

# GENERALIZATION OF RAYLEIGH MAXIMUM LIKELIHOOD DESPECKLING FILTER USING QUADRILATERAL KERNELS

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## Abstract

Speckle noise is the most prevalent noise in clinical ultrasound images. It visibly looks like light and dark spots and deduce the pixel intensity as murkiest. Gazing at fetal ultrasound images, the impact of edge and local fine details are more palpable for obstetricians and gynecologists to carry out prenatal diagnosis of congenital heart disease. A robust despeckling filter has to be contrived to proficiently suppress speckle noise and simultaneously preserve the features. The proposed filter is the generalization of Rayleigh maximum likelihood filter by the exploitation of statistical tools as tuning parameters and use different shapes of quadrilateral kernels to estimate the noise free pixel from neighborhood. The performance of various filters namely Median, Kuwahura, Frost, Homogenous mask filter and Rayleigh maximum likelihood filter are compared with the proposed filter in terms PSNR and image profile. Comparatively the proposed filters surpass the conventional filters.

## Keywords:

Rayleigh Maximum Likelihood Estimator, Speckle Suppression, Statistical Inference, Quadrilateral Kernel, Homogeneity Region

## 1. INTRODUCTION

Fetal echocardiography is a versatile imaging modality useful for prenatal diagnosis of congenital heart disease. It illustrates inevitable diagnostic details and is regularly used in obstetric investigations. This modality has diverse virtues like non-invasive nature, cost effective and continuous improvement in image quality [6]. On the other hand these ultrasound images have certain demerits. Speckle noise is inherent in clinical ultrasound images which makes it very difficult to interpret fine diagnostic facets and limits the detectability of low contrast lesions approximately by a factor of eight [2]. Well trained radiologists can only interpret diagnostically important details effectively from Ultrasound images. Obstetricians and gynecologists find it difficult to interpret diagnostic significant details because the speckle noise degrades the image consequently they cannot draw useful conclusions from the images [4]. Typically prenatal diagnosis has to be performed well in advance in the first trimester of pregnancy. So the impact of removing speckle noise in Ultrasound images is high to help the untrained gynecologists in terms of diagnosis. This scenario obviously provides greater impact for appropriate design of robust despeckling filter.

Speckle is a random, deterministic, interference pattern formed in coherent imaging [1]. Effective despeckling can be done by making proper inference about the speckle statistics in ultrasound images. Many statistical models have been proposed to model the speckle pattern, although Rayleigh distribution is largely used to represent the fully developed speckle noise [7].

The histogram of the amplitude of RF envelope ultrasound signal backscattered from a uniform area with a high scattered density follows a Rayleigh distribution with mean proportional to standard deviation [3]. Here speckle modeling can be performed as system identification. Hence the despeckling becomes a parameter estimation process based on estimating the speckle free intensity of the image from pixel corrupted with speckle noise. Thus the statistical behavior of multiplicative speckle noise is well modeled using Rayleigh distribution and the proposed filter makes use of robust Maximum likelihood estimator to estimate the noise free pixel of image [6]. The proposed filter is contrived for simultaneous speckle noise suppression and enhancement of edges in the images.

## 1.1 MOTIVATION AND JUSTIFICATION OF PROPOSED WORK

Maximum Likelihood estimation is a parameter estimation technique holding substantial importance in statistical estimation. Mathematical modeling is performed for studying the behavior of the system with unknown parameter  $p$ . Likelihood principle states that all the relevant information in the sample is contained in the likelihood function. First partial derivative of the log-likelihood functions with respect to parameter  $p$  is equated to zero. Solve the equation for  $p$ . The value of the parameter that is most likely exists in sample is the maximum likelihood estimator [8]. Maximum Likelihood estimation approach has diverse merits like it requires minimal model assumptions and converges in probability to the true parameter value in noisy observations.

## 1.2 OUTLINE OF THE PROPOSED WORK

The proposed filter is based on Rayleigh Maximum likelihood estimator to strike the balance between speckle suppression and edge enhancement. The filter uses statistical inference techniques as tuning parameter and to discriminate the edge from background. The various parameters like coefficient of variation, mean deviation and range of pixel intensities are calculated within different shapes of quadrilateral kernels.

Conventional despeckling filters perform spatial filtering in a square shaped kernel based on statistical calculation between neighborhood pixels and center pixel [5]. Those conventional filters fail to provide adequate noise attenuation in edge region due to inhibition of smoothing near edges i.e., noise remain intact even after filtering and be liable to blur the fine details from the image.

The proposed filter investigates the effect of varying the size and shape of the regular window as different types of

quadrilateral kernels like rectangle (RMLQ1) and trapezoid (RMLQ2) in first case. The generalization of ideal maximum likelihood filter is devised as unified framework of homogenous rotating mask averaging filter with Rayleigh Maximum likelihood filter (RMLHomo) in the second case.

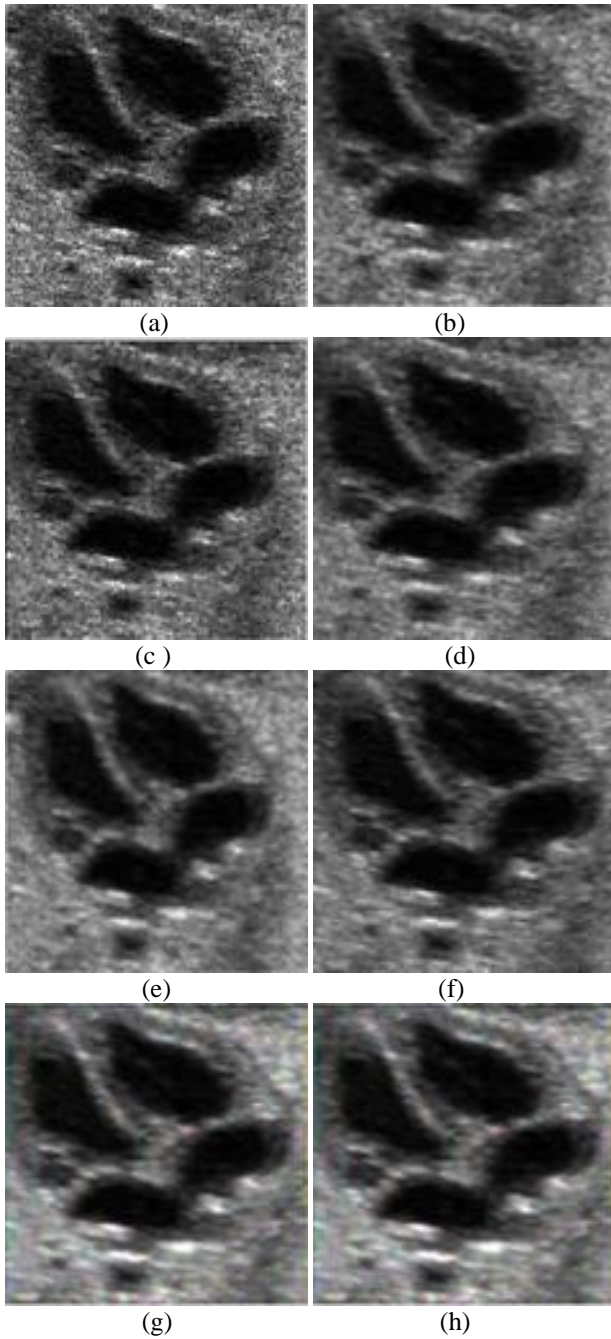


Fig.1. Results of fetal heart image (a). Noisy Image (b). Median filter (c). Kuwahura filter (d). Frost filter (e). Homogeneous filter (f). RML filter (g). RML-Q filter (h). RMLHomo filter

## 2. METHODOLOGY

The methodology for the design of two cases of proposed filters namely generalized Rayleigh Maximum Likelihood despeckling filters are discussed below.

## 2.1 MATHEMATICAL MODELING

The Rayleigh-Maximum likelihood filter is generalized by using of quadrilateral kernels for discrimination of background from edge region and maximum likelihood estimator for despeckling.

### 2.1.1 Speckle Noise Model:

The behavior of the speckle statistics in ultrasound image is established using Rayleigh model [7]. The robust maximum likelihood estimation approach is adopted to estimate

$$f(a,b) = g(a,b) * \eta(a,b) \tag{1}$$

where,  $a = 1, 2, \dots, M$  and  $b = 1, 2, \dots, N$

$f(a, b)$  is the observed noisy ultrasound image corrupted by speckle noise,  $g(a, b)$  is noise free image and  $\eta(a, b)$  is multiplicatively corrupted speckle noise pattern in ultrasound Eq.(1) image corrupted by speckle noise,  $g(a, b)$  is noise free image and  $\eta(a, b)$  is multiplicatively corrupted speckle noise pattern in ultrasound image. The distribution of speckle noise pattern is well approximated by independently and identically distributed Rayleigh probability density function.

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

$\sigma_\eta^2$  represents shape parameter of Rayleigh distribution. The RML estimator for shape parameter  $\sigma_\eta^2$  is formulated as [7].

$$g(a,b) = \sqrt{\left( \frac{1}{2\Omega\sigma_\eta^2} \sum_{(a,b) \in \Omega} f^2(a,b) \right)} \tag{3}$$

Table.1. Comparative analysis of PSNR metrics

Sl. No.	Filter Types	PSNR Values
1	Median	27
2	Frost	29
3	Kuwahura	20.7
4	Homogenous	24.38
5	RML	33.49
6	RMLQ1	34.23
7	RMLQ2	34.12
8	RMLHomo	34.45

Basically images are ghettoized into two class namely heterogeneous area (diagnostically significant edge region) and homogenous area (smooth background). The background is represented by dark pixels intensity where minimum like operation of the filter (suppress speckle noise) is preferred and the edge region is represented by bright pixels where maximum like operation of the filter (enhances the features) is preferred. The tuning parameter is used for the intention of changing the operating mode of the filter while encountering the change in region from edge to smooth.

## 2.2 DISCRIMINATION PARAMETERS

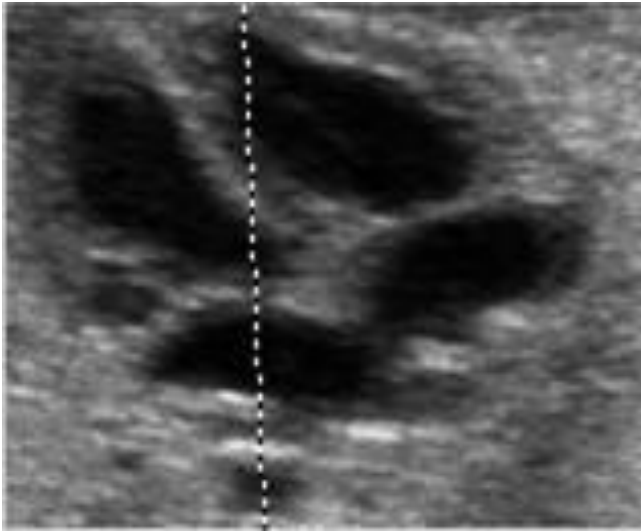
The proposed filters discriminates the smooth and edge region of image by using new statistical measures as filter tuning (region discrimination) parameters.

### 2.2.1 Coefficient of Variation (C):

This statistical measure is used as tuning parameter in Rayleigh Maximum Likelihood [7]. Region discrimination is performed by comparing coefficient of variation  $C$  (ratio of standard deviation to mean) with  $S$  (Standard deviation of constant area).

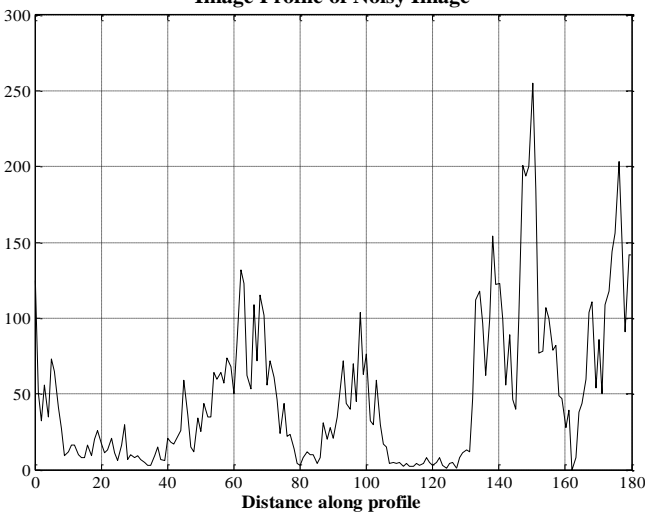
$$C = \frac{\sigma(g)}{\mu(g)} \tag{4}$$

$$S = \sigma(\text{area}(g)) \tag{5}$$



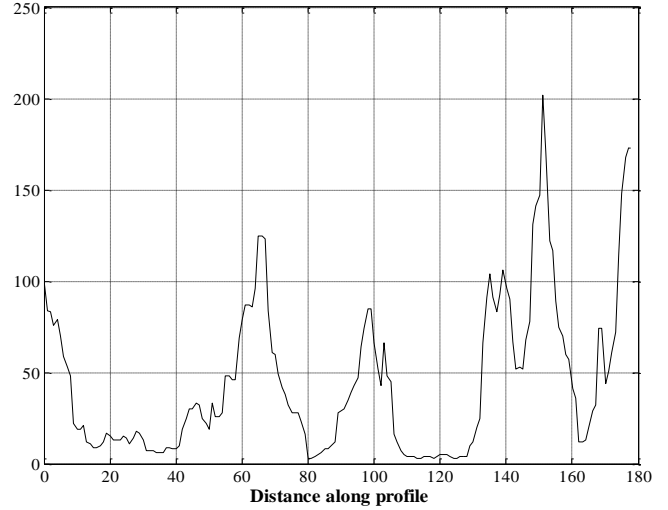
(a)

Image Profile of Noisy Image



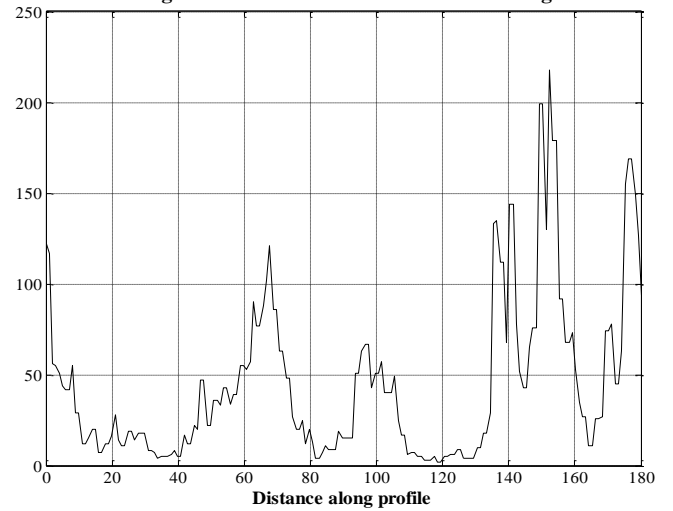
(b)

Image Profile of Median Filter Output



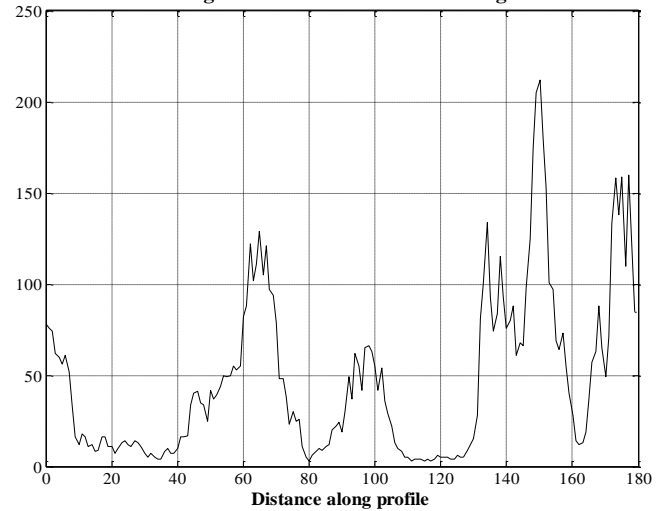
(c)

Image Profile of the Kuwahara Filtered Image



(d)

Image Profile of Frost Filtered Image



(e)

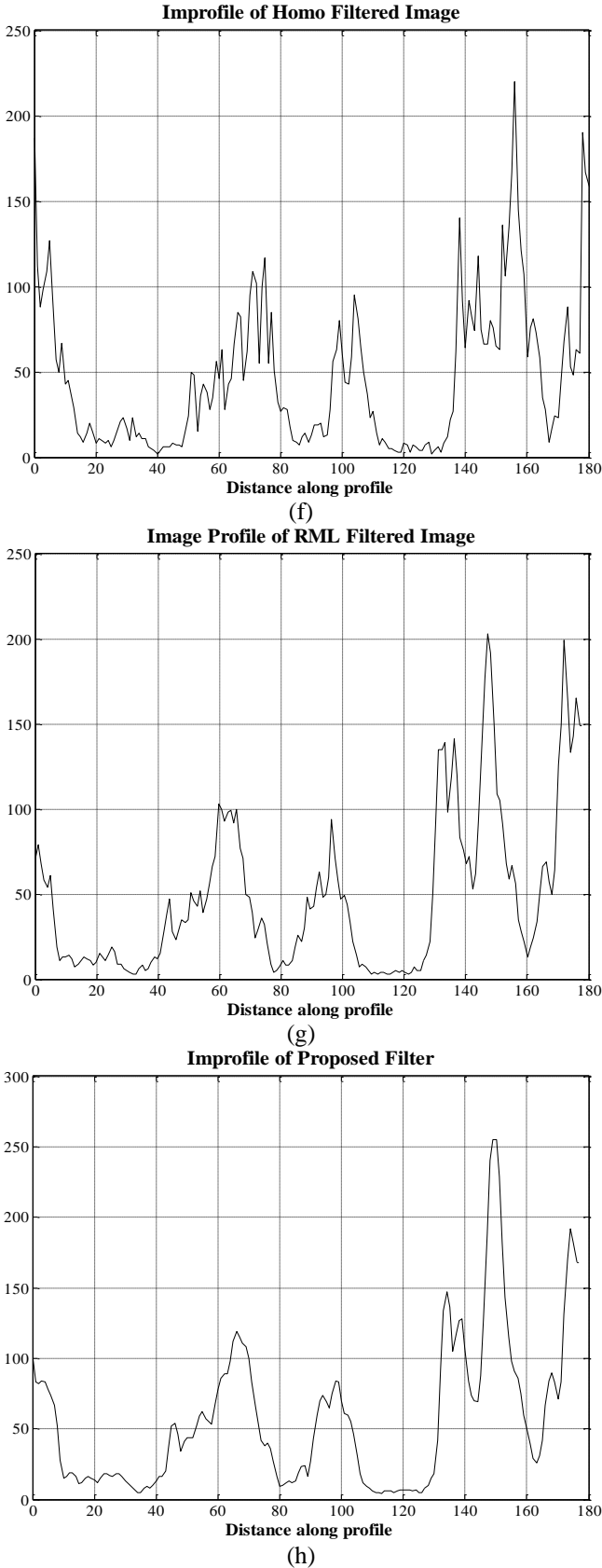


Fig.2. Image profile computation for various filters (a). Scan line for improfile calculation (b). Noisy image (c). Median filter (d). Kuwahura filter (e). Frost filter (f). Homogenous filter (g). RML filter (h). Proposed filter

In every quadratic kernel sliding over the entire image, the value of  $C$  is calculated and is compared with  $S$ . If  $C > S$ , the filter identifies the region within the kernel as homogeneous smooth background. If  $C < S$ , the filter identifies the region within the kernel as heterogeneous edgy region.

**2.2.2 Coefficient of Mean Deviation ( $D_x$ ):**

Coefficient of mean deviation represented by  $D_x$  is calculated using the formula,

$$D_x = \frac{\sum [X - \bar{X}]^2}{n} \tag{6}$$

$D_x$  is a statistical measure which is used for judging variability of sample pixel intensities. It is basically used as relative measure of dispersion. It renders the study of central tendency of a series more precise by throwing light on the brightness of average intensity. It is a better measure of variability than range as it takes into consideration the values of all items of a series [10]. The coefficient of mean deviation measure If  $D_x > S$ , the filter identifies the region within the quadrilateral kernel as background. If  $D_x < S$ , the filter identifies the region within the kernel as edge.

**2.2.3 Statistical Range ( $R$ ):**

Range is one of the statistical measures of dispersion. Range of the pixel intensities within the kernel is calculated as the difference between maximum intensity and the minimum intensity. If Range  $R > \text{Threshold}$ , the filter identifies region within the kernel as background. If Range  $R < \text{Threshold}$ , the filter identifies region within the kernel as edge.

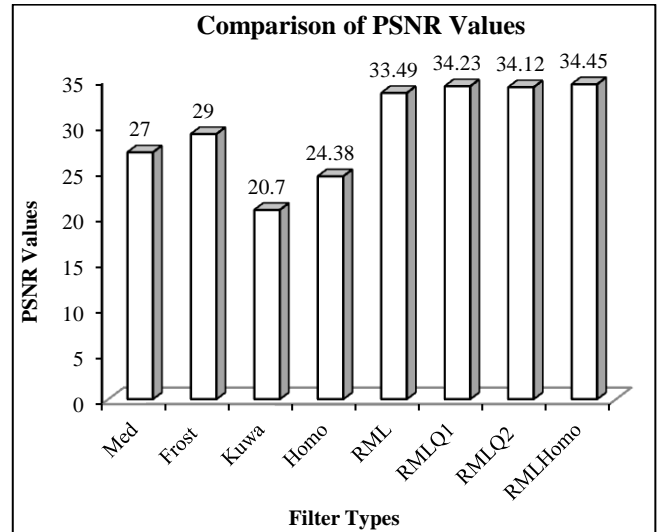




Fig.3. Comparative analysis of PSNR value

Table.2. PSNR for proposed filters with different discrimination parameters

Sl. No.	Filter types/Discrimination parameters	C	$D_x$	R
1	RML	33.49	34.20	31.85
2	RMLQ1	34.23	36.21	32.33
3	RMLQ2	34.12	36.3	33.42
4	RMLHomo	34.45	36.45	32.22

### 2.3 ALGORITHM 1: RMLQ1 & RMLQ2

- 1) Read image and corrupt with speckle noise.
- 2) Discrimination of background from edge region is performed by computing any one of the following statistical measures ( $C$ ,  $D_x$  and  $R$ ).
- 3) Compute tuning parameters  $2\sigma_\eta^2 = \alpha S$  if region is smooth and  $2\sigma_\eta^2 = \alpha E$  if region is edge.
- 4) Compute Maximum likelihood estimation. Two quadrilateral shaped kernels used in the proposed filters are

-  - RMLQ1 filter uses Rectangle shaped kernel.
-  - RMLQ2 filter uses Trapezoidal shaped kernel.

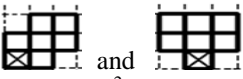
### 2.4 ALGORITHM 1: RMLHomo

The RMLHomo filter is devised by unifying the homogeneity mask averaging filter with existing RML filter. The option of Homogenous rotation masking is chosen because averaging using rotating mask is a non-linear smoothing method that avoids edge blurring while searching for the homogeneity region in the neighborhood kernels[9].

- 1) Read image and corrupt with speckle noise.
- 2) Rotate  $3 \times 3$  kernel within  $5 \times 5$  pixel kernel.
- 3) Detect homogenous region with minimum brightness dispersion  $\sigma^2$

$$\sigma^2 = \frac{1}{n} \left( \sum_{(a,b) \in R} \left( f(a,b) - \frac{1}{n} \sum_{(a,b) \in R} f(a,b) \right)^2 \right) \quad (7)$$

- 5) Compute RML estimate for the selected kernel with most homogenous region and replace it with middle pixel.

- 6)  shaped kernels are rotated to compute  $\sigma^2$  to generalize the RML filter as RMLHomo filter.

## 3. RESULTS AND EVALUATION

Despeckling is carried out using ultrasound fetal heart image by corrupting it with speckle noise with noise variance density of 0.08. Fig.1 shows the simulated output for conventional and proposed filters. The image profile is computed to visualize the smoothing effect of despeckling filter. The proposed filters are compared with conventional Median, Frost, Kuwahura, Homogeneous mask averaging filter and Rayleigh Maximum likelihood filter. Fig.2 shows the image profile for the conventional filters and proposed filters. Image profile of the proposed filter exemplifies that it strikes the balance between speckle suppression and edge preservation.

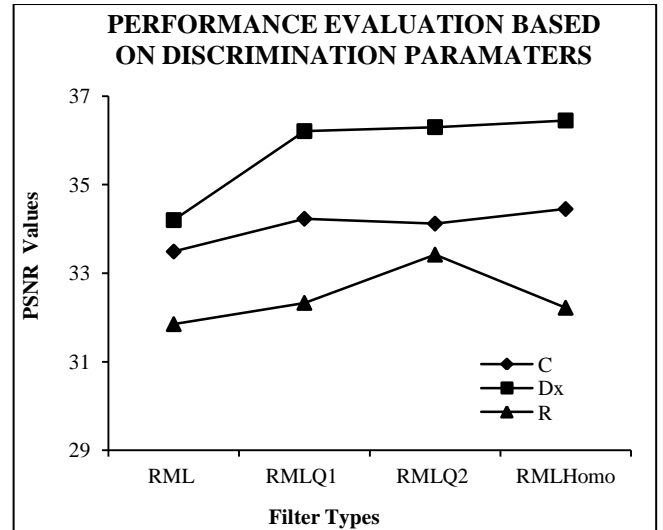


Fig.4. Evaluation with new discrimination parameters

The performance of the proposed filters RMLQ1, RMLQ2 and RMLHomo are quantitatively compared with various standard filters in terms of most familiar image quality metric namely Peak signal to noise ratio metric.

### 3.1 PEAK SIGNAL TO NOISE RATIO

PSNR index depends on Mean Square Error index, which measures the quality change between the original image  $g(a, b)$  and despeckled image  $f(a, b)$ .

$$MSE = \frac{1}{MN} \sum_{a=1}^M \sum_{b=1}^N (g(a,b) - f(a,b))^2 \quad (8)$$

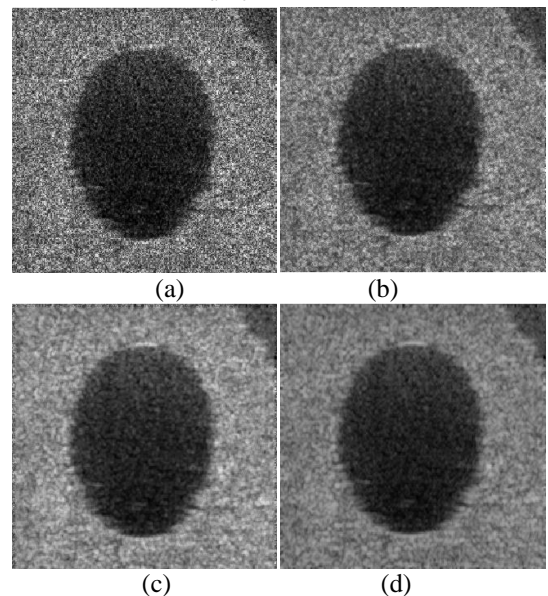


Fig.5. Result for Ultrasound Phantom image (a). Noisy Image (b). RML filter (c). RMLQ filter (d). RMLHomo filter

PSNR measures the image fidelity of both original and despeckled image to compute closeness of both images.

$$PSNR = -10 \log_{10} \frac{MSE}{g(a,b)_{\max}^2} \quad (9)$$

In the above equation  $g_{\max}(a,b)^2$  represents the maximum intensity of original image. The PSNR value is higher for a better processed image.

Table.1 lists the PSNR metric values comparatively computed for the various filters. Fig.3 illustrates the comparative analysis of PSNR value for various filters. This figure demonstrates the improved performance of the proposed filter. Table.2 lists the PSNR values evaluated for ideal and proposed filters with various discrimination parameters. Fig.4 illustrates the performance evaluation of proposed filters and it clearly shows the performance ascendancy in PSNR value of  $D_x$  parameter as better discrimination parameter or tuning parameter of the filter. Fig.5 shows the despeckled results of ultrasound phantom image for ideal RML filter and the proposed filters.

#### 4. CONCLUSION

The results obtained with the proposed filters obviously prove the performance improvement obtained with the usage of quadrilateral kernels and unifying homogeneity measure with the ideal maximum likelihood despeckling filter. It is apparent that the proposed filters are capable of preserving the edges as well as suppressing the speckle noise. The proposed filter unambiguously assists the untrained obstetricians and gynecologists as a secondary observer to interpret diagnostic information from ultrasound images and draw useful conclusion on the subject of clinical diagnosis. In future, it is proposed to make use of artificial intelligent tools to tune the filter appropriately. The use of soft computing tools like fuzzy Logic definitely further improves the performance of the ideal Maximum likelihood filter in order to remove speckle noise and preserves fine details from clinical ultrasound images.

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