RESEARCH ARTICLE OPEN ACCESS

Despeckling B-Mode Breast Ultrasound Images using Hybrid Statistical Filter: a of VM

Dr.P.K.Saranya*
*(Department of Computer Science, Vellalar College for Women, Erode-12, Tamilnadu, India

ABSTRACT
Speckle is a noise component in Breast ultrasound images (BUS) that leads to false therapeutic decision making in cancer diagnosis. Hence need to be suppressed without degrading edge and texture information of the image. In this work, a statistical filter is designed by combining Average, Variance and Median of pixels in a specific kernel. The designed hybrid statistical filter (AoVM) with different kernel sizes varying from 3x3 to 11x11 is applied on images corrupted with speckle noises ranging from 0.01 to 0.3. Metrics like Mean Square Error, Peak Signal to Noise ratio and Speckle Suppression Index are used to evaluate the performance of the filter. The filter yields around 70% of Peak Signal Noise Ratio (PSNR) values for all kernel sizes. The results of Mean Square Error rate (MSE) and Speckle Suppression Index (SSI) also found to be better than the existing Gaussian, Lee and M3 Filter in suppressing the noises while preserving the edges.

Keywords - Breast Ultrasound, Speckle noise, Spatial filter, Local Statistics, Gaussian, Lee, M3, AofVM filter

DATE OF SUBMISSION: 15-01-2020 DATE OF ACCEPTANCE: 31-01-2020

I. INTRODUCTION

Recent development in medical imaging techniques identify Ultrasound and its allied equipment as one of the best systems to visualize and quantify blood flow and tissue elasticity properties, and also for the clinical applications for the diagnosis cancer [1], [2]. The best part of Ultrasound examination is that it is a painless and non-invasive procedure. Moreover, nowadays in medical field, ultrasound scanning is made compulsory for supplementing mammogram to diagnose Breast cancer. Breast Ultrasound (BUS) is also the recommended screening tool for young women, pregnant women and for patients who cannot be subjected to Mammograms. During the image acquisition process, the images are degraded by speckle noise caused by the coherent processing of back scattered signals from multiple distributed objects. The noise also reduces the contrast resolution and makes it hard for the radiologists to identify normal and abnormal tissues [3]. Speckle pattern is always in the form of multiplicative noise which is directly proportionate to the local grey level in the image. The multiplicative noise is generally more difficult to remove because the intensity of the noisy pixel varies with the image intensity [4]. The speckle noise model is given in equation (1).

$$I_{ij} = O_{ij} * n_{ij} \qquad (1)$$

where the speckle image I_{ij} is the product of the original image O_{ij}, and the non-Gaussian noise n_{ij}. The indices i, j represent the spatial position of the pixel over the image.

To suppress speckle, a better filtering method is required as a preprocessing technique in Computer Aided Diagnosis systems. The filters are designed either in spatial, frequency or multi-scale domain. Filters used in spatial domain include Mean, Median, Wiener, Lee, and Gaussian filter, and other hybrid or modification of the statistical filters [5], [6], [7], [8], [9], [10], [11]. Many researchers had come up with variants or combinations of mean and median statistical measures to design new filters for suppressing the noise without degrading the edge information [17], [18], [19], [20].

Hence the main objective of this work is to propose a novel statistical (Average of Variance and Median – AofVM) filter that computes median and variance for suppressing reasonable amount of speckle noise without edge degradation. The remaining part of the paper is organized as follows: Section 2 describes the methodology of the proposed AofVM filter. Section 3 briefly shows the extensive experimental analysis using statistical parameters. The work is concluded with a scope for future in Section 4.

II. SPATIAL FILTERS USING STATISTICS

Lee [12], Kuan, Frost [13] and few other Researchers have proposed various denoising algorithms using local statistics. The working principle behind these algorithms are described using sub-region statistics to estimate statistical measures over different pixel windows varying from 3x3 to 15x15 [13]. Various Statistics measures used in linear and nonlinear spatial filters are Mean, Median, Mode, Variance, Standard deviation, Skewness and Kurtosis [14].

Linear spatial filtering i.e. Mean filtering has the tendency to create a new intensity value and smoothen the image. Mean filter for an image of size M x N with a kernel or mask ‘f’ of size m x n is expressed in equation (2) [15].

$$g(x,y)=\frac{\sum_{s=-a}^{a}\sum_{s=-b}^{b} f(x+s,y+t)}{mxn} \qquad (2)$$

where a=int(m/2), b=int(n/2) and m and n are odd, positive integers. If m and n are of size 3x3 then a and b is equal to 1.

Order-Statistic (Nonlinear / Ranking) Filter like Median filter replaces the central pixel value by the realistic pixel intensity which is calculated based on its neighborhood and preserves sharp edges. It is implemented by arranging the neighborhood pixels from the smallest to the largest gray level value for obtaining median value [16]. Given a window W of size m x n, the intensity value of the pixels $I_1 \ldots I_3 \ldots I_{m \times n}$ are arranged in ascending order, the median is calculated as depicted in equation (3).

$$\tilde{X} = \begin{cases} I_{((mxn)+1/2)} & \text{if m x n is odd} \\ \frac{1}{2}\left(I_{(mxn)/2} + I_{((mxn)+1/2)}\right) & \text{if m x n is even} \end{cases} \qquad (3)$$

This filter replaces the pixel value which is less than half of its neighborhood in kernel.

Gaussian Filter [22], [23] is a 2-D convolution smoothing operator like mean filter to `blur' images and smoothen the noise detail but it uses a different kernel that represents the shape of a Gaussian (`bell-shaped') hump. The 2D Gaussian distribution with mean zero and standard deviation σ =1 is represented as

$$G(x,y)=\frac{1}{2\pi\sigma^2}e^{-\frac{x^2+y^2}{2\sigma^2}} \qquad (4)$$

where x, y is the local coordinate of an image and σ is the standard deviation.

Lee filter [11] is one of the effective filters in removing speckle noise and smoothing the image especially in homogeneous or low variance areas. In high variance areas, the statistical parameters mean and standard deviation are adjusted to preserve edges. Since Speckle noise in US images represents multiplicative error model, the Lee filter is applied to the image after the multiplicative noise value is approximated.

Thangavel et al. [21] has proposed M3 filter, a combination of linear (Mean) and non-linear (Median) filters in which the kernel slides along the pixels of the whole image using sliding window concept. During kernel convolution, the M3 filter replaces the central pixel value of each kernel with the maximum value among the mean and median of the kernel. M3 filter achieves good performance than the traditional linear and non-linear filters in suppressing the noises, but degrades edge information proportionately on increasing levels of speckle noise and kernel sizes.

III. AofVM Filter for Despeckling Breast Ultrasound Images

The proposed hybrid spatial filter combines the linear and nonlinear filtering techniques and local statistics to produce a hybrid method to smoothen the image as well as preserve the edges. For the experimental purpose, the original image is contaminated by Speckle Noise to obtain a corrupted image. The corrupted image is then subjected to Gaussian, Lee, M3 and AofVM filters and their performance are evaluated using MSE, PSNR and SSI metrics. The performance of the filtering process is carried out over 50 BUS images with 5 different kernel sizes (3 x 3, 5 x 5, 7 x 7, 9 x 9 and 11 x 11) and 5 speckle noise levels (0.01, 0.05, 0.1, 0.2 and 0.3).

Design of efficient filtering technique is a challenging task since it is necessary to smoothen the image as well as preserve the edge components for the extraction of Region of Interest during segmentation process. The proposed filter, a combination of Average, Variance and Median measures, is designed to overcome this problem. Median filter is a non linear order static filter that preserves the edge since the central pixel assumes one of the values of its neighborhood and eliminates any unwanted artifacts with an intensity value less than the median value [24]. The local statistics Variance determines the average dispersion of the intensity values in the sub image4. The formula for calculating the variance is given in equation (5).

$$\sigma^2=\frac{1}{MxN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(I_{ij}-\overline{x}\right)^2 \qquad (5)$$

where is the mean intensity value of the noisy image I of size M × N. The variance of intensities in a sub image may represent the amount of speckle noise in the image.

The computation steps of the proposed filter is shown in Fig. 1 and its sample calculation is shown in Fig. 2.

AofVM filtering Algorithm for speckle noise removal in BUS image
Input: Noisy BUS Image I and

Output: Denoised BUS Image Q

Step 1: Fix the kernel 'f' of size m x n and zeros are Padded to the required number of rows and columns according to the kernel size for handling borders of the image.
Step 2: Let f_c is the central pixel of the kernel.
Step 3: For each column, sort the pixels and calculate the sum of median of column median and median of column variance
S = median (col-median (f)) + Median (col- variance (f))
Step 4: For each row, sort the pixels and calculate the sum of median of row median and median of row variance
R = median (row-median (f)) + Median (row-variance(f))
Step 5 : Replace the central pixel value f_c with $(f_c + R + S)/3$
Step 6: Repeat step 2, 3, 4 and 5 until all the pixels of an image is convoluted by AofVM
Step 6: Repeat step 2, 3, 4 and 5 until all the pixels of an image is convoluted by AofVM filter

Fig.1. AofVM filtering Algorithm for Speckle noise removal

Fig. 2 shows the sample calculation of proposed filter for the sub-region 'f' of size 3x3. The value S as 0.8041 is obtained from column wise computation, after summing up the medians of Column median and variance.

The value R as 0.7491 is obtained from row wise computation, after summing up the medians of Row median and variance. Finally the central pixel value fc, 0.6324 is replaced by 0.7285, which is the average of S, R and fc values.

0.8147	0.9134	0.2785	**Column wise computation** S=median(median(f))+ median(var(f)) S= 0.6324+0.1718= **0.8042**
0.9058	0.6324	0.5469	**Row wise computation** R=median(median(f))+ median(var(f)); R=0.6324+0.1167=**0.7491**
0.1270	0.0975	0.9575	
Kernel f(3, 3)			Central pixel value f_c =0.6324 f_c=(S + R + f_c)/3; f_c =**0.7285**

Fig. 2. Sample Calculations for a 3 x 3 Sub-region using AofVM filtering

IV. EXPERIMENTAL ANALYSIS AND DISCUSSION

Experiment is conducted over 50 B-mode BUS images collected from an www.ultrasound cases.info database to analyse the strength and weakness of the proposed work. The proposed filter is implemented in MatLab simulation environment and compared with Gaussian, Lee and M3 filter. The BUS images are contaminated by 5 different speckle noise levels - 0.01, 0.05, 0.1, 0.2 and 0.3 respectively to cover 10% to 30% of noise. The kernel sizes 3x3, 5x5, 7x7, 9x9 and 11x11 are applied to filters to analyse edge preservation during filtering.

Speckle is a multiplicative model where the amount of dispersion of noises is not static, so the experiments are conducted to identify the stability of the proposed filter for speckle suppression in various levels. The kernel sizes are increased to reduce computational time and processing high dimensional B-Mode BUS images. The visual perception of Gaussian, Lee, M3 and AofVM filters with different sizes of kernels applied to suppress various noise levels for a sample BUS image are shown in Fig. 3, Fig. 4, Fig. 5 and Fig. 6 respectively. The Figures clearly shows the variation in image using filters during preprocessing.

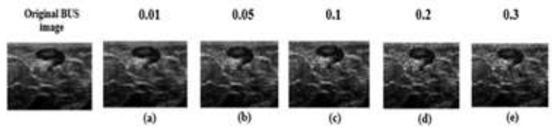

Fig.3. Original image, 3(a)-3(e). Image contaminated by various speckle noise levels

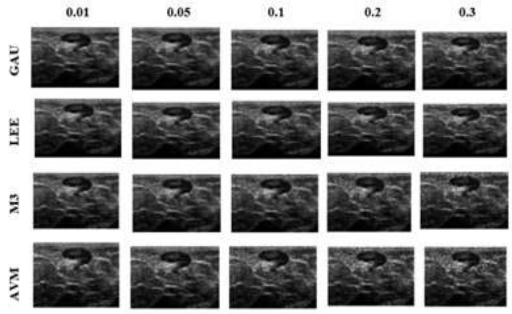

Fig. 4. Denoised image by Gaussian (Gau), Lee, M3 and AofVM filters with 3x3

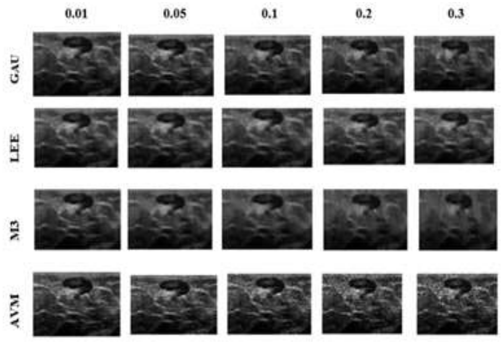

Fig. 5. Denoised image by Gaussian (Gau), Lee, M3 and AofVM filters with 7x7

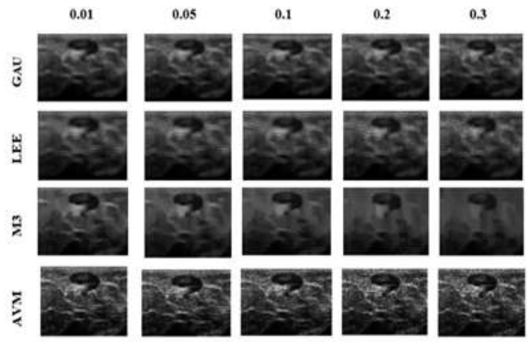

Fig. 6. Denoised image by Gaussian (Gau), Lee, M3 and AofVM filters with 11x11

It is observed from Fig.s 4, 5, and 6, the AofVM filter maintains the quality of images with reasonable amount of speckle filtering along with edge preservation. Gaussian and Lee filters start producing blurriness from 7x7 kernel size whilst M3 filter start degrades the region of interest. These filters degrade the essential edge details that are needed for further analysis in computer aided diagnosis system.

But AofVM filter maintains stableness for various kernels and 0.01 to 0.5 speckle noise levels and produces a very minute blurriness only for 11x11 kernel. From visual perception, it is observed that AofVM filter suits well for preprocessing contaminated BUS image.

This can be also quantitatively verified using standard performance metrics such as Mean Square Error (MSE), Peak signal Noise Ratio (PSNR) and Speckle Suppression Index (SSI) to substantiate the visual perceptions. The formulae for these metrics are shown in Table 1.

Table 1. Parameter Metrics for Evaluating Speckle Reduction

Metrics	Formula
MSE	$\frac{1}{MxN} \sum_{i=1}^{M}\sum_{j=1}^{N}\left(I_{ij}-Q_{ij}\right)^2$ **(6)**
PSNR	$10.\log_{10}\left(\frac{MAXi_1^2}{MSE}\right)$ **(7)**
SSI	$\left(\frac{\sqrt{var(I_{m,n})}}{mean(I_{m.n})}\right) x \left(\frac{mean(Q_{m.n})}{\sqrt{var(Q_{m,n})}}\right)$ **(8)**

The parameter MSE is widely used to quantify the change in image quality between the original image (I) and denoised image (Q) [3]. MSE is calculated along with PSNR to strongly prove the filter performance than the visual perception. The PSNR measures the image fidelity, by closely identifying the percentage of resemblance between the original and denoised image. The SSI measures the ratio of coefficient of variance of original and denoised image in suppressing the speckle noise. Lower value of SSI indicates large amount of speckle suppression in the image [25]. Better filtering methods always yield minimum MSE and SSI and Maximum PSNR values.

Average of all these metrics for 50 speckle contaminated BUS images that are denoised by Gaussian, Lee, M3 and AofVM filters with 3x3, 5x5, 7x7, 9x9 and 11x11 kernel sizes are shown in Table 2, Table 3 and Table 4, and the same are graphically presented in Fig. 7, Fig. 8 and Fig. 9 respectively.

Table 2. Average MSE values of filters with different kernel sizes for various speckle noise levels

KERNEL SIZES	**FILTERS**	**Average MSE Values↓**				
		SPECKLE NOISE LEVELS				
		0.01	**0.05**	**0.1**	**0.2**	**0.3**
3x3	**Gau**	0.00793	0.00795	0.01181	0.01675	0.02190
	Lee	0.01592	0.01597	0.02461	0.03471	0.04494
	M3	0.00019	0.00022	0.00028	0.00040	0.00051
	AOFVM	**0.00007**	**0.00009**	**0.00012**	**0.00020**	**0.00027**
5x5	**Gau**	0.01100	0.01250	0.01474	0.02001	0.02516
	Lee	0.02042	0.02438	0.02969	0.04129	0.05211
	M3	0.00021	0.00028	0.00036	0.00052	0.00067
	AOFVM	**0.00008**	**0.00011**	**0.00015**	**0.00022**	**0.00029**
7x7	**Gau**	0.01291	0.01436	0.01669	0.02181	0.02724
	Lee	0.02275	0.02705	0.03298	0.04485	0.05683
	M3	0.00025	0.00032	0.00041	0.00059	0.00076
	AOFVM	**0.0001**	**0.00012**	**0.00016**	**0.00023**	**0.00030**
	Gau	0.01443	0.01586	0.01802	0.02339	0.02875

	Lee	0.02513	0.02959	0.03531	0.04810	0.06035
	M3	0.00027	0.00034	0.00045	0.00064	0.00082
9x9	**AOFVM**	**0.00011**	**0.00013**	**0.00017**	**0.00023**	**0.00030**
	Gau	0.01563	0.01688	0.01936	0.02452	0.02965
	Lee	0.02722	0.03157	0.03818	0.05075	0.06299
	M3	0.00028	0.00037	0.00047	0.00068	0.00088
11x11	**AOFVM**	**0.00011**	**0.00014**	**0.00017**	**0.00024**	**0.00031**

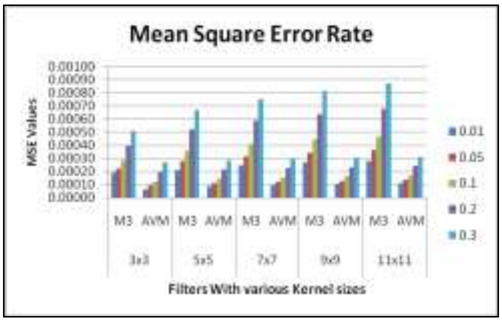

Fig. 7. Overall Average MSE values of M3 and AOFVM filter with different kernel sizes and speckle noise levels

For each noise level, the average MSE values of Gaussian, Lee, M3 and AofVM filters are reported in Table 2. From Table 2, it is observed that MSE values of Gaussian, Lee and M3 filters for 3x3, 5x5, 7x7, 9x9 and 11x11 kernel sizes are higher than AofVM filter and also produce slightly blurred image and disbanding edges. It shows that Gaussian and Lee filters produces far higher MSE variation with Original image and is not depicted in Fig. 7. Hence the graphical representation of the MSE values for M3 and AofVM filters is alone depicted in Fig. 7.

From Table 2, it is keenly observed that for each noise level and kernel size, the average MSE values of AofVM filter are always 30% lesser when compared to M3 filter and much lesser to Gaussian and Lee filter. From these analyses it is concluded that AofVM filter preserves the image detail at maximum level for all kernel sizes and noise levels than the Gaussian, Lee and M3 Filters.

Table 3. Average PSNR values of various filters with 3x3 to 11x11 kernel sizes

KERNEL SIZES	**FILTERS**	**Average PSNR Values↑**				
		SPECKLE NOISE LEVELS				
		0.01	**0.05**	**0.1**	**0.2**	**0.3**
	Gau	69.13	69.12	67.40	65.88	64.72
	Lee	66.10	66.09	64.21	62.72	61.60
	M3	67.50	67.46	65.68	64.56	63.15
3x3	**AOFVM**	72.08	71.54	69.73	67.82	66.53
	Gau	67.71	67.16	66.45	65.12	64.12
	Lee	65.03	64.26	63.40	61.97	60.96
	M3	66.90	65.95	64.97	63.55	62.52
5x5	**AOFVM**	71.07	70.35	69.01	67.39	66.22
	Gau	67.02	66.56	65.90	64.74	63.78
	Lee	64.56	63.81	62.95	61.61	60.58
	M3	66.49	65.55	64.53	63.10	62.05
7x7	**AOFVM**	70.54	69.80	68.68	67.20	66.07
	Gau	66.54	66.13	65.57	64.44	63.54
	Lee	64.13	63.42	62.65	61.31	60.32
	M3	66.21	65.27	64.24	62.78	61.73
9x9	**AOFV**	70.2	69.42	68.48	67.0	65.98

	M	1			6	
11x11	Gau	66.19	65.86	65.26	64.24	63.41
	Lee	63.78	63.14	62.31	61.08	60.14
	M3	65.99	65.05	64.02	62.54	61.47
	AOFVM	70.06	69.23	68.34	66.97	65.91

It is observed from Table 3, AofVM filter with 3x3, 5x5, 7x7, 9x9 and 11x11 kernel sizes yields high PSNR values compared to other filters. The Gaussian, Lee and M3 filters yield similar average PSNR values eventually, but M3 filter degrades the maximum edge information.

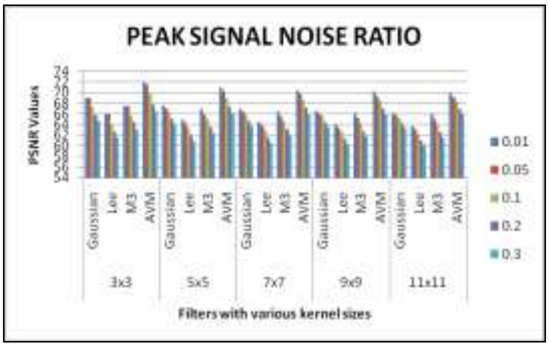

Fig. 8. Overall Average PSNR values of Gaussian, Lee, M3 and AOFVM filter for 50 BUS images

The higher PSNR value of AofVM filter yields maximum similarity of pixel values with the original image and proves its maximum edge preservation. On comparing the overall average PSNR values with Gaussian, Lee and M3 filters for 3x3 to 11x11 kernel sizes, the AofVM filter yields 5% high PSNR values for all kernel sizes for various speckle noise levels and the variation is graphically shown in Fig. 8.

Table 4. Average SSI value for various speckle noise levels for 50 BUS images

KERNEL SIZE	**FILTERS**	**Average SSI Values↓**				
		SPECKLE NOISE LEVELS				
		0.01	**0.05**	**0.1**	**0.2**	**0.3**
3x3	**Gau**	0.038	0.037	0.140	0.262	0.346
	Lee	0.029	0.045	0.099	0.205	0.272
	M3	0.001	0.092	0.175	0.310	0.402
	AOFVM	0.001	0.031	0.097	0.192	0.262
5x5	**Gau**	0.081	0.101	0.178	0.290	0.407
	Lee	0.077	0.078	0.157	0.260	0.340
	M3	0.055	0.155	0.255	0.397	0.492
	AOFVM	0.012	0.060	0.129	0.222	0.319
7x7	**Gau**	0.115	0.155	0.217	0.341	0.441
	Lee	0.115	0.124	0.187	0.292	0.346
	M3	0.097	0.225	0.347	0.502	0.602
	AOFVM	0.035	0.120	0.160	0.255	0.302
9x9	**Gau**	0.149	0.204	0.237	0.363	0.469
	Lee	0.152	0.176	0.184	0.280	0.349
	M3	0.125	0.255	0.400	0.565	0.662
	AOFVM	0.055	0.140	0.110	0.115	0.239
11x11	**Gau**	0.185	0.238	0.289	0.387	0.494
	Lee	0.191	0.205	0.235	0.295	0.385
	M3	0.155	0.292	0.437	0.610	0.700
	AOFVM	0.065	0.155	0.227	0.230	0.202

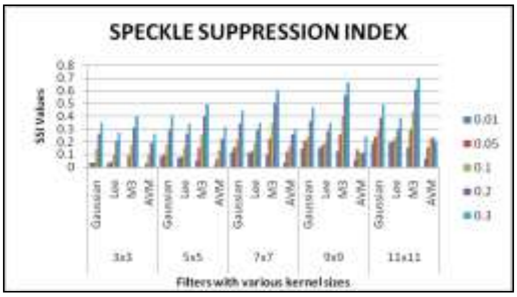

Fig. 9. Overall Average SSI values of Gaussian, Lee, M3 and AOFVM filter for 50 BUS images

For each kernel size, it is observed from Table 4 that AofVM filter on 50 BUS images yields 20% less SSI values compared to Gaussian, Lee and M3 filters which show its reasonable amount of speckle noise suppression in image without any blurriness. The pictorial representation of SSI value comparison is shown in Fig. 9. From these observations, it is found that AofVM filtering techniques maintains the stability of sharpness and produces very less blurriness in image for large sizes of kernel. AofVM filter designed using local statistics, preserves the edge details and suppresses the speckle noise from BUS images, and outperforms other filters with minimum MSE, maximum PSNR and minimum SSI values for 3x3, 5x5, 7x7, 9x9 and 11x11 kernel sizes and 0.01, 0.05, 0.1, 0.2 and 0.3 speckle noise levels.

V. CONCLUSION

The existence of speckle noise in the ultrasound image is undesirable since it degrades image quality. This study proposes a new hybrid spatial model -AofVM filter, a combination of Average, Variance and Median to preserve the edge as well as suppress the noise. The performance of the proposed filter is compared with the existing Gaussian, Lee and M3 filters using Metrics like Mean Square Error, Peak Signal to Noise ratio and Speckle Suppression Index. The filters uses various kernel sizes ranging from 3x3 to 11x11 to suppress 0.01 to 0.3 speckle noise levels. The proposed filter proved to be a better filter with 30% lower Mean Square Error values and 5% higher Peak Signal Noise Ratio than Gaussian, Lee and M3 filters without degradation of edges for all the kernel sizes varying from 3x3 to 11x11. The work may be further extended to other medical domains and various types of noises. It can also be hybridised with other single and multi-scale domain filters for further improvement in speckle suppression.

REFERENCES

[1]. K. Kirk Shung, Diagnostic Ultrasound: Past, Present, and Future, Journal of Medical and Biological Engineering, 31(6), 2011

[2]. Y. Zhou Ultrasound diagnosis of breast cancer, J. Med. Imaging Health Informatics, 3 (157), 2013

[3]. S. Kalaivani Narayanan and R.S.D. Wahidabanu, A View on Despeckling in Ultrasound Imaging, International Journal of Signal Processing, Image Processing and Pattern Recognition, 2(3), 2009

[4]. P.S. Hiremath, Prema , Akkasaligar and Sharan Badiger, Speckle Noise Reduction in Medical Ultrasound Images, Advancements and Breakthroughs in Ultrasound Imaging, 2013

[5]. M.S.Lee,C.L.Yen,S.K.Ueng,Speckle reduction with edges preservation for ultrasound images : using function spaces approach, IET Image Processing, 6, 2012, 813-821

[6]. Quinones, Jorge and Perito,Flavio, Reduction of Speckle Noise by Using an Adaptive Window, Rev.ing.univ.Medellin[online], 11, 2012, 179-190

[7]. Fabijanska and D. Sankowski, Noise adaptive switching median-based filter for impulse noise removal from extremely corrupted images, IET Image Processing, 5, 2011, 472

[8]. Y. Guo, H. D. Cheng, J. Tian, and Y. Zhang, A novel approach to speckle Reduction in ultrasound imaging, Ultrasound in Medicine and Biology, 35, 2009, 628

[9]. G. Gajanand, Algorithm for Image Processing Using Improved Median Filter and Comparison of Mean, Median and Improved Median Filter, International Journal of Soft Computing and Engineering (IJSCE), 1(5), 2011

[10]. Azadeh Noori Hoshyar, Adel Al-Jumailya, Afsaneh Noori Hoshyar, Comparing the Performance of Various Filters on Skin Cancer Images, Procedia Computer Science, 42, 2014, 32 – 37

[11]. Vikrant Bhateja, Mukul Misra, Shabana Urooj, Bilateral Despeckling Filter in Homogeneity Domain for Breast Ultrasound Images, Conf.public.ICACCI, IEEE, 2014, 1027-1032

[12]. Jong-Sen Lee, Digital image enhancement and noise filtering by use of local statistics, IEEE Transactions on Pattern Analysis and Machine Intelligence, 2(2), 1980

[13]. P.Christos. Loizou, Constantinos S. Pattichis, Costas Pattichis, Despeckle Filtering Algorithms and Software for Ultrasound Imaging, Morgan & Claypool Publishers, 2008

[14]. Wagner.R.F, Smith. S.W, Sandrik. J.M, Lopez. H, Statistics of speckle in ultrasound B-scans, IEEE Trans. Sonics Ultrason. 30 , 1983, 156–163

[15]. Gonzalez. R.C and R.E. Woods, Digital Image Processing, 3rd Edition Prentice Hall , 2008

[16]. Njeh, O. B. Sassi, K. C. Ahmed, and B. H. Mida, Speckle noise reduction in breast ultrasound images: SMU (SRAD Median Unsharp)Approach, Proc.IEEE 8th International Multi- Conference on Systems, Signals and Devices, 2011, 1–6

[17]. C.N.Mariana, Luminita M. and Laura O, Comparative Approach for Speckle Reduction in Medical Ultrasound Images, Romanian j.Biophysics 20, 2010, 13-21

[18]. O. V. Michailovich and A.Tannenbaum, Despeckling of medical ultrasound images, IEEE Trans. Ultrason. Ferroelect., FrEq. Control, 2006, 53 64

[19]. R.Sivakumar, M.K. Gayathri and D.Nedumaran, Speckle filtering of ultrasound B-Scan images – A comparative study between spatial and diffusion filters, IEEE conference on open systems (ICOS 2010),Kuala Lumpur, Malaysia, 2010
[20]. Sean Finn, Martin Glavin, and Edward Jones, Member Echocardiographic Speckle Reduction Comparison, IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control, 2011
[21]. K.Thangavel, R. Manavalan, and I. Laurence Aroquiaraj, Eliminating Speckle Noise from ultrasound medical images: a non-linear approach, Intelligent Computing Models Narosa Publishing House, New Delhi, , 2009 173-180
[22]. Wang Xiaofeng, Geng Guohua, Guo Hongbo, An improved image enhancement algorithm and its application in: Computer Applications and Software, 2008, 25 39-40
[23]. Mohamed Saleh Abuazoum, Efficient analysis of medical image de-noising for MRI and ultrasound images, Masters thesis, Universiti Tun Hussein on Malaysia, 2012
[24]. Simily Joseph, Kannan Balakrishnan , Balachandran Nair , Reji Rajan Varghese, Ultrasound Image Despeckling using Local Binary Pattern Weighted Linear Filtering, I.J. Information Technology and Computer Science, 06, 2013, 1-9
[25]. N. Monika, Payal M. Ghutke, Implementation of Cost efficient image enhancement Technique Reduce Speckle in Ultrasound Images, International Journal on Recent and innovation Trends in Computing and Communication, 2, 2014, 2927

Dr.P.K.Saranya “ Despeckling B-Mode Breast Ultrasound Images using Hybrid Statistical Filter: A of VM” *International Journal of Engineering Research and Applications (IJERA*), vol.10(01), 2020, pp 38-45.