Binary Connectedness Based RML Filter for Speckle Reduction in Ultrasound Images

P. John Vivek and C.Ganesh
Paavai Engineering College
Namakkal, Tamilnadu

S.Sridevi
Assistant professor
Department of ECE
Paavai Engineering College
Namakkal, Tamilnadu

S.Nirmala, Ph.D
Centre for Advanced Research
Rasipuram. Tamilnadu

ABSTRACT

Image denoising has become a very essential exercise all through the diagnosis especially in case of medical image processing involving ultrasound. Speckle is a multiplicative noise that degrades ultrasound images. The existence of speckle noise in ultrasound images reduces its resolution and contrast there by degrading the diagnostic accuracy of the ultrasound image. The presence of speckle noise in fetal ultrasound images make the conditions worse to carry out prenatal diagnosis of congenital heart disease. This is due to the impact of edge and local fine details that are not very clear for diagnosis. Thus there is a vital need for the development of a robust speckle reduction filter to enhance the quality of the speckle affected image and to preserve the essential features. In this paper, we propose a despeckling filter which is based on the concept of binary connectedness that uses an algorithm for computing the degree of connectedness of a pixel to all the other in a subjective neighborhood and it distinguishes the edge and background region present in an image. The proposed filter utilizes the Rayleigh distribution to model the speckle noise and establishes binary connectedness to distinguish edge from background region hence called as Binary connectedness based RML filter. The performance of the proposed filter is tested and compared with several existing despeckling filters including Median, Kuwahura and Frost filters to prove its expertise in terms several performance indices and image profile. Experimental results shows that the proposed filter removes the speckle noise effectively and thus outshine the conventional filters.

Keywords

Binary connectedness, Rayleigh distribution, Maximum likelihood estimator, Despeckling, Edge and background detection.

1. INTRODUCTION

Fetal echocardiography is the ultrasonic evaluation of the human fetal cardiovascular system. It is used for prenatal diagnosis of congenital heart disease. General ante partum obstetrical ultrasound has become a standard part of gestational care and is commonly used for the determination of fetal age, size, gender, or well-being and for the detection of congenital anomalies. They are non invasive in nature, cost effective and help in achieving continuous improvement in image quality. Performance and interpretation of fetal echocardiography requires a unique set of advanced skills and knowledge [1]. The fetal heart is of small size and dynamic in nature. Ultrasonic imaging is a widely used medical imaging procedure because it is economical, comparatively safe, transferable, and adaptable [7]. Though, one of its main shortcomings is the poor quality of images, which are affected by speckle noise. Only well skilled radiologists can deduce diagnostically important details effectively from the ultrasound images. Speckle in B-scans is seen as a granular structure which is caused by the constructive and destructive coherent interferences of back scattered echoes from the scatterers that are typically much smaller than the spatial resolution of medical ultrasound system. This phenomenon is common to laser, sonar and synthetic aperture radar imagery (SAR). Speckle pattern is a form of multiplicative noise and it depends on the structure of imaged tissue and various imaging parameters. Speckle degrades the target delectability in B-scan images and reduces the contrast, resolutions which affect the human ability to identify normal and pathological tissue. Usually prenatal diagnosis has to be performed well in advance in the first trimester of pregnancy. So the removal of speckle noise from ultrasound images and videos helps the untrained gynecologists in diagnosing the abnormalities. Thus it is much essential to develop a robust despeckling filter. The choice of despeckling filter and speckle model plays an important role in the design of despeckling methods and it differs from application to application. Speckle filtering is a central pre-processing step for feature extraction, analysis, and recognition from medical imagery measurements. An appropriate method for speckle reduction is one which enhances the signal to noise ratio while conserving the edges and lines in the image. There are also many statistical models are available to model the speckle noise pattern, although Rayleigh distribution is largely used to represent the fully developed speckle noise [2]. The ultrasound signal which gets backscattered with high level of scattered density follows a Rayleigh distribution with mean proportional to standard deviation [3]. The pixels that are free of speckle noise are estimated to achieve despeckling. Here, discrimination of edge and background region of the image is very important. The proposed filter achieves this differentiation based on binary connectedness which involves Degree Of Connectivity between the adaptive threshold image pixels.

1.1 Outline Of The Proposed Work

Speckle suppression and Edge enhancement are collectively handled by the proposed Binary connectedness RML filter. The proposed filter aims at developing an algorithm for computing the degree of connectedness of a pixel to all other pixels in an arbitrary neighborhood to differentiate edge and back ground region. It also carries out the despeckling of the ultrasound images efficiently than conventional speckle reduction filters.

2. METHODOLOGY

The method for despeckling of ultrasound images using the proposed Binary connectedness RML filter and Rayleigh maximum likelihood is described below.

2.1 Speckle Noise Model in Ultrasound Images

The presence of speckle noise produces a negative impact on prenatal diagnosis of ultrasound images. Ultrasound based diagnostic medical imaging technique is used to visualize a fetus during routine and emergency prenatal care. Compared to other imaging techniques used like Magnetic Resonance Imaging (MRI) and Computed Tomography (CT), ultrasound imaging is cost effective and also gives a clear picture of soft tissues that is not possible using a x-ray or others.

The modeling of speckle noise in ultrasound images is achieved through Rayleigh's distribution [2]. In the medical literature, speckle noise is referred as "texture" and thus holds valuable diagnostic information. Noise free pixel intensity is estimated from the speckle noise affected image by following maximum likelihood estimation approach [2].

Generalized mathematical model of speckle noise is given by,

$$G(u,v)=O(u,v)*\eta(u,v) \tag{1}$$

For u=1, 2……M and v=1, 2 ……. N

Where G(u,v) represents the observed noisy ultrasound image, O(u,v) represents original image which is free of noise component, η(u,v) represents multiplicative speckle noise component added to the image. Rayleigh probability density function models the distribution of speckle noise pattern, which is given by,

$$O(x;\sigma_n^2) = \frac{x}{\sigma_n^2} e^{-x^{2/2\sigma_\eta^2}} \tag{2}$$

Where σ_η^2 denotes the shape parameter of Rayleigh distribution. The ML estimator is given by,

$$F(u,v)=\sqrt{\left(\frac{1}{2\|\omega\|\sigma_n^2}\sum_{(u,v)\in\omega} G^2(u,v)\right)} \tag{3}$$

The estimation of noise free pixel intensity from the corrupted pixel intensities is done by the above equation.

2.2 Filter Tuning Parameter

The images are classified as Heterogeneous area (edge region) and homogeneous area (smooth background). Dark pixels represent the background region and the bright pixels represent the edge region. Tuning parameter of a filter makes the filter to be adaptive, which is represented by α. The maximum likelihood (ML) estimator which is given in the equation (3) has a filter tuning parameter $2\sigma_n^2$. By applying the binary connectedness concept to determine the pixel connectivity and from the inference of the connectivity rules, the tuning of filter parameter is done by assigning $2\sigma_n^2$ to α_E for Edge tuning and assigning $2\sigma_n^2$ to α_B for Background tuning. The fuzzy inference system acts as the backbone of the proposed work to distinguish edge and background region.

2.3 Fuzzy sets: Terminologies

The concept of fuzzy set and fuzzy logic is used in image processing to handle the uncertainty, vagueness and imprecision. Fuzzy logic relies on the concept of fuzzy set. Fuzzy sets are fully defined by its membership functions. Membership function is a function in [0,1] that represents the degree of belonging. In image processing the intensity values are set at either 0 or 1, which is the concept of describing image intensity as a fuzzy set [5]. The members of a fuzzy set are members to some degree, known as Degree of Membership (DOM). DOM can be associated with gray or intensity levels of an image with bright pixels intensity level are scaled as '1' and dark pixels intensity as '0'.

An M X N image can be considered as an fuzzy singletons, each having a value of membership denoting its degree of possessing some property (brightness, darkness, edginess, blurredness etc.). In the notion of fuzzy sets one may therefore write the characteristic function of the image as,

$$\mu_G(u,v)= \{1 \text{ or } 0\} \tag{4}$$

Fuzzy membership function has a value of 1 if a fuzzy set 'G' with an element referred by the location or coordinates (u,v) is present in G, else has a value of 0 if the element is not present in G. If the value of the membership function has any value between 0 and 1, then the element of the fuzzy set maintains a partial or borderline relationship with the fuzzy set G. The degree of membership (DOM) is given by the following equation,

$$\mu_G(u,v)= \frac{G(u,v)}{K} \tag{5}$$

G(u,v) is an image and K is the local maximum intensity in the neighborhood. Let us consider two fuzzy sets E and F. Union denotes the maximum of the two membership functions of the two fuzzy sets. The union of two fuzzy sets E and F gives another fuzzy set G whose membership function is,

$$\mu_G(u,v)=\max\{\mu_E(u,v),\mu_F(u,v)\} \tag{6}$$

Intersection of two fuzzy sets is the minimum of the membership functions of the two fuzzy sets E and F., which is given by,

$$\mu_G(u,v)=\min\{\mu_E(u,v),\mu_F(u,v)\} \tag{7}$$

If a fuzzy set E is empty its membership function has a value of '0' i.e. $\mu_E(u,v)=0$, if not empty the value of membership function is '1' i.e. $\mu_E(u,v)=1$. It is essential to know the concept of path that connects a pixel a with b. A contiguous degree of membership between the pixels a and b indicates the existence of a path between them. Path is denoted by ρ that connects two pixels whose representation is given by,

$$\rho= \{a=(u_0,v_0),(u_1,v_1),\ldots\ldots,(u_n,v_n)=b\} \tag{8}$$

Where $a_0 = (u_0, v_0)$; $a_1 = (u_1, v_1)$; $a_n = (u_n, v_n)$

If there are three paths between the pixels a and b $\in F$, it is denoted by ρ_1, ρ_2, and ρ_3, representing path1, path2 and path3 between the pixels a and b. The strength of the path called as path strength is computed to determine the connectedness between the pixels, which have to be determined for all pairs of pixels. It is defined as the minimum of DOM among the pixels on the path,

$$S_F(\rho)=\min\{(\mu_F(u,v))\} \quad (9)$$

Where $u=u_0, u_1 \ldots\ldots u_n$ and $v= v_0, v_1, \ldots\ldots, v_n$

Fuzzy connectedness or Degree of Connectedness between any two pixels a and b which are present in the fuzzy set F is defined as the strength of the strongest path between the pixels. It is given as,

$$C_F(a,b)=\max\{S_F(\rho)\} \quad (10)$$

Two pixels a and b present in F are said to be connected, if there exists a path such a way that each pixel present on the path has a DOM greater than or equal to the minimum value of DOM of the two pixels a and b.

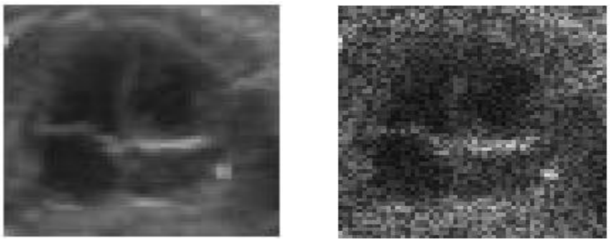
$$\mu_F(a_i) \geq \min \{\mu_F(a), \mu_F(b)\} \quad (11)$$

2.4 Binary Connectedness:

Thresholding of an image O at a particular gray or intensity level i.e., 't' for example yields a binary image denoted by

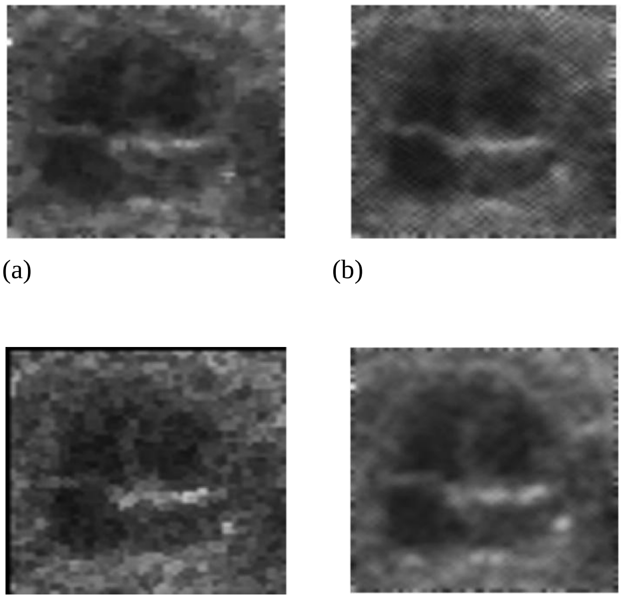
$$B_i(a) = \begin{cases} 1, & O(a) \geq 0 \\ 0, & O(a) < 0 \end{cases} \quad (12)$$

This is achieved by forming 3x3 sub regions of the original image, after converting the image to gray scale to determine the pixels connectivity. There exists a binary connectedness between the pixels a and b if they are in the same connected component in the 3x3 window.



(a) (b)

Fig. 1. Ultrasound fetal heart image (a) Original image (b) Speckle affected image with noise variance of 0.07



(a) (b)

(c) (d)

Fig. 2. Filtered ultrasound fetal heart image output (a) Median filter (b) Frost filter (c) Kuwahura filter (d) Binary Connectedness RML filter

3. PROPOSED METHOD

Design of the proposed filter is based on the development of two important modules for speckle noise reduction in fetal heart images. Which is Module 1: Determining the connectivity between the pixels which are present in 3 X 3 neighbourhood of the image which identifies the edge and background region. Module 2: Despeckling of the input image using the proposed filter employing Rayleigh Maximum Likelihood approach for the estimation of noise free pixel.

3.1 Algorithm: Module1

Step 1: Image fuzzification: Intensity range of the input image is scaled to have any value between 0 and 1, not more than that i.e., greater than 1. DOM will have a value between 0 and 1.

Step 2: By considering any two pixels a and b in the neighbourhood, three different paths connecting a and b is defined.

Step 3: Path strength of all possible paths between the pixels are computed.

Step 4: Binary connectedness between the pixels and their neighbor is computed.

Step 5: If there exists connectivity between the pixels: It implies an edge region else a smooth background region.

3.2 Algorithm: Module2

Step 1: Input ultrasound image of fetal heart is corrupted with speckle noise of particular noise variance.

Step 2: Identification of edge and background region is done using the algorithm specified in the module1.

Step 3: Computation of tuning parameter of the filter is done. The filter is made to operate as a minimum filter by the tuning of smooth parameter (α_B : Background region) and the filter operates as a maximum filter by the tuning of edge parameter (α_E: Edge region).

Step 4: Estimation of the noise free pixel intensity is achieved through Rayleigh Maximum Likelihood estimator shown in the equation (3).

4. PERFORMANCE EVALUATION

Performance of the proposed binary connectedness RML filter is determined by carrying out simulations in MATLAB software. The performance of this proposed filter is compared with the other filters for despeckling. This is done using the performance comparison using some performance metrics like Peak signal to noise ratio (PSNR), Suppression Mean Preservation Index (SMPI), Equivalent Number of Looks (ENL)…etc.

4.1 Speckle Suppression and Mean Preservation Index (SMPI):

It is a measure of speckle suppression ability. Smaller the value of the index indicates better performance of the filter for noise reduction.

$$SMPI=Q^* \frac{\sqrt{var(F_{u,v})}}{\sqrt{var(G_{u,v})}} \qquad (13)$$

The equation for Q is:

$$Q=U+ \left|mean(G)-mean(F)\right| \qquad (14)$$

$$U= \frac{Max(mean(F)-Min(mean(F))}{mean(G)} \qquad (15)$$

Where G is the image with speckle noise. F is the filtered image.

4.2 Equivalent Number of Looks (ENL)

This index represents the speckle noise variance which is proportional to the mean intensity squared.

$$ENL= \frac{(Mean)^2}{Variance} \qquad (16)$$

If ENL is large, then the spread of speckle is small and also the filter is said to have a higher efficiency in smoothing speckle noise over homogeneous area. Figure 5 shows the plot of ENL of the proposed filter, Frost filter and the Median filter.

4.3 Feature Similarity Index Measure (FSIM)

This measure computes the similarity between the original image $O(i, j)$ and despeckled image $F(i, j)$. PC_1 and PC_2 are the PC maps extracted from the original and despeckled images respectively. Phase congruencies (PC) of the images are denoted by PC_1 and PC_2. G1 and G2 are the GM (Gradient Magnitude) maps that are extracted from the images. Computation of this index involves the computation of local similarity map followed by the pooling of the similarity map in to a single similarity score. Similarity measure is computed as shown below for PC_1 and PC_2

$$S_{PC}(x)= \frac{2PC_1(x).PC_2(x)+T_1}{PC_1^2(X)+PC_2^2(X)+T_1} \qquad (17)$$

Next, similarity measure is computed for G_1 and G_2

$$S_G(x)= \frac{2G_1(x).G_2(x)+T_2}{G_1^2(X)+G_2^2(X)+T_2} \qquad (18)$$

The combined similarity is,

$$S_L= [S_{PC}(x)]^{\alpha}.[S_G(x)]^{\beta} \qquad (19)$$

Feature Similarity Index between the original and the despeckled or filtered image is,

$$FSIM= \frac{\sum_{x\epsilon\omega} S_L(x).PC_m(x)}{\sum_{x\epsilon\omega} PC_m(x)} \qquad (20)$$

4.4 Peak Signal to Noise Ratio (PSNR)

It is a ratio which is used as a quality measurement between the original image and the reconstructed image or filtered image. PSNR is expressed in terms of the logarithmic decibel scale. Higher the value of the PSNR, closer the filtered image is to the original.

$$PSNR= -10\log_{10} \frac{MSE}{O_{max}(u,v)^2} \qquad (21)$$

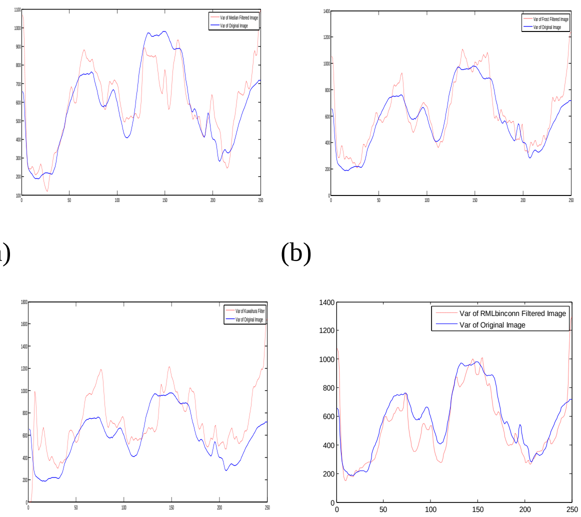
Where $\underset{max}{O}(i, j)^2$ is the maximum intensity of original image. MSE is the Mean Square Error Index, which is the squared difference between the original image and the filtered image. Comparison of the PSNR values of the proposed filter with the Median and Frost filters are presented in the Figure 6.

4. 5 Mean Square Error (MSE)

Mean Square Error is the average squared difference between the original image and the filtered image. It is computed pixel-by-pixel by adding up the squared differences of all the pixels and dividing by the total pixel count. It is given by,

$$MSE(O,F)= \frac{1}{MN} \sum_{u=1}^{M} \sum_{v=1}^{N} \left(O(u,v)-F(u,v)\right)^2 \qquad (22)$$

Where O(u,v) represents the original image and F(u,v) represents the filtered image.



(a) (b)

(c) (d)

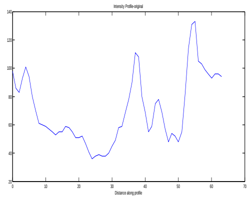
Fig. 3. Variance of the filtered image versus the variance of the original image (a) Original (b) Speckle afftected (c) Median filter (d) Frost filtered (e) Kuwahura filtered and (f) Binary Connectedness RML filter images.

4. 6 Universal Quality Index (UQI)

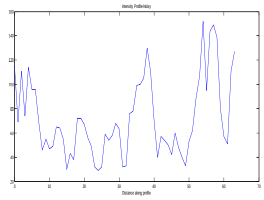
This index is proposed by Wang and Bovik to model any image distortion through the combination of three factors: Loss of correlation, Luminance distortion and Contrast distortion. Let O be the original image, $O = \{o_i, Where\ i = 1\ to\ M\}$ and the filtered image,F $=\{f_i, Where\ i = 1\ to\ N\}$. The Quality Index is given by,

$$Q= \frac{4\sigma_{of}\,\bar{o}\,\bar{f}}{(\sigma_o^2+\sigma_f^2)\left[(\bar{o})^2+(\bar{f})^2\right]} \qquad (23)$$

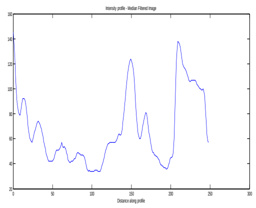
Where $\bar{o}\ \bar{f}$ denote mean values of O and F, σ_o^2 and σ_f^2 denote the variances of them, σ_{of} represents covariance between the images. The dynamic range of Q is from -1 to +1. The UQI and FSIM metrics of the proposed filter to that of Median and Frost filters are shown in the Figure 5.



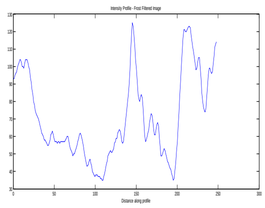
(a)



(b)



(c)



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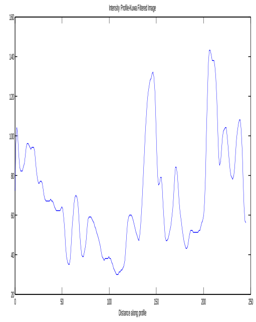
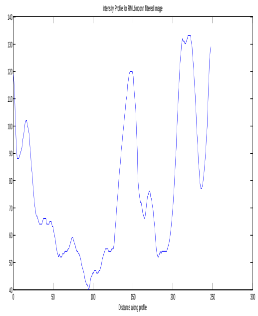


(e)



(f)

Fig. 4. Image profile of (a) Original (b) Speckle afftected (c) Median filter (d) Frost filtered (e) Kuwahura filtered and (f) Binary Connectedness RML filter images

5. DISCUSSION

Despeckling of fetal heart images is carried out using the proposed filter making the diagnosing process easy for the detection of any abnormalities. Figure 1 shows the input fetal heart image and the image with speckle noise. Speckle noise makes the image unclear for discriminating edge and background region. Figure 2 shows the filtered output of various existing filters and the proposed Binary Connectedness RML filter for despeckling and edge discrimination. Variance of the original image and the filtered image are shown in Figure 3. Image profile for the existing filters and the proposed filter is shown in Figure 4 which reflects the smoothing effect of various filters on the speckle affected ultrasound fetal heart image. Comparison of the proposed filter with the existing filters is shown in terms of the performance metrics in the Table 1 and Table 2. The performance of the proposed filter is better than the existing.

Table I

COMPARISON OF PROPOSED BINARY CONNECTEDNESS RML FILTER IN TERMS OF PEAK SIGNAL TO NOISE RATIO (PSNR), UNIVERSAL QUALITY INDEX (UQI) AND MEAN SQUARE ERROR (MSE)

S.No	Noise Variance	PSNR			UQI			MSE		
		Median	Frost	RML BC	Median	Frost	RML BC	Median	Frost	RML BC
1	0.01	34.05	31.80	34.29	0.9978	0.9937	0.9988	29.073	32.733	27.171
2	0.02	31.79	30.62	32.45	0.9963	0.9926	0.9974	33.137	35.087	31.509
3	0.03	29.96	29.69	31.21	0.9940	0.9910	0.9963	35.815	36.501	33.951
4	0.04	29.24	29.10	30.11	0.9929	0.9901	0.9950	36.993	38.297	36.147
5	0.05	28.31	28.32	29.41	0.9910	0.9882	0.9944	39.392	40.351	37.182
6	0.06	27.86	27.37	28.49	0.9886	0.9810	0.9936	40.896	40.434	38.470

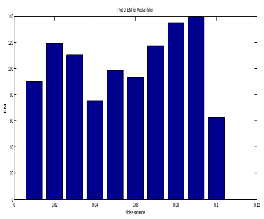
Table II

COMPARISON OF PROPOSED BINARY CONNECTEDNESS RML FILTER IN TERMS OF FEATURE SIMILARITY INDEX (FSI), EQUIVALENT NUMBER OF LOOKS (ENI) AND SPECKLE SUPPRESSION AND MEAN PRESERVATION INDEX (SMPI)

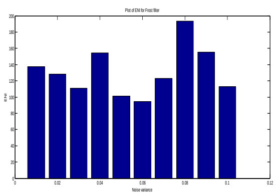
S.No	Noise Variance	FSI			ENI			SMPI		
		Median	Frost	RML BC	Median	Frost	RML BC	Median	Frost	RML BC
1	0.01	0.9370	0.9411	0.9474	90.190	137.479	137.486	4.8442	2.21734	1.8445
2	0.02	0.9167	0.9178	0.9371	119.102	128.257	129.313	4.8007	1.9300	1.8316
3	0.03	0.9015	0.8918	0.9259	110.361	111.014	130.668	4.9800	2.9600	2.8913
4	0.04	0.8826	0.8790	0.9226	75.332	154.311	156.238	5.1527	1.8770	1.1434
5	0.05	0.8721	0.8610	0.9141	98.488	101.273	108.242	5.3506	1.9402	1.3827
6	0.06	0.8687	0.8467	0.9070	93.082	94.573	97.408	6.1810	2.0773	1.1027

6. CONCLUSION

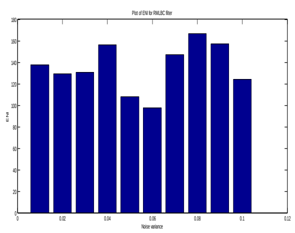
Simulation results show that the proposed Binary connectedness RML filter has proven its performance in terms of better performance metrics compared to those filters that were developed before. The proposed filter provides both the edge preservation as well as speckle noise reduction. It helps untrained obstetricians and gynecologists to diagnose the ultrasound image for the presence of any abnormalities. Thus the proposed filter is well suited to be used as a secondary observer in assisting the physicians.



(a)



(b)



(c)

Fig. 5. Plot of Equivalent Number of Looks metrics for (a) Median filter (b) Frost filter and (c) RML BC filter

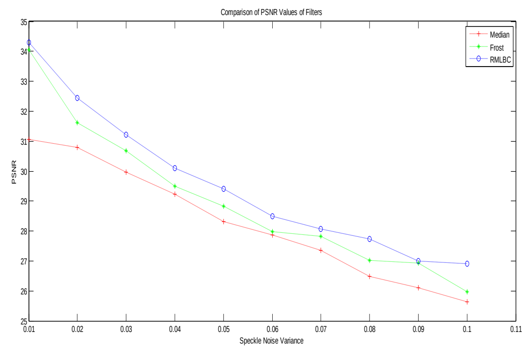


Fig. 6. Comparison of the PSNR values of the Median, Frost and the proposed Binary Connectedness RML filter.

7. ACKNOWLEDGMENT

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