ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 2, Issue 9, September 2015

An Experimental Study on Speckle Noise Mitigation Techniques

Dr. E. Jebamalar Leavline

Assistant Professor, Department of Electronics and Communication,
University College of Engineering, BIT Campus, Tiruchirappalli – 620 024, India.

Abstract: Speckle is a granular type of noise which is often encountered in medical diagnostic images such as ultrasound images. The presence of speckle noise degrades the visual clarity of the image. Hence, mitigating the effect of speckle noise is essential before any image processing and analysis techniques. This paper presents a study on several speckle mitigation methods and their performance is compared in terms of well known image quality assessment methods.

Keywords: Speckle mitigation, Image noise removal, Wavelet filtering, Speckle reducing anisotropic diffusion

I. Introduction

Speckle noise appears as granules that degrades the quality of images. It is classified as a multiplicative type of noise. If *f(x,y)* be the uncorrupted image of size N×N, *(x,y)* be the spatial coordinates, and *n(x,y)* be the noise function, then the noisy image observation *g(x,y)* with multiplicative speckle noise is given by Equation (1).

$$g(x,y) = f(x,y) \times n(x,y) \quad \forall x,y \le N \quad (1)$$

However, this multiplicative model is converted into additive noise model by simple logarithmic transformation as shown in Equation (2).

$$\ln(g(x,y)) = \ln(f(x,y)) + \ln(n(x,y)) \; \forall x,y \le N \quad (2)$$

Hence, the process of despeckling is simplified to an estimation problem that estimates the information from the noisy observation and may be described as in Equation (3).

$$f(x,y) = g(x,y) - \hat{n}(x,y) \; \forall x,y \le N \quad (3)$$

Many speckle reduction techniques have been proposed in the literature. They are broadly classified as linear filtering, nonlinear filtering, diffusion filtering and multiscale filtering [1]. The speckle filters such as first order statistics filter belongs to the family of linear filters. Several non linear filters such as Homomorphic filter [2], Kuan filter [3], Lee filter [4], Frost filter [5] have also been proposed. Another class of filters called diffusion filters are based on parabolic partial differential equations in divergence form and it is further classified as linear and non linear diffusion filters [6,7]. Multiscale filtering is another promising approach for speckle mitigation which employs various multiscale transforms to represent the images for speckle noise removal.

This paper presents a detailed study on the state-of-the-art speckle mitigation schemes. The rest of the paper is organized as follows. Section II describes the state-of-the-art speckle mitigation schemes. Section III summarizes the image equality assessment metrics used in this study. The experimental results are discussed in Section IV and the paper is concluded in Section V.

II. Speckle mitigation techniques

This section describes various speckle mitigation algorithms that are studied in this paper.

A. *First Order Statistics Filter*

This filter utilizes the local statistics of the image corrupted by speckle noise for despeckling [1]. These filters utilize the first-order statistics such as the variance and the mean of the neighborhood for despeckling. Further, these filters are spatial domain filters applied directly on the pixels by a technique called sliding/moving window. The despeckling performance of these filters highly depends on the size of the moving window. The typical size of the moving window is [5×5] to [15×15].

ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 2, Issue 9, September 2015

B. Homomorphic Filter

It is a special type of filter that is suitable for handling multiplicative type of noise such as speckle noise [2]. It assumes that the images are represented with illumination – reflectance model. It is worth mentioning that the illumination component is normally has slow spatial variation and the reflectance component varies abruptly. So, the low frequencies of the Fourier transform of the natural log of an image are associated with illumination and high frequencies with reflectance. The schematic diagram of homomorphic filtering is shown in Figure 1.

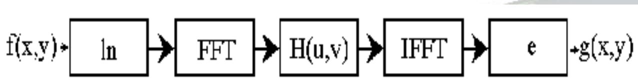

Fig. 1. Block diagram of Homomorphic filtering

C. Kuan Filter

Kuan filter considers the non stationary local statistics (mean and variance) of the image. It is very much suitable for handling signal dependent noise such as speckle, film-grain and poisson noises. It does not require any apriori information about the original image. All the non-stationary image statistical parameters needed for the filter can be estimated from the noisy image itself [3].

D. Lee Filter

It is also called as sigma filter and it is a modified version of the local statistics filter proposed by J. S. Lee. It preserves edges better than the local statistics filter and is less sensitive to outliers. This filter works by averaging over the neighborhood by only including the pixels that have a value not deviating from the current pixel by more than a given range. This range is defined by the standard deviation of the pixel values within the neighborhood and hence it is called as sigma filter. If there is only less number of pixels in this range within the neighborhood, then all the pixels in the neighborhood are averaged [4].

E. Frost Filter

Frost et al. modeled the functional form of an optimum filter with minimum MSE criterion for smoothing images corrupted with multiplicative noise such as radar images [5]. This filter is adaptive in nature by using locally estimated parameter values so as to yield minimum MSE estimates within the homogeneous areas of an image. This filter preserves the edges of the images. Frost filter in computationally efficient and it is easy to implement in spatial domain.

F. Anisotropic Diffusion Filter

It is a partial differential equation based spatial domain speckle filter. Despeckling is carried out by altering the image by solving a partial differential equation (PDE). Smoothing is carried out depending on the image edges and their directions. Anisotropic diffusion is an efficient nonlinear technique and it simultaneously performs contrast enhancement and noise reduction. It improves the quality of the image by smoothing homogeneous image regions and by retaining edges [6].

G. Speckle reducing anisotropic diffusion (SRAD)

This filter is a variant of anisotropic diffusion filter. It modifies the anisotropic diffusion filter by altering gradient based edge detector with an instantaneous coefficient of variation for speckle mitigation. This instantaneous coefficient of variation combines a normalized gradient magnitude operator and a normalized Laplacian operator to act like an edge detector for speckle images [7].

H. Wavelet Filtering

Wavelet filtering for speckle reduction is a well known multiresolution technique that represents the image in frequency domain in contrary to the methods described above. The discrete wavelet transform decomposes the images into four frequency subbands at each scale as shown in Figure 2.

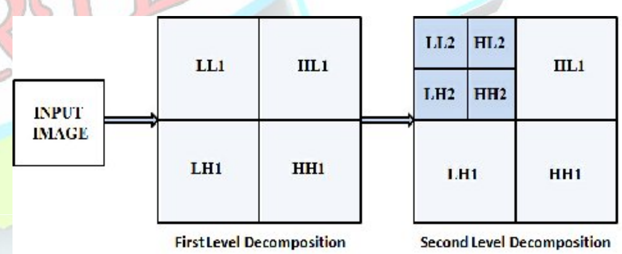

Fig.2. Subbands of 2D – DWT decomposition

After decomposition, the noise parameters are estimated from the wavelet coefficients of HH1 band and a suitable threshold is calculated using any one of the shrinkage rules [8,9]. Then, the wavelet coefficients are shrinked using either soft or hard threshold. Finally, the thresholded coefficients are reconstructed using inverse discrete wavelet transform. The wavelet transform based despeckling has many advantages such as multiresolution, critical sampling, computational efficiency and reliable hardware

ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 2, Issue 9, September 2015

implementations. However, despeckling using other multiscale transforms has also been proposed in the literature [10, 11].

III. IMAGE QUALITY ASSESSMENT METRICS

A. Mean Square Error:

The most frequently used image quality measure is the deviations between the original and the despeckled images namely mean square error (MSE). Lower the MSE, better is the despeckling algorithm [12]. If f(x,y) is the original clean image, i(x,y) is the denoised image then MSE is given by Equation (4).

$$MSE = \frac{1}{MN}\sum_{X=1}^{M}\sum_{Y=1}^{N}(f(X,Y)-i(X,Y))^2 \quad (4)$$

B. Peak Signal to Noise Ratio:

Larger PSNR indicates a smaller difference between the original uncorrupted image and the denoised image. This is the most widely used objective image quality/distortion measure [12]. The main advantage of this measure is ease of computation. However, it is not a robust indicator of image equality under specific conditions. PSNR is calculated in dB using Equation (5),

$$PSNR = 20\log_{10}(F_{\max}/\sqrt{MSE}) \quad (5)$$

where Fmax=255 for an 8-bit image.

C. Structural Similarity Index:

Structural similarity index is based on the assumption that the human visual system (HVS) is highly adapted for extracting structural information from the scene, and therefore a measure of structural similarity should be a good approximation of perceived image quality. Multi-scale structural similarity method introduced in [13] is an image synthesis-based approach to calibrate the parameters that weight the relative importance between different scales. The original image is designated as scale 1 and the highest scale is M. The luminescence comparison l(x,y)is calculated only at scale M. At jth scale, the contrast c(x,y) and structural s(x,y) comparisons are calculated using Equation (6) to Equation (9).

$$l_M(x,y) = \frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1} \quad (6)$$

$$c_j(x,y) = \frac{2\sigma_x\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2} \quad (7)$$

$$s_j(x,y) = \frac{\sigma_{xy} + C_3}{\sigma_x\sigma_y + C_3} \quad (8)$$

where $C_1=(K_1L)^2$, $C2=(K_2L)^2$ and $C3= C_2/2$. L is the dynamic range of the image. K_1 and K_2 are two scalar constants equal to 0.01 and 0.03 respectively. The multiscale SSIM is calculated as in Equation (9).

$$SSIM(x,y) = [l_M(x,y)]^{\alpha_M} \cdot \prod_{j=1}^{M}[c_j(x,y)]^{\beta_j}[s_j(x,y)]^{\gamma_j} \quad (9)$$

IV. EXPERIMENTAL RESULTS AND DISCUSSION

A. Experimental Setup

The experiments have been carried out with MATLAB R2007b on a set of standard gray scale images. The speckle mitigation performance of the state of the art filters such as Order Statistics Filter, Homomorphic Filter, Kuan Filter, Lee Filter, Frost Filter, Anisotropic Diffusion, SRAD and Wavelet Filtering are compared in terms of MSE, PSNR and SSIM.

B. Results and Discussion

The comparison of MSE, PSNR and SSIM on standard gray scale images degrade by speckle noise of density 0.04 is shown in Table 1, Table 2 and Table 3 respectively. Table 4 shows the comparison of time elapsed in seconds for various speckle mitigation techniques on images of different sizes. Comparison of PSNR, SSIM at various noise densities on Lena Image are shown in Figure 3 and Figure 4 respectively. Figure 5 shows the despeckled images using the methods compared.

ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 2, Issue 9, September 2015

TABLE I

COMPARISON OF MSE ON DIFFERENT IMAGES WITH SPECKLE NOISE DENSITY 0.04

Image	First Order Statistics Filter	Homomorphic Filter	Kuan Filter	Lee Filter	Frost Filter	Anisotropic Diffusion	SRAD	Wavelet Filtering
Cameraman	320.29	562.48	473.53	378.59	411.64	409.03	303.89	496.87
Barbara	412.93	738.06	663.87	619.54	597.85	526.01	581.33	687.78
Goldhill	273.65	462.15	421.96	331.38	359.23	301.44	392.66	420.72
House	117.42	186.50	208.15	132.26	114.65	157.60	114.61	140.66
Lena	135.06	242.48	249.09	169.48	172.67	178.88	254.02	219.30
Mandrill	540.37	1275.86	1150.65	1109.02	1081.64	900.35	777.37	1227.82
Monarch	290.82	1177.80	744.38	710.80	770.31	638.06	381.82	900.79
Peppers	186.33	358.29	349.34	259.49	276.26	242.99	238.88	365.57
Tulips	579.79	935.08	759.38	692.41	773.15	596.45	709.38	928.20
Zelda	95.09	188.91	172.24	128.13	131.22	121.83	169.88	161.39

TABLE II

COMPARISON OF PSNR ON DIFFERENT IMAGES WITH SPECKLE NOISE DENSITY 0.04

Image	First Order Statistics Filter	Homomorphic Filter	Kuan Filter	Lee Filter	Frost Filter	Anisotropic Diffusion	SRAD	Wavelet Filtering
Cameraman	23.08	20.63	21.38	22.35	21.99	22.01	23.30	21.17
Barbara	21.97	19.45	19.91	20.21	20.36	20.92	20.49	19.76
Goldhill	23.76	21.48	21.88	22.93	22.58	23.34	22.19	21.89
House	27.43	25.42	24.95	26.92	27.54	26.16	27.54	26.65
Lena	26.83	24.28	24.17	25.84	25.76	25.61	24.08	24.72
Mandrill	20.80	17.07	17.52	17.68	17.79	18.59	19.22	17.24
Monarch	23.49	17.42	19.41	19.61	19.26	20.08	22.31	18.58
Peppers	25.43	22.59	22.70	23.99	23.72	24.27	24.35	22.50
Tulips	20.50	18.42	19.33	19.73	19.25	20.38	19.62	18.45
Zelda	28.35	25.37	25.77	27.05	26.95	27.27	25.83	26.05

TABLE III

COMPARISON OF SSIM ON DIFFERENT IMAGES WITH SPECKLE NOISE DENSITY 0.04

Image	First Order Statistics Filter	Homomorphic Filter	Kuan Filter	Lee Filter	Frost Filter	Anisotropic Diffusion	SRAD	Wavelet Filtering
Cameraman	0.697	0.568	0.537	0.538	0.609	0.577	0.700	0.542
Barbara	0.660	0.516	0.546	0.546	0.557	0.618	0.535	0.500
Goldhill	0.609	0.455	0.568	0.568	0.518	0.644	0.439	0.473
House	0.760	0.679	0.587	0.587	0.701	0.628	0.778	0.655
Lena	0.777	0.671	0.644	0.644	0.708	0.678	0.720	0.649
Mandrill	0.596	0.259	0.370	0.370	0.336	0.484	0.449	0.284
Monarch	0.820	0.600	0.660	0.660	0.685	0.703	0.732	0.633
Peppers	0.756	0.661	0.647	0.647	0.694	0.689	0.694	0.622
Tulips	0.636	0.469	0.589	0.589	0.536	0.656	0.490	0.462
Zelda	0.816	0.708	0.730	0.730	0.757	0.766	0.692	0.715

ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 2, Issue 9, September 2015

TABLE IV

COMPARISON OF TIME ELAPSED IN SECONDS FOR VARIOUS SPECKLE MITIGATION TECHNIQUES ON IMAGES OF DIFFERENT SIZES

Image Size	First Order Statistics Filter	Homo-morphic Filter	Kuan Filter	Lee Filter	Frost Filter	Anisotropic Diffusion	SRAD	Wavelet Filtering
256×256	0.158	0.211	7.672	0.427	7.190	0.102	0.948	0.482
512×512	0.126	0.389	30.661	1.236	27.984	0.361	3.358	1.034
1024×1024	0.381	1.399	120.595	4.238	112.747	1.158	11.369	3.258

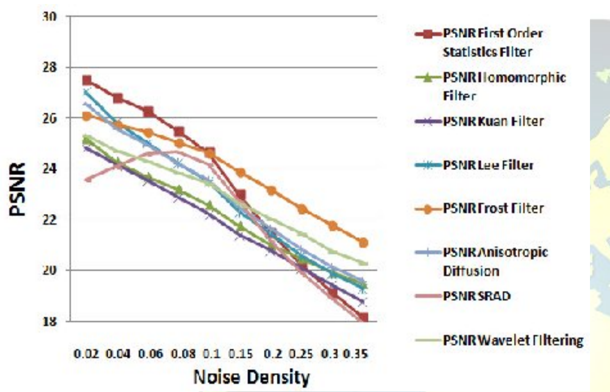

Fig. 3. Comparison of PSNR at various noise densities on Lena Image

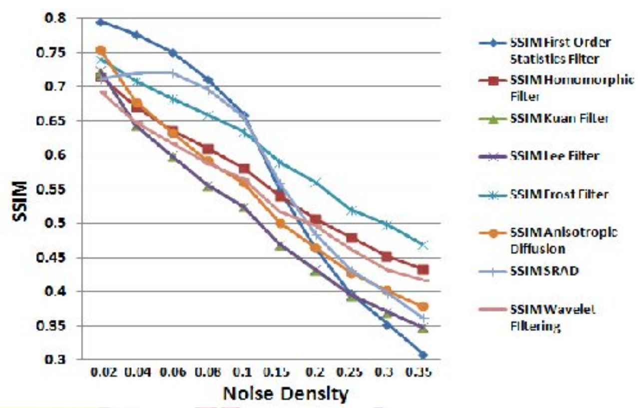

Fig.4. Comparison of SSIM at various noise densities on Lena Image

Fig. 5. Comparison of despeckled images (Speckle noise density 0.04)

From the experimental results we observe that at lower speckle noise densities, the first order statistic filter performs better and at higher noise levels Frost filter yields better performance. In computational point of view, first order statistics filter is computationally cheaper and Kuan filter is more expensive. However, the performance of the despeckling methods compared depends on the image characteristics and the level of noise present.

V. CONCLUSION

This paper studied several speckle mitigation techniques such as order statistics filter, homomorphic filter, Kuan filter, Lee filter, Frost filter, anisotropic diffusion, SRAD and wavelet filtering and their despeckling performance is compared in terms of mean square error, peak signal to noise ratio and structural similarity index. The experimental

ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 2, Issue 9, September 2015

results show that the order statistic filters are performing better with less computational effort. SRAD method removes speckle better, but it over smooths the edges. However, the despeckling performance may be further improved by efficient multiscale despeckling techniques.

REFERENCES

[1] Loizou, Christos P., and Constantinos S. Pattichis. "Despeckle filtering algorithms and software for ultrasound imaging." *Synthesis lectures on algorithms and software in engineering*., vol.1, pp. 1-166, 2008.

[2] Jain, Anil K. Fundamentals of digital image processing. Prentice-Hall, Inc., 1989.

[3] Kuan, Darwin T., et al. "Adaptive noise smoothing filter for images with signal-dependent noise." *IEEE Transactions on Pattern Analysis and Machine Intelligence*", vol.2, pp. 165-177, 1985.

[4] Lee, Jong-Sen. "Digital image smoothing and the sigma filter." *Computer Vision, Graphics, and Image Processing* voll. 2 pp. 255-269, 1983.

[5] Frost, Victor S., et al. "A model for radar images and its application to adaptive digital filtering of multiplicative noise." *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 2, pp. 157-166, 1982.

[6] Weickert, Joachim. "A review of nonlinear diffusion filtering." *Scale-space theory in computer vision. Springer Berlin Heidelberg*, pp. 1-28, 1997

[7] Yu, Yongjian, and Scott T. Acton. "Speckle reducing anisotropic diffusion." *IEEE Transactions on Image Processing,* vol. 11, pp. 1260-1270, 2002.

[8] Leavline, E. Jebamalar, S. Sutha, and D. Asir Antony Gnana Singh. "Wavelet domain shrinkage methods for noise removal in images: A compendium."*International Journal of Computer Applications,* vol.33, pp. 28-32,2011.

[9] Sutha, S., E. Jebamalar Leavline, and D. A. A. G. Singh. "A comprehensive study on wavelet based shrinkage methods for denoising natural images."*WSEAS Transactions on Signal Processing*, vol.9,pp. 203-215,vol.2013.

[10] Leavline, Epiphany Jebamalar, Shunmugam Sutha, and Danasingh Asir Antony Gnana Singh. "Fast multiscale directional filter bank-based speckle mitigation in gallstone ultrasound images." *JOSA A,* vol. 31, pp. 283-292, 2014.

[11] Leavline, Epiphany Jebamalar, Shanmugam Sutha, and Danasingh Asir Antony Gnana Singh. "On The Suitability Of Multiscale Image Representation Schemes As Applied To Noise Removal."

[12] Leavline, Epiphany Jebamalar, Shanmugam Sutha, and Danasingh Asir Antony Gnana Singh. "On The Suitability Of Multiscale Image Representation Schemes As Applied to Noise Removal." pp. 1135-1147, vol. 10, 2014.

[13] Leavline, E. Jebamalar, and S. Sutha. "Gaussian noise removal in gray scale images using fast Multiscale Directional Filter Banks." In IEEE *International Conference on Recent Trends in Information Technology (ICRTIT),* pp. 884-889., 2011.

[14] Z. Wang, E. P. Simoncelli and A. C. Bovik, "Multi-Scale Structural Similarity for Image Quality Assessment", *Proceedings of the 37th IEEE Asilomar Conference on Signals, Systems and Computers, Pacific Grove, CA,* pp.9-12 ,2003.