An Efficient EDGE Preserving Filter for Ultrasound Kidney Images

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***Abstract :*-The speckle reduction is an important preprocessing step, required to improve the quality of the ultrasound imaging system. This paper mainly focuses on reduction of speckle noise to smooth an image while preserving edges. Here the performance analysis of Adaptive Bilateral Filter (ABF) for speckled ultrasound kidney images is presented. The despeckling method is used to for image processing, segmentation and analysis to achieve better interpretation of kidney ailments. Root Mean Square Error (RMSE), Peak Signal To Noise Ratio (PSNR) and Structural similarity index (SSIM) are chosen as performance metrics for estimating the effectiveness of ABF and the same is compared to Lee filter and Wavelet Thresholding.**

Keywords: Ultrasound Images, Kidney Stone, Speckle Noise, Bilateral Filtering, Adaptive Bilateral Filter.

INTRODUCTION

Ultrasound imaging has many uses in medicine, for the diagnosis of a wide variety of condition disturbing the organs and soft tissues of the body including heart, blood vessel, liver, gall bladder, spleen, kidney, pancreas, uterus, ovaries, bladder, eyes and prostate. It helps physicians during precise medical procedures to detect soft tissue injuries.

Ultrasound imaging is the coherent imaging system which can be deteriorated if a speckle noise appears at the time of procuring images by sensors. Ultrasound imaging techniques are widely used in medical imaging technique instead of CT, MRI, etc., because of its non-invasive nature, absence of radiation and low cost. However, the ultrasound images are severely affected by speckle noise. Speckle noise is a multiplicative noise which can affects all coherent imaging systems. Speckle is caused by backscattering of incident waves towards the sensor. This wave with different phases causes a random granular pattern in the acquired image due to constructive and destructive interference [1]. The denoising step is necessary before analyzing the ultrasound image data. The quality of ultrasound image degrades due to the speckle noise which includes suppression of boundaries, edges and structural details. The preservation of edges is very important during diagnosis of various organs. The speckle reduction is also a primary factor that limits the contrast [2], thereby reducing the effectiveness of a segmentation and classification algorithms.

In [1], the bilateral filter was applied to additive white Gaussian noise corrupted medical images with different value of variance. The performance of bilateral filter was measured using PSNR for different noise variance between 0.01 and 0.05. The PSNR value was obtained between 19.94 and 16.27dB. The experiment results show the performance of the bilateral filter depends upon the parameters such as window size (w) and standard deviations (σ_d, σ_s). From experiments it has been observed that the bilateral filter was advantageous in terms of its good results, simplicity and efficient algorithms. However, author concluded that the performance of the bilateral filter is poor while removing salt and pepper noise.

In [2], a fully automatic bilateral filter designed was proposed by Simone Balocco et.al. The filter was tested on 50 vivo ultrasound images by embedding noise statistics, which has its effect on edge preservation and segmentation. A coronary artery of 3mm average diameter is used as image database and the segmentation error reduces from about 0.3mm to 0.1mm representing 20% and 60% of the arterial radius respectively. The bilateral filter was superior in enhancing the outline of the vessel membrane and preserves the sharp vessel edges, and hence improved the accuracy of applied snake segmentation algorithm.

C. Tomasi and R. Manduchi in [3] presented a model of bilateral filtering for denoising the images without affecting the edge details. The parameters used for bilateral filtering were arbitrarily chosen. The authors suggested that the Gaussian domain filtering can be replaced analogously, different types of domain filters can be combined with the range filters and a new scale space can be described in which σ_r the range filter parameter is corresponding to scale. Moreover the author experimented the proposed bilateral filter with different value of σ_d and σ_r. In the new scale space, detail loss occurs when increasing σ_r, while edge preservation ensured at all range scales that were below maximum image intensity value. In [4], Ming Zhang and Bahadir K. Gunturk recommended a different image denoising framework called multiresolution bilateral filter which combines the bilateral filter with wavelet thresholding technique. In this, an image is decomposed using a wavelet transform into approximation and detail sub-bands. The noise in approximation subbands are deal with the bilateral filter and details are treated with wavelet thresholding. This proposed algorithm eliminates the noise very effectively in real noisy images. The optimal selection filter parameter is also done in [4]. The proposed technique was compared with other filtering techniques in terms of PSNR. The PSNR value is improved than other compared techniques.

An integrated approach was proposed in [5], which combines the bilateral filter, edge detection and edge enhancement based on suitable color spaces. This approach efficiently reduces the noise while edge preservation and enhancement could be obtained by avoiding false edge detection that occurs because of noise. This integrated approach shows better results on the textures but most of the image noise was filtered out. In [6] and [7], the multiresolution approach combined with bilateral filtering was presented. It removes noise in the approximation subband or low frequency subband of the wavelet decomposed image. This hybrid filtering outperforms than the other denoising methods.

In [8], the bilateral filtering was applied to ultrasound images as a preprocessing to achieve better measurement of the follicles. The proposed speckle reducing bilateral filter reduces speckle in both high intensity region and low intensity regions of ultrasound images. In [9], Jong-Woo Han et al. proposed a novel interpolation framework in which denoising and image sharpening methods were embedded. In this frame work the bilateral filter was used to decompose the image into the detail and base layers. Adaptive thresholding methods were used to denoise detail layers to preserve textures in detail layers. The edge preserving interpolation is applied to both layers.

Some of the speckle reduction filters were tested for real time ultrasound images and the performance were analyzed in [10] in terms of PSNR, RMSE and SSIM. The wavelet thresholding technique and Lee filter are identified as a better speckle reduction filters in terms of quantitative visual analysis. However, the edge details are suppressed during the application of the above mentioned filters. Hence it affects the detection of exact organ boundaries. In this paper the state-of-art bilateral filtering technique is applied to the real ultrasound kidney images with stones. The noise removal performance with preservation of edges are analyzed and compared with Lee filter and wavelet thresholding.

PROPERTIES OF SPECKLE NOISE

The speckle is an unwanted property of the image as it masks small differences in gray level and it also tends to degrade the resolution and contrast of ultrasound images [2]. Speckle is basically a statistical process that contains useful information for analysis, identification and classification of tissues, which is obtained by the statistics of back- scattered signals. For tissue characterization, the statistical modeling of ultrasound backscattered echoes from body is the important step. The Rayleigh, K-model, Nakagami distribution, Alpha stable distribution, etc., and other mixed compound statistical model have been proposed in [12] to model the envelope of ultrasound backscattered signal. The fully developed speckle in the RF echo can be modeled as complex Gaussian PDF with zero mean. The speckle distribution follows Rayleigh PDF, is described as

$$P_R(f(X),\sigma) = \frac{f(X)}{\sigma^2}\exp\left(\frac{-f(X)^2}{2\sigma^2}\right) \quad (1)$$

Where, $f(X)$ is the pixel intensity of the image and σ^2 is the shape parameter of the distribution and also the noise variance in terms of noise measurement. Figure 1 shows the typical Rayleigh PDF generated using Matlab with variance value as 0.05.

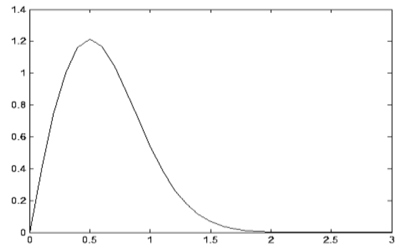


Figure 1. Plot of a typical Rayleigh Distribution curve

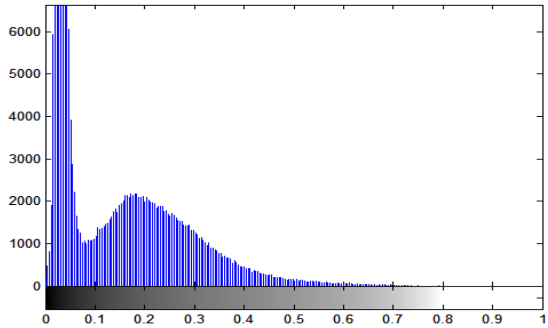


Figure 2. Histogram plot of Ultrasound kidney image

Figure 2 shows the histogram of the ultrasound kidney image used in this paper for testing the performance of the adaptive bilateral filter. The envelope of the histogram plot follows the Rayleigh PDF curve. The noise statistics of the ultrasound image can be determined using the Rayleigh PDF parameter estimation method.

Since the speckle noise is data dependent noise, it is multiplicative in nature. The speckle corrupted ultrasound image can be modeled in [14] as

$$F(X) = I(X)M(X) \quad (2)$$

Where, $F(.)$ - Speckled image
$I(.)$ - Noise free image
$M(.)$ - Multiplicative noise

CLASSICAL BILATERAL FILTERING

The nonlinear and non-iterative bilateral filtering concept was developed by Tomasi and Manduchi [3] for edge preservation and smoothing of noisy image. The bilateral filtering replaces a pixel of the noisy image by a weighted value depends on the geometric distance and photometric

distance. Based on choice of weighting functions, many types of bilateral filters were developed.
Let us consider a pixel location X which is center pixel in given window and Y is any another pixel in the same window. Then the output of bilateral filter is designed as [4]

$$\tilde{F}(X) = \frac{1}{C}\sum_{Y\in N(X)} F(Y-X).G(F(Y)-F(X)).F(Y) \quad (3)$$

$$\tilde{F}(X) = \frac{1}{C}\sum_{Y\in N(X)} e^{\frac{-\|Y-X\|}{2\sigma_d^2}} . e^{-\frac{|F(Y)-F(X)|^2}{2\sigma_r^2}} . F(Y) \quad (4)$$

Where, $\|Y-X\|$ is the Euclidean distance between two pixels X, Y and can be written as

$$\|Y-X\| = \sqrt{X^2+Y^2} \quad (5)$$

$$\tilde{F}(X) = \frac{1}{C}\sum_{Y\in N(X)} e^{\frac{-(X^2+y^2)}{2\sigma_d^2}} . e^{-\frac{|F(Y)-F(X)|^2}{2\sigma_r^2}} . F(Y) \quad (6)$$

The C is the normalization constant and is given by

$$C = \sum_{Y\in N(X)} e^{\frac{-(X^2+y^2)}{2\sigma_d^2}} . e^{-\frac{-|F(Y)-F(X)|^2}{2\sigma_r^2}} \quad (7)$$

F(X) is the center pixel in the given mask and *F(Y)* is the any other pixel other than the center pixel in the given window. $|F(Y)-F(X)|$ measures the distance between the two intensity value of pixels X and Y. The first term $F(Y-X)$ in the equation (12) relates to low pass Gaussian domain filter that measures closeness of geometric distance of two pixels, whereas the second term $G(F(Y)-F(X))$ corresponds to low pass range filter, which measures the photometric similarity between *F(Y)* and *F(X)*. The normalization factor C in (12) preserves the DC component after filtering [6,9]. The σ_d and σ_r in equation are the geometric spread in domain and photometric spread in range respectively [3]. The σ_d value decides the amount of low pass filtering and σ_r decides the amount of range filtering required. More specifically, an image is scaled up or down by adjusting σ_d and amplified or attenuated by adjusting σ_r.
The experimental results determine that the performance of the bilateral filter depends upon the parameters such as window size (w) and standard deviations (σ_d, σ_s).

ADAPTIVE BILATERAL FILTER FOR SPECKLED IMAGES

Convention bilateral filter (equation (4), (6) and (7)) used in speckled images yields poor results. Since the multiplicative noise is difficult to remove, it is necessary to improve the behavior of the filter as [8].

$$\tilde{F}(X) = \frac{1}{C}\sum_{Y\in N(X)} e^{\frac{-\|Y-X\|^2}{2\sigma_d^2}} . e^{-\frac{-|F(Y)-F(X)|^2}{2\|F(X)\|^2\sigma_r^2}} . F(Y) \quad (8)$$

Where,

$$C = \sum_{Y\in N(X)} e^{\frac{-(X^2+y^2)}{2\sigma_d^2}} . e^{-\frac{-|F(Y)-F(X)|^2}{2\|F(X)\|^2\sigma_r^2}} \quad (9)$$

$\tilde{F}(X)$ in equation (8) describes the adaptive bilateral filter.
The behavior of the filter can be enriched by replacing Gaussian range filter in terms of Rayleigh probability function [2]. In this paper equation (7) & (8) is used to remove the speckle in ultrasound kidney images there by making the diagnosis and detection of calculi and cyst effectively.

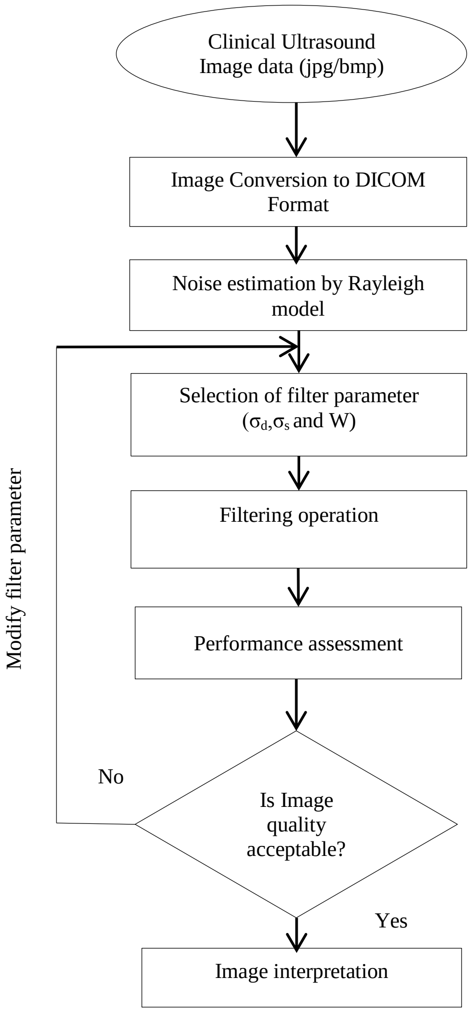


Figure 3. Filtering Algorithm

METHODOLOGY

In this paper, the general mathematical and experimental methodology of bilateral filter for ultrasound image denoising is defined. The mathematical analysis of adaptive bilateral filter in equation (7) and (8) developed for 2-D speckled ultrasound image is done.
The Rayleigh PDF modeling of speckle corrupted image is utilized to estimate the noise variance. The adaptive bilateral filter is applied to real time ultrasound image and its performance is analyzed in terms of various quantitative metrics and compared with other speckle filter such as Lee filter and wavelet filter discussed in previous sections.

PERFORMANCE EVALUATION

The performance of the suggested ABF is analyzed in terms of RMSE, PSNR and SSIM.

The RMSE can be defined as

$$\mathrm{RMSE} = \sqrt{\frac{\sum(f(x,y)-F(x,y))^2}{MN}} \quad (10)$$

And the PSNR is given by

$$PSNR = 20\log_{10}\frac{255}{RMSE}\ \text{dB} \quad (11)$$

The SSIM is another image quality metric which is correlated to the visual perception of human sensory system of vision. It can be exploited as a benchmark to measure the image quality, thereby checking the performance of various image processing algorithms. The SSIM quantifies the similarity measurement of two images in three components namely luminance, contrast and structural. The luminance between two images is determined by mean intensity of pixels in the image, contrast by standard deviation of image and the structural by the correlation between two images [13]. Let $f(x,y)$ is the noise free original image and $F(x,y)$ denoised image. Hence

$$L(f,F) = \frac{2\mu_f\mu_F + C_1}{2\mu_f^2 + \mu_F^2 + C_1} \quad (12)$$

$$C(f,F) = \frac{2\sigma_f\sigma_F + C_2}{2\sigma_f^2 + \sigma_F^2 + C_2} \quad (13)$$

$$S(f,F) = \frac{\sigma_{fF} + C_3}{\sigma_f\sigma_F + C_3} \quad (14)$$

Where,
μ_f, the mean and σ_f, the standard deviation of an image f(x,y) over the selected window.
μ_F, the mean and σ_F, the standard deviation of an image F(x,y) over the selected window.
σ_{fF} is the co-variance between the original and denosied image over a window.
C_1, C_2 and C_3 are constants.

The SSIM is the manipulation of three components (equation 13, 14, 15).

Set $C_3 = C_2/2$

$$SSIM(f,F) = \frac{(2\mu_f\mu_F + C_1)*(2\sigma_{fF} + C_2)}{(\mu_f^2 + \mu_F^2 + C_1)*(\sigma_f^2 + \sigma_F^2 + C_2)} \quad (15)$$

The mean SSIM is the average of all local windows. The window is moved through the image considering one pixel at a time. The SSIM value lies between -1 and 1 for bad and good similarity between the original and despeckled images respectively. The choice of σ_d=1, σ_r=10 are used for analysis. When compared to Lee filter and wavelet filter output, the bilateral output has better PSNR while edge information is preserved.

EXPERIMENTAL SETUP

To do this analysis, images are collected from a Voluson Ultrasound machine of GE Heathcare product. The real time image processing and interpretation reports are represented in DICOM data model [10]. It is a standard image format used by radiological hardware. DICOM files contain high resolution images and it requires large memory size when it is stored or transferred. They are compressed before any storage or transfer in any of the file formats such as JPEG, PNG, BMP etc., since the other file formats have losses during compression. Later, it is necessary to use DICOM images during image processing and interpretation. The DICOMIZER open source software is used in this research to convert any file format to DICOM file (.dcm). To view the DICOM image, Micro Dicom open source software is being used. Both are available as open source software.

RESULTS AND DISCUSSION

The adaptive bilateral filter given by equation (8) has been applied to ultrasound kidney image having stone with noise variance = 0.1 and the result of the bilateral filtering as shown in Figure 5 using the filter parameter σ_d=1, σ_r=10 and mask size of 5X5. The noise reduction performance of the filtered image is shown in Table 1-3. For comparison, Lee multiplicative filter with mask 3x3 and wavelet thresholding techniques are used. In wavelet thresholding the noise is smoothen with blurred edges. The Lee filter removes the noise and preserves the edges better than wavelet thresholding, but there is still some edge enhancement required. Visually the bilateral filtered image yields good results with less loss of data and the stone can be easily identified when compared to the other two filters. The performance of the Adaptive Bilateral Filter depends on suitable selection of the parameters σ_d, and σ_r.. For speckle corrupted ultrasound images with noise variance = 0.1 shown in Figure 6, the value of parameters σ_d = 1,3,10 and σ_r =10,50,100 have been used in this paper to evaluate the ABF performance. As already discussed the σ_d is the domain filter which is a Gaussian low pass filter. The high σ_d value, broadens the Gaussian width and makes the bilateral filter to essentially acts as a range filter and no loss of detail occurs. But it compresses the image histogram and makes the filtered output image unclear. Likewise, σ_r has smaller value then the range filter dominates and preserves the edges. For large value of σ_r, the range filter has little effect.
The bilateral filter presented in this paper is non-iterative. It has been tested on several ultrasound kidney images but only the sample results discussed in this paper. In order to evaluate the effectiveness of ABF, the performance metrics such as RMSE, PSNR and SSIM are tabulated in Table 1-3 is developed for different noise variance levels. The comparisons among the performance metrics are shown in Figure 5 (a)-(c).

S. No	Noise Variance	Speckle Filters		
		Bilateral Filter	Wavelet Thresholding	Lee Filter
1.	σ = 0.5	0.1151	10.7276	7.8345
2.	σ = 0.3	0.0927	10.3725	7.4361
3.	σ = 0.1	0.0570	7.9386	6.5023
4.	σ = 0.05	0.00433	6.052	5.8174
5.	σ = 0.03	0.0364	4.9562	5.2838
6.	σ = 0.01	0.0280	3.0598	4.2470

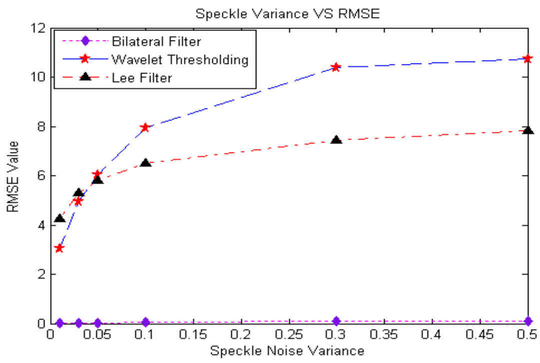
Table 1. RMSE comparison of Bilateral Filter, Wavelet Thresholding and Lee Filter

S. No	Noise Variance	Speckle Filters		
		Bilateral Filter	Wavelet Thresholding	Lee Filter
1.	σ = 0.5	66.8992	27.5208	30.2506
2.	σ = 0.3	68.7900	27.8132	30.7039
3.	σ = 0.1	73.0072	30.1359	31.8694
4.	σ = 0.05	75.4035	32.4883	32.8362
5.	σ = 0.03	76.9192	34.2279	33.6719
6.	σ = 0.01	79.1743	38.4170	35.5691

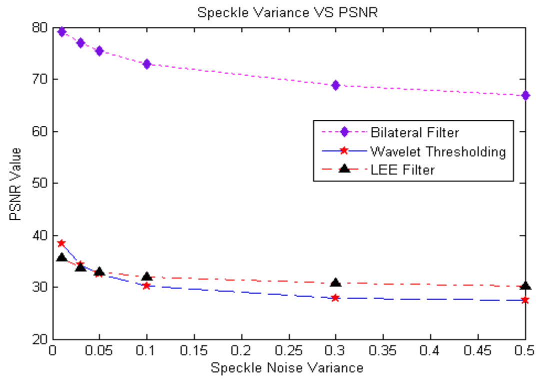
Table 2 . PSNR comparison of Bilateral Filter, Wavelet Thresholding and Lee Filter

S. No	Noise Variance	Speckle Filters		
		Bilateral Filter	Wavelet Thresholding	Lee Filter
1.	σ = 0.5	66.8992	27.5208	30.2506
2.	σ = 0.3	68.7900	27.8132	30.7039
3.	σ = 0.1	73.0072	30.1359	31.8694
4.	σ = 0.05	75.4035	32.4883	32.8362
5.	σ = 0.03	76.9192	34.2279	33.6719
6.	σ = 0.01	79.1743	38.4170	35.5691

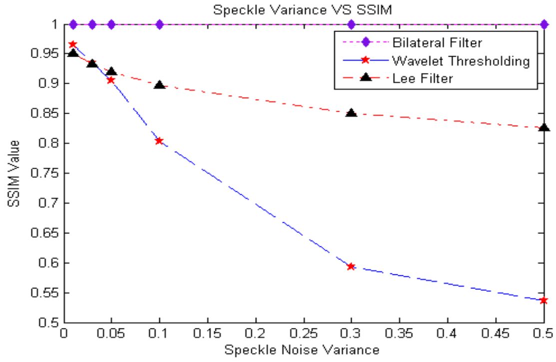
Table 3 . SSIM comparison of Bilateral Filter, Wavelet Thresholding and Lee Filter



(a)



(b)



(c)

Figure 4. (a)-(c) Comparison Graph of RMSE, PSNR and SSIM between Bilateral Filter, Wavelet Thresholding and Lee Filter

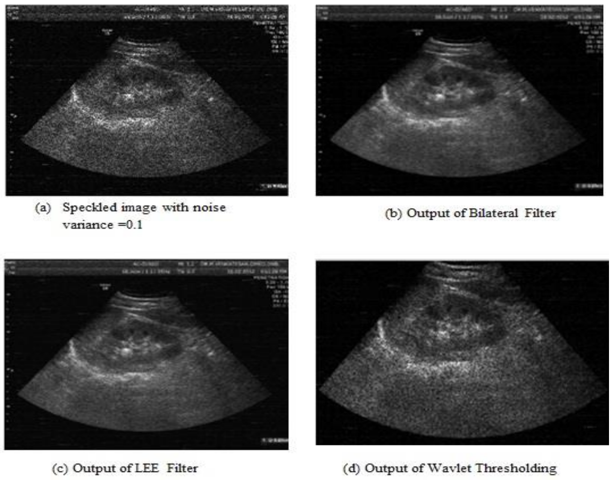


Figure 5. The Filtered Images of the Bilateral Filter, Lee Filter, Wavelet Thresholding for the speckled image with noise vairance =0.1

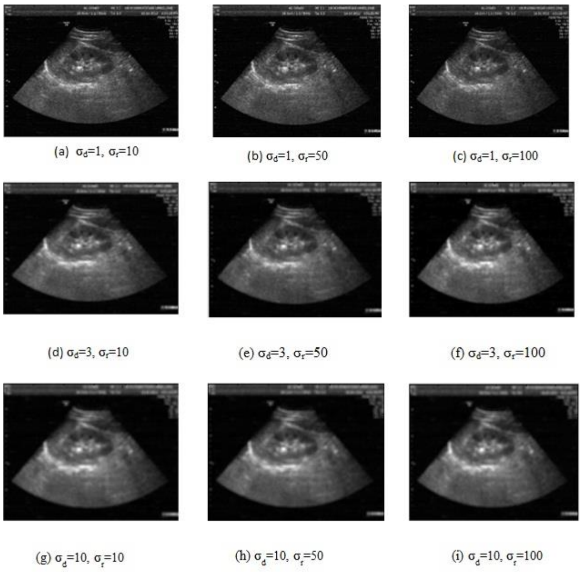


Figure 6. Filtered images using the proposed filter for various values of σ_d and σ_r

CONCLUSION

This paper presents an analysis of medical ultrasound image denoising based on adaptive bilateral filter (ABF). The performance of ABF for speckled image was tested using various ultrasound images of kidney. For various values of σ_d and σ_r, the noise reduction property of the filter was analyzed. The better noise reduction of ABF gives trouble free analysis of kidney images. This may improve the further image processing technique such as segmentation and classification. The future work needs improvement in the performance of the ABF by means of hybridization or by replacing filter kernels with different other kernels.

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REFERENCES

[1] Devanand Bhonsle, Vivek Chandra, G.R. Sinha "Medical Image Denoising Using Bilateral Filter' I. J. Image, Graphics and Signal /processing, Vol. 6, pp. 36-43, July 2012.

[2] Simone Balocco, Carlo gatta, Oriol Pujol, Josepa Mauri, Petia Radeva "SRBF: Speckle Reducing Bilateral Filtering" Ultrasound in Medicine and Biology, 36(8):1353-63, August 2010.

[3] C. Tomasi and R. Manduchi "Proceedings of the IEE International Conference on computer vision, 1998.

[4] Ming Zhang and Bahadir K. Gunturk " Multiresolution Bilateral Filtering for Image Denoising" IEEE Transaction on Image Processing, Vol. 17, No. 17, December 2008.

[5] Wen-Chung Kao and Ying-Ju Chen "Multistage Noise Filtering and Edge Detection for Color Image Enhancement" IEEE Transaction on Consumer Electronics, Vol.51, No.4, November 2005.

[6] V Naga Prudhivi Raj and T. Venkateswarlu "Ultrasound Medial Image Denoising Using Hybrid Bilateral Filtering" International Journal of Computer Applications, Vol.56, No. 14, October 2012.

[7] SHI Wenxuan, LI Jie, WU Minyuan "An Image Denoising Method Based on Multiscale Wavelet Thresholding and Bilateral Filtering", Wuhan University Journal of Natural Science, Vol.15 No.2, pp. (148-152), 2010.

[8] Jinshan Tang, Shengwen Guo, Qingling Sun, Youpin Deng, Dongfeng Zhou "Speckle reducing bilateral filter for cattle follicle segmentation" International Confernce on Bioinformatics & Computational Biology, July 2009.

[9] Jong-Woo Han, Jun-Hyung Kim, Sung-Hyun Cheon, Jong-Ok Kim, Sung-Jea Ko "A Novel Image Interpolation Method Using the Bilateral Filter" IEEE Consumer Electronics (ICCE) 2010.

[10] Loganayagi.T "Comparative Evaluation of Speckle Reduction Filters for Ultrasound Kidney Images" Proceeding (785) Engineering and Applied Sciences, December 2012.

[11] R. N. J. Graham, R. W. Perriss, A. F. Scarbrook, "DICOM demystified: A review of digital file formats and their use in radiological practice" Clinical Radiology, Elsevier(2005) 60, 1133-1140, 2005.

[12] Torborn Eltoft, "Modeling the amplitude statistics of ultrasonic images", IEEE Transaction on Medical Imaging, Vol.25, No.25, pp. 229-240, 2006.

[13] Alain Hore and Djemel Ziou, Image Quality metrics: PSNR vs SSIM, IEEE International Conference of Pattern Recognition, pp. 2366-2369, 2010.

[14] Oleg V. Michailovich and Allen Tannenbaum, "Despeckling of Ultrasound images" IEEE Transaction on Ultrosonics, Ferroelectrics and Frequency Control Vol.53, No.1, pp. 64-78, 2010.