

A Novel Approach for Speckle Reduction and Enhancement of Ultrasound Images

Shruthi G

Department of ECE, R N Shetty
Institute of Technology
Channasandra, Bangalore-61

Usha B S

Department of ECE, R N Shetty
Institute of Technology
Channasandra, Bangalore-61

Sandya S

Department of ECE, R N Shetty
Institute of Technology
Channasandra, Bangalore-61

ABSTRACT

In recent years, ultrasonography is being used for effective diagnosis of various organs such as the heart, kidney, prostate, liver, ovary, uterus, thyroid glands etc. Unfortunately, one of its shortcomings is the low contrast, high noise images which are an inevitable byproduct. This is due to an artifact known as “Speckle” which obscures fine details in an image and may lead to erroneous diagnosis. Hence Speckle Filtering is a prerequisite in ultrasonography, provided that the features of interest for diagnosis are not lost. This paper presents a Hybrid and multistage Filtering approach in order to reduce the Speckle noise and improve the visual quality for better diagnosis. The performance of our approach is compared with the other Speckle reduction Filters on the basis of image quality parameters like Peak Signal to Noise Ratio (PSNR), Effective Number of Looks (ENL), Image Quality Index (IQI) and Mean Structure Similarity Index Map (MSSIM). We could achieve in Multistage approach a better performance with higher value of PSNR (79.915), IQI (0.9497), MSSIM (0.9945) and ENL (0.0984) compared to Hybrid Filter.

General Terms

Ultrasound Image, Speckle Noise, Linear Filter, Non-linear Filter

Keywords

Spatial Filter, Hybrid Filter, Multistage Filter, Matlab

1. INTRODUCTION

Ultrasound imaging techniques are widely used in medical diagnosis. It is advantageous as it is non-invasive, safe, affordable, high acceptance by patients and an added advantage of portability of the ultrasound machine. But the images produced by ultrasonography are of poor quality and low contrast. Degradation of the image quality is due to the presence of artifacts such as dropout/shadowing, reverberation, Speckle, noise, clutter which may be a source of confusion for the interpreting physician. Among these Speckle noise is the major contributor to the low quality of the image which is visible in all ultrasound images as a granular noise that is spread throughout the image [1].

In Ultrasound Imaging Technique, the images are produced by interfering echoes of a transmitted waveform that are reflected from the organ being diagnosed. These echoes coming with random phases tends to superimpose constructively and destructively to form an interference pattern, known as Speckle noise [1]. It tends to obscure and mask diagnostically important details, thereby distracting the diagnosis. Hence, Speckle reduction is one of the critical pre-processing techniques to improve the image quality and possibly the diagnostic potential of medical ultrasound imaging.

This paper is organized as follows: Section 2 provides the mathematical model for Speckle noise. Section 3 discusses various Speckle reduction filters for ultrasound medical images. Section 4 discusses Filter assessment parameters. Section 5 provides experimental results and discussion. Section 6 provides Hybrid/Multistage filtering approach. Section 7 concludes this paper.

2. MATHEMATICAL MODEL FOR SPECKLE NOISE

The nature of Speckle noise pattern in ultrasound imaging depends on the number of scatters per resolution cell, spatial distribution and characteristics of the imaging system. Based upon these, the Speckle pattern is categorized into fully formed Speckle (Rayleigh distribution), non-randomly distributed Speckle with long order range (k-distribution) and with short range order (Rician distribution) [2]. Most of the studies on Speckle in ultrasound imaging reveals it as a fully formed Speckle and can be modelled as multiplicative noise. This is given by [3],

$$f(x, y) = Z(x, y) * u(x, y) + \alpha(x, y) \quad (1)$$

Where $f(x, y)$ is the noisy image and $Z(x, y)$ denotes the intensity of the image without Speckle, $u(x, y)$ and $\alpha(x, y)$ are the multiplicative and additive noise components. In ultrasound images the multiplicative noise component $u(x, y)$ is prominent and hence the primary goal of this work is to remove $u(x, y)$ with preservation of fine details in the image for proper diagnosis. Hence, equation (1) can be simplified as

$$f(x, y) = Z(x, y) * u(x, y) \quad (2)$$

3. SPECKLE REDUCTION METHODS

The Speckle reduction Filters can be classified as Spatial domain and Frequency domain Filters. The Spatial domain Filter involves modification of pixels on the image itself. The Frequency domain Filter involves filtering in the transform domain.

Spatial domain Filters are preferred because it is easier to implement on real-time systems and they work faster than other methods like multi-resolution or wavelets based Filters. The Spatial domain Filters are classified into Linear and nonlinear Filters [3]. Let $g(x, y)$ and $f(x, y)$ be despeckled and original images respectively.

3.1 Linear Filters

Linear filtering is filtering method in which the value of an output pixel is a linear combination of the values of the pixels in the input pixel's neighbourhood. The Linear filters considered for Speckle reduction are *Mean filter*, *Adaptive weighted mean Filter*, *Switching based Adaptive Weighted*

Mean Filter and Convolution based Filters like Gaussian, bilateral Filters.

3.1.1 Mean Filter

It is widely used for removal of additive noise and less effective for multiplicative Speckle noise [4]

$$g(x, y) = \frac{1}{mn} \sum_{s,t \in S_{xy}} f_{s,t} \quad (3)$$

Where, S_{xy} represents the set of coordinates in a rectangular sub image window of size $m \times n$ centered at (x, y) .

3.1.2 Adaptive Weighted Mean Filter

It is based on local statistics such as mean, variance and standard deviation. This will effectively preserve the edges and features of the image. The standard adaptive mean filters for Speckle reductions are based on the multiplicative model. The Filters considered are *Lee, Frost and Kuan Filter*.

3.1.2.1 Lee Filter

Lee is used primarily to filter Speckled data [5]. A simple Lee Filter is described by the following equations:

$$g(x, y) = f_{mean} + k|f(x, y) - f_{mean}| \quad (4)$$

Where k is a weighing function which ranges between 0 & 2.

$$g(x, y) = \begin{cases} f_{mean} & k = 0 \\ f_{i,j} & k = 1 \\ f_{mean} + k|f(x, y) - f_{mean}| & k = 2 \end{cases}$$

The Lee Filter works as follows:

If the variance over an area is low or constant, then the smoothing will be performed. Otherwise, smoothing will not be performed.

3.1.2.2 Kuan Filter

Kuan Filter smoothens the image with preservation of sharp details in an image [6]. Kuan Filter is given by

$$g(x, y) = f_c(x, y) * W(x, y) + f_m(x, y) * (1 - W) \quad (5)$$

Where,

$$W = 1 - \frac{C_u^2}{(C_i^2 + C_u^2)}$$

$$C_u = \sqrt{\frac{1}{ENL}}$$

$$C_i = S/I_m$$

f_c = center pixel in filter window, f_m = mean value of intensity within window, S = standard deviation of intensity within window.

3.1.2.3 Frost Filter

It is an exponentially damped circularly symmetric filter that uses local statistics while preserving edges in ultrasound images. The replacement of pixel is based on the distance from the filter center, the damping factor, and the local variance. Frost filter expression is given by [7]:

$$g(x, y) = e^{-kC_i^2(x', y')(x, y)} \quad (6)$$

Where k is a constant controlling the damping rate, and (x', y') denotes the pixel to be filtered. It is seen that when the variation coefficient ($C_i(x', y')$) is small, the filter behaves

like a Low Pass Filter when k is large it has a tendency to preserve the original observed image.

3.1.3 Switching Based Adaptive Weighted Mean Filter (SAWM)

It is able to filter the noise from image even when the SNR is $> 60\%$. This filter is good in preserving the details of the image. It works in two phases [8]:

- i) Detect the noisy pixel using directional difference based noise detector.
- ii) For the detected noisy pixel, filtering is done using adaptive weighted mean Filter. SAWM is given by following equations:

The set of noisy pixels $S_{x,y}$ in $W_{(x,y)}$ of image $f_{(x,y)}$ is defined as

$$S_{x,y} = \{(x + s, y + t) | (x + s, y + t) \in W_{x,y} \wedge (f_{(x+s,y+t)} \leq F_r \vee f_{(x+s,y+t)} \geq F_{z-r+1})\}$$

Where Z is the size of the window, s and t represents the step size and r ranges from 1 to $(Z - 1)/2$

To discriminate between noisy pixel and edge pixel, four sub windows are taken. For each sub window, the weighted mean value of the difference between centre pixel and its neighboring pixels is calculated. The minimum of four absolute weighted mean values is determined by

$$D_{x,y} = \min \{ | \bar{a}_{x,y}^k | \mid 1 \leq k \leq 4 \} \quad (7)$$

If centre pixel is noisy, then $D_{x,y}$ will take a larger value. If the centre pixel is noise-free, then $D_{x,y}$ will take small value. Thus it can be seen that $D_{x,y}$ with threshold T is used to detect pixel as noisy or noise-free. The detected noisy pixels are processed through adaptive weighted mean Filter. The output of SAWM can be represented by

$$g(x, y) = b_{x,y} * f'_{x,y} + (1 - b_{x,y}) * f_{x,y} \quad (8)$$

Where $b_{x,y}$ is the binary flag (1 for noisy pixel and 0 for noise-less pixel), $f'_{x,y}$ is the weighted mean of noise-free pixels in the filtering window.

3.1.4 Gaussian Smoothing

The Gaussian Smoothing operator is used to 'blur' images and remove noise. It uses a different kernel that represents the shape of a Gaussian ('bell-shaped') hump [4]. An isotropic (*i.e.* circularly symmetric) Gaussian has the form

$$g(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (9)$$

The idea of Gaussian smoothing is to use this 2-D distribution as a 'point-spread' function, and this is achieved by convolution.

3.1.5 Bilateral Filter

It is a convolution based Linear Filter. There are many types of bilateral Filters depending on the choice of weighting functions. For Gaussian based bilateral Filter, it can be expressed as [9-11]:

$$\overline{g(X)} = \frac{1}{C} \sum_{Y \in N(X)} e^{-\frac{||Y-X||^2}{2\sigma_d^2}} e^{-\frac{||g(Y)-g(X)||^2}{2\sigma_r^2}} \quad (10)$$

Where $\overline{g(X)}$ is the output pixel value, $g(Y)$ is the input pixel values, X and Y are the coordinates vectors, and σ_d^2 & σ_r^2 are the parameters controlling the fall-off of weights in Spatial and intensity domains, respectively, $N(X)$ is a Spatial neighborhood of pixel $g(X)$, $\| \cdot \|$ is Euclidean distance, C is used for the normalization and is expressed as

$$C = \sum_{Y \in N(X)} e^{-\frac{\|Y-X\|^2}{2\sigma_d^2}} e^{-\frac{\|g(Y)-g(X)\|^2}{2\sigma_r^2}} \quad (11)$$

In bilateral Filter, the choice of σ_d^2 & σ_r^2 is very important. If their values are too high, it will act as smoothing Filter. If their values are too low, the noise cannot be removed.

3.2 Non-linear Filters

Non-linear filtering is filtering in which the value of an output pixel is a Non-linear combination of the values of the pixels in the input pixel's neighborhood. It tends to preserve edges compared to Linear Filters. The Non-linear Filters considered for Speckle reduction are *median*, *Adaptive median Filter*, *Weiner Filter* and *diffusion Filter*.

3.2.1 Mean Filter

It provides excellent noise-reduction capability with less blurring .It is not used for Speckle removal because of its smoothing property [4]. It is expressed as:

$$g(x, y) = \text{median}\{f_{s,t}\} \quad s, t \in S_{xy} \quad (12)$$

3.2.2 Adaptive Mean Filter

It preserves edges and smoothens the noise-free pixel. It can be used for Speckle suppression but not effective in preserving the intrinsic details [4]. Detection of noisy pixel and filtering are done by the following steps:

1. Initialize the window size $w=3, 5, 7 \dots$
2. Compute $S_{x,y}^{\min,w}$, $S_{x,y}^{\text{med},w}$ and $S_{x,y}^{\max,w}$ which are the minimum, median and maximum pixel values in $S_{x,y}^w$ respectively.
3. If $S_{x,y}^{\min,w} < S_{x,y}^{\text{med},w} < S_{x,y}^{\max,w}$, then go to step5.else $w=w+2$.
4. If $w \leq w_{\max}$ then go to step 2.Otherwise replace $f_{x,y}$ by $S_{x,y}^{\text{med},w_{\max}}$.
5. If $S_{x,y}^{\min,w} < f_{x,y} < S_{x,y}^{\max,w}$ then $f_{x,y}$ is not a noise candidate, else replace $f_{x,y}$ by $S_{x,y}^{\text{med},w}$.

3.2.3 Diffusion Filter

It is based on Partial differential equations (PDE) and takes advantage of the locality and anisotropy of certain differential equations. It is found that operators of this class are capable of smoothing images without ‘‘crossing’’ the boundaries between their homogeneous regions. [12] Discusses Non-linear PDE for smoothing images in continuous domain. It is given by:

$$\frac{\partial I}{\partial t} = \text{div}[\partial c(|\nabla I|). \nabla I] \quad (13)$$

Where ∇ is the gradient operator, div is the divergence operator, $\| \cdot \|$ denotes the magnitude, $c(|\nabla I|)$ is the diffusion coefficient and I is the original image.

Speckle Reducing Anisotropic Diffusion (SRAD) [13] is proposed for Speckle d images. It is the combination of diffusion and lee Filters. It utilizes the coefficient of variation which serves as edge detector and it exhibits high values at edges and low values in homogeneous regions. Thus it ensures edge preservation and edge enhancement.

3.2.4 Weiner Filter

It restores the image in the presence of blur as well as noise. It is based on the computation of local image variance. When the local variance of the image is large, the smoothing is little. If the variance is small, the smoothing will be high [3].

4. FILTER QUALITY ASSESSMENT PARAMETERS

The performance of each Filter is quantified for ultrasound images of normal right kidney and liver (which contains Speckle noise) using the quality assessment parameters. The parameters are shown in Table 1. Let x and y denote the original and deSpeckle d image.

TABLE 1: Filter Assessment Parameters

SL No	Filter Assessment Parameters
1.	<p>Peak Signal to Noise Ratio (PSNR): It provides the quality of the image in terms of the power of the original and denoised image [14]-[15]. MSE is Mean Square Error which quantifies the amount of despeckling between original and despeckled images.</p> $PSNR = 10 \log_{10} \frac{255^2}{MSE}$ <p>Where,</p> $MSE = \frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N (x_{ij} - y_{ij})^2$
2.	<p>Effective Number of Looks (ENL): It is the measurement of statistical fluctuations introduced by Speckle. A large ENL value represents better quality performance of despeckled image [15]. NSD is Noise Standard Deviation which finds the content of Speckle noise in the image. Small NSD value represents the clear image.</p> $ENL = \frac{[NMV]^2}{[NSD]^2}$ $NSD = \frac{1}{MN} \text{sort} \sum_{i=1}^M \sum_{j=1}^N (x_{ij} - NMV)^2$ $NMV = \frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N x_{ij}$
3.	<p>Image Quality Index (IQI): It represents the degree of distortion of the image in terms of loss of correlation, luminance distortion and contrast distortion. When IQI is nearer to unity, distortion is less [14].</p> $IQI = \frac{4\sigma_{xx}(x_{ij})(y_{ij})}{(\sigma_x^2 + \sigma_y^2)(x_{ij}^2 + y_{ij}^2)}$
4.	<p>Mean Structure Similarity Index Map (MSSIM) and Structure Similarity Index Map (SSIM): They are used to compare luminance, contrast and structure between the original and despeckled images. The value of MSSIM should be closer to unity in order to have optimal measure of similarity [14].</p> $MSSIM = \frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N SSIM[(x_{ij}), (y_{ij})]$ <p>Where,</p> $SSIM = \frac{(2\mu_x \mu_y + c1)(\sigma_{xy} + c2)}{(\mu_x^2 + \mu_y^2 + c1)(\sigma_x^2 + \sigma_y^2 + c2)}$

5. EXPERIMENTAL RESULTS

In this section, the results obtained for section 3 i.e., Linear and Non-linear Spatial domain Filters are discussed. Table 2 shows the filter quality assessment parameters PSNR, IQI,

ENL, MSSIM and execution time required. Figure 2 shows the plot of PSNR and IQI, ENL, MSSIM and Figure 3 shows the subjective analysis of various Filters.

From the subjective analysis (Figure 3) and inspection of Filter assessment parameters (Table 2) calculated, the following inferences have been made:

- Mean, Lee and Kuan Filter have almost similar values of PSNR (around 33). These Filters over smoothens the image and fails to preserve the edges.
- The SAWM has better value of PSNR (43.741), IQI (0.9304), ENL (0.0481) and MSSIM (0.9850). It preserves edges without excessive smoothing.
- With the sigma value of 2, Gaussian Filter provides contrast enhancement. It has better PSNR (62.424) value. For higher values of sigma, it brightens the image and hence the features of images will be lost.
- Bilateral Filter provides smoothing as well as preserves details. But it does not provide contrast enhancement. The bilateral Filter has high PSNR (74.558), MSSIM (=1) value compared to other Filters.
- The standard median Filter provides less edge preservation capability and does more smoothing.
- Adaptive median Filter preserves edges. It has better PSNR (42.440) values and MSSIM (0.9767) values.
- The performance of SRAD and Wiener Filter is almost similar both qualitatively and quantitatively. For larger iterations the SRAD Filter over smoothens the image resulting in loss of details.
- From Table 3, it is evident that among all Linear and Non-linear Filters, bilateral Filter has a faster execution time.

The following are the features desired by any efficient Speckle Filter - smoothing the noise (high PSNR), contrast enhancement and edge preservation. It is observed from the above results and discussions that no single Filter is satisfying all the above required features. Hence there is a need for a new filtering algorithm that has an improvement over the listed set of Filters (Table 2). A new Hybrid/Multistage filtering method is thus proposed that satisfies these requirements which are discussed in section 6.

6. HYBRID/MULTISTAGE FILTERING APPROACH

Smoothing the noise, contrast enhancement and edge preservation are the features listed for a good Speckle Filter. The Filters discussed above could satisfy one or more features but none of them satisfied all the requirements. In Hybrid/Multistage filtering approach, Filters which were observed to give better performance with the listed features are cascaded and hence be at the advantage of getting most features satisfied. In this paper Hybrid Filter and Multistage Filter are considered

a) Hybrid Filter [SRAD and Gaussian Filter]: The combination of Linear and Non-linear Filter is called "Hybrid" Filter which is shown in Figure 1(a). In the first stage Non-linear Filter and in the second stage Linear Filter is used. Non-linear SRAD Filter is considered as it provides smoothing (PSNR=34.669) with good preservation of edges (Figure 3j) and Linear Gaussian Filter has the PSNR (62.424) and improves the contrast of an image. Hence this combination will satisfy the requirements listed for a good Speckle Filter. The performance of the Hybrid Filter can be seen in Table 2 and Figure 3(m).

b) Multistage Filter [Adaptive and Gaussian bilateral Filter]: In this method two Linear Filters which provide better performance in terms of smoothing, preservation of edges and contrast enhancement are cascaded. In the first stage, the SAWM Filter is used as it provides a PSNR (43.74) with less distortion (IQI=0.98). In the second stage, Gaussian bilateral Filter is considered which has PSNR (74.55) and MSSIM (=1) which preserves edges as well as smoothens the noise. The Gaussian Filter with the sigma value of 2 and window size of 3x3 can also provide contrast enhancement. The performance of Multistage Filter is shown in Table 2 and Figure 3(n).

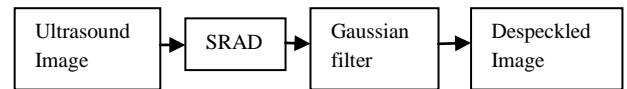


Figure 1a. Hybrid Filter

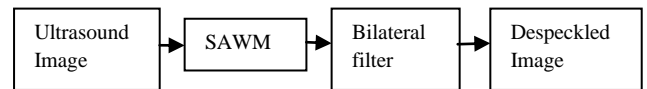


Figure 1b. Multistage Filter

6.1 Results and Discussions

The results of Hybrid and multistage Filters are shown in Figure 3 and Table 2. From Table 2, it is observed that Hybrid Filter presents better smoothing (PSNR =63.423), lesser distortion (IQI =0.7407), lower Speckle content (ENL =0.0689) and better contrast (MSSIM =0.8077) than SRAD and Gaussian Filter implementations. From Figure 3(m), it is observed that the Hybrid Filter has a better smoothing of noise, preserves edges and improves the contrast of the images. For larger iterations (>5), this Filter over smoothens the image and fails to preserve edges. This Filter performs better than SRAD and Gaussian Filters which can be seen both in qualitative analysis (Table 2) and subjective analysis (Figure 3).

The Multistage Filter has a PSNR (79.915), IQI (0.9497), MSSIM (0.9945) and ENL (0.0984). The above results indicate that the Multistage Filter provides better smoothing (as PSNR value is high), less distortion (as IQI near to unity), lower Speckle content (ENL value is high) and good contrast (as MSSIM value is high). From subjective analysis shown in Figure 3(n), it is seen that the Multistage Filter provides smoothing, edge preservation and contrast enhancement. It is more efficient than SAWM and Gaussian bilateral filter except execution time which is observed qualitatively in Table 2 and quantitatively in Figure 3.

From the above discussions, it is observed that Hybrid and Multistage Filter satisfies all the requirements listed for a Speckle reduction Filter. The performance of Multistage Filter is better as it has higher values of PSNR, IQI, ENL and MSSIM compared to Hybrid Filter. As seen in subjective analysis (Figure 3(m) and Figure 3(n)), the Multistage Filter has lesser Speckle noise, good preservation of edges and improved contrast than Hybrid Filter. From Table 2, it is observed that execution time of Hybrid Filter is lesser than Multistage Filter. But on the other hand, the Multistage Filter gives better performance compared to Hybrid Filter which is seen both in quantitative and subjective analysis.

TABLE 2: Comparison of PSNR, MSSIM, ENL, IQI and Execution Time for Spatial Domain Filters

Parameters	PSNR		MSSIM		ENL		IQI		Execution Time in seconds Kidney/Liver
	Kidney	Liver	Kidney	Liver	Kidney	Liver	Kidney	Liver	
Mean Filter	28.471	34.671	0.9112	0.8525	0.0697	0.0562	0.8614	0.7922	2.866
Lee Filter	35.996	34.662	0.8775	0.8415	0.0398	0.0352	0.8360	0.7919	10.437
Frost Filter	27.041	26.018	0.8228	0.8162	0.0376	0.0338	0.8019	0.7703	6.326
Kuan Filter	35.991	34.527	0.8516	0.8249	0.0397	0.0336	0.8256	0.7902	6.572
SAWM	43.741	41.915	0.9850	0.9658	0.0481	0.0481	0.9304	0.9601	17.107
Gaussian smoothing	62.424	59.352	0.6474	0.6025	0.0613	0.0641	0.6039	0.6397	0.8405
Bilateral Filter	74.558	79.207	0.9919	1.0000	0.0970	0.0966	0.7512	0.7149	0.2364
Median Filter	33.567	35.118	0.9358	0.8419	0.0697	0.0650	0.8855	0.8032	1.9905
Adaptive Median Filter	42.440	40.667	0.9767	0.9516	0.0697	0.0652	0.9480	0.9379	12.763
SRAD	34.669	33.467	0.8743	0.7328	0.0665	0.0651	0.7271	0.6922	1.1036
Weiner Filter	33.227	33.655	0.7149	0.6950	0.0651	0.0652	0.6070	0.5933	1.9267
Hybrid Filter	63.423	61.948	0.8077	0.8141	0.0689	0.0676	0.7407	0.7534	1.9234
Multistage Filter	79.915	92.740	0.9945	0.9843	0.0984	0.0789	0.9497	0.9695	17.302

Plot of metric parameters:

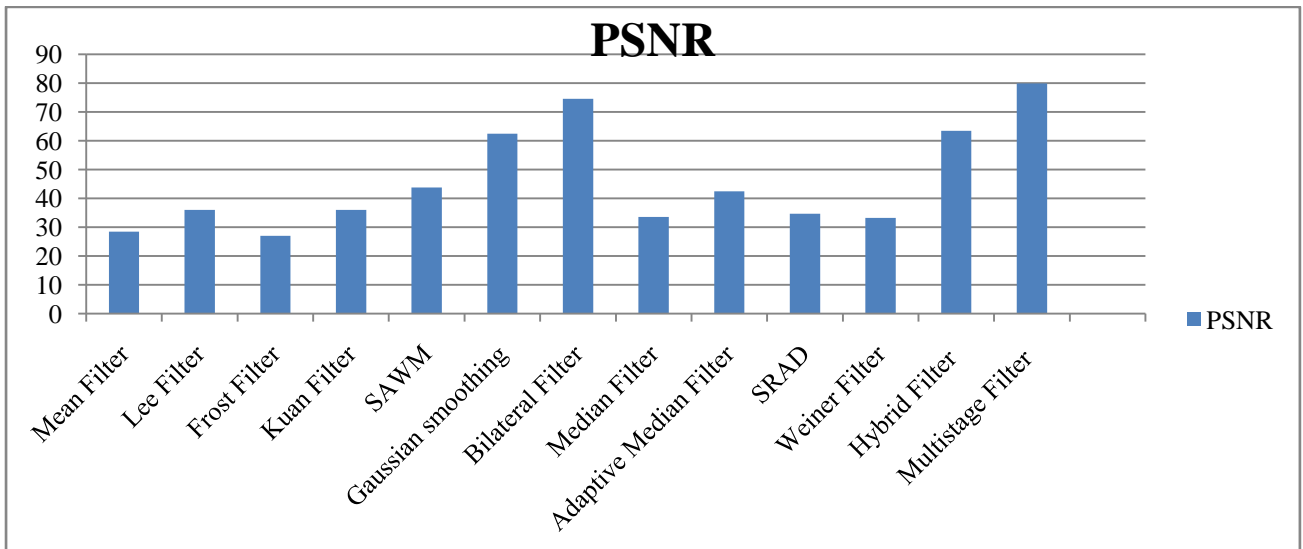


Figure 2a PSNR plot for Filters

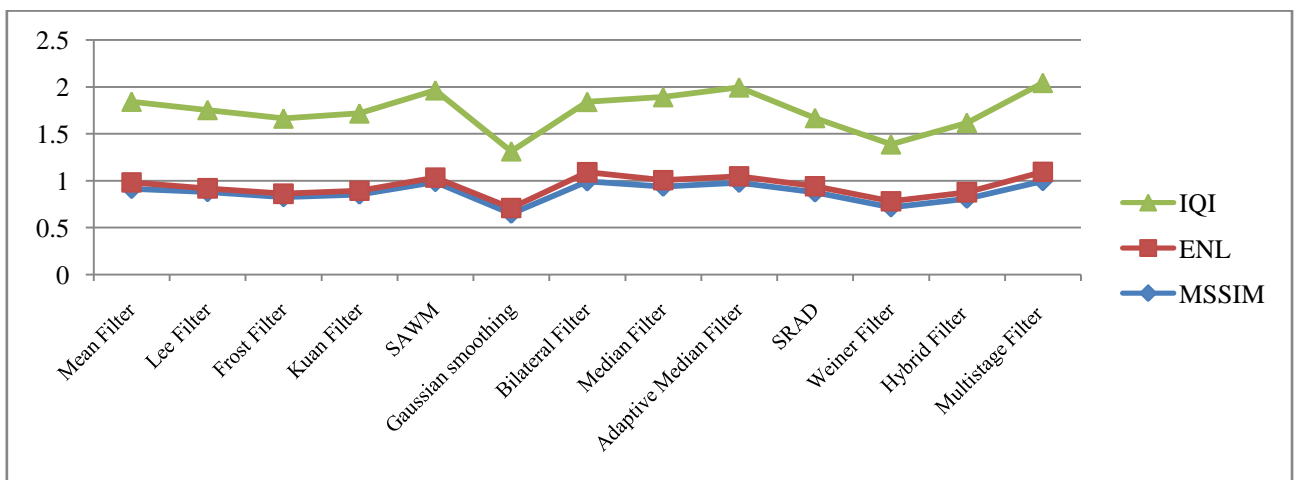


Figure 2b IQI, ENL and MSSIM chart for Filters

Image 1: Ultrasound Image of Normal Right Kidney

Image 2: Ultrasound Image of Liver

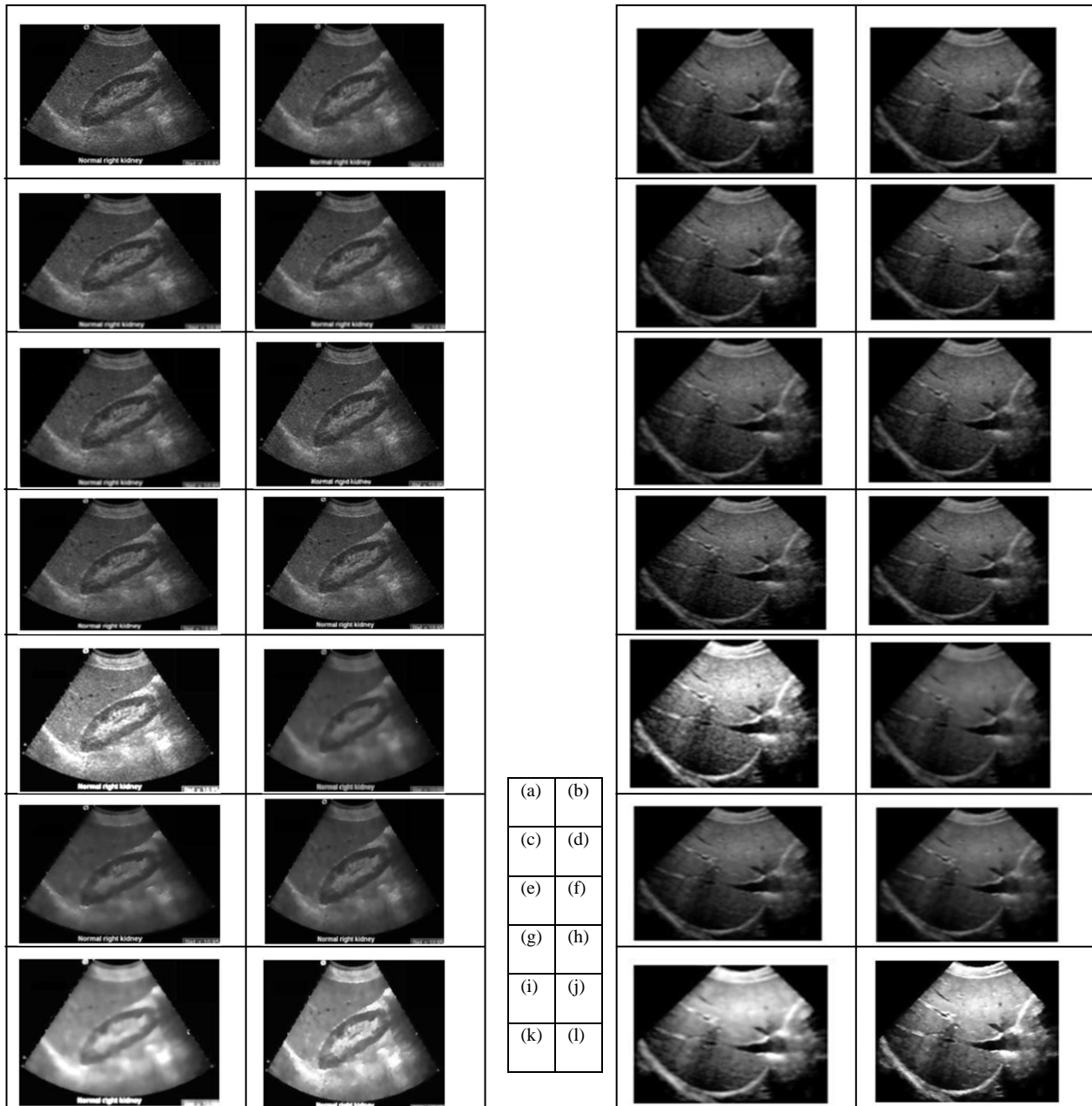


Figure 3:a)Original Image b)Mean c)Lee d)Frost e)Kuan f)SAWM g)Median h)Adaptive Median i)Gaussian smoothing j)SRAD k)wiener l)Bilateral Filter m)Hybrid Filter n)Multistage Filter

7. CONCLUSION

The key issues in enhancement of medical ultrasound images are Speckle reduction, edge retention and contrast enhancement. In this study, the performance of various Spatial Domain Speckle filtering algorithms including our proposed Hybrid/Multistage Filters are tested on ultrasound images of kidney and liver. Experimental results shows (Refer Table [1-2] and graph[Fig 2]) that the our approach give an improved

PSNR(>61), IQI (>0.74), MSSIM (>0.8) and ENL (>0.067) compared to other filters.

The Multistage approach gives better performance with higher value of PSNR (>79), IQI (>0.94), MSSIM (0.9945) and ENL (0.0984) compared to Hybrid Filter PSNR (62), IQI (0.81), MSSIM (0.8) and ENL (0.067). The subjective analysis shows that the Multistage Filtering approach reduces significantly the Speckle, preserves the edges and improves the contrast but has a higher execution time (17.3secs) compared to Hybrid

Filter (1.92 secs). Improvements can be made to reduce the execution time of multistage Filter.

8. ACKNOWLEDGMENTS

Our sincere thanks to R N S Institute of Technology for the Lab support provided in executing the work. Our extended thanks to Dr. Vipula Singh, Professor, ECE, RNSIT for her valuable technical inputs.

9. REFERENCES

- [1] Oleg V. Michailovich and Allen Tannenbaum., "Despeckling of Medical Ultrasound Images", IEEE Transactions On Ultrasonics, Ferroelectrics, And Frequency Control, Vol. 53, No. 1, January 2006.
- [2] Khaled Z. AbdElmoniem, Yasser M. Kadah and AbouBakr M. Youssef, "Real Time Adaptive Ultrasound Speckle Reduction and Coherence Enhancement", 078032977/00/\$10© 2000 IEEE, pp. 172-175.
- [3] A.K. Jain, Fundamental of Digital Image Processing. Englewood Cliffs, NJ: Prentice-Hall, 1989.
- [4] R.C. Gonzalez and R.E. Woods: 'Digital Image Processing', Addison- Wesley Publishing Company, 2002.
- [5] J.S. Lee, "Refined filtering of image noise using local statistics," Journal of Computer Graphic and Image Processing, vol. 15, pp. 380-389, 1981.
- [6] D.T. Kuan, A.A. Sawchuk, T.C. Strand, and P. Chavel, "Adaptive restoration of images with Speckle ", IEEE Trans. ASSP., vol. 35,no. 3, pp. 373-383, March 1987.
- [7] V.S.Frost, J.A.Stiles, K.S.Shanmugam and J.C.Holtzman, "A model for radar images and its application for adaptive digital filtering of multiplicative noise", IEEE Transactions on pattern analysis and machine inelligence, Vol.4, No.2, pp.157- 165, 1982.
- [8] Filter Xuming Zhang and Youlun Xiong., "Impulse Noise Removal Using Directional Difference Based Noise Detector and Adaptive Weighted Mean", IEEE Signal Processing Letters, Vol. 16, No. 4, April 2009.
- [9] Tomasi C, Manduchi R., "Bilateral filtering for gray and color images",. Proc.Int. Conf. Computer Vision 1998, 839-846.
- [10] Phelippeau H, Talbot H, Akil M, Bara S., "Shot noise adaptive bilateral filter", Proceedings of the 9th International Conference on Signal Processing 2008,864-867
- [11] Barash D., "Fundamental relationship between bilateral filtering, adaptive smoothing, and the nonlinear diffusion equation", IEEE Transactions on Pattern Analysis and Machine Intelligence 2002, 24:844-847.
- [12] P. Perona and J. Malik, "Scale space and edge detection using anisotropic diffusion," IEEE Trans. Pattern Anal. Machine Intell, Vol.12, pp. 629–639, 1990.
- [13] Yongjian yu and scott t. Acton., "Speckle reducing anisotropic diffusion", IEEE Transactions On Image Processing, Vol. 11, No. 11, November 2002
- [14] R. Sivakumar, M. K. Gayathri and D. Nedumaran., "Speckle Filtering of Ultrasound B-Scan Images - A Comparative Study of Single Scale Spatial Adaptive Filters, Multiscale Filter and Diffusion Filters", IACSIT International Journal of Engineering and Technology, Vol.2, No.6, December 2010 ISSN: 1793-8236 .
- [15] D.Sakrison, "On the role of observer and a distortion measure in image transmission,"IEEE Transaction on Communication. Vol 25, pp. 1251-1267, November, 1977.