Analysis of Different Filters for Image Despeckling : A Review

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Abstract**—**Digital image acquisition and processing in clinical diagnosis plays a significant part. Medical images at the time of acquisition can be corrupted via noise. Removal of this noise from images is a challenging problem. The presence of signal dependent noise is referred as speckle which degrades the actual quality of an image. Considering, several techniques have been developed focused on speckle noise reduction. The primary purpose of these techniques was to improve visualization of an image followed by preprocessing step for segmentation, feature extraction and registration. The scope of this paper is to provide an overview of despeckling techniques.

Keywords**—***Image Despeckling, Speckle Noise, Speckle Filters.*

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I. Introduction

Medical imaging involves the ultrasound imaging which serves as the most crucial part in the detection and identification of various distinct objects internally. This non-invasive imaging technique is highly efficient in generating real-time images with high accuracy rate without posing any effects on humans. Enhanced quality of image could be easily achieved through it [1][2]. Identification of organs such as brain, spleen, kidney, uterus etc. consisting of highly tender tissues needs right imaging for carrying out medical operations. Various objects are required to be identified correctly and distinctively which is achieved through ultrasound imaging [3]. Coherent interferences of back shattered echoes that are either constructive or destructive cause speckle. Medical ultrasound system has relatively greater spatial resolution than scatters that are responsible for back shattered echoes. The internal structure of tissue along with several imaging parameters determines the speckle pattern that is multiplicative in nature. This multiplicative natured noise degrades the resolution of image resulting in low contrast. The diagnostic value is influenced by the poor image quality. This means the low quality image is incapable of providing fine details regarding the blurred or low contrasted portions in the image. Due to the insufficient information gained through the ultrasound imaging no accurate diagnostic observations or conclusions can be made. The ultrasound imaging processes including segmentation and registration becomes considerably slow and less reliable due which speckle must be minimized essentially for performing ultrasound imaging. Sensor receives the reflected incident wave by the primary scatterers. Numerous such scatterers are present in a various resolution cells. Either constructive or destructive interferences are performed by the backscattered coherent waves randomly. These coherent waves are of different phases. Speckle is random granular pattern that corrupts the obtained image by causing disturbance in interpreting and analyzing the image [2]. An image with speckle is given by the following equation:

$$v1 = f_1 u \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

where,

$f = \{f_1, f_2, f_3, \ldots. f_n\}$ is a noise-free ideal image.
$v = \{v_1, v_2, v_3, \ldots., v_n\}$is speckle noise.
$u = \{u_1, u_2, u_3, \ldots., u_n\}$is a unit mean random field.

Noise is majorly introduced in an image in ultrasound imaging by speckle which necessarily requires appropriate preprocessing. The processes applied for this purpose must not manipulate any prominent feature in image. The minimization of such speckle in ultrasound imaging is required for the following reasons:

1. For comprehensive analysis of ultrasound image.
2. Speckles make the image blurred and obscured. Therefore, its elimination is required for obtaining clean image with significant detailed boundaries.
3. The speed and accuracy level of preprocesses such as segmentation and registration that can be either automatic or semi-automatic is hindered by speckles. Thus, removal of speckles must essentially be performed as a preprocessing task for ultrasound imaging.

II. Speckled Image Modeling

The generalized design of image is mentioned in [10] which provides basis for [11][12]. This is given by the equation mentioned below:

$$I(u, v) = f(u, v). m(u, v) + a(u, v) \ldots\ldots\ldots\ldots\ldots\ldots (2)$$

where,
The calculated image is represented by I, Original image is represented by f, Multiplicative noise is represented by m, Additive noise is represented by a, Axial and lateral indices of an image are represented by u and v respectively.
Despite various limitations offered by this formulation that are mentioned in [13] it is still being used for ultrasound imaging and SAR image construction. Only the multiplicative speckle noise is considered as the major source of noise introduction in image. Therefore, additive noise represented by a in the above

equation can be neglected so as to obtain minimized form of equation that is given below:

$$I(u,v) \approx f(u,v)m(u,v) \dots \dots \dots \dots \dots (3)$$

The observation made in [4] indicates that amplitude of speckle noise is determined by image sqaure root which considers the speckle noise to be additive noise. In the above eqaution (3) I represents the image before filtering process. For the purpose of despecking the logarithmic transformation is performed on the image obtained from equation(3). This transformation performs the conversion of multiplicative speckle noise given by m into additive speckle noise represented by a.

On the application of logarithms on eqaution(2) gives the following equation:

$$I_1(u,v) = f_1(u,v) + m_1(u,v) \dots \dots \dots \dots \dots (4)$$

where,

The logarrithmic form of I, f and m are represented by $I_,$, f_1 *and* m_1 respectively.

Therefore the problem of speckle removal is achieved by neglecting the additive speckle noise in ultrasound imaging formulated in above equation. Various suppression techniques are available for the purpose of rejecting this additive speckle noise. These techniques use the noise properties of speckles that are mentioned in [4].The consideration of noise as WGN in manifold technique for despeckling offers several limitations which make it less preferable.

III. STANDARD DESPECKLING TECHNIQUES

Availability of various distinct filters for speckle despeckling helps in achieving ultrasound imaging with enhanced visual analysis of image and with better noise reduction capabilities along smoothing effects. Median Lee, Enhanced Frost, Standard Frost, Kuan, Weiner and SRAD are some of the popular filters for solving the problem of speckle reduction.

Most of the filters used perform filtering process in spatial domain that involves the filtering Kernel. A kernel is a small movable square window whose size must be falling in the range of 3-by-3 to 33-by-33. The large sized window may cause loss of significant information due to over smoothing. The center pixel is related to its neighboring pixels statistically which provides the basis for filtering process. In case a window with smaller size than the specified range will affect the efficiency of speckle reduction process. Therefore a window with a size of 3-by-3 or 7-by-7 is considered optimal.

3.1 Median Filter

On the application of median filters the center pixel is replaced by the median value which is computed for all pixels lying in the local window [4]. The median filtering is employed in the cases that require edges to be preserved. Such cases include noise patterns consisting of strong spiked structures. This non-linear technique requires excessive time for computing the intensity value corresponding for each set.

3.2 Wiener filter

The Weiner Filter is popularly known as Least Mean Square filter which is given by the following equation [5].

$$f(u,v) = \left[\frac{H(u,v)^*}{H(u,v)^2 + \left[{Sn(u,v)}/{Sf(u,v)} \right]} \right] G(u,v) \dots \dots (5)$$

In the above equation, H(u,v) and $H(u,v)^*$ represents the degradation function and its conjugate complex respectively. G (u,v) is the degraded image. The power spectra of actual image and the noise is given by Sf(u, v) and Sn(u, v) respectively. Wiener Filter assumes noise and power spectra of object a priori.

3.3 Lee Filter

The preservation of edges is performed by using local statistics by Lee Filter which work on the basis of multiplicative speckle model [6]. The smoothing o image is performed only if the variance over a particular region of image is high. In case the variance of area is low or constant then no smoothing process will be accomplished. This is given by the equation given below:

$$Img(i,j) = Im + W * (Cp - Im) \dots \dots \dots \dots \dots (6)$$

Where,

Img gives the pixel value at position i,j after filtering process

Im represents the mean intensity of filter window, Cp shows the center pixel, W is a filter window which is computed from the following equation:

$$W = {\sigma^2}/{(\sigma^2 + \rho^2)} \dots \dots \dots \dots \dots \dots .. (7)$$

where

$\sigma^2$is the variance of the pixel values within the filter window which is given by the equation mentioned below:

$$\sigma^2 = \left[{1}/{N} \sum_{j=0}^{N-1} (X_j)^2 \right] \dots \dots \dots \dots \dots \dots \dots . (8)$$

In the above equation, N and Xj represent the size of filter window and value of pixel at j respectively.

The additive noise variance ρ is given by the following equation:

$$\rho^2 = \left[{1}/{M} \sum_{i=0}^{M-1} (Y_i)^2 \right] \dots \dots \dots \dots \dots (9)$$

Here, The size of image and each pixel value of image are given by M and Yj respectively.

The mean intensity value (Im) of filter window will be given as result in case no smoothening process is performed. In other cases, Cp and Im is evaluated followed by its product with W to calculate the sum of product obtained and Im. The major limitation of lee filter is that is tends to avoid speckle noise nearer to edges.

3.4 Kuan Filter

Unlike Lee filter, Kuan filter does not involves the estimation on the noise variance falling inside filter window. This operates on the multiplicative order approach with local linear minimum square error [7].It tends to convert the multiplicative speckle noise model into additive linear model. The ENL parameter requirement serves as the only limitation of this filter. The weighting function W is evaluated by using the equation given below:

$$W = \left(1 - {C_u}/{C_i}\right) / {1 + C_u} \dots\dots\dots\dots\dots (10)$$

The approximated noise variation coefficient (C_u) is used to evaluate weighing function which is obtained by the following equation:

$$C_u = \sqrt{1/ENL} \dots\dots\dots\dots\dots (11)$$

The variation coefficient (Ci) of image is given by:

$$C_i = S/Im \dots\dots\dots\dots\dots (12)$$

where,
Standard deviation in filter window is given by S and Mean intensity within window is given by Im

3.5 Frost Filter

Frost filter performs adaptive filtering in spatial domain. The approach of multiplicative noise order is followed. The application of exponential weighting factors provides the adaptation to noise variance within the filter window [8]. The weighting factor M is given by the following equation:

$$M_n = \exp(-(DAMP * (S/Im)^2) * T) \dots\dots\dots\dots\dots (13)$$

With reducing variance within the window weighting factor also tends to minimize. The estimate of exponential damping of image is given by DAMP factor. This factor indicates the extent of damping which means with increasing value of damping which is mostly equal to 1 the damping effect gets heavier. S is defined as the standard deviation of window. T and Im are the absolute distance value of pixel from neighboring pixels and mean value within window respectively. The filtered pixel value is replaced by value obtained from weighted sum of individual pixel values P_n and their associated weights represented by M_n over the net weighted value. This can be calculated from the equation mentioned below:

$$Img(i,j) = \sum P_n * M_n / \sum M_n \dots\dots\dots\dots\dots (14)$$

The adjustment of different parameters is determined by local variance in distinct area. Extensive smoothing is performed during filtering when the variance value is reduced. Edges are preserved due to less smoothing in high variance within filtering window.

3.6 Enhanced Frost Filter

The improved version of Frost filter is popularly called as Enhanced Frost filer [9]. Radar image is partitioned into different target regions that are classified as homogeneous, heterogeneous and isolated. The filtering of each area is accomplished by the application of exponential weighing factor M by the following equation:

$$M_n = \exp(-DAMP * (C_i - C_u/C_{max} - C_i) * T) \dots\dots\dots (15)$$

where,
The local coefficient of variation of filter window is represented by C_i given by the followig equation:

$$C_i = S/Im \dots\dots\dots\dots\dots (16)$$

The speckle coefficient of variation (C_u) of the image is given by:

$$C_u = 1/\sqrt{ENL} \dots\dots\dots\dots\dots (17)$$

The upper speckle coefficient of variation (C_{max}) is evaluated by the following equation:

$$C_{max} = \sqrt{(1 + 2/ENL)} \dots\dots\dots\dots\dots (18)$$

The local coefficient of variation C_i within filter window is compared with speckle coefficient of variation C_u to partition the image into distinct parts and classifying into different classes.The filtered pixel value is replaced by intensity mean Im of window in the cases involving the C_i lesser thanC_u. This forms the homogeneous class. The heterogeneous class is formed when the C_i lies in the range of lower to upper speckle coefficient of variation. In this the total weighted value is used to replace filtered pixel value that is represented by the equation mentioned below:

$$Img(i,j) = \sum P_n * M_n / \sum M_n \dots\dots\dots\dots\dots (19)$$

For the purpose of preservation of image quality removal of speckles is performed in a controlled manner. The third class is formed by replacement of filtered pixel by center pixel value within the filter window which done when C_i higher than the upper thresholdC_{max}. Relatively higher edge and image texture preservation levels can be obtained by Enhanced Frost filters than Frost filtering.

3.7 Gamma/MAP Filter

Forested areas, agricultural lands and oceans are considered to be gamma distributed areas. The Gamma or Maximum A Posteriori (MAP) filters aims to eliminate the loss of information related to the texture of image of such scenes [10]. The probability density function of the coefficient of variation and contrast ratio that can be derived theoretically provides the basis for the smoothing process. MAP filters operate over this coefficient of variation and contrast ratio that makes it relatively more efficient than Lee and Frost filters. MAP algorithm is similar to Enhanced Frost filter with the only difference that value of filtered pixel. Cases that involve the local coefficient of variation C_i lying in the range of C_u and C_{max} thresholds have the value of filtered pixel determined by Gamma estimated contrast ratios within the filter window. This can be obtained by the equation mentioned below:

$$Img(i,j) = \left((W - ENL - 1) * Im + \sqrt{D}\right) / (2 * W) \dots\dots (20)$$

where,
W is the weighting function which is given by the following equation:

$$w = (1 + C_u^2)/(C_i^2 - C_u^2) \dots\dots\dots\dots\dots (21)$$

D is calculated using the equation as follows:

$$D = Im * Im * (W - ENL - 1) * (W - ENL - 1) + 4 * W * ENL * Im * C_p \dots\dots\dots\dots\dots (22)$$

The speckle coefficient of variation of filter window is represented by C_i which can be obtained by the following equation:

$$C_i = S/Im \dots\dots\dots\dots\dots (23)$$

The speckle coefficient of variation of equivalent number of looks is represented by C_u which is calculated as:

$$C_u = 1/\sqrt{ENL} \dots\dots\dots\dots\dots (24)$$

The upper speckle coefficient of variation of image is represented by C_{max} is given by the equation written below:

$$C_{max} = \sqrt{2} * C_u \dots\dots\dots\dots\dots (25)$$

When C_{max} is smaller than that of C_i value than value of center pixel is used to replace the filtered value pixel. The mean value of filter window is used to replace the filtered value pixel in case the value of C_u is greater than C_i value.

3.8 SRAD Filter

Partial Differential Equation(PDE) is used by SRAD filters to operate for achieving reducing spackles in ultrasound imaging.The image scale space is generated by the filters that are based on PDE approach. Number of filtered images are formed that vary from fine to coarse. These images then combine to form a set of images which is referred to as image scale space. The process of generating scale space does not consider size and shape of filter window. Through this filtering, smoothing of image spackles is performedthrough anisotropic diffusion methodology.The resultant image based on imput intensity image $I_0(x, y)$ with a definite power besides having image support(Ω) bearing non-zero values only is evaulated by PDE through equation mentioned below:

$$\begin{cases} \partial I(x, y; t)/\partial t = div[c(q)\Delta I(x, y; t)] \\ I(x, y; 0) = I_0(x, y), \left(\partial I(x, y; t)/\partial \underset{n}{\rightarrow}\right)/\partial\Omega = 0 \end{cases} \dots\dots\dots\dots\dots (26)$$

Here,
The border of Ω is represented by $\partial\Omega$ whose outer normal is shown by $\underset{n}{\rightarrow}$

C(q) is calculated by using the following eqaution:

$$c(q) = \frac{1}{1 + [q^2(x, y; t) - q_0^2(t)]/[q_0^2(t)(1 + q_0^2(t))]} \dots\dots\dots\dots\dots (27)$$

Or

$$c(q) = exp\{-[q^2(x, y; t) - q_0^2(t)]/[q_0^2(t)(1 + q_0^2(t))]\} \dots\dots\dots (28)$$

where,
$q_0(t)$ denotes speckle scale function, q(x,y;t) denotes the instantiationcoefficient of variation evaluated by following equation:

$$q(x, y; t) = \sqrt{\frac{\left(\frac{1}{2}\right)\left(\frac{|\Delta t|}{t}\right)^2 - \left(\frac{1}{4^2}\right)\left(\frac{\Delta^2 t}{t}\right)^2}{\left[1 + \left(\frac{1}{4}\right)\left(\frac{\Delta^2 t}{t}\right)\right]^2}} \dots\dots\dots\dots\dots (29)$$

The detection of edges in imagery is achieved through instantiation coefficient of variation q(x,y;t). The value of spackle function is high on edges and contrast features but bears significantly lower values in areas that are homogeneous.

The value of instantiation coefficient of variation varies significantly near $qq_0(tt)$ in homogeneous areas of image that clearly indicates the manipulations achieved by isotropic diffusion. The smoothing process that is performed on image by SRAD is fully controlled and monitored by speckle scale function denoted by $qq_0(tt)$. This can be approximated by using the below mentioned equation:

$$q_{\mathbf{0}}(t) = \frac{\sqrt{var\,[z(t)]}}{\overline{z(t)}} \dots\dots\dots\dots\dots (30)$$

Here,
The intensity variance is denoted by$\sqrt{var[z(t)]}$. Mean homogeneous area at point t is denoted by $\overline{z(t)}$

IV. RELATED WORK

In 2009, J. L. Mateo et al. [1] presented the comparison based study of several distinct techniques employed for achieving speckle noise elimination found in ultrasound imaging. The proposed work showed the use of Fourier filtering technique that involved Fourier transform followed by Inverse Fourier transform on the basis of single parameter in order to generate enhanced quality images. The removal of noise generated by speckle was done through the use of mean filter in Adaptive weighted mean filtering technique. The value of weights associated with it were maximum at center of filter window that kept on decreasing while moving towards outer boundaries. The noise reduction obtained by this was considerably low and caused image related information loss too. The loss of information also occurred in Wavelet filtering due to removal of certain frequency values so as to eliminate noise. The multiplicative speckle noise was converted to additive noise in homomorphic filtering which employed log transformation function along with Fourier Transform for noise removal.

In 2010, Tay PC et al. [2] proposed a work that focused upon the use of squeeze box filtering(SBF) for noise reduction which was based on iterative approach. The noise was removed by suppressing outliers as a local mean of neighborhood. A 3 × 3 sized window was used to determine image pixel outliers that were considered to be local minimums and maximums. The computed value of local mean replaced each outlier from center to the outer pixels of window. The iteration was performed after the process of replacement of all the outlier pixel still the time of convergence was attained. SBF provided enhanced image quality in terms of contrast, segmentation and structural similarity. A limitation offered by this approach was generation blurred artifacts with irregular intensity pattern.

In the same year, Ashish Khare et al. [3] presented technique for speckle reduction that employed Daubechies complex wavelet transform based algorithm. By the use of complex scaling coefficient strong edges were traced which was followed by the application of shrinkage mechanism on the value of this scaling coefficient. The coefficient was processed in its wavelet domain so as to trace the points that were not edges. The statistical parameters of adaptive natured complex wavelet coefficient determined the shrinkage mechanism. The preservation of shape and phase could be achieved by this proposed technique due to the reason that only magnitude value is manipulated by shrinkage.

In 2011, G.G. Bhutada et al. [4] introduced a methodology that classified the image regions as homogeneous, non-homogeneous or isolated on the basis of their variance. Both wavelet and curvelet transform characteristics were used for designing such technique. The curvelet transform performed the edge detection task via denoising that wavelet transform was incapable of performing. Homogeneous region were added with fuzzy edges due to denoising by Curvelet but it retained the directional information. The proposed methodologies used the combination of Curvelet transform with adaptive fusion of noise free images generated by WT-TNN.

In 2012, Parrilli S et al. [5] presented a methodology that employed the suppressing coefficients in wavelet domain caused due to presence of noise in image. This was called as Wavelet-based despeckling. The wavelet transform in 2-D was accomplished prior to the application of shrinkage function to manipulate the noisy coefficients. The last process applied 2-D inverse wavelet transform that might cause loss of image information.

In the same year, G. Andria et al. [6] introduced a technique that performed the filtering of vertical and diagonal details of image with a linear approach. This filtering was carried out by Gaussian filter. The filter was kernel sized that was determined by speckle noise amplitude.

In 2014, G Umamaheswari et al. [7] addressed the problem of denoising medical ultrasound images by suggesting the use of adaptive window hybrid median filter. The image areas determined size of window of hybrid filter. Smooth regions were distinguished from the edged ones by the sobel edge operate. Unless the center window pixel was edge pixel a window with size of 3×3 is preferred while in other cases 5×5 sized- window is selected.

In the same year, Meriem et al. [8] introduced method based on multiplicative regularization through an adaptive window. With the change in the structure of image shape, size and orientation of window also varied. The proposed technique provided non-uniform smoothing in image. To retain region boundaries relatively lower level of speckle elimination was performed in detailed regions than in homogeneous regions.

Norashikin Yahya et al. [9] presented noisy speckle removal technique based on subspace that included the conversion of multiplicative speckle noise into additive one. This conversion was performed by applying logarithmic transformation which was followed by the vector space decomposition into noise subspaces and distinct signal. The residual signal subspace was required in clean image approximation process. Clean image accompanied by nullifying the noise subspace an enhanced form of image was obtained. Image distortion which was achieved through linear approximation was required to be minimum while the remaining noise energy was kept within limits of specified threshold.

S. Bama et al. [10] introduced a method for speckle reduction that was modeled the coefficients in wavelet domain. After modeling of coefficients was performed they were exposed to diffusion filtering. Curvelet transform that was entirely un-decimated Atrous based was evaluated. Shrinkage function for curvelet transform application on coefficients was determined by MAP approximation. A portion of curvelet coefficient was filtered by Perona Malik Anisotropic Diffusion filter (PMAD). Rest of the coefficient was applied with shrinkage function for modeling purpose. Besides retaining the prominent contents of image considerable noise reduction levels could be achieved through PMAD which was scale space transformation. Through successive convolution of image with diffusion filter each image was formed individually.

This process preserves the key information in the original image and removes the speckle noise. Therefore, significant information was preserved with less noisy speckles.

In 2015, JuZhanga et al. [11] presented the study of faster bilateral filter that operated over wavelet transformation. Laplace distribution was the generalized form of modeled wavelet coefficients of noise-free signal whereas Gaussian distribution was modeled form of speckle noise. To achieve wavelet shrinkage function Bayesian maximum a posteriori was required to suppress the high-pass components of noisy speckle in wavelet domain. In order to perform the suppressing of low frequency components of noisy speckle fast bilateral filter were employed.

In the same year, Xiaowei Fu et al. [12] proposed the algorithm that was based on an adaptive DTCWT for the purpose of removing speckles. The proposed technique used adaptive threshold function which was quantum inspired. A new quantum- inspired function was generated by the use of coefficients in dual-tree complex wavelet transform domain. The noisy speckles were removed by the process that required this threshold function to combine with Bayesian framework.

Ju Zhang et al. [13] presented the comparison based study of different filters that were capable of removing speckles. The proposed study showed the results of despeckling ultrasound images of breast by distinct filters. Those filters were distinguished into different classes such as anisotropic diffusion filter, multi-scale filter, local adaptive filter, non-local means filter and hybrid filter. Prior to the filtering of image, Rayleigh distribution followed by the logarithmic transformation was applied in order to transform multiplicative noise into additive one. The modeling of noisy speckles was done by Gaussian distribution. Blind image quality metric (NIQE) was used for measuring image quality.

Deep Gupta et al. [14] introduced a technique for eliminating the speckle noise which was based on discrete ripplet transform (DRT) and required no-linear bilateral filter(NLBF). Various characteristics such as localization, directionality, multi-scale and anisotropy were described by DRT technique. Representation of noisy coefficients by ripplet transformation that was higher dimensional generalized form of curvelet transform proved to be much more efficient. The soft and NeighShrink thresholding algorithms were employed for thresholding DRT coefficients for evaluating performance. Preservation of edges was achieved by the application of bilateral filter on noisy ripplet coefficient. This improved the efficiency level of denoising. The value of weighted sum of neighboring pixels was used to replace each pixel value in bilateral filtering process that included domain filter and range filter. Pratt's figure of merit (FOM) along with edge keeping index (EKI) determines the level of edge preservation.

V. CONCLUSION AND FUTURE SCOPE

The survey has conducted in this paper, which concludes that all standard speckle filters performed well. However, they have some constraints as resolution degradation. In addition to this, some artifacts such as blurred edges and irregular intensity pattern are retained in the filtered image. Considering, an effective and simple approach can be proposed in future to preserve original image's quality.

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