original image, ηx: multiplicative noise

The Log transform leads then to the following equation

$$u(x,y) = \log\big(f(x,y)\big) = \log\left(f_0(x,y)\right) + \log\left(\eta_s\right)$$

However, several choices for the diffusion weight functions λ1 and λ2 are possible, depending on the considered application. For our denoising problem, we propose using:

$$\begin{cases} \lambda_1 = \dfrac{c}{\sqrt{1+N}} \\ \lambda_2 = c.\sqrt{\dfrac{1+\lambda_+}{1+\lambda_-}} \end{cases}$$

In the NLM filter, the estimated intensity NLM ($g(i,j)$) of pixel (i,j) is the weighted average of all of the voxel intensities in the noisy image, which is defined as follows:

$$\mathrm{NLM}(g(i,j)) = \sum_{l=0}^{N_x-1}\sum_{m=0}^{N_y-1} w(i,j,l,m)g(l,m)$$

Where Nx and Ny represent the size of the image; NLM ($g(i,j)$) is the intensity of the image at location (i, j) as estimated by the NLM filter; and g(l, m) is the intensity of the noisy image at location (l, m). Meanwhile, w (i,j, l, m) is a weighting coefficient and is defined as follows:

$$w(i,j,l,m) = \frac{1}{Z(i,j)} e^{-\frac{G_a \left\| g(N_{i,j}) - g(N_{l,m}) \right\|^2}{h^2}}$$

To combine NLM with local statistics, the patches that are used to compute the weighting coefficient and the normalizing constant are not derived directly from the noisy images. The patches are first smoothed by local statistics.

V. RESULTS AND DISCUSSION

In this section, the original synthetic image is shown in Fig. 1(a). This image includes a rectangle, an oval, a line, a triangle, and a cardioid. Given that various speckle removing methods use the multiplicative noise model. The different noise levels (σ = 0.2, 0.4, 0.6, and 0.8) are incorporated into the original image. An example of noise (σ = 0.6) is presented in Fig.2 The corresponding results with σ = 0.6 are depicted in Figs Significant noise is observed in Figs. 1(c)-1(h), thus indicating that the results obtained with the median, additive, addnoise, local means, are unsatisfactory. The results generated with NLM shows on figure 2.

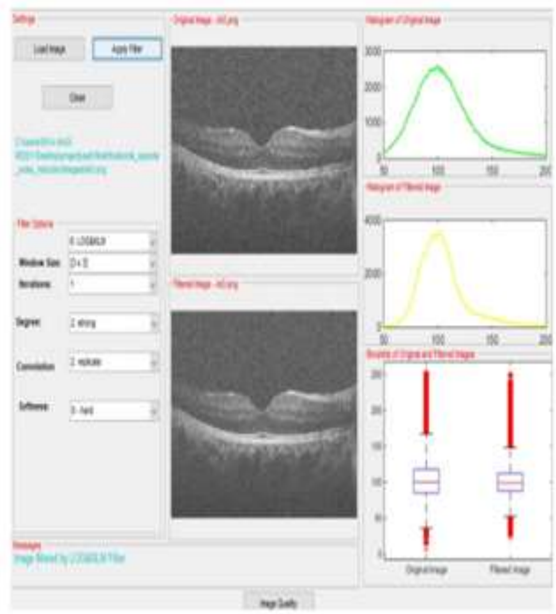

Fig 2: Final Result

A. IMAGE QUALITY METRICS

n order to compare the results from the Lograthamic transformation with NLM denoising approach, we used two quantitative assessment metrics including signal-to-noise ratio (SNR), and structural similarity index (SSIM). PSNR compares the signal of the Ultrasound image to its background noise. SSIM score measures the image quality based on structural similarity between the ground truth and despeckled images.

$$PSNR = 10\log_{10}\left(\frac{\max(I^2)}{\sigma_n^{\,2}}\right)$$

$$SSIM\left(I_{GS}, I\right) = \frac{\left(2\mu_{I_{GS}}\mu_I + C_1\right)\left(2\sigma_{I_{GS}}\mu_I + C_2\right)}{\left(\mu_{I_{GS}}^{\,2} + \mu_I^{\,2} + C_1\right)\left(\sigma_{I_{GS}}^{\,2} + \sigma_I^{\,2} + C_2\right)}$$

Where GS I, I, and ^ I are GS, noisy, and the estimated (despeckled) images, respectively. σ n is the speckle noise variance. C1 and C2 are constants; 1 C = 6.5025 and 2 C = 58.5225. Our results from 56 data sets showed that on average, integration of AWF with CSRF, improves the SNR, and SSIM metrics. When testing different window sizes (i.e., 3 × 3 to 13 × 13), we observed that a window size of 9 by 9 pixels for the despeckling methods yields optimum qualitative and quantitative results. Window sizes smaller than 9 by 9 pixels did not effectively improve the quality of the images. Similarly, window sizes greater than 9 by 9 pixels smoothed the edges and deteriorated small structures. It is worth mentioning that the window size 9 by 9 pixels may not be appropriate for Ultrasound images of other organs, e.g. retina. For the mean filter in the third and final step of NLM, a 3 × 3 window was used to smooth the borders of the clusters and alleviate the problem of quantization pattern. Please note that a window size of 3 × 3 has a negligible effect on major edges, i.e., the ones that are diagnostically important.

Table I: Performance Evaluation

s.no	FILTER	MSE(mean square error)	PSNR(peak signal to noise ratio)	SSI(structural similarity index)
1	Add noise filter	212.0326	27.8771	0.67543
2	Additive noise filter	314.5283	28.1645	0.37362
3	LM filter	222.0879	27.6759	0.51358
4	Median filter	1469.556	19.4692	0.12488
5	LOG & NLM FILTER	87.8092	37.705	0.82642

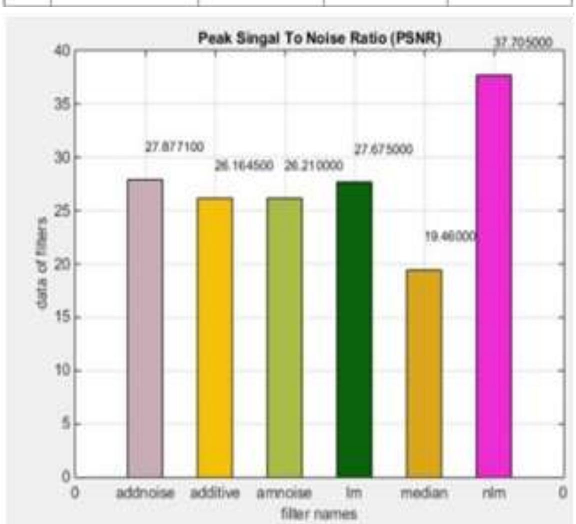

Fig 3. PSNR Comparison with Other Filter

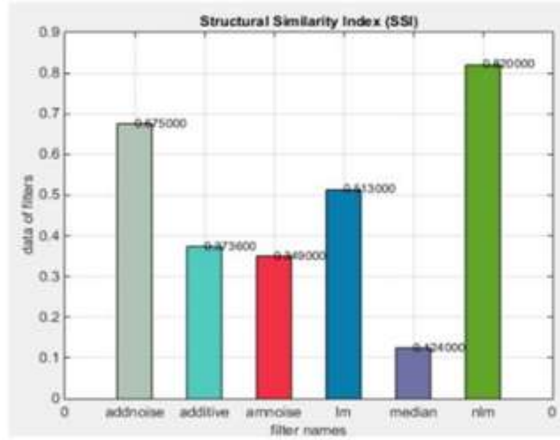

Fig 3. SSI Comparison with Other Filter

VI. CONCLUSION

Non-Local Means is a popular image denoising algorithm implemented in the spatial domain. In this thesis we have proposed a statistics based improvement for the Non-Local Means algorithm with Logarithmic transformation. The key of this improvement is to reduce the size of the feature space, which reduces the patch similarity measurement time and increases the overall despeckling performance. We have utilized a statistical t-test to reduce the dimensionality of the feature space. This reduced feature space is used during the despeckling process. The proposed method has three parameters. The patch size, the search region size and the threshold value for the t-test. We optimized these parameters on a set of test images. The optimized parameters are used in our proposed method to improve the performance of the denoising scheme. We have extensively tested and analyzed our proposed method using both objective and subjective measures. We have also compared the proposed method with the various image denoising algorithms. Experimental results show that our proposed method provides the best running time among all other algorithms in all test cases at various noise levels. It also provides a good denoising improvement in terms of the PSNR and the SSIM values.

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