A Comparative Study of Speckle Reduction Filters for Ultrasound Images of Poly Cystic Ovary

G.Vasavi, S.Jyothi,

Abstract: *Ultrasound imaging is the most commonly used modality in medical diagnosis and it is corrupted by speckle noise,which is multiplicative in nature. Hencethere is a need to reduce the speckle noise in ultrasound images for a better diagnosis. In this paper we discuss and compare the performance of various speckle reduction filtersnamely Median, Wiener, Gaussian, Bilateral, Guided, Anisotropic Diffusion and Non-Local Means (NLM). Evaluation of the filters is done by considering different performance metrics for image quality such asMean Square Error(MSE), Signal to Noise Ratio (SNR), Peak Signal to Noise Ratio(PSNR), Structural Similarity Index (SSIM) and determines the best suitabledespeckling filter for the ultrasound images of polycystic ovary.*

Index terms: Ultrasound images, Speckle noise, Filtering techniques, Image quality metrics, Polycysticovary.

I.INTRODUCTION

Medical ultrasound or ultrasonography is a non-invasive diagnostic tool used toview the imagesof internal parts of a human body. Ultrasound imaging uses sound waves to produce images which help to diagnose the disease. It uses a small transducer (probe) and ultrasound gel which is placed directly on the skin. High-frequency sound waves are transmitted from the probe into the human body. The transducer collects the sounds that bounce back and the computer uses the sound waves to generate an image. Unlike other modalities like X-ray,MRI,CT,ultrasound images has many advantages because of its low cost, not harmfuland portability. But the only disadvantage is the ultrasound images are degraded by the speckle noise which makes the image analysis difficult and also to the diagnosis doneby a physician.

Hence to enhance the quality of the image, speckle reduction is very important step in pre-processing. An efficient speckle reduction filter can produce accurate results and helps in the correct diagnosis of the disease.

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G.Vasavi, Research scholar, Department of Computer Science, SPMVV, Tirupati, A.P, India

S.Jyothi, Department of Computer Science,
Professor, SPMVV, Tirupati ,A.P, India, Vasavi.gotte@gmail.com, jyothi.spmvv@gmail.com

A polycystic ovary is an ovary which contains 12 or more follicles(cysts) of size 2–9mm. The ovary contains many small antral(not dominant) follicles with eggs in them, the follicles do not develop and mature properly which leads to the formation of cysts in the ovaries[1].

In this paper ultrasound images, the importance of denoising those images and polycystic ovary are discussed in section 1. Section 2 describesthe speckle noise,various filters proposed and the evaluation metrics. Section 3 shows the experimental results and in section 4 conclusions are drawn.

II. MATERIALS AND METHODS

A. Speckle noise

Speckle is a kind of granular noise that inherently exists and degrades the quality of themedical ultrasound images.Speckle is most often considered the dominant source of noise in ultrasound imaging and should be processed without affecting important features of an image.Speckle is an undesirable property of the image as it masks small differences in grey level[2].Speckle is generally considered as a correlated multiplicative noise and can be converted to additive noise by applying a log operation. And the log-based speckle noise is an additive noise and can be approximated by a Gaussian probability density.

The mathematical representation of speckle noise model is given by[3].

$$A(i,j) = B(i,j) \times n(i,j) \quad (1)$$

Considering a 2-D image of size M×N, where A(i,j) is the noisy image,B(i,j) is the original image and n(i,j) is the noise,(i,j) represents pixel positions in the image.

Applying logarithmic operation on equation (1)

$$\ln(A(i,j)) = \ln(B(i,j)) + \ln(n(i,j)) \quad (2)$$

Equation (2) can be written as

$$x(i,j) = y(i,j) + z(i, j)$$

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(3)

here z(i,j)is the additive noise which can be removed easily.

B. Speckle Reduction filters

In image processing speckle removal is considered the crucial step in pre-processing, as it acts an obstacle for image analysis for the operations segmentation, feature extraction and classification.The removal of this multiplicative noise from an ultrasound image is a big challenge. There are different types of filters namely linear filters, nonlinear filters, diffusion filters.Various despeckling filters which have been proposed earlier are applied on the ultrasound images. Lee filter[4], Frost filter[5], Kaun filter[6], are the filters initially designed for Synthetic Aperture Radar (SAR) images and later applied for ultrasound imaging. Some of the denoising filters are described belowwhich are applicable for the ultrasound images of polycystic ovaries.

a. Median filter

The medianfilter[7]is a simple nonlinear filter in which the middle value of pixel in the window is replaced with the median value of its neighbors. The pixel values are arranged according to the ascending order and the middle value is chosen as the median. The size of theneighbourhood consideredis [3, 3] for better results.

b. Wiener filter

Wiener filter[15] is linear filter which is also known as Least Mean Square Filter. It can restore images even if they are corrupted or blurred. It reduces noise from image by comparing with the desired noiseless image. Wiener filter is based on computation of local image variance. Hence larger the local variance of the image then smoothing is done in lesser amount and if the local variance is small it performs more smoothing. Wiener filter is given by

$$f(u,v)=\left[\frac{H(u,v)^*}{H(u,v)^2+\left[\frac{Sn(u,v)}{Sf(u,v)}\right]}\right]G(u,v)$$

where H(u,v) is the degradation function and H(u,v)* is its complex conjugate. $Sf(u,v)$ is power spectra of original image, $Sn(u,v)$ is power spectra of noisy images and $G(u,v)$ is the degraded image

c. Gaussian filter

Gaussian filter [16] is a local linear filter that smoothes the noisy image. It suppresses the noise by preserving the features of the image, but blurs the edges. Gaussian filter is given by

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

where σ is the standard deviation of Gaussian distribution. Pixels in the centre of the kernel have higher weights than those on the periphery. Larger values of σ produce a blur. The kernel size must be increased with increasing σ to maintain the nature of the Gaussian filter. A gaussian kernel coefficient depends on the value of σ.

d. Bilateral filter

Bilateral filter [13]smoothes the images by preserving edges, by means of a nonlinear combination of neighbhoring image values. It is non iterative in nature. Bilateral filter is a combination of range and domain filtering. Itcomputes the filtering output at each pixel as the average ofneighboring and similar pixels, weighted by the bothspatial and intensity distance. The Bilateral filter is described as

$$BF(\mathbf{x}) = k^{-1}(x)\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\mathbf{f}(\xi)c(\xi,\mathbf{x})s\big(\mathbf{f}(\xi),\mathbf{f}(\mathbf{x})\big)\,d\xi$$

with a normalization

$$k(\mathbf{x}) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}c(\xi,\mathbf{x})s\big(\mathbf{f}(\xi),\mathbf{f}(\mathbf{x})\big)d\xi$$

where $\mathbf{f}(\mathbf{x})$ is the input image, $c(\xi,\mathbf{x})$ is the geometric closeness between the pixel**x**and a near point ξ and $s\big(\mathbf{f}(\xi),\mathbf{f}(\mathbf{x})\big)$ is the photometric similarity between the pixels**x**and ξ.

e. Guided filter:

Guided filter [10] is a linear edge preserving smoothing filter, which involves a guidance image I, an input image *x*, and an output image y. Both I and *x* are identical.The output at the pixel i is expressed asthe weighted average:

$y_i = \sum_j W_{ij}(I) * x_i$

where i and j are pixel indexes. The filter kernel W_{ij} is afunction of the guidance image I and independent of *x*. Thisfilter is linear with respect to*x*.

f. Anisotropic Diffusion

Diffusion filters suppress the speckle noise of an image by applying a partial differential equation (PDE).Anisotropic diffusion is an efficient nonlinear technique for performing contrast enhancement and noise reduction. It is used for smoothing imagein a continuous region, and retains image edges without requiring any information from the image power spectrum. It can bedirectly applied to the images. Perona and Malik [14] proposed the following nonlinear PDE for anisotropic diffusion, known as PMAD:

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

where ∇ is the gradient operator and div is the divergence operator, $c(|\nabla I|)$ is diffusion coefficient.

$$c(|\nabla I|) = \frac{1}{1+\left(\frac{\nabla I}{k}\right)^2}$$

where *k*is an edge magnitude parameter. The PMAD method uses the gradient magnitude todetect an image edge or boundary as a step discontinuity in intensity.If $|\nabla I| \gg K$,then $c(|\nabla I|)\to 0$ and the filter preserves the pixel. If $|\nabla I| \ll K$thenc$(|\nabla I|)\to 1$ andisotropic diffusion (Gaussian filtering) is achieved.

A variant of nonlinear anisotropic diffusion method, speckle reducing anisotropic diffusion(SRAD) [11] is proposed by Y. Yu et al. forremoval of speckle noise in ultrasound and SAR images.

g. NonLocalMeans(NLM) filter

Non local means filter was originally introduced by A. Buadas et al. [8] for reduction of Gaussian noise. In this method the pixels in the noisy image are replaced by the weighted average of the similar pixels in the neighbourhood.Given a discrete noisy image f = {f(i) | i∈ I}, the denoised value of NL[f(i)] for pixel iis calculated as weighted average of all pixels in the image.

NL[f(i)] =$\sum_{j \in I} w(i,j) f(j)$

where the weight {w(i, j)} is the similarity between the pixels i and j,satisfying the conditions 0 ≤ w(i, j) ≤ 1 and$\sum_j w(i,j) = 1$. The similarity between two pixels i and j depends on the neighborhoods N_i and N_j. The similarity is measured as the decreasing function of weighted Euclidean distance.

d(i,j) = E||f(Ni) – f(Nj)||$^2_{2.a}$ a>0 is the standard deviation of Gaussian kernel.
The weights are given by

w(i,j) = $\frac{1}{Z(i)} e^{\frac{-d(i,j)}{h^2}}$

z(i) = $\sum_j e^{\frac{-d(i,j)}{h^2}}$, z(i) is a normalization constant and h is degree of filtering.

The pixels with similar neighborhood have larger weights. Dissimilar neighborhood has lesser weights.
Later improvements were done to NLM filter to remove the multiplicative noise using Bayesian formulation by introducing a new statistical distance measure to comparethe patchesis the Pearson distance and the filter is known as OBNLM. In theOptimized Bayesian Non Local Means[12] a block wise approach is introduced to reduce the computing time.
The Bayesian formulation of Non local means filter is given by

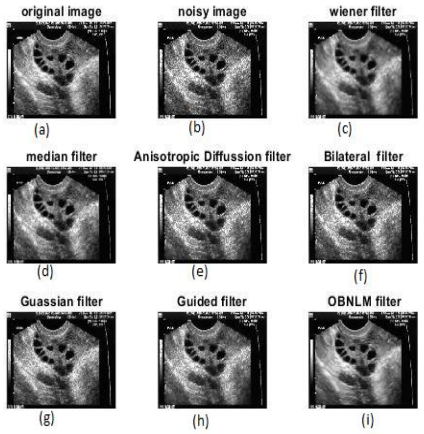
NL(u)(B_{ik}) = $\frac{\frac{1}{|v_{ik}|}\sum_{j=1}^{|V_{ik}|} p\left(u(B_{ik})\middle|u(B_j)\right)u(B_j)}{\frac{1}{|v_{ik}|}\sum_{j=1}^{|V_{ik}|} p\left(u(B_{ik})\middle|u(B_j)\right)}$

where$p\left(u(B_{ik})\middle|u(B_j)\right)$ is the probability density function (pdf) of$u(B_{ik}$)conditional to $u(B_j$).

C. Image Quality Metrics

In order to measure the performance of the above despeckling filters, the following fourmetrics are considered.
1. Mean Square Error(MSE):
Given an original image I, with dimensions M×N, noisy image N and denoised image F. The mean square error of original and filtered image is given by

$$\text{MSE} = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N}[F(x,y) - I(x,y)]^2$$



For identical images MSE is equal to zero otherwisea maximumup to 255.
2.Signal to Noise Ratio(SNR):

SNR is a common measurement to evaluate the speckle reduction filter by computing theratio between the original image and MSE. HigherSNR values shows that the filteringtechnique is better, and the denoised image quality is high.

$$\text{SNR} = 10\log_{10}\frac{\sigma^2}{MSE}$$

where σ^2=$\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(f^2(i,j))$and f(i,j) is an original image

3. Peak Signal to Noise Ratio(PSNR):

It is a metricused for the performance of the speckle noise reduction. It is a ratio between the maximum possible power of the signal and the noise image. The PSNR can be calculated as follows:

$$\text{PSNR}= 10log_{10}\left(\frac{255^2}{MSE}\right)$$
$$= 20log_{10}\left(\frac{255}{\sqrt{MSE}}\right)$$

Higher the values of PSNR, morethe quality of an image.
4.Structural Similarity Index (SSIM)[9]:
This index is another metric for measuring the similarity between two images. This metric has much better consistency with the qualitative appearance of the image.

$$\text{SSIM}(x,y) = \frac{\left(2\mu_x\mu_y + C_1\right)\left(2\sigma_{xy} + C_2\right)}{\left(\mu_x^2 + \mu_y^2 + c1\right)\left(\sigma_x^2 + \sigma_y^2 + c2\right)}$$

where meanμ_x=$\frac{1}{N}\sum_{i=1}^{N} x_i$

and standard deviation $\sigma_x = \left(\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu_x)^2\right)^{\frac{1}{2}}$

C_1=$(K_1 L^2)$,L is the dynamic range of pixels vlues.
C_2=$(K_2 L^2)$,$K_1$and K_2 ≪1.

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III.EXPERIMENTAL RESULTS AND DISCUSSION:

In this section we discuss the experimental results obtained, which shows the efficiency of the proposed filterson the ultrasound images of polycystic ovary. For the purpose of experimentation five synthetic ultrasound images are considered. The speckle noise of variance 0.04 is introduced into the original test images. The window size of the median and wiener filters is taken as 3×3. The experiments are conducted in MATLAB, image quality metrics PSNR, SNR, MSEand SSIM are used for the evaluation of filters.

Experimental results of various filters proposed areillustrated in figure1 to figure5. Each figure consists of original ultrasound image of polycystic ovary, noisy image and the despeckledimages obtained using proposed filtering methods.

Figure 1:Results obtained from different filters for polycystic ovaryimage.(a) original image 1 (b) noisy image with variance($\sigma = 0.04$) (c) Wiener filter (d) Median filter (e) AD filter (f) Bilateral filter (g) Gaussian filter (h) Guided filter (i) OBNLM filter

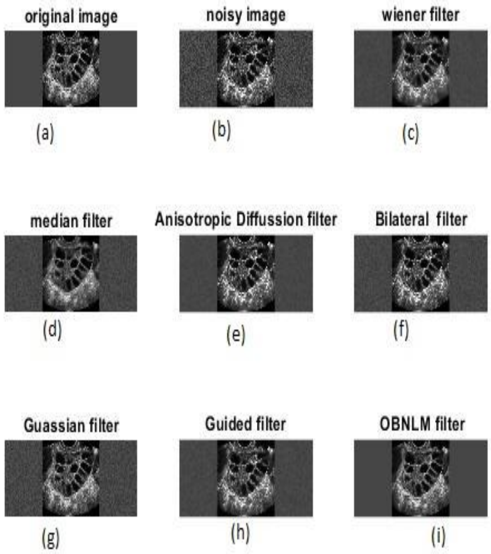


Figure 2: (a) original image 2 (b) noisy image (c) Wiener filter (d) Median filter (e) AD filter (f) Bilateral filter (g) Gaussian filter (h) Guided filter (i) OBNLM filter

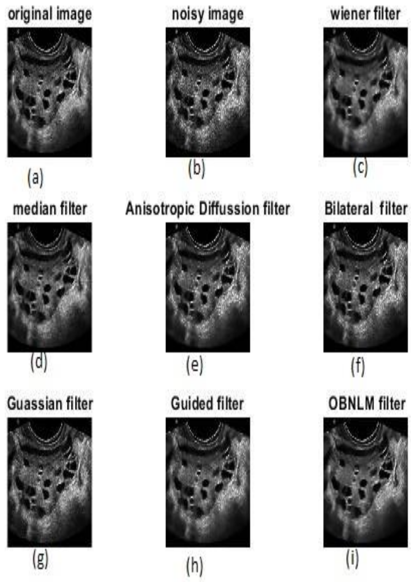


Figure 3: (a) original image3 (b) noisy image (c) Wiener filter (d) Median filter (e) AD filter (f) Bilateral filter (g) Gaussian filter (h) Guided filter (i) OBNLM filter

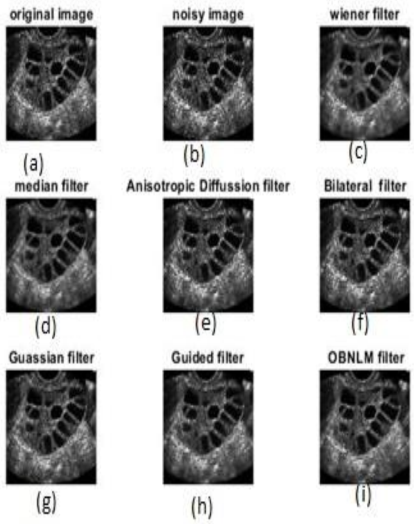
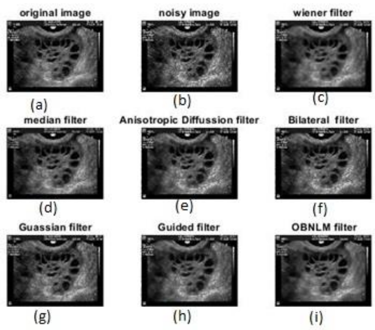


Figure 4: (a) original image4 (b) noisy image (c) Wiener



filter (d) Median filter (e) AD filter (f) Bilateral filter (g) Gaussian filter (h) Guided filter (i) OBNLM filter

Figure 5: (a) original image5 (b) noisy image (c) Wiener filter (d) Median filter (e) AD filter (f) Bilateral filter (g) Gaussian filter (h) Guided filter (i) OBNLM filter

The outcomes of the filtering techniques Median, Wiener, Gaussian, Guided, AD, Bilateral and OBNLM are compared and presented in table1 to table5. The tables consists of statistical values for the five synthetic images with their performance measures PSNR, SNR, MSE and SSIM for the proposed methods used in speckle noise removal of ultrasound images. The quantitative values in the tables prove that OBNLM filter gives better results than other filters.

Higher the values of PSNR and SNR, higher are the performances of the filters. MSE must be low which shows a high quality image as it represents the error between the images. SSIM values ranges from 0 to 1 indicating minimum and maximum similarity values, higher values indicates that the images are identical.

Table 1: Image quality metrics forthe polycystic ovary image 1 using different filters.

Filters/metrics	**PSNR**	**SNR**	**MSE**	**SSIM**
Median	21.62	13.5	447	0.74
Wiener	25.38	17.46	188	0.81
Gaussian	24.68	16.7	221	0.84
Guided	24.24	16.3	244	0.80
PMAD	23.14	15.36	315	0.78
Bilateral	23.51	15.72	289	0.80
OBNLM	**27.62**	**19.74**	**112**	**0.88**

Table 2:Image quality metrics for the polycystic ovary image 2 using different filters.

Filters/ metrics	**PSNR**	**SNR**	**MSE**	**SSIM**
Median	23.15	12.50	314	0.59
Wiener	26.71	16.38	138	0.78
Gaussian	26.52	16.18	144	0.64
Guided	27.47	17.11	114	0.83
PMAD	26.64	16.30	140	0.87
Bilateral	26.69	16.43	139	0.74
OBNLM	**27.58**	**17.18**	**113**	**0.91**

Table 3:Image quality metrics for the polycystic ovary image 3 using different filters.

Filters/metrics	**PSNR**	**SNR**	**MSE**	**SSIM**
Median	22.87	11.84	335	0.70
Wiener	27.76	17.14	108	0.80
Gaussian	27.70	17.01	110	0.87
Guided	26.97	16.28	130	0.83
PMAD	26.28	15.70	152	0.84
Bilateral	26.61	16.01	141	0.86
OBNLM	**30.57**	**19.81**	**58**	**0.86**

Table 4 :Image quality metrics for the polycystic ovary image 4 using different filters.

Filters/metrics	**PSNR**	**SNR**	**MSE**	**SSIM**
Median	22.70	11.81	348	0.65
Wiener	25.06	14.57	202	0.77
Gaussian	26.62	16.17	141	0.88
Guided	25.69	15.17	175	0.81
PMAD	24.69	14.33	220	0.79
Bilateral	25.46	15.02	184	0.85
OBNLM	**26.98**	**16.45**	**130**	**0.82**

Table 5:Image quality metrics for the polycystic ovary image 5 using different filters.

Filters/metrics	**PSNR**	**SNR**	**MSE**	**SSIM**
Median	23.22	12.62	309	0.70
Wiener	27.77	17.51	108	0.83
Gaussian	27.08	16.89	127	0.83
Guided	26.93	16.66	131	0.79
PMAD	26.25	16.12	154	0.79
Bilateral	26.44	16.31	147	0.82
OBNLM	**28.69**	**18.53**	**87**	**0.83**

Further analysis of the quantitative results can be represented as graphs.

The evaluation of thedespeckling filters is done by the performancemetrics PSNR, SNR, MSE, SSIM values by considering five ultrasound images of ovary is represented in graph1 to graph4. Graph1 shows the PSNR values, graph2 gives SNR values, similarly graphs 3 and 4 represents MSE and SSIM values respectively.

Experiments are also conducted on the 50 real ultrasound images and calculated the statistical results and the graphical analysis are drawn. The values obtained using the synthetic images and real images are almost identical for all the metrics. It shows that OBNLM filter is very efficient for the removal of speckle noise in the ultrasound images.

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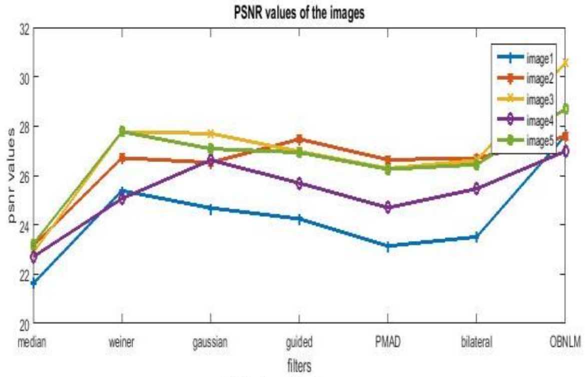

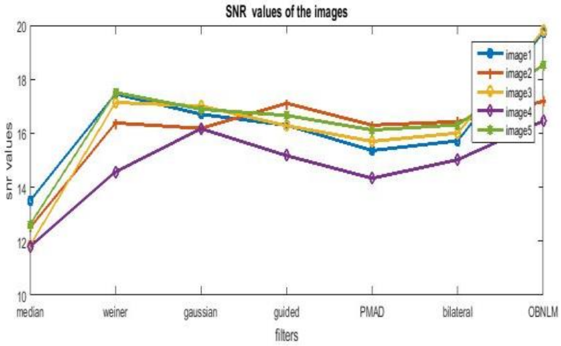

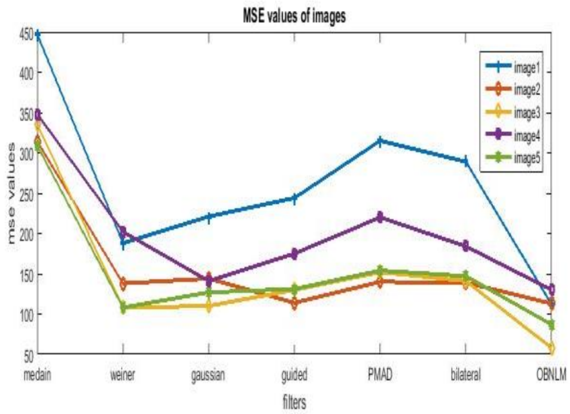

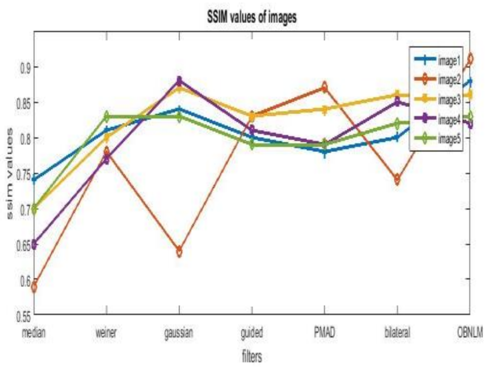

After the analysis of graphs and tables for the synthetic and real ultrasound images of the polycystic ovaries the following observations are made. The quality metrics PSNR, SNR, MSE,SSIM values for the method OBNLM are more effective as compared to other filtering techniques. Except in the graph4 representing SSIM values, there is a small deviation ofGaussian filter for image2 as compared with other images. For the remaining performance measures the statistical values of the filters for the ultrasound images are nearly same.

IV. CONCLUSION

In this paper, sevendifferent speckle filters Median, Wiener, Gaussian, Guided, AD, Bilateral and OBNLM are discussed. Experiments are conducted on 50 real ultrasound images of polycystic ovary. The experimental results have been compared and evaluated to find the efficient of speckle filter by using the parameters PSNR, SNR,SSIM and MSE. It is shown that OBNLM filter outperforms than other denoising filters. The numerical comparison is done using tables and visualization by the graphs. So we can conclude that OBNLM filter performs well and it is more appropriate among the proposed filters to remove the speckle noise by preserving the edges of the filtered image. In future, this work is extended to find a more efficient despeckling filter based on OBNLM for the ultrasound images of polycystic ovary.

REFERENCES

1. [1]P. S. Hiremath and Jyothi R. Tegnoor,"Follicle Detection and Ovarian Classification in Digital Ultrasound Images of Ovaries", Advancements and Breakthroughs in Ultrasound Imaging,chap-7pp 167-198,2013.
2. [2] C. B. Burckhardt, "Speckle in ultrasound B-mode scans," *IEEE Trans.SonicsUltrason.*, vol. UE-25, no. 1, pp. 1–6, Jan. 1978.
3. [3]Kie B. Eom, "Speckle reduction in Ultrasound images using nonisotropicadaptive filtering," Ultrasound in Medicine & Biology, Vol.37, No. 10, pp. 1677- 1688, 2011.
4. [4] J.-S. Lee, "Speckle analysis and smoothing of synthetic aperture radarimages," *Comput. Graph. Image Process.*, vol. 17, no. 1, pp. 24–32,1981.
5. [5] Frost VS, Stiles JA, Shanmugan KS, Holtzman JC." A model for radar images and its application to adaptive digital filtering of multiplicative noise". IEEE Trans Pattern Anal Machine Intel 1982;4:157–166.
6. [6]D. Kuan, A. Sawchuk, T. Strand, and P. Chavel, "Adaptive restorationof images with speckle," *IEEE Trans. Acoust., Speech, Signal Process.*,vol. ASSP-35, no. 3, pp. 373–383, Mar. 1987.
7. [7] R.C. Gonzalez and R.E. Woods, Digital Image Processing, second ed. Prentice Hall, 2002
8. [8] A. Buades, B. Coill, and J. -M. Morel, "A non-local algorithm for imagedenoising," in *Proc. omput. Soc. Conf. Comput. Vis. Pattern Recognit.*,vol. 2. pp. 60-65, 2005
9. [9] Z. Wang, A. C. Bovik, H. R. Sheikh and E. P. Simoncelli, "Image quality assessment: From error visibility to structural similarity," *IEEE Transactions on Image Processing*, vol. 13, no. 4, pp. 600-612, Apr. 2004.
10. [10] K. He, J. Sun, and X. Tang, "Guided image filtering," IEEE Trans. Pattern Anal. Mach. Intell., vol. 35, no. 6, pp. 1397-1409, June 2013.
11. [11] Y. Yu and S. T. Acton, "Speckle reducing anisotropic diffusion," *IEEE Trans. Image Process.*, vol.11, no. 11, pp. 1260-1270, Dec. 2002.
12. [12] P. Coupe, P. Hellier, C. Kervrann, and C. Barillot, "Nonlocal means-basedspeckle filtering for ultrasound images," *IEEE Trans. Image Process.*, vol.18, no. 10, pp. 2221-2229, Oct. 2009.
13. [13] C. Tomasi and R. Manduchi, "Bilateral filtering for gray and color images,"in *Proc. Int. Conf. Comput. Vis.*, pp. 839-846, 1998.
14. [14]P. Perona and J. Malik, "Scale space and edge detection usinganisotropic diffusion," *IEEE Trans. Pattern Anal. Machine Intell.*, vol.12, pp. 629–639, 1990.
15. [15] J.Jyoti and Rajveer Shastri "A Study Of Speckle Noise Reduction Filters" Signal & Image Processing : An International Journal (SIPIJ) Vol.6, No.3, June 2015.
16. [16] R.A. Haddad and A.N. Akansu, "A Class of Fast Gaussian Binomial Filters for Speech and Image Processing," IEEE Transactions on Acoustics, Speech, and Signal Processing, vol. 39, pp 723-727, March 1991.