Performance Comparison of Different Despeckled Filters for Ultrasound Images

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ABSTRACT

Ultrasound (US) is an economical, non-ionizing, transferable, and adaptable imaging technique which have a major role in diagnosing the diseases and in image guided surgery. But due to higher frequency absorbed by tissue and skin it cannot penetrate deeply in comparison to lower frequency. So, it gives degraded quality image by echo signals and we get an inferior quality noisy image with some clinical information loss. There are various filters which despeckle the noisy US image and preserve the clinical details. In this paper, we compare the performance of four despeckle filters: Median filter, Lee Filter, Frost Filter, and Speckle Reducing Anisotropic Diffusion (SRAD) Filter in terms of peak signal to noise ratio (PSNR) and structural similarity index measure (SSIM) performance index. We have selected two parameters as: window size (3x3, 5x5, 7x7, for all iteration number 10) and number of iteration (20, 30, 40, for all window size 3x3) for performance comparison. Finally, we have seen that SRAD filter is more efficient for removing Speckle noise in comparison to other stated filters, but the performance of median filter is also good enough for speckle noise reduction.

Keywords: Ultrasound imaging, SRAD filter, Meadian filter, Lee filter, Frost filter.

INTRODUCTION

In recent years, significant technological advancements and progress in image processing in a number of areas have been achieved, however, still a number of factors in the visual quality of images, hinder the automated analysis [16], and disease evaluation [17]. These include imperfections of image acquisition instrumentations, natural phenomena, transmission errors, and coding artifacts, which all degrade the quality of image in the form of induced noise [18 – 22].

US Imaging is a boon technology which have a major role in diagnosing the diseases and in image guided surgery. US is economical, comparatively safe, transferable, and adaptable imaging technique. Though, one of its main shortcomings is the poor quality of images, which are affected by speckle noise. Speckle noise is multiplicative behavior in nature. Due to this behavior, Doctor/Radiologist feel uncomfortable in diagnosis of a patient because of sometimes clinical details looks like speckle noise or, sometimes speckle noise look like clinical details. That's why despeckling is very important in US imaging. Despeckling is a pre-processing step for feature extraction, analysis, and recognition, etc. from medical imagery measurements. There are various filters for despeckling at pre-processing stage. But, we select four filters as Median filter, Lee Filter, Frost Filter, and SRAD filter for despeckling which have done filtering in spatial domain. We have

tested these filters for images shown in figure (1) and obtain their performance. The important property of image despeckling filter is that it should completely remove speckle noise with preserving edges.

Basically, here the performance of these filters is measured by peak signal to noise ratio (PSNR) and structural similarity index measure (SSIM) performance index. We have selected two parameters as: window size (3x3, 5x5, 7x7, for all iteration number 10) and number of iteration (20, 30, 40, for all window size 3x3) for performance comparison of these filters. This is the freshness of the work.

BACKGROUND

Speckle noise model

Here, we represent g(x,y,z) the degraded quality image, ξ(x,y,z) the noise which degraded the quality of the image and introduced in image during acquisition process, f(x,y,z) the original image (noisy image i.e. that we want to restore). During some image acquisition process, such as MRI, additive noise introduced which is represented by Gaussian variable of zero mean and a given standard deviation. Mathematically, the additive noise degraded quality image can be represented by [9]:

$$g(x,y,z)=f(x,y,z)+\xi(x,y,z) \qquad ...(1)$$

And, during some image acquisition process such as US imaging, multiplicative noise, known as speckle, introduced which is represented by variable of mean and standard deviation. Mathematically, the speckle noise degraded quality image can be represented by:

$$g(x,y,z)=f(x,y,z)n(x,y,z)+\xi(x,y,z) \qquad ...(2)$$

where, and are multiplicative and additive noise component respectively. As, [2] we see the effect of additive noise behavior is very small in compared to multiplicative noise behavior. So, we neglect the additive noise behavior in speckle noise, then simplified model which is mathematically expressed as:

$$g(x,y,z)=f(x,y,z)n(x,y,z) \qquad ...(3)$$

Median Filter for Speckle

The median filter is a non-linear image denoising technique. This filtering technique is good for reduction of speckle noise. This technique is used as a pre-processing step to improve the result of later processing. This filtering technique is most widely used in image processing because it preserves edges of the image and removes noise portion only. This filter is to run through the image pixel by pixel, replacing each pixel value with the median of neighboring pixels, instead of the average of all neighboring pixels. The pattern of neighbors is called the "window", which slides, pixel by pixel, over the entire image. Most smoothing techniques are effective for image denoising in smooth patches/regions, but does not preserve the edge information [10]. the median filter is implemented as:

$$f(x,y,z)=median \{g(s,t,u),(s,t,u)\in S_{(x,y,z)} \} \qquad ...(4)$$

where, depends on the ordering of pixel values of in the window . be the input degraded quality image, be the output denoised image, and be a neighborhood of pixels defined by:

$$S_{(x,y,z)}= \{(x+s,y+t,z+u),-a\leq s\leq a,-b\leq t\leq b,-c\leq u\leq c)\} \qquad ...(5)$$

of size m*n, where are positive integers.

LEE Filter for Speckle

The Lee filter reduces the speckle noise by applying a spatial filter to each pixel in an image, which filters the data based on local statistics calculated within a square window. The value of the center pixel is replaced by a value calculated using the neighboring pixels [11]. This pointwise linear filter is based on the minimum mean square error (MMSE), and produced speckle noise free image based on the following equation (value of filtered pixel):

$$f(x,y,z)=L\_M+ K*(P\_C-M*L\_M) \qquad ...(6)$$

where, $K = M * \dfrac{L_V}{\left((L_M^2 * MV)+(M^2 * L_V)\right)}$ and $MV = \dfrac{1}{NLooks}$ and K= weight function,

P_c—Center pixel value of kernel/window (Median value)

L_M—Local mean of filter window

L_V—Local variance of filter window

M—Multiplicative noise mean (Default value: 1)

MV—Multiplicative noise variance (Default value: 0.25)

Table 1: PSNR and SSIM Results on Performance comparison of different filters for image 1

	PSNR	SSIM
w=3, Iteration = 10		
LEE Filter	23.889	0.63966
Frost Filter	23.8795	0.632
SRAD Filter	25.7362	0.77948
Median Filter	24.3214	0.67509
w=5, Iteration = 10		
LEE Filter	23.4234	0.61548
Frost Filter	23.3748	0.59612
SRAD Filter	25.7437	0.79748
Median Filter	24.4718	0.6832
w=7, Iteration = 10		
LEE Filter	23.0825	0.60298
Frost Filter	23.0267	0.57206
SRAD Filter	25.8662	0.80847
Median Filter	25.1432	0.6995
w=3, Iteration = 20		
LEE Filter	23.5837	0.61661
Frost Filter	23.5621	0.60863
SRAD Filter	43.7895	0.9745
Median Filter	23.7861	0.6123
w=3, Iteration = 30		
LEE Filter	23.3994	0.60459
Frost Filter	23.3757	0.5953
SRAD Filter	44.8842	0.9923
Median Filter	24.0041	0.6437
w=3, Iteration = 40		
LEE Filter	23.2611	0.5955
Frost Filter	23.2391	0.58599
SRAD Filter	45.0808	0.9966
Median Filter	24.2921	0.67221

Nlooks: Number of looks (Specifies the number of looks of the image. This is used to calculate the Multiplicative noise variance and control the amount of smoothing applied to the image. Using a smaller value for the Number of Looks leads to more smoothing, and a larger value preserves more image features [12].)

The for a homogeneous region of an image is the ratio between the mean squared to the variance. The is defined as follows:

$$NLooks = \frac{L_M^2}{L_V^2}$$

The local mean L_M of filter window is defined as (from eq. (5)):

$$L_M = \frac{1}{(2a+1)(2b+1)(2c+1)} \sum_{x-a}^{x+a} \sum_{y-b}^{y+b} \sum_{z-c}^{z+c} [f(x,y,z)]$$

...(7)

Similarly, the local variance L_V of the filter window is defined as:

$$L_V = \frac{1}{(2a+1)(2b+1)(2c+1)} \sum_{x-a}^{x+a} \sum_{y-b}^{y+b} \sum_{z-c}^{z+c} [f(x,y,z) - L_M]$$

...(8)

From eq. (8), if value of is negative, in that case we have a very homogeneous area, should be set to zero. Then estimate is given by the local mean . If value of is very high, this indicates a very high contrast region (or, an edge presence) and = . These extreme cases are in accordance with the Bayesian approach that is adopted in this linear MMSE filter [1].

FROST Filter for Speckle

The FROST filter is used to design an adaptive filter algorithm to reduce speckle noise in spatial domain and computationally very efficient. This filter preserves the important features of image at the edges. It is a MMSE convolutional filter for speckle reduction. The Frost filter is an exponentially damped circularly symmetric filter that uses local statistics within individual filter windows. The pixel being filtered is replaced with a value calculated based on the distance from the filter center, the damping factor, and the local variance. The Frost filter requires a damping factor (define the extent

of smoothing). The Damping Factor value defines the extent of exponential damping. The smaller the value is, the better the smoothing ability and filter performance. After application of the Frost filter, the denoised images show better sharpness at the edges [3], [7], [11], [13]. The algorithm used in the implementation of the Frost filter is as follows: From eq. (6):

$$\hat{f}(x, y, z) = L_M + K * P_C$$

where, $K = e^{-(B \cdot S)}$, where, $B = D * \left(\frac{L_V}{L_M^2}\right)$, and S—Absolute value of the pixel distance from the center pixel to its neighbors in the filter window, D—Exponential damping factor (Default value:1)

The factor D is chosen such that when in a homogeneous region, B approaches zero, yielding the mean filter output; at an edge B becomes so large that filtering is inhibited completely [7].

Speckle Reducing Anisotropic Diffusion (SRAD) Filter

SRAD is a partial differential equation (PDE) technique for image enhancement and denoising. SRAD smooths the imagery and enhances edges by inhibiting diffusion across edges and allowing isotropic diffusion within homogeneous region [15]. Diffusion is a physical process to create equilibrium concentration differences without destroying or, creating body mass. This physical observation expressed equilibration property by Fick's law of diffusion equation [4]:

$$\frac{\partial u(x,y,z;t)}{\partial t} = \nabla \cdot \left(D(x,y,z;t) \nabla u(x,y,z;t) \right)$$
$$= \frac{\partial}{\partial x}\left(D(x,y,z;t) \times \frac{\partial}{\partial x} u(x,y,z;t) \right)$$
$$+ \frac{\partial}{\partial y}\left(D(x,y,z;t) \times \frac{\partial}{\partial y} u(x,y,z;t) \right)$$
$$+ \frac{\partial}{\partial z}\left(D(x,y,z;t) \times \frac{\partial}{\partial z} u(x,y,z;t) \right)$$

with initial condition $u_0(x,y,z) = u(x,y,z; t=0)$ which is noisy image/input image. $u(x,y,z;t)$ is the output image. D is diffusion coefficient, known as symmetric positive definite tensor, which depend on local structure of (if D is constant, then filter is isotropic diffusion filter and if D is not constant, then filter is anisotropic diffusion filter) and and denote the divergence operator and gradient operator, respectively, is the initial image, i.e. noisy image, t is temporal variable. Eq. (9), Linear Anisotropic Diffusion (LAD), is an elliptic Partial Differential Equation (PDE). Here, is a given field of symmetric positive definite diffusion tensors where &! is an open region of and is boundary of &!. Eigenvectors of these tensors define preferential diffusion directions, and the Eigenvalues their corresponding coefficients.

Table 2: PSNR and SSIM Results on Performance comparison of different filters for image 2

	PSNR	SSIM
w=3, Iteration = 10		
LEE Filter	27.6073	0.71911
Frost Filter	27.1898	0.70044
SRAD Filter	30.4787	0.82994
Median Filter	29.7661	0.86084
w=5, Iteration = 10		
LEE Filter	25.7121	0.6231
Frost Filter	25.4078	0.58327
SRAD Filter	29.8732	0.8011
Median Filter	29.5625	0.8241
w=7, Iteration = 10		
LEE Filter	24.8834	0.58895
Frost Filter	24.5747	0.53582
SRAD Filter	29.2547	0.7961
Median Filter	29.1321	0.8019
w=3, Iteration = 20		
LEE Filter	26.1317	0.63893
Frost Filter	25.9914	0.6208
SRAD Filter	29.5088	0.85245
Median Filter	26.0687	0.62511
w=3, Iteration = 30		
LEE Filter	25.4983	0.60145
Frost Filter	25.4248	0.58355
SRAD Filter	31.5179	0.95269
Median Filter	26.6608	0.65966
w=3, Iteration = 40		
LEE Filter	25.1159	0.57862
Frost Filter	25.0607	0.56113
SRAD Filter	34.5492	0.97378
Median Filter	27.7395	0.71693

Evolution rule eq. (9) is complemented with an initial condition   at time t = 0. If has pixels of vector type, then their components are treated independently [6].

By using finite difference method, eq. (9) given as:

$$\frac{\partial}{\partial x}\left(D(x,y,z;t)\times\frac{\partial}{\partial x}u(x,y,z;t)\right)$$

which is expressed as

$$\frac{\partial}{\partial x}\left(D(x,y,z;t)\times\frac{\partial}{\partial x}u(x,y,z;t)\right)$$

$$\approx \frac{\partial}{\partial x}\left\{D(x,y,z;t)\frac{1}{\Delta x}[u(x+\Delta x,y,z;t)-u(x,y,z;t)]\right\}$$

$$\approx \frac{1}{\Delta x^2}\left\{ \begin{array}{l} D(x,y,z;t)\begin{bmatrix}u(x+\Delta x,y,z;t)-u(x,y,z;t)\\ -u(x,y,z;t)+u(x-\Delta x,y,z;t)\end{bmatrix}\\ +[D(x+\Delta x,y,z;t)-D(x,y,z;t)]\begin{bmatrix}u(x+\Delta x,y,z;t)\\ -u(x,y,z;t)\end{bmatrix}\end{array}\right\}$$

$$\approx \frac{1}{\Delta x^2}\left\{\begin{array}{l}D(x+\Delta x,y,z;t)[u(x+\Delta x,y,z;t)-u(x,y,z;t)]\\ +D(x,y,z;t)[u(x-\Delta x,y,z;t)-u(x,y,z;t)]\end{array}\right\}$$

where "$\approx$" shows that the R.H.S. part of the equation is the difference approximation of the
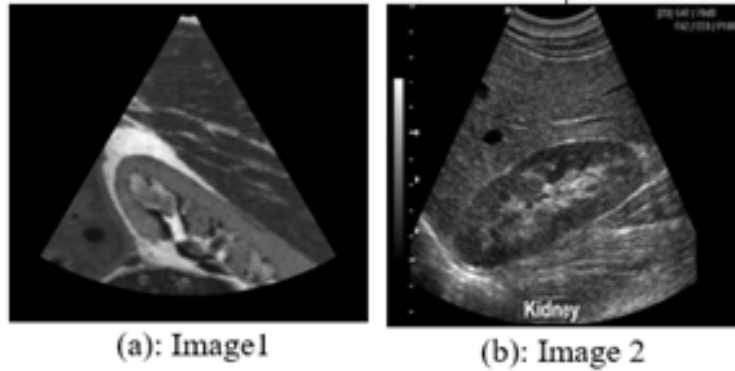

(a): Image1   (b): Image 2

**Fig. 1: Experiment results obtain from
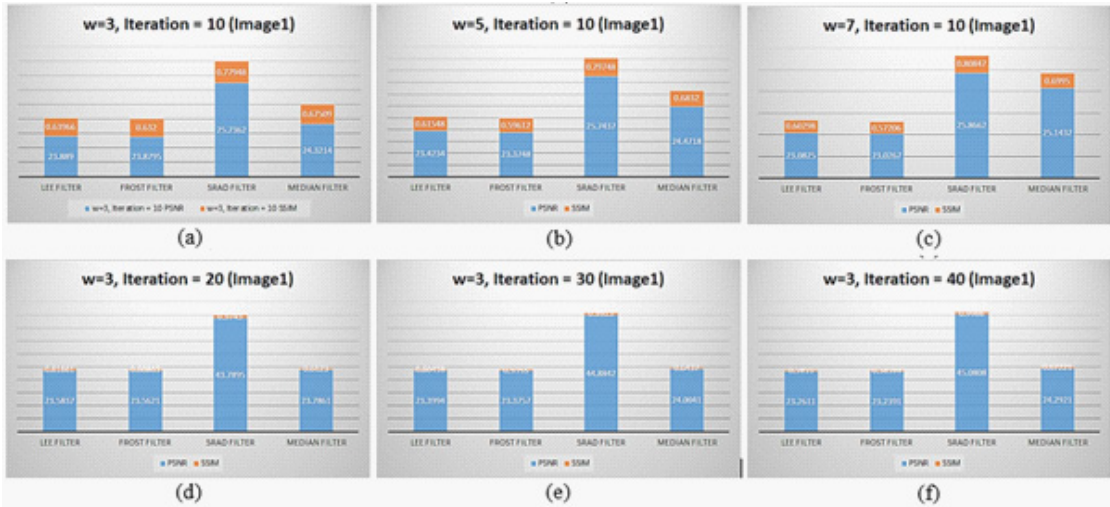real B-mode US image of human kidney**

**Fig. 2: The graphs are plotted for PSNR and SSIM result values for different filters (Image1). These
graphs show that SRAD filter is more efficient for removing Speckle noise,but the performance of
median filter is also good enough for Speckle noise reduction**

L.H.S. part.
Similarly, we have

$$\frac{\partial}{\partial y}\left(D(x,y,z;t) \times \frac{\partial}{\partial y}u(x,y,z;t)\right)$$

$$\approx \frac{1}{\Delta y^2}\left\{ \begin{array}{l} D(x,y+\Delta y,z;t)[u(x,y+\Delta y,z;t)-u(x,y,z;t)] \\ + D(x,y,z;t)[u(x,y-\Delta y,z;t)-u(x,y,z;t)] \end{array}\right\}$$

...(11)

and

$$\frac{\partial}{\partial z}\left(D(x,y,z;t) \times \frac{\partial}{\partial z}u(x,y,z;t)\right)$$

$$\approx \frac{1}{\Delta z^2}\left\{ \begin{array}{l} D(x,y,z+\Delta z;t)[u(x,y,z+\Delta z;t)-u(x,y,z;t)] \\ + D(x,y,z;t)[u(x,y,z-\Delta z;t)-u(x,y,z;t)] \end{array}\right\}$$

...(12)

All the values of eq. (10), eq. (11), and eq. (12) inserting in eq. (9) to obtain difference approximation of $\frac{\partial u(x,y,z;t)}{\partial t}$. Put $\Delta x = 1$, $\Delta y = 1$, and $\Delta z = 1$ we get:

$$\frac{\partial u(x,y,z;t)}{\partial t}$$

$$\approx \left\{ \begin{array}{l} D(x+1,y,z;t)[u(x+1,y,z;t)-u(x,y,z;t)] \\ + D(x,y,z;t)[u(x-1,y,z;t)-u(x,y,z;t)] \end{array}\right\}$$

$$+ \left\{ \begin{array}{l} D(x,y+1,z;t)[u(x,y+1,z;t)-u(x,y,z;t)] \\ + D(x,y,z;t)[u(x,y-1,z;t)-u(x,y,z;t)] \end{array}\right\}$$

$$+ \left\{ \begin{array}{l} D(x,y,z+1;t)[u(x,y,z+1;t)-u(x,y,z;t)] \\ + D(x,y,z;t)[u(x,y,z-1;t)-u(x,y,z;t)] \end{array}\right\}$$

...(13)

So, obtaining discrete realization of anisotropic diffusion filter for $u(x,y,z;t)$ image from eq. (13):

$$u(x,y,z;t+1) = u(x,y,z;t)$$

$$+ \left\{ \begin{array}{l} D(x+1,y,z;t)[u(x+1,y,z;t)-u(x,y,z;t)] \\ + D(x,y,z;t)[u(x-1,y,z;t)-u(x,y,z;t)] \end{array}\right\}$$

$$+ \left\{ \begin{array}{l} D(x,y+1,z;t)[u(x,y+1,z;t)-u(x,y,z;t)] \\ + D(x,y,z;t)[u(x,y-1,z;t)-u(x,y,z;t)] \end{array}\right\}$$

$$+ \left\{ \begin{array}{l} D(x,y,z+1;t)[u(x,y,z+1;t)-u(x,y,z;t)] \\ + D(x,y,z;t)[u(x,y,z-1;t)-u(x,y,z;t)] \end{array}\right\}$$

...(14)

In eq. (14), we can see that the major problem is selection of diffusion coefficient $D(x,y,z;t)$ in anisotropic diffusion filter.

Most of the diffusion filters are simply modifications of perona-malik filter [5] where D is constant (scalar coefficient based on gradient of the image $D\nabla u(x,y,z;t)$ which avoids diffusion near the boundaries and applies it in homogeneous areas). To create a speckle imagery affected smooth region [7] propose a new anisotropic diffusion filter Speckle reducing anisotropic diffusion (SRAD). SRAD selects finite power intensity image $u_0(x,y,z)$ and having none zero-valued intensities over the image domain &!, and we get the output image $u(x,y,z;t)$ by following PDE:
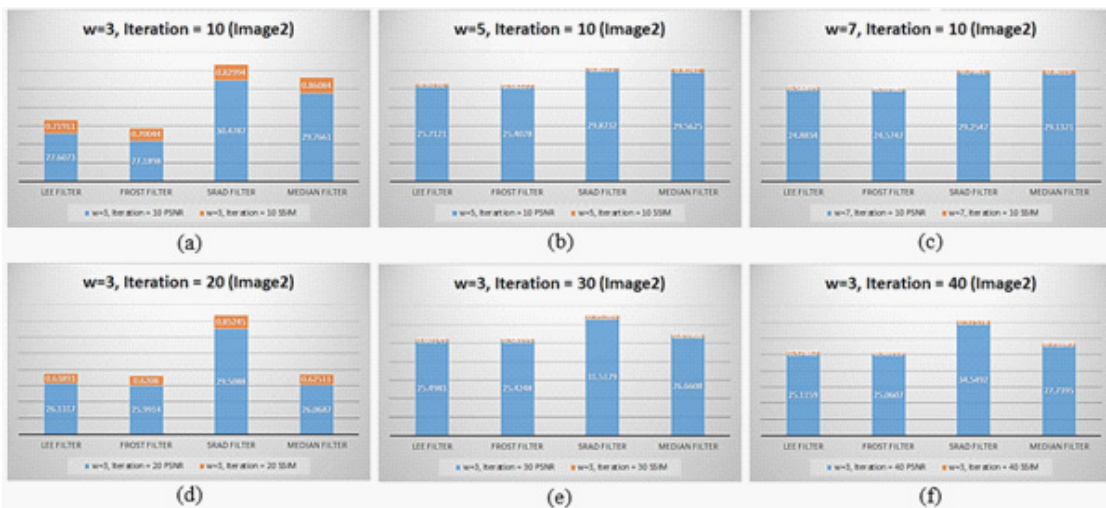

Fig. 3: The graphs are plotted for PSNR and SSIM result values for different filters (Image2). These graphs show that SRAD filter is more efficient for removing Speckle noise, but the performance of median filter is also good enough for Speckle noise reduction

$$\begin{cases} \frac{\partial u(x,y,z;t)}{\partial t} = \nabla \cdot [C(q) \nabla u(x,y,z;t)] \\ u(x,y,z;0) = u_0(x,y,z) \\ \frac{\partial u(x,y,z;t)}{\partial \vec{n}} \Big|_{\partial n} = 0 \end{cases}$$

...(15)

where $\partial\Omega$ denotes the boundary of &!, $\vec{n}$ is the outer normal to the , and is coefficient of diffusion which is defined as a decreasing function of the instantaneous coefficient of variation. Eq. (15) is known as SRAD PDE.

$$C(q) = \frac{1}{1 + \frac{q^2(x,y,z;t) - q_0^2(t)}{q_0^2(t)[1 + q_0^2(t)]}}$$

...(16)

$$C(q) = \exp\left[-\left\{\frac{q^2(x,y,z;t) - q_0^2(t)}{q_0^2(t)(1 + q_0^2(t))}\right\}\right]$$

...(17)

In eq. (16) and (17), $q(x,y,z;t)$ is the instantaneous coefficient of variation serves as the edge detector in speckled imagery, $q_0(t)$ is the speckle scale function and is estimation parameter related to the coefficient of variation of noise. is determined by:

$$q(x,y,z;t) = \sqrt{\frac{\frac{1}{3}\left(\frac{|\nabla u(x,y,z;t)|}{u(x,y,z;t)}\right)^2 - \left(\frac{1}{6}\right)^2 \left(\frac{\nabla^2 u(x,y,z;t)}{u(x,y,z;t)}\right)^2}{\left[1 + \left(\frac{1}{6}\right)\left(\frac{\nabla^2 u(x,y,z;t)}{u(x,y,z;t)}\right)\right]^2}}$$

...(18)

In case of 2-D, instantaneous coefficient of variation $q(x,y;t)$:

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

...(19)

EXPERIMENTAL RESULTS

Images

We consider the two 'true' B-Mode US image of human kidney presented in [8] and [14] are used in this experiment, shown in figure 1. This real US image is used for quantitative analysis. The size of the both 'true' B-Mode US image of human

kidney is 522x469x24 (figure 1(a)) and 640x445x24 (figure 1(b)) (in pixel unit) in x, y, and z directions respectively. For experiment purpose, we add speckle noise in both images with standard deviation ó = 0.4.

Two performance metrics were used in our experiments to measure the algorithm performance, one is called Peak Signal to Noise Ratio (PSNR) which is used for accuracy and precision of the 'true' image and other is called Structural Similarity Index Measure (SSIM) which is used for quality similarity between two images (original image and filtered image) [9].

Results

We select different parameter to compare the performance of four filters, named: Median filter, Lee Filter, Frost Filter, and SRAD filter. Initially, we fixed iteration number on 10, and vary window size as 3x3, 5x5, and 7x7. Then, fixed window size on 3x3 and vary iteration number as 20, 30, and 40. Table – 1 and Table – 2 show performance of these different spatial filters in removing the speckle noise in image 1 and image 2 respectively, in terms of PSNR and SSIM performance index. The graphs show in figure 2 and figure 3 that SRAD filter is more efficient for removing Speckle noise in comparison to other stated filters, but the performance of median filter is also good enough for speckle noise reduction.

CONCLUSIONS

In this paper, we present a quantitative analysis of four filters: named: Median filter, Lee Filter, Frost Filter, and SRAD filter. These filters are used for speckle noise reduction. The performance analysis of these filters measure on the basis of the performance index PSNR and SSIM under different parameter selection. We have selected two parameters as: window size (3x3, 5x5, 7x7, for all iteration number 10) and number of iteration (20, 30, 40, for all window size 3x3) for performance comparison. After the quantitative analysis and with the help of corresponding result graphs, we have concluded that SRAD filter is more efficient for removing Speckle noise in comparison to other stated filters, but the performance of median filter is also good enough for speckle noise reduction.

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