# A View on Ultrasonogram Denoising Techniques

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***Abstract*—Ultrasonograms are ultrasound medical images. Even if there are multiple modalities of medical image acquisition, ultrasonogram is mostly used because it is non-invasive, practically harmless to human body, portable, accurate, has low acquisition cost and has the capability of forming real time imaging. However, the presence of noise components is more on ultrasound image compared to other costlier methods like CT and MRI. The great challenge of ultrasound medical image denoising is to preserve the edges and all fine details of an image when reducing the noise. Many denoising techniques have been proposed for effective suppression of speckle noise in ultrasound images. In this paper a detailed survey on different techniques for ultrasound image denoising is done. Also the techniques are compared based on certain parameters and it is analysed that multiscale methods have better performance in despeckling.**

***Keywords*-Ultrasonogram; Speckle; Medical Image Denoising; Ultrasound Image; Despeckling;**

## I. INTRODUCTION

Medical Ultrasound imaging is done using ultrasonic waves in 3 to 20 MHz range. Ultrasound waves produced from the transducer travel through body tissues and on reaching an object or surface with different texture or acoustic nature, it is reflected back. These echoes received by the apparatus (the transducer array) are then changed into electric current. These signals are shown on a display device in real time after amplifying and conditioning it. Image generated by Ultrasound Scanning is called an Ultrasonogram. The resolution of the image will be better by using higher frequencies but this will limit the depth of penetration. There are different modes of ultrasound imaging. The most common modes are [1]:

b-mode: this is the basic two-dimensional intensity mode,

m-mode: this is used to assess moving body parts (e.g:cardiac movements) from the echoed sound and

colour mode: pseudo colouring done based on the detected cell motion using Doppler analysis.

However, Ultrasound image contains more noise content especially speckle noise, than any other imaging modality.

### A. Speckle Noise

Noise suppression techniques require the model of noise present i image. The signal dependent noise model for speckle in ultrasound images can be represented as follows [1]:

$$f\left(x,y\right)=g\left(x,y\right).\eta_m\left(x,y\right) \tag{1}$$

Speckle noise can be modelled by following distributions depending on the number of scatterers per resolution cell called scatterer number density (SND) as follows [2]:

- Rayleigh distribution: For large SND speckle can be modelled with this distribution having Signal to Noise Ratio (SNR) of 1.92
- K distribution: For Non Randomly distributed with Long-Range order (NRLR), a generalized version of Rayleigh distribution called the K-distribution can be used.
- Rician distribution: For Non Randomly distributed with Short-Range order (NRSR)the Rician distribution can be used.

The general requirements for ultrasound image denoising are to effectively suppress speckle noise while retaining useful details of the image for analysis and diagnosis.

The rest of the paper is organized as follows: Section II surveys the various speckle reduction methods. Section III contains the observation and analysis from the survey and section IV concludes the work.

## II. DESPECKLING TECHNIQUES

Several techniques have been proposed for despeckling ultrasound images. The classification and theoretical overview of existing despeckling techniques are as follows [1]:

### A. Compounding Methods

In compounding methods a series of ultrasound images of the same target are acquired from different scan directions and with different transducer frequencies or under different strains. Then the images are averaged to form a composite image. The merit of this method is that it can improve the target detectability. But they suffer from degraded spatial resolution and increased system complexity [2].

### B. Postaquisition Methods

Post acquisition methods operate on the image after it has been envelope detected. The advantage of this method is it does not require a specific mode of scanning and many hardware modifications. The post acquisition image processing technique is explained to fall under two categories: Single scale spatial filtering methods and Multi scale methods.

*1) Single scale spatial filtering methods:* Filtering operations that are performed directly on the pixels of an image is referred as spatial filtering. Different spatial filtering methods for speckle reduction include:

*Lee filter:* Lee filter forms an output from weighted average which is calculated using sub-region statistics over different pixel windows. It is also called Minimum Mean Square Error (MMSE) filter, and is based on linear speckle noise model and the utilization of MMSE criterion. It produce speckle free image governed by the relationship given in the following equation [3].

$$U\left(x,y\right)=I\left(x,y\right)W\left(x,y\right)+I^{'}\left(x,y\right)\left(1-W\left(x,y\right)\right) \quad (2)$$

where $I^{'}\left(x,y\right)$ is the mean value of the intensity within the filter window, and $W\left(x,y\right)$ is the adaptive filter coefficient calculated using the following formula,

$$W\left(x,y\right)=1-\frac{C_B^2}{C_I^2+C_B^2} \quad (3)$$

where $C_I$ is the coefficient of variation of the noised image and $C_B$ is the coefficient of variation of the noise. In general, the value of $W\left(x,y\right)$ approaches zero in uniform areas, i.e., it approaches unity at edges which results in little modification of pixel values near edges. So it can use local statistics to effectively preserve edges. It is also computationally simple. But this filter tends to ignore speckle noise near edges.

*Kaun filter:* Kaun filter has the same form as the Lee filter but is different in its weighting function, since it makes no approximation to the original model. Like Lee filter they are also computationally simple but is considered to be superior to Lee filter. Kaun filter is a local linear Mean Square Error $(MSE)$ filter based on multiplicative order. Like Lee filter, it does not make approximation on the noise variance within the filter window. The multiplicative model of speckle is modelled as additive linear form in this filter. The representation for speckle free image is same as that of Lee filter, but vary in the representation for adaptive Filter coefficient $W\left(x,y\right)$ which is represented as [3]:

$$W\left(x,y\right)=\frac{1-\frac{C_B^2}{C_I^2}}{1+C_B^2} \quad (4)$$

The problem with Kaun filter is that it relies on the Equivalent Numbers of Looks (ENL) from an image to determine a different weighted W to perform the filtering.

*Median filter:* This filter replaces the middle pixel in the window with the median value of its neighbours [3]. The idea used here is to examine a sample of the input and decide whether it is representative of the signal. This is done with a window (local filtering) consisting of an odd number of samples. The values in this window are sorted into numerical order, the median value that is the centre value of the window is selected as the output. After discarding the old sample, a new sample is acquired, and the calculation repeats. The mathematical form of Median filter is represented in the following equation,

$$\widehat{f}=median\{g\left(s,t\right)\} \quad (5)$$

where $(s,t)\in S_{xy}$

In median filter, single and unrepresentative pixel in a neighbourhood will not affect the median value significantly. The main problem with this filter is that the median filter would blur edges and tiny details.

*Weiner filter:* Weiner filtering restores images in the presence of blur and noise. It is also known as Least Mean Square filter, which is given by the following expression [3]:

$$f\left(u,v\right)=\left[\frac{H\left(u,v\right)^{*}}{H\left(u,v\right)^{2}+\frac{S_n(u,v)}{S_f(u,v)}}\right] \quad (6)$$

$H\left(u,v\right)$ is the degradation function and $H\left(u,v\right)^{*}$ is its conjugate complex. $f\left(u,v\right)$ is the degraded image. Functions $S_f\left(u,v\right)$ and $S_n\left(u,v\right)$ are power spectra of original image and the noise. This Filter assumes noise and power spectra of object a priori. It performs smoothing of the image based on the computation of local image variance. When the local variance of the image is large, the smoothing will be little. On the other hand, if the variance is small, the smoothing will be better. Since Weiner filter is adaptive it produces better quality results than other linear filtering methods. Weiner filter is able to preserve edges and other high-frequency informations in the image. The main problem with this filter is that it requires more computation time than linear filtering.

*Frost filter:* The Frost filter is an adaptive and exponentially weighted averaging filter. It is based on the ratio of the local standard deviation to the local mean of the degraded image, which is referred as the coefficient of variation [4]. It replaces the pixel of interest with a weighted sum of the values within the moving kernel which moves across the image. This weighting factors decreases with distance and increases in accordance with the increase in variance of the kernel. This filter assumes speckle noise as multiplicative and stationary, which follows the statistics given in the following equation,

$$img\left(i,j\right)=\frac{\Sigma P_n*M_n}{\Sigma M_n} \quad (7)$$

where $M_n$ is the weight of $n^{th}$ pixel and $P_n$ is the $n^{th}$ pixel. Frost filters are locally based filters that compromise between the averaging in homogeneous regions and preserving at edges and features. Its coefficients depends on the local statistics in the moving windows. In case of the low coefficients, the filter tends to be average and in case of high coefficients, it will preserve the sharp features.

*Enhanced Frost filter:* The Enhanced Frost filter is an extension of the Frost filter. It further divides the images into homogeneous, heterogeneous and isolated point target areas [4]. Compared to Frost filter, it better preserves the edges and textures of an image. The filtered image using this filter can be represented as follows,

$$\widehat{R}(t) = \begin{cases} \overline{I}(t) & if C_I(t) \leq C_u(t) \\ I(t).M(t) & if C_{min}(t) < C_I(t) < C_{max}(t) \\ I(t) & if C_I(t) > C_{max}(t) \end{cases} \tag{8}$$

where $C_u(t)$ is the variation coefficient of speckle at time t and $C_I(t)$ is the variation coefficient of the image at time t. $C_{min}(t)$ and $C_{max}(t)$ are minimum and maximum values of variation coefficients respectively.

*Improved Lee filter:* Improved Lee filter classifies the total image area into three classes, homogeneous, heterogeneous and a third calss. Filtering at these 3 classes are different. Homogeneous areas are filtered using low pass filter, heterogeneous areas using Lee filter and in the third class original pixels are retained. These filters overcomes disadvantage of Lee filter by filtering all pixels including the one at edges.

*Improved Kaun filter:* Enhanced Kaun filter is based on same region classification as explained in Improved Lee filter [4]. The main difference between these filters resides in the processing of the heterogeneous regions. Improved Kaun filter exploit the sigmoid function to the modification of weighted function $W(t)$. Then, the modified weighted factor $W^{'}(t)$ can be expressed as given in the equation:

$$W^{'}(t) = \frac{1}{1 + exp(W(t)) - 0.5} \tag{9}$$

This filter is better in comparison with Kaun filter.

*Gamma or Maximum a posterior (MAP) filter:* Gamma or Maximum a posterior (MAP) filter as similar to Enhanced Frost filter [4]. The difference between both is that Gamma or MAP filter minimizes the loss of texture information by assuming that if $C_I$ is between $C_u$ and $C_{max}$ the value of filtered pixel values are gamma distributed.

*Diffusion filters:* Diffusion filters can be directly applied on the image for removing the speckle noise by solving partial differential equation (PDE).

Anisotropic diffusion filters use anisotropic diffusion method based on PDE for smoothing image on a continuous domain. Perona and Malik replaced classical isotropic diffusion equation by this anisotropic diffusion method so it is referred as Perona and Malik Anisotropic Diffusion (PMAD). The diffusion is described by the given equation [5],

$$\frac{\partial I}{\partial t} = div\left[c(\nabla I).\nabla I\right] \tag{10}$$

$$I(t=0) = I_0 \tag{11}$$

where $\nabla$ is the gradient operator, the 'div' divergence operator denotes the magnitude, $c(x)$ is the diffusion coefficient, and $I_0$ is the initial image. The two diffusion coefficients are given by the equations:

$$c(x) = \frac{1}{1 + \left(\frac{x}{k}\right)^2} \tag{12}$$

and

$$c(x) = exp\left[-\left(\frac{x}{k}\right)^2\right] \tag{13}$$

where k is an edge magnitude parameter. Here image edge boundary can be detected using gradient magnitude. These filters perform can perform contrast enhancement and noise reduction without requiring the power spectrum information of the image. But these method is unable to retain subtle features such as small cysts and lesions in the filtered ultrasound image.

Speckle Reducing Anisotropic Diffusion Filter (SRAD) is a non-linear and space-variant filter. These filters produces a family of resulting images based on an iterative diffusion process. The diffusion coefficient in these filters serves as the edge detector, producing high values at edges or features and low values in homogeneous regions. These filters exploits the instantaneous coefficient of variation in reducing the speckle. SRAD is an anisotropic diffusion method specifically designed for smoothing speckled imagery. If the given intensity image is $I_0(x,y)$, having finite power and non zero values over the image support $\Omega$, the output image $I(x,y;t)$ is produced according to the following PDE [5]:

$$\frac{\partial I(x,y;t)}{\partial t} = div\left[c(q)\,\Delta I(x,y;t)\right] \tag{14}$$

$$I(x,y;0) = I(x,y), \frac{\partial I(x,y;t)}{\partial \overrightarrow{n}} |\partial\Omega = 0 \tag{15}$$

where $\partial\Omega$ denotes the border of $\Omega$, $\overrightarrow{n}$ is the outer normal to the $\partial\Omega$. SRAD is able to achieve a balance between despeckling and edge preserving in ultrasound images. So SRAD filtering approach is performing better than traditional despeckling filters and the conventional anisotropic diffusion method in terms of speckle reduction, edge preservation and image clarity.

Detail Preserving Anisotropic Diffusion (DPAD) is explained as a modified SRAD filter which rely on Kaun filter. This method is combined with matrix anisotropic diffusion method which is designed to preserve and enhance small vessel structures and is referred as oriented speckle reducing anisotropic diffusion.

*2) Multiscale methods:* These methods are often referred to as wavelet shrinkage techniques [6]. Most wavelet shrinkage techniques assume a multiplicative noise model and so convert the multiplicative speckle into additive noise with a logarithmic transformation. This additive noise is assumed to obey Gaussian distribution and is then processed through soft-thresholding or Bayesian estimation based on the assumed Gaussian distribution. Several multi scale methods based on wavelet and pyramid have been proposed for despeckling in ultrasound imaging. But such an assumption proved to be oversimplified and result in decreased performance in despeckling.

The best type of wavelet that could be used for speckle reduction in ultrasound images is Daubechies due to its higher PSNR value. It is proved that the wavelet based methods gets better results both in terms of speckle reduction and signal detail preservation. The wavelet filter is found suitable for removing the speckle in ultrasound images and improving the image qualities as well. In addition to this the method is also easy to implement and the statistics are easy to estimate and characterize. Recently many approaches to image de nosing have been proposed, some of them are based on single wavelet and the others based on multiple wavelets. Both, single wavelet and multiple wavelets are explained to have their own advantages and limitations. For instance, multiple wavelets possess simultaneously orthogonality, symmetry, and short support, while a single wavelet cannot possess all these properties at the same time. So multiple wavelets are more flexible than single wavelet. But the member of single wavelet family is much more abundant than multiple wavelets, and it is easy to calculate. The basic approach based on wavelet transform ( both single wavelet transform and multiple wavelets transform) has the following three steps [6]:

1) Compute the WT coefficients of the signal;

2)Perform some specified processing on these coefficients;

3) Compute the inverse WT to obtain the processed image.

Among these different wavelet methods are differentiated by step 2. Many methods based on WT were proposed, which can be classified by the selection of wavelet or threshold. According to [7] performance of wavelet based methods are better than spatial filters in denoising.

In thresholding methods the wavelet coefficients which are smaller than the predefined threshold are regarded as contributed by noise and so removed. The different wavelet based thresholding methods are Visushrink, Bayes shrink, Modified Bayes shrink, Bivariate shrink, Sure shrink, Minimax threshold,Waveshrink, Cycle spinning etc. Normal shrink outperforms Bayes shrink and Sure shrink in terms of noise removal performance. Also, the denoising performance depends on the thresholding methods that is whether it is hard threshold or soft threshold. In practice, soft thresholding is found more popular than hard threholding since it reduces the abrupt sharp edges that occurs in hard thresholding and also provides more visually pleasant recovered images. The process of the conventional wavelet denoising by thresholding is shown in figure 1.

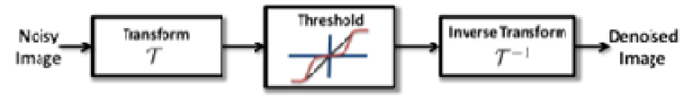


Figure 1. Operations in threshold-based denoising.

Thresholding methods have 2 major drawbacks. First, it is difficult to find optimal solution for all kinds of images. Second, the same noise model cannot be used for the diverse resolutions,since the selected threshold may not match the specific distribution of the signal and the noise components in all scales well. Thresholding techniques have difficulty in determining an appropriate threshold.

To overcome the disadvantages of thresholding methods Bayesian estimation method was proposed [8][9] . In this method noise free signal is approximated based on the distribution model of noise free signal and that of noise. This method uses a suitable probability density function $(pdf)$ initially for modelling the wavelet coefficients of the image. It was recognized that these methods can achieve noise reduction and feature preservation, if it employs more accurate statistical description of the signal and noise components. In this context, there are two general statistical models which are of particular interest, Generalized Gaussian $(GG)$ distribution and Symmetric alpha-Stable $(S\alpha S)$, among which latter is superior to former, especially for despeckling logarithmically transformed medical ultrasound images. It was found that the performance of Bayesian denoising algorithm can be significantly improved if the inter scale dependencies between wavelet coefficients are effectively modelled and exploited. Reasonable distribution models are also crucial for the successful application of these techniques to ultrasonograms.

Coefficients correlation methods according to [10] is an undecimated or over complete wavelet domain denoising method which utilizes the correlation of useful wavelet coefficients across scales. This method does not rely on the exact prior knowledge of the noise distribution and is more flexible and robust compared to other wavelet based methods. Pyramid based denoising methods belongs to multiscale methods and are based on thresholding procedure of the transform coefficients. Generally, the denoising algorithm is explained to have the following three steps[10]:

1. Apply the pyramid decomposition algorithm to noisy data and obtain the vector;

2. Apply thresholding operator to the residual signal values;

3. Apply the pyramid reconstruction algorithm to the thresholded vector to invert the pyramid transform.

The simplest and most widely used operator make use of the hard and soft thresholding schemes. In this method quadrature mirror filters are not needed as in the case of wavelet transform since the pyramid transform has low pass filter properties in it.

Different alternative wavelet based ultrasound image denoising methods are compared in [11], which include curvelet and contourlet and it was analysed that curvelet and contourlet transforms are very useful in medical image denoising and gives improved performance over wavelets in terms of MSE and SNR. Curvelet transform is an extension of the wavelet transform that aims to deal with interesting phenomena occurring along curves. Eventhough wavelets are well suited to point out the singularities, they have limitations with orientation selectivity and hence do not represent changing geometric features along edges of image effectively. In [12], it was explained that curvelet based method performs superior as compared to other methods like contourlet in reducing speckle noise content of ultrasound images. It also indicate effective edge preservation in comparison to filtering techniques using the adaptive filters and SRAD by incorporating a directional component to the traditional wavelet transform. But transform-based denoising methods often suffer from unwanted artifacts, e.g., nonsmooth edges and pesudo-Gibbs phenomena.

## III. Observation

The Compounding methods involve hardware modifications that make the imaging process expensive and inconvenient. Another approach to speckle reduction is using post processing techniques like median, Lee, Frost, Kaun and Gamma filters. But these filters are having common limitations like their performance depends heavily on the shape and size of moving window, they are not directional, they only inhibit smoothing near edges and do not enhance it and the thresholds used in the enhanced filters are adhoc and produce artifacts in the filtered images. Anisotropic diffusion-based methods are widely used for speckle reduction. Among these SRAD provides strong speckle suppression compared to other spatial filters. However diffusion process is very sensitive to several key parameters and the adopted models of speckle, which makes the approach not very robust. In past two decades, with the advent of the multi resolution analysis in denoising, a significant breakthrough was made in the field of image denoising. Wavelets have been universally regarded as extremely powerful tool for analysis and are found to perform better than spatial filtering methods. But the wavelet based methods has the disadvantage that they cant capture edges and contours properly due to isotropic property. To overcome the difficulties, some anisotropic transform were proposed to represent the signals which include ridget transform,contourlet transform, shearlet transform and curvelet transform. Even though these transforms were able to obtain better denoising effect, the complication of constructing directional filters remained.

The summarization of survey is represented in table 1, from which it can be analysed that comparatively multiscale methods has better despeckling performance.

## IV. Conclusion

Speckle is a major source that cause low SNR of ultrasound images. Effective despeckling in ultrasound images is critical prior to the application of other image processing approaches on it. Image denoising techniques are well developed at present time. Although diverse denoising filters for ultrasound images are available in literature which are termed as edge and feature preserving, they all suffer from limitations. So a lot still has to be done to adopt them optimally for ultrasound image denoising. A detailed survey of different despeckling techniques together with their comparison is done here. As a result of the survey it is analysed that from among the existing despeckling methods, multiscale methods has better despeckling performance.

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Table I
OBSERVATION AND ANALYSIS

| | Compounding Methods | Single Scale Methods | Multiscale Methods |
|---|---|---|---|
| Target detectability | Yes | Yes | Yes |
| Expensive | Yes | No | No |
| Inconvenient | Yes | No | No |
| Performance | Less | Depends on moving window | More |
| Edge enhancement | Yes | No | Yes |
| Artifacts | No | Yes | Yes |
| Best despeckling for | - | SRAD | Curvelet Transfroms |
| Complexity in designing filters | No | No | Yes |