Despeckling of Ultrasound Medical Images: A Survey

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Abstract—**Digital image acquisition and processing techniques plays important role in clinical diagnosis. Medical images are generally corrupted by noise during their acquisition and transmission. Removing noise from the original medical image is still a challenging problem for researchers. Ultrasound imaging is widely used for diagnosis over the other imaging modalities like Positron Emission Tomography (PET), Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) due to its noninvasive nature, portable, accurate, harmless to the human beings and capability of forming real time imaging. The presence of signal dependant noise known as speckle degrades the usefulness of ultrasound imaging. The main purpose for speckle reduction is to improve the visualization of the image and it is the preprocessing step for segmentation, feature extraction and registration. Over a period, a number of methods have been proposed for speckle reduction in ultrasound imaging. While using techniques for speckle reduction as an aid for visualization, certain speckle contains diagnostic information and should be retained. The scope of this paper is to give an overview about despeckling techniques in ultrasound medical imaging.**

***Index Terms*—speckle noise, speckle filters, wavelet transform, curvelet transform, contourlet transform**

I. Introduction

Ultrasound imaging plays major role in medical imaging due to its non-invasive nature, accurate, low cost, capability of forming real time imaging, harmless to the human beings and continuing improvement in image quality [1] and [2]. It is used for imaging soft tissues in organs like spleen, uterus, liver, heart, kidney, brain etc. Speckle [3] is found in ultrasound imaging and other coherent imaging modalities. It is caused by the constructive and destructive coherent interferences of back scattered echoes from the scatters that are much smaller than the spatial resolution of medical ultrasound system. Speckle pattern is a form of multiplicative noise and it depends on the structure of imaged tissue and various imaging parameters.

Speckle noise in medical ultrasound images reduces the contrast and image resolution which affect the diagnostic value of the ultrasound imaging. It obscures and blurs image detail significantly, degrades the image quality and hence decreases the difficulty for the observer to discriminate fine detail of the image during diagnostic examination. It also reduces the speed and accuracy of ultrasound image processing tasks such as segmentation and registration. Therefore, speckle reduction is always an important prerequisite for ultrasound image processing tasks.

In this paper, we do a survey of different image processing techniques used in enhancing the quality and information content in the ultrasound image. The remainder of the paper is organized as follows. Section II covers the speckle filtering methods; Section III discusses the different parameters for analyzing despeckling filter performance. Section IV provides a summary of the analysis as well as the conclusions drawn out of the survey.

II. Speckle Filtering Methods

Over the years, several techniques have been proposed to despeckle ultrasound images. There are two major classifications of speckle reduction filters namely compounding method and post acquisition method [4]. Compounding method improves the target delectability but suffer from degradation of spatial resolution and system complexity increases due to hardware modification. Post acquisition methods include spatial adaptive methods and multiscale methods which do not require any hardware modification, but improve the image details and reduce the speckle noise through algorithm implementation. This paper presents survey of spatial filtering methods and multiscale methods in removing the speckle noise and preserving the diagnostics information in ultrasound images.

A. Spatial Filtering Methods

Spatial filter is based on the ratio of local statistics, which improves smoothing in homogenous regions of the B-scan images where speckle is fully developed and reduces appreciably in the other regions of the image in order to preserve the useful details of the image [4]. Spatial filters like Lee and Kuan filter work directly on the intensity of the image using local statistics [5]-[7]. Different types of filters are used in the applications of despeckling in ultrasound imaging. The most commonly used types of filters are:

- Mean filter [8] is a simple filter and does not remove the speckles but averages it into the data.

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This is the least satisfactory method of speckle noise reduction as it results in loss of detail and resolution. It has the effect of blurring the image. This filter is optimal for additive Gaussian noise whereas the speckled image obeys a multiplicative model with non Gaussian noise. Therefore mean filter is not the optimal choice.

- Median filter [9] are used for reducing speckle due to their robustness against impulsive type noise and edge preserving characteristics. The median filter produces less blurred images. The disadvantage is that to find the median it is necessary to sort all the values in the neighborhood into numerical order and this is slow because an extra computation time is needed to sort the intensity value of each set.
- Frost filter [10] is an adaptive and exponentially-weighted averaging filter based on the coefficient of variation which is the ratio of the local standard deviation to the local mean of the degraded image. The Frost filter replaces the pixel of interest with a weighted sum of the values within the nxn moving kernel. The weighting factors decrease with distance from the pixel of interest. The weighting factors increase for the central pixels as variance within the kernel increases. This filter assumes multiplicative noise & stationary noise statistics and follows the following formula.

$$DN = \sum_{nxn} K \alpha e^{-\alpha|t|} \tag{1}$$

where $\alpha = \left(\frac{4}{n\bar{\sigma}^2}\right)\left(\frac{\sigma^2}{\bar{I}^2}\right)$

K = normalization constant

$\bar{I}$ = local mean

σ = local variance

$\bar{\sigma}$ = image coefficient of variation value

$|t| = |X - Xo| + |Y - Yo|$, and

n = moving kernel size

- Lee filter [5] and [6] is based on the multiplicative speckle model and it can use local statistics to effectively preserve edges and features. Lee filter is based on the approach that if the variance over an area is low, then the smoothing will be performed. Otherwise, if the variance is high (e.g. near edges), smoothing will not be performed. Lee filter can be described by

$$W(X,Y) = 1 - (C^2_B / (C^2_I + C^2_B)) \tag{2}$$

where *W(X,Y)* is the adaptive filter coefficient. C_I is the coefficient of variation of the noised image and C_B is the coefficient of variation of the noise.

- Kaun filter [11] is considered to be more superior to the Lee filter. Kaun filter is a local linear minimum square error filter based on the multiplicative model. It does not make approximation on the noise variance within the filter window. The filter models the multiplicative model of speckle into an additive linear form, but it relies on the Equivalent Number of Looks (ENL) from an image to determine a different weighted W to perform the filtering. The weighted function W is computed as follows:

$$W = (1 - C_u / C_i) / (1 + C_u) \tag{3}$$

The weighting function is computed from the estimated noise variance coefficient of the image, C_u computed as follows:

$$Cu = \sqrt{1/ENL}$$

and C_i is the variation coefficient of the image computed as follows:

$$C_i = S / I_m$$

where *S* is the standard deviation in filter window. The only limitation with kaun filter is that the ENL parameter is needed for computation.

- Enhanced Frost and Enhanced Lee filter [12] are used to alter the performance locally based on the threshold value. Pure averaging is induced when the local coefficient of variation is below a lower threshold. The filter performs a strict all pass filter when the l0cal coefficient of variation is above a higher threshold. When the coefficient of variation is in between the two thresholds, a balance between averaging and identity operation is computed.
- Gamma Map filter [13] is used to minimize the loss of texture information. This approach is better than the Frost and Lee filter and it uses the coefficient of variation and contrast ratio whose probability density function will determine the smoothing process. The algorithm is similar to Enhanced Frost filter except that the local coefficient of variation falls between the two thresholds; the filtered pixel value is based on the Gamma estimation of the contrast ratios within the appropriate filter window. The filter requires assumption about the distribution of the true process and the degradation model. Different assumptions lead to different MAP estimators and different complexities.
- Wiener filter [14] and [15] restores images in the presence of blur as well as noise. Its purpose is to reduce the amount of noise present in a signal by comparison with an estimation of the desired noiseless signal. Wiener filter performs smoothing of the image based on the computation of local image variance. When the local variance of the image is large, the smoothing is less. When the variance is small, Wiener performs more smoothing. This approach provides better results than linear filtering. It preserves edges and other high frequency information of the images, but

requires more computation time than linear filtering.

- Diffusion filtering: Perona and Malik [16] proposed non linear partial differential equation for smoothing imaging on a continuous domain. This diffusion is described by

$$\frac{\partial I}{\partial t} = div\left[C\left(\|\nabla I\|\right).\nabla I\right] \quad (4)$$

$$I(t = 0) = I_0$$

where div is the divergence operator, $\|\nabla I\|$ is the gradient magnitude of the image I, $C(\|\nabla I\|)$ is the diffusion coefficient or the diffusitivity function and I_0 is the original image. In the anisotropic diffusion method the gradient magnitude is used to detect an image edge or boundary a step discontinuity in intensity.

An edge sensitive diffusion method called speckle reducing anisotropic diffusion (SRAD) has been proposed to suppress speckle while preserving edge information [17]. A tensor based anisotropic diffusion method called non linear coherent diffusion (NCD) used for speckle reduction and coherent enhancement [18].

The above mentioned diffusion methods can preserve or even enhance prominent edges when removing speckle. Nevertheless, the methods have one common limitation in retaining subtle features such as small cysts and lesions in ultrasound images.

B. *Multiscale Methods*

Several multi scale methods based on wavelet, curvelet and contourlet have been proposed for speckle reduction in ultrasound imaging.

- Wavelet Transform

For one-dimensional piecewise smooth signals, like scan lines of an image, wavelets have been established as the right tool, because they provide an optimal representation for these signals [19]. Medical ultrasound images are not simply stacks of 1-D piecewise smooth scan-lines; discontinuity points (i.e. edges) are located along smooth curves (i.e. contours) owing to smooth boundaries of physical objects. Thus, images contain intrinsic geometrical structures that are key features in visual information. As a result of a separable extension from 1-D bases, wavelets in 2-D are good at isolating the discontinuities at edge points, but will not see the smoothness along the contours. In addition, separable wavelets can capture only limited directional information – an important and unique feature of multidimensional signals.

The complex wavelet transform is one way to improve directional selectivity and only requires O(N) computational cost. However, the complex wavelet transform has not been widely used in the past, since it is difficult to design complex wavelets with perfect reconstruction properties and good filter characteristics [20] and [21]. One popular technique is the dual-tree complex wavelet transform proposed by Kingsbury [22] and [23] which added perfect reconstruction to the other attractive properties of complex wavelets, including approximate shift invariance, six directional selectivities, limited redundancy and efficient O(N) computation.

The 2-D complex wavelets are essentially constructed by using tensor-product 1-D wavelets. The directional selectivity provided by complex wavelets (six directions) is much better than that obtained by the discrete wavelet transform (three directions), but is still limited. These disappointing behaviors indicate that more powerful representations are needed in higher dimensions.

- Curvelet Transform

Candes and Donoho [24] pioneered a new expansion in the continuous two-dimensional space $\mathbb{R}^2$ using curvelets. This expansion achieves essentially optimal approximation behavior for 2-D piecewise smooth functions that are C^2 curves. The curvelet transform was developed initially in the continuous domain [24] via multiscale filtering and then applying a block ridgelet transform [25] on each bandpass image. Later the second generation curvelet transform [26] was defined directly via frequency partitioning without using the ridgelet transform. Both curvelet constructions require a rotation operation and correspond to a 2-D frequency partition based on the polar coordinate. This makes the curvelet construction simple in the continuous domain but causes the implementation for discrete images – sampled on a rectangular grid – to be very challenging. In particular, approaching critical sampling seems difficult in such discretized constructions.

The curvelet transform is very efficient in representing curve-like edges. But the curvelet transform still have two main drawbacks: 1) they are not optimal for sparse approximation of curve features beyond C^2 singularities 2) the discrete curvelet transform is highly redundant.

- Contourlet Transform

The contourlet transform is a 2-D transform technique developed for image representation and analysis [27] by Do and Vetterli. It was originally defined in the discrete domain, but the authors [27] proved its convergence in the continuous domain. It was constructed in a discrete-domain multi resolution and multi direction expansion using non-separable filter banks. This construction resulted in a flexible multiresolution, local and directional image expansion using contour segments, and thus it is named the contourlet transform. Contourlets are an extension of curvelets. Contourlets are implemented by using a filter bank that decouples the multiscale and the directional decompositions. The multiscale decomposition is done by Laplacian pyramid, then a directional decomposition is done using a directional filter bank.

The contourlet transform has several distinguishing features. 1) The contourlet expansions are defined on rectangular grids, and thus offer a seamless translation to the discrete world, where image pixels are sampled on a rectangular grid. To achieve this feature, the contourlet kernel functions have to be different for different directions and cannot be obtained by simply rotating a single function. This is a key difference between the contourlet and the curvelet systems in [24], [27]. 2) As a result of being defined on rectangular grids, contoulets have 2-D frequency partition on centric squares, rather than on centric circles for curvelets and other systems defined on polar coordinates. 3) Since the contourlet functions are defined via iterated filter banks like wavelets, the contourlet transform has fast bank algorithms and conventional tree structures. 4) The contourlet construction provides a space-domain multiresolution scheme that offers flexible refinements for the spatial resolution and the angular resolution.

The contourlet transform provides a multiscale and multidirectional representation of an image. It is also easily adjustable for detecting fine details in any orientation at various scale levels [28] resulting in good potential for effective image analysis. Moreover, the decoupling of multiscale decomposition guarantees a flexible structure for image analysis.

III. Performance Metrics

TABLE I. Performance Metrics

Performance Metrics	Mathematical Expression
Mean Square Error (MSE)	MSE = $\frac{1}{MN}\sum_{j=1}^{M}\sum_{k=1}^{N}\left(X_{j,k}-X'_{j,k}\right)^2$
Root Mean Square Error (MSE)	RMSE = $\sqrt{\frac{1}{MN}\sum_{j=1}^{M}\sum_{k=1}^{N}\left(X_{j,k}-X'_{j,k}\right)^2}$
Peak Signal to Noise Ratio (PSNR)	PSNR = 10 $\log_{10}\left(\frac{255^2}{MSE}\right)$
Signal to Noise Ratio (SNR)	SNR = 10 $\log_{10}\left(\frac{\sigma_g^2}{\sigma_e^2}\right)$
Contrast to Noise Ration (CNR)	CNR = $\frac{\lvert\mu'-\mu''\rvert}{\sqrt{\sigma_1^2+\sigma_2^2}}$
Noise Standard Deviation (NSD)	NSD = $\frac{SORT((\sum_{j=1}^{M}\sum_{k=1}^{N}(X_{j,k}-\bar{X}_{j,k})^2)}{MN}$ where NMV = $\frac{\sum_{j=1}^{M}\sum_{k=1}^{N}X_{j,k}}{MN}$
Equivalent Number of Looks (ENL)	ENL = $\frac{NMV^2}{NSD^2}$
Figure of Merit (FOM)	FOM = $\frac{1}{\max(N_e,N_i)}\sum_{j=1}^{N}\frac{1}{1+d_j^2\alpha}$

To quantify the performance improvements of the speckle reduction method and enhancing the useful image information various measures are used. The following established performance metrics found in literatures [28]-[31] are calculated in this study and their mathematical expression, significance are given in Table I.

IV. Conclusion

Although all standard speckle filters perform well on ultrasound images but they have some constraints regarding resolution degradation. These filters operate by smoothing over a fixed window and it produces artifacts around the object and sometimes causes over smoothing. Wavelets perform well for 1-D images and has few limitations in the higher dimensions related to directionality and anisotropy. Curvelet constructions require a rotation operation and correspond to a partition of the 2D frequency plane based on polar coordinates. This makes the curvelet idea simple in the continuous domain but causes problems in the implementation of discrete images. In particular, approaching critical sampling seems difficult in discretized constructions of curvelets. For contoulets, it is easy to implement the critically sampling. The key difference between contourlets and curvelets is that the contourlet transform is directly defined on digital-friendly discrete rectangular grids. Since contourlets overcome the limitations of wavelets and curvelets it will be better suited for speckle reduction of ultrasound medical images.

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