

# A New Osrad Filter for Despeckling of Medical Ultrasound Images

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**Abstract:** *Speckle noise is an inherent nature of ultrasound images, which results in poor image interpretation and diagnosis. Oriented speckle reducing Anisotropic diffusion filter improves the speckle reduction and edge preservation in these images. In regions of weak edges, the diffusion coefficient is less sensitive. An ideal diffusion coefficient should act so as to diffuse homogeneous regions and sensitive to the edge region which could be well realized by a sigmoid function. In this paper, we propose a new OSRAD filter based on sigmoid function. The diffusion coefficient is chosen to be uniform in the homogeneous region, and decreases rapidly in the transition region which improves weak edges and details. The sigmoid function based OSRAD performs directional filtering of the image along the structures which reduces the blocking effect of diffusion coefficient and enhances the speckle suppressing ability. The proposed filter gives better performance in edge preservation and speckle noise reduction in comparison to the existing diffusion filters.*

**Key words:** Anisotropic diffusion, Sigmoid function, adaptive median filter.

## I. INTRODUCTION

Ultrasonography is an imaging technique, which is non-invasive, free from ionizing radiations, portable, cost effective and forms real-time images. These merits made ultrasound imaging a most widely used imaging modality. However, the resolution of this imaging system is greatly affected by the presence of speckle noise that arises from the coherent nature of ultrasound imaging system. Speckle is a random interference pattern, present in all coherent imaging systems and it affects the resolution of an ultrasound image.

Many filtering approaches for the post processing of speckled images of B-mode ultrasound system have been devised. Speckle noise is considered as a multiplicative noise, and many techniques have been developed for speckle suppression to improve the image quality. Among them, non linear filters are recently preferred due to their smoothing in homogeneous regions and edge preserving capabilities. In anisotropic diffusion filtering, several despeckling methods like Perona and Malik anisotropic diffusion filter[1]. Speckle reducing anisotropic diffusion (SRAD)[2],and Oriented speckle reducing anisotropic diffusion (OSRAD)[3], have been developed in the non linear filtering techniques. These diffusion techniques allow the contrast enhancement and noise reduction by using proper diffusion co-efficient. They preserve and enhance the prominent edges, while removing the speckle noise. The SRAD exploits the instantaneous coefficient of variation; to

reduce the speckle noise.SRAD provides superior performance in comparison to the existing anisotropic diffusion filters. Despite its progress, it causes blocking artifact due to the imperfect design of the diffusion coefficient. In SRAD the instantaneous coefficient of variation serves as a edge detector, and this presents larger values at the edges, and smaller value in the homogeneous regions. The diffusion coefficient is implemented through a decreasing function. In this case, when the diffusion coefficient is small it causes blocking artifact in the homogenous region, and increase in the value results in failure to preserve the details at the edges. To make up this short coming, an ideal diffusion coefficient has to be chosen which should act so as to diffuse homogeneous regions with speeds changing sensitively. This can be realized by a sigmoid function which is devised as a New speckle reducing anisotropic diffusion filter (NSRAD) [4].The NSRAD strengthens the sensitivity of the transition region to preserve more details and weak edges. A non-scalar component is added to the SRAD, and this filter performs directional filtering, termed as Oriented Speckle Reducing Anisotropic Diffusion filter (OSRAD).The diffusion matrix in the OSRAD uses the smoothing coefficients in the maximal curvature and minimal curvature directions. In this paper, a new matrix is devised based on the OSRAD and NSRAD to jointly implement the merits of these two filters. Several algorithms have been proposed based on the histogram statistics for threshold selection [5][6][7].

The organization of the paper is as follows. Section II deals with the overview on diffusion based despeckle filters. Section III describes the proposed filter. Section IV deals about the Evaluation methodology. Section V Presents the Results and discussion. Section VI deals with the Conclusion and future Scope, respectively.

## II Overview On Diffusion Based Despeckle Filters

### 1.Adaptive Threshold Anisotropic Diffusion filter

Selection of threshold is an important issue in the anisotropic diffusion filters. Using threshold one can adjust the upper and lower limit of smoothing, as well as sharpening which reduces the undesirable noisy defects. The adaptive threshold  $T_{xy}$ , in diffusion coefficient function varies in accordance with the difference between the two variances, which gives a measure of intensity contrast in that neighborhood and is given by the eqn (1),

$$T_{xy} = \begin{cases} T_{high} & \text{when } \sigma_{w_{xy}}^2 < a_0 \sigma_{\xi}^2 \\ T_{inter} & \text{when } \sigma_{w_{xy}}^2 \approx a_0 \sigma_{\xi}^2 \\ T_{low} & \text{when } \sigma_{w_{xy}}^2 > a_0 \sigma_{\xi}^2 \end{cases} \quad (1)$$

Where  $T_{xy}$  is an adaptive threshold at a pixel position  $(x, y)$  of the image. The proposed adaptive edge threshold function  $T_{xy}$  which fulfils the above criteria can be now defined as ,

$$T_{xy} = \frac{1}{1 + e^{-\left(a_0 \sigma_{\xi}^2 - \sigma_{w_{xy}}^2\right)q}} \quad (2)$$

Where  $a_0$  is a positive constant with value less than or equal to one for low contrast areas, and greater than one for high contrast areas.  $q$  is a constant whose value is greater than zero. From Eq.(2), it is clear that the adaptive edge threshold  $T_{xy}$  is a function of global gray level variances  $\sigma_{\xi}^2$  and local gray. Modified Tukey's Biweight function is used as the gradient. The filter uses modified anisotropic diffusion kernel which considers the possible neighbor pixels in eight different directions. The discrete form of the proposed diffusion filter is given as follows ,

$$I_{i,j}^{t+1} = I_{i,j}^t + \frac{\tau \lambda}{|\eta_s|} \left[ \begin{array}{l} (1/dy)^2 d_{NE} \nabla_{NE} I + (1/dy)^2 d_{SE} \nabla_{SE} I + \\ (1/dx)^2 d_{NE} \nabla_{NE} I + (1/dx)^2 d_{NW} \nabla_{NW} I + \\ (1/dd)^2 d_{NE} \nabla_{NE} I + (1/dd)^2 d_{SE} \nabla_{SE} I + \\ (1/dd)^2 d_{NW} \nabla_{NW} I + (1/dd)^2 d_{SW} \nabla_{SW} I \end{array} \right]_{i,j} \quad (3)$$

where  $\lambda$  is a constant and is chosen as  $0 < \lambda < 1/4$  for the numerical stability.  $|\eta_s|$  represents the number of neighbors for the pixel considered.  $dx, dy$  are the unit distance of the pixel in  $x$  and  $y$  directions respectively.  $dd$  is the diagonal pixel distance from the center pixel and it is 1.414 times the unit distance.  $d_{NE}, d_{NW}, d_{SE}, d_{SW}$ , are the diffusion coefficients calculated in northeast, northwest, south-east and south-west direction.  $\nabla_{NE} I, \nabla_{NW} I, \nabla_{SE} I$  and  $\nabla_{SW} I$  are the image gradients calculated in north-east, north-west, south-east and south-west directions, respectively.

## 2. New Speckle Reducing Anisotropic Diffusion filter

To make up the shortcoming of SRAD as analyzed before, an ideal diffuse coefficient should act so as to diffuse homogeneous regions with speeds changing stolidly, but the transition regions with speeds changing sensitively. This can be realized by a sigmoid function. So a new speckle reducing anisotropic diffusion filter (NSRAD) can be written as follows:

$$\frac{\partial u}{\partial t} = \text{div}[c(q) \nabla I(x, y; t)] \quad (4)$$

with new diffuse coefficient,

$$c(q) = 1 - \frac{1}{1 + \exp(-k(q^2 - \beta q_0^2))} \quad (5)$$

Where  $k > 0$ , it is a tunable parameter to control the dropping speed of the diffusion coefficient. In (4),  $\beta$  is the rate of the homogeneous regions to the noise and it is referred as the homogeneous region control coefficient.

## III. PROPOSED FILTER

### A NEW ORIENTED SPECKLE REDUCING ANISOTROPIC DIFFUSION FILTER

A new anisotropic diffusion model is proposed by combining matrix anisotropic diffusion with sigmoid function based diffusion coefficient filter for better medical ultrasound image restoration. The concept is to add to the sigmoid function Anisotropic Diffusion filter, a non-scalar component which can perform directional filtering of the image along the structures. Thus, this filter reduces the blocking effect of diffusion coefficient and enhances the speckle suppressing ability Sigmoid function based Anisotropic Diffusion filter gives better performance in edge preservation and speckle noise reduction in comparison to the existing anisotropic diffusion filters.

Formally, Sigmoid Function based Anisotropic Diffusion is written as,

$$I(t=0) = I_0 \quad (6)$$

$$\frac{\partial u}{\partial t} = \text{div}[c(q) \nabla I(x, y; t)] = \text{div} \left( \begin{bmatrix} c(q) & 0 & 0 \\ 0 & c(q) & 0 \\ 0 & 0 & c(q) \end{bmatrix} \nabla I \right) \quad (7)$$

The diffusion matrix is a scalar, so it can be written as,

$$D = c(q) I \quad (8)$$

Where,  $I$  is the identity matrix. In the case of the flux diffusion we use the directions of the gradient and principal curvature directions on a smoothed version of the image. The use of the gradient and its associated principal curvature directions, more effectively extracts the local orientation of the image than the Eigen values of the structure tensor, which is better deployed in the regions of close structures. For 2D images, only one coefficient ' $c_{tang}$ ' is tangential coefficient normal to the both  $c_x$  and  $c_y$ , which is obtained from the eigen vector of the smoothed image, and the obtained  $c_{tang}$  is normalized using the following function for the better image restoration.

$$c_{tang}(x, y) = \frac{1}{1 + \left(\frac{c_x^2 + c_y^2}{32}\right)} \quad (9)$$

and the diffusion coefficient associated with instantaneous coefficient of variation is given as,

$$c(q) = \left[ 1 - \frac{1}{1 + \exp(-k(q^2 - \beta q_0^2))} \right] \quad (10)$$

Therefore new diffusion matrix can be written, in the basis (v0, v1), as

$$D = \begin{bmatrix} c(q) & 0 \\ 0 & c_{\text{tang}}(x, y) \end{bmatrix} \quad (11)$$

Thus, the overall Directional Sigmoid function based anisotropic diffusion PDE,

$$\frac{\partial u(x, y; t)}{\partial t} = \text{div} \left( \begin{bmatrix} c(q) & 0 \\ 0 & c_{\text{tang}}(x, y) \end{bmatrix} \nabla I(x, y; t) \right) \quad (12)$$

### Discretization

Assuming a sufficiently small time step size of  $\Delta t$  and sufficiently small spatial step size of  $h$  in  $x$  and  $y$  directions, we discretize the time and space coordinates as follows,

$$c_{i,j}^n = c \left[ q \left( \frac{1}{I_{i,j}^n} \sqrt{|\nabla_R I_{i,j}^n|^2 + |\nabla_L I_{i,j}^n|^2} \right), \frac{1}{I_{i,j}^n} \nabla^2 I_{i,j}^n \right] \quad (13)$$

where

$$\nabla_L I_{i,j} = [I_{i,j} - I_{i-1,j}, I_{i,j} - I_{i,j-1}]$$

$$\Delta I_{R,i,j} = [I_{i+1,j} - I_{i,j}, I_{i,j+1} - I_{i,j}]$$

$$I_{i,j}^n = I_{i+1,j}^n + I_{i-1,j}^n + I_{i,j+1}^n + I_{i,j-1}^n - I_{i,j}^n$$

$$d_{i,j}^n = \frac{1}{h^2} \left[ \begin{bmatrix} c_{i+1,j}^n(q) & 0 \\ 0 & c_{\text{tang}}(i,j) \end{bmatrix} (I_{i+1,j}^n - I_{i,j}^n) + \begin{bmatrix} c_{i,j+1}^n(q) & 0 \\ 0 & c_{\text{tang}}(i,j) \end{bmatrix} (I_{i,j+1}^n - I_{i,j}^n) \right]$$

The numerical approximation is given by update equation,

$$I_{i,j}^{n+1} = I_{i,j}^n + \frac{\Delta t}{8} d_{i,j}^n \quad (15)$$

### Speckle noise simulation

There are numerous computational procedures involving ultrasound images, such as filtering and segmentation. Unfortunately, the validation of these techniques in clinical images is hindered by the lack of gold standard ground-truth image. One solution is to create a synthetic dataset of simulated ultrasound images for which gold standard ground-truth is known and predefined. Therefore, for this study, speckle noise was simulated using Field II, which was developed by Jensen (1996)[8][9] in Mathworks MatLab\_ (Natick, MA, USA) and is available for free download at (Jensen 2011). To facilitate this study reproduction, the ultrasound images of a cyst were simulated as proposed by Jensen (2011) and will be referred in this work, as Sim1 with 600 x 400 pixels. The original image is the Gold standard image on which the field II simulation is

implemented to create images of different speckle patterns. Fig.4 represents the gold standard ground truth image of a cyst.

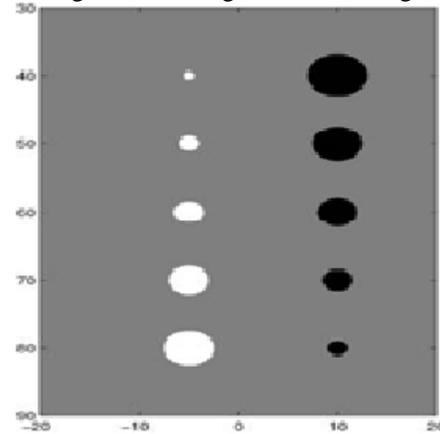


Fig .1. Gold Standard Ground Truth Image of Cyst

The simulation is generated with the linear array transducer. The five small bright white dots along the left side at axial distances 40, 50, 70 and 80 of Fig.4 were placed to simulate the Point Spread Function (PSF) of the ultrasound imaging system. The other relevant parameters of the Field II simulation for an ultrasound system attached to linear array are listed in Table 1.

Table 1. Field II Simulation – Input Parameters

Parameters	Values
Transducer Center Frequency	3MHz
Sampling Frequency	100MHz
Speed of Sound	1540 m/s
Width of Element	$5.13E-04 \text{ m}$
Height of Element	5.00E-03 m
Kerf Number of Physical Elements in	192
Number of Active Elements in	64

Table 2. Philips HDI 5000 Scanner Settings

Scan Head Information	
Scan head name	L7-4 ,38 mm
Number of elements	128
Scan head label	Linear Array L7-4
Operating Frequency	7.0-4.0 MHz
Doppler frequency	4.0MHz

Table.1 mentions the parameters for the speckle simulation of cyst images using Field II simulation software. The transducer center frequency and the number of scatterers is varied and the experiment is conducted for a series of 20 test images with differing speckle distribution. In one series, the transducer center frequency was 3 MHz and 5 MHz in the other with differing uniformly distributed scatter-profiles were created for the gold-standard image, shown in fig .1. The two series, thus, have distinct speckle patterns. In other words, 40 different images with differing speckle patterns are tested.

#### IV EVALUATION METHODOLOGY

Quantitative evaluation metrics are applied in this work, to allow for a more accurate assessment of relative performance between the various filters examined

. Both numerical and functional evaluation were considered. To compare the performance of the filters discussed above, a series of quantitatively simulated speckle images were created and then filtered. The filter were tested on real ultrasound images also.

##### Numerical Parameters

The numerical evaluation of the filters involved calculating the mean, standard deviation, Mean square error and the structural similarity[11][12][13].

##### (i) Peak Signal to Noise Ratio (PSNR)

Peak Signal to Noise Ratio (PSNR) of a denoised image with respect to the original image denotes the closeness of the denoised image to the original image. A higher the PSNR value, indicates the denoised image is closer to the original image. The general equation to compute the PSNR is given in eqn (16)

$$PSNR = 10 \log_{10} \frac{(255)^2}{MSE} \quad (16)$$

Where, MSE indicates the Mean Square Error.

##### (ii) Structural Similarity Index Measure (SSIM)

The structural similarity index measure (SSIM),<sup>18</sup> measures the closeness between two images and is derived from a mathematically defined universal quality index. This index is used here to compare the gold-standard images (original image) with the speckle filtered images.

The SSIM takes three different comparisons into consideration: Correlation (s), Luminance (l) and Contrast (c) (Wang et al. 2004).

$$s(I_{GS}, I_F) = \frac{\sigma_{GS, F}}{\sigma_{GS} \sigma_F} \quad (17)$$

$$l(I_{GS}, I_F) = \frac{2 \cdot \mu_{GS} \cdot \mu_F}{\mu_{GS}^2 + \mu_F^2} \quad (18)$$

$$c(I_{GS}, I_F) = \frac{2 \cdot \sigma_{GS} \cdot \sigma_F}{\sigma_{GS}^2 + \sigma_F^2} \quad (19)$$

$$SSIM(I_{GS}, I_F) = s(I_{GS}, I_F) \cdot l(I_{GS}, I_F) \cdot c(I_{GS}, I_F) \quad (20)$$

where  $I_{GS}$  is the gold- standard image,  $\mu_{GS}$  and  $\sigma_{GS}^2$  are the mean and variance of the gold-standard image respectively.  $I_F$  is the filtered image,  $\mu_F$  and  $\sigma_F^2$  are the mean and variance of the filtered image respectively.  $\sigma_{GS} \sigma_F$  is the covariance between

gold-standard and filtered images. After simplifications, the SSIM is given by

$$SSIM(I_{GS}, I_F) = \frac{(2 \cdot \mu_{GS} \mu_F + C_1)(2 \cdot \sigma_{GS} \sigma_F + C_2)}{(\mu_{GS}^2 + \mu_F^2 + C_1)(\sigma_{GS}^2 + \sigma_F^2 + C_2)} \quad (21)$$

where  $C_1 = 0.01 \cdot dr$  and  $C_2 = 0.03 \cdot dr$ , with  $dr=255$  (eight-bit image) representing the range of the ultrasound images. The SSIM is calculated using an 8 x 8 pixel sliding window over the whole image and the mean value is obtained. The mean value ranges from -1 to 1 ( $-1 \leq Q \leq 1$ ), the highest value is 1 and occurs if  $I_F = I_{GS}$ , shows perfect similarity, whereas the lowest value occurs if  $I_F = 2 \cdot \mu_{GS} - I_{GS}$  which shows no similarity.

#### REAL ULTRASOUND IMAGES

In this work, we have taken the ultrasound image of polycystic ovaries (PCOS). The target of the real data is to despeckle it, in order to provide a better clarity. The parameters of the HDI 5000 Scanner for observing the real data is given below in Table.2.

The scanned PCOS image of size 768 x 576 pixels is taken using HDI 5000 scanner[14]. The target of the real data is to provide a despeckled clinical image with a better resolution. Evaluation is done based on the parameters discussed in section IV. The input image is a speckled image, acquired from the HDI 5000 scanner, on which the despeckled filters are applied.

The simulation is generated with the linear array transducer. The five small bright white dots along the left side at axial distances 40, 50, 70 and 80 of Fig.6 were placed to simulate the ultrasound systems Point Spread Function (PSF). The other relevant parameters of the field II simulation for an ultrasound system attached to linear array are listed in table 2.

process ran for 100 iterations. The user can adjust the window and the number of iterations to fine tune the features for SRAD the smoothing time step is 0.8 and the despeckling different applications. To evaluate numerical accuracy, we use adaptively with 50 iterations, with a time step of 0.5. In the Sig-

SNR, SSIM and CNR. Cyst phantom is created with transducer center Cyst phantom is created with transducer center Frequency 3.5MHz, scatterer distribution of 50,000 and frequency 3.5MHz, scatterer distribution of 1,00,000 and r of scan lines set to 50 is considered for analysis. Number of scan lines set to 50 is considered for analysis. performance of our novel OSRAD algorithm with that of SRAD (Speckle reducing anisotropic diffusion filter) and Sig-SRAD. In the SRAD method, the despeckling process ran the discussed in the section IV. The input image is a speckled image, acquired from a HDI 5000 scanner, on which the despeckle filters are applied. We have compared the of this work is to provide a despeckled clinical image with better resolution. Evaluation is done based on the parameters The scanned Poly Cystic Ovarian Syndrome image of size 768 x 576 pixels is taken using HDI 5000 scanner.

#### RESULTS AND DISCUSSION

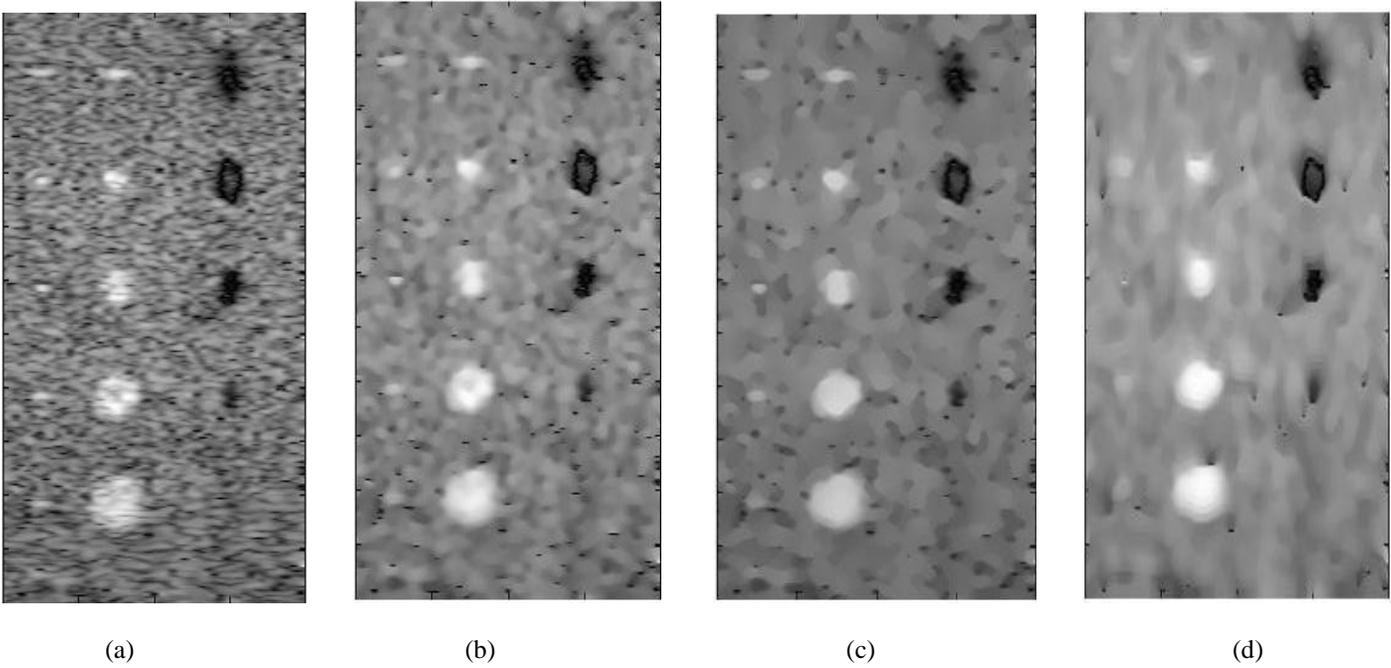


Figure.2 (a) Cyst image (b) ATAD filter image(c) Sigmoid of function based AD (SFAD) filter image (d) Proposed filter output

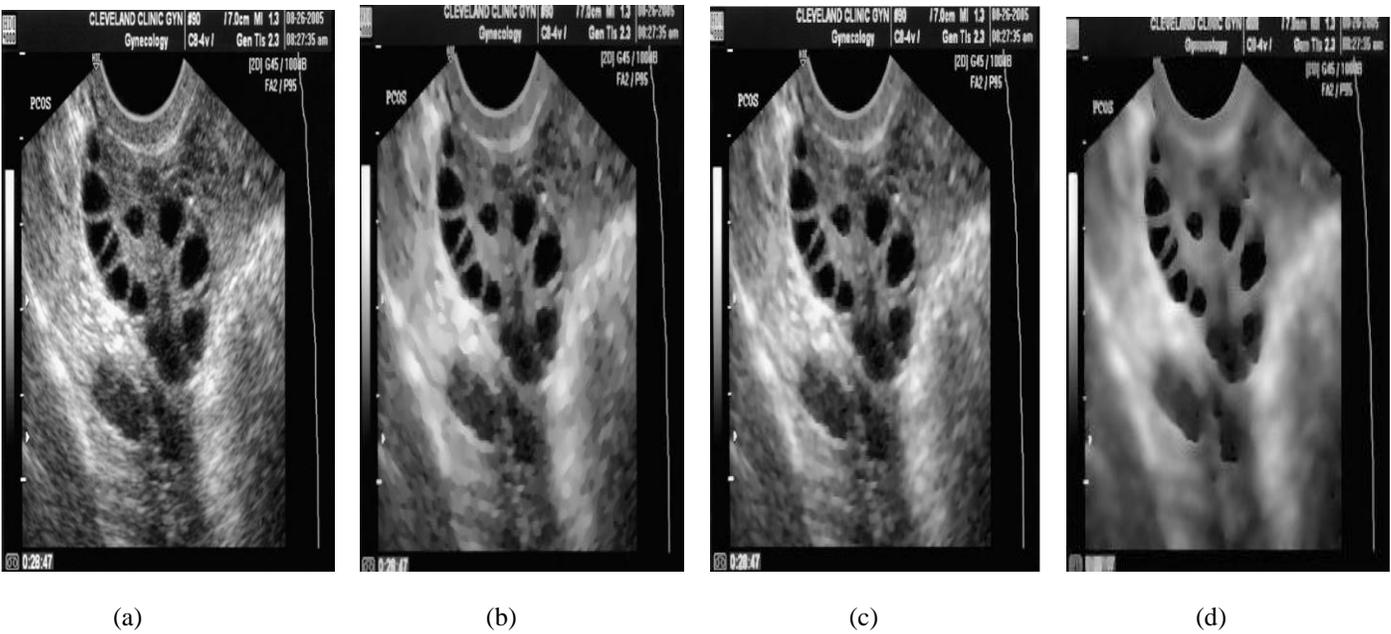


Figure .3 (a)PCOS image (b) ATAD filter image(c) Sigmoid of function based AD (SFAD) filter image (d) Proposed filter output

Table 3. Numerical Performances of Field II simulated image

FILTER TYPE	MSE	PSNR	SSIM x 100%
ATAD	7.35E-04	71.92	94
SFAD	5.44E-04	80.7752	98.88
<b>Proposed Filter</b>	<b>4.52E-04</b>	<b>81.578</b>	<b>98.94</b>

Table .4. Numerical Performances of the real PCOS image

FILTER TYPE	MSE	PSNR	SSIM x 100%
ATAD	0.0046	68.8679	89.0029
SFAD	0.0035	72.694	94.6
<b>Proposed Filter</b>	<b>0.0026</b>	<b>73.9938</b>	<b>96.4</b>

REFERENCES

1. Perona P, Malik J. Scale-space and edge detection using anisotropic diffusion. *IEEE Trans Pattern Anal Mach Intell.* 1990; 12:629-39.

2. Yongjian Yu and Scott T.Action, Senior Member, *IEEE," Speckle Reducing Anisotropic Diffusion". IEEE Transaction on I mage Processing.vol.11, No.11, November 2002.*

3. Krissian K, Westin C F, Kikinis R, Vosburgh K G *Oriented speckle reducing anisotropic diffusion.IEEE Transactions on Image Processing, 2007, 16(5):1412-1424*

4. Li Can-F ei, WANG Yao-Nan, XIAO Chang-Yan,LU Xiao, "A New Speckle Reducing Anisotropic Diffusion for Ultrasound Speckle", *Acta Automatica Sinica, 2012, 38(3):412-418.*

5. N. Otsu., A threshold selection method from gray-level histogram , *IEEE Transactions on Systems, Man and Cybernetics 8 (1979) 62-66.*

6. Dah-Chung Chang, Wen-Rong Wu, *Image contrast enhancement based on a histogram transformation of local standard deviation, IEEE Transactions on Medical Imaging 17(4) (1998) 518-531.*

7. Nafis uddin Khan, K. V. Arya, Manisha Pattanaik. *Histogram statistics based variance controlled adaptive threshold in anisotropic diffusion for low contrast image enhancement. Journal of signal processing 93, (2013) 1684-1693.*

8. Jensen JA. *Field: a program for simulating ultrasound systems. Med Biol Eng Comput.* 1996; 34:351-3.

9. Jensen JA. *Field II Simulation Program; 2011. Available from: URL: <http://field-ii.dk/>.*

10. Gonzalez RC, Woods RE. *Digital Image Processing. 2nd ed. Upper Saddle River, NJ: Prentice Hall; 2002.*

11. Pratt WK. *Digital Signal Processing. New York: Wiley; 1977.*

12. Wang Z, Bovik AC, Sheikh HR, Simoncelli EP, *Image quality assessment: from error visibility to structural similarity. IEEE Trans Image Proc.* 2004; 13:600-12.

13. Loizou CP, Pattichis CS. *Despeckle Filtering Algorithms and Software for Ultrasound Imaging. San Rafael, CA: Morgan & Claypool; 2008.*

14. McDicken N. *Diagnostic Ultrasound. New York: Churchill Livingstone; 1991*