International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-8 Issue-2, July 2019

Effects of various De-Speckling Filters on Brachial Plexus Ultrasound Imaging

Ankur Bhardwaj, Sanmukh Kaur, Anand Prakash Shukla, Manoj Kumar Shukla

Abstract*: *Medical Ultrasound images are generally corrupted by Speckle noise. It deteriorates the quality of ultrasound imaging and video that makes it difficult to observe visually. Because of which resolution and contrast of the image is reduced. Despeckling of medical US images is an important process for diagnostic of disease. In this paper effect of various existing despeckling filter on ultrasound images has been studied. All the filters have been implemented in a framework and result are observed in the form of various parameters such as GAE, MSE, SNR, SRMSE, PSNR, UIQI, SSIM, AD, SC, MD. The results obtained have been used for statistically comparing the performance of the filters. It is also analyzed that which type of filters are more suited for particular type of images, noise and other conditions. This will also provide guidelines for the researchers for designing of new filters in future.

Index Terms*: *Mean Square Error, Peak Signal to Noise Ratio, Speckle Noise, Structural Similarity Index Measure.

I. INTRODUCTION

From last three decades there is a great change experienced in medical imaging technology. Formerly only X- Rays radiographs are available but now Images of living objects can be captured using modalities like Ultrasound, CT-Scan, MRI-scan(Magnetic Resonance Imaging) etc. During acquiring the image there could be some kind of distortion that inversely affects the diagnosis that depends on these images. The rapid progress of ultrasound imaging modality has provided an unprecedented way to diagnose illness in-vivo and noninvasively in the medical imaging field. However, its quality is degraded due to existence of speckle noise. This in turn reduces the correct- ness of abnormality detection by the doctor. Hence, improvement in the quality of US images post-processing of the data is extremely important. Speckle noise has granular appearance in the image that damages the texture of the image [1], which possibly carried significant facts regarding various features of tissues and organs. To remove the noise present in images along with simultaneous retention of important image features is still found to remain an essentially elusive and tricky problem in medical image processing. Many efforts introduced by researchers to devise different despeckling methods for speckle reduction in US images.

The speckle suppression and detail retention are the main issues of US images. The speckle noise despeckling techniques can be categorize as: linear filtering, non-linear filtering, anisotropic diffusion filtering and wavelet filtering. Researchers have discussed more about speckle noise reduction. K. Bala Prakash et.al describes the techniques to remove speckle noise from im ages including Ultrasound, Synthetic Aperture Radar Images and Photo graphic images [2]. It compared the values of statistical measures such as SSIN, Signal to noise ratio, peak signal to noise ratio and root mean square error and shows the best image resulting from corresponding filter. Shrimali et al. used the morphological image processing technique to parameters like shape size of speckle noise via using a adequate structuring element [3]. In the Multiscale methods, single scale methods are applied to several sub-images. These subimages are obtained by us- ing wavelet decomposition. Now a days wavelet transforms are used for re covering signals from noisy ultrasound image [4, 5, 6]. Nonlinear Coherent Diffusion (NCD) filter describes by Abd-Elmoniem et al. [7], transforms the multiplicative speckle signals to additive Gaussian noise in Logarithm compressed US images. Another method proposed by Yu et al. named Speckle reducing anisotropic diffusion (SRAD) technique [8, 9] is the expansion of the Perona-Malik diffusion model which is a technique whose aim is to reduce noise without abolishing consider- able components like edges, lines or other details that are relevant for the interpretation of image. Oriented SRAD (OSRAD) filter [10] is the improvement of SRAD, is based on matrix anisotropic diffusion and can formulate the diverse diffusion adjacent to the principal curvature directions. Several mechanism [11, 12, 13] are there based on Rayleigh distribution metric for denoising ultrasound images. Unlike other methods, denoising of ultrasound images by nonlocal methods has been done be Guo et al [14]. This method used the MAP technique of Rayleigh distribution to modifies the original nonlocal method. The pursuance of this method is satisfactory but on the other hand the calculated efficiency is very small as large amount of time has been consumed by the algorithm to com- pute the MAP method of Rayleigh distribution.

Revised Manuscript Received on 30 July 2019.
***** Correspondence Author

Ankur Bhardwaj*, Scholar, Department of Computer Science & Engineering, Amity University, Noida (U.P), India.

Sanmukh Kaur, Associate Professor, (Guide), Department of Electronics & Communication, Amity University, Noida (U.P), India.

Anand Prakash Shukla, Professor, (Co-Guide), Department of Computer Science & Engineering, KIET Group of Institutions, Ghaziabad (U.P), India

Manoj Kumar Shukla, Associate Professor (Co-Guide), Department of Computer Science & Engineering, Amity University, Noida (U.P), India.

Wang [15] proposed a modified technique for denoising the US image for speckle suppression and edge enhancement. Deka [16] proposed a sparse coding technique to remove speckle noise over a learned overcomplete dictionary. This technique thoroughly removes speckle noise by joining an existing pre-processing stage prior to an adaptive dictionary that might be attained for sparse representation. The outcomes seem to be better but the dictionary learning is a slow process that raises the time complexity. In this work effect of various existing despeckling filter on ultrasound images has been studied. All the filters have been implemented in a framework and result have been found and analyzed in the form of various quality parameters such as MSE, SNR, SRMSE, PSNR, UIQI, SSIM, AD, SC, GAE, MD. The results obtained have been used for statistically comparing the performance of the filters.

II. Filters for Speckle Filtering

There are certain filters that can be applied for denoising the speckle noise. Here we use 12 image-despeckling filters as: (i) Linear Scale (ii) Entropy Map (iii) Hybrid Median (iv) Kuan (v) Lee (vi) Lee Diffusion (vii) Anistropic Diffusion (viii) Log Compress (ix) Median (x) Local Enhancement Filter (xi) SRAD Filter (xii) Wavelet Filter. Here we discuss all these filters separately.

i) Linear Despeckle Filter

This filter use two parameters: mean of a pixel window and first order statistics such as variance. Mathematically it could be represented through a multiplicative noise model [17, 18] as shown in equation (1).

$$f_{i,j} = \hat{g} + k_{i,j}(g_{i,j} - \hat{g}) \qquad (1)$$

here $f_{i,j}$, is the estimated pixel value without noise, $g_{i,j}$, is the value of pixels in moving neighborhood with noise, g is the local average value of an $M\,X N$ area of an image, pixel $g_{i,j}$, $k_{i,j}$is a weighting factor, with $k[0,1]$, while i, j represents the pixel coordinates. $k_{i,j}$, a function of the local statistics in a moving neighborhood and is defined [18] as:

$$k_{i,j} = (1 - \bar{g}^2\sigma^2)/(\sigma^2(1+\sigma^2)) \qquad (2)$$

$$k_{i,j} = \sigma^2/(\bar{g}^2\sigma^2 + \sigma^2) \qquad (3)$$

$$k_{i,j} = (\sigma^2 - \sigma^2)/\sigma^2 \qquad (4)$$

The values σ^2 shows variance of moving neighborhood and σ^2 , represent the noises variance of the image. A logarithmically compressed image is used to compute the mean noise variance by using multiple neighborhoods of larger dimensions than of filtering window [18].

ii) Median filtering

Median Filtering is a type of nonlinear filtering. Here we took the median of gray values of pixels in a particular window and placed it at the original pixel. Median filter considerably reduced the noise as well as preserve the edges of the image. In median filtering ordering of the elements of a set is taken into consideration rather than taking the mean.

iii) Hybrid median

The Hybrid Median filter is an expansion of the Median filter [19]. It uses a window of size 5X5 for filtering. Hybrid median filter considered three different windows normal, x-shape and cross shape window. Here we took a 5X5 pixels window for filtering. The main observation of this filter is to conserves the edge that can further utilize to enhance edges of different organs of ultrasound images.

iv) Lee Filter

Lee filter is proposed by Jon Sen Lee in 1981[20]. We can compute the signals strength of the center pixels cell in the filter window by using least square approach from the calculated value of that cell. Lee filter works well in edge preservation. The major quality of Lee filter is that it produces similar output values as input values in high contrast regions and for uniform areas it produces a value adjacent to the local mean [21].The Lee filter can be formulate as:

$$I_{i,j} = \bar{I} + W * (C_{pi} - \bar{I}) \qquad (5)$$

Where, I is the post filtering pixel values, $\bar{I}$ is mean value of intensity of filter neighborhood, C_{pi} center pixel, W filter neighborhood weighted function. Lee filter is not effective for de-speckling near edges.

v)Kuan filter

Kuan filter was formed by Kuan, Nathan and Kurlander in 1987. Kuan filter considered as better filter than that of Lee filter. The filter uses a most similar probability approach to approximate the actual signal value for the center pixel of the filter kernel and suppose that speckle noise follows a negative exponential distribution, and maximizes the local mean, a probability function involving the center pixel value, and the standard deviation of noise [21]. The Weighted function W is for Kuan filter is formulated as,

$$W = \frac{\left(1 - \frac{C_u}{C_i}\right)}{1 + C_u} \qquad (6)$$

Here,

C_u= estimated noise variation coefficient.

C_i= variation coefficient of image.

vi) SRAD filter

Speckle reducing anisotropic diffusion filter removed speckle noise from the image without changing its valuable information and retains image edges. SRAD serves better than the usual techniques like Frost, Lee, Kuan filters as a low pass filter and also preserving the edges and features [22].

vii) Local Enhancement

Local enhancement considered the local properties of the image by a kernel moves throughout the images pixel to pixel. The histogram equalization process is applied at the center pixel of the filter that replaces the original value of histogram of that center pixel in window.

viii) Anistropic Diffusion filter

Perona and Malik [23] Anistropic Diffusion (PMAD) technique used the concepts of nonlinear partial differential equation (PDE) and mathematically it is defined as:

$$\frac{\partial I}{\partial t} = \mathrm{divg}[\mathrm{cof}(|\nabla I|).\nabla I] \quad (7)$$

$$I\ (t=0) = I0$$

Here ∇ is the gradient operator, the divg divergence|| operator, denotes the magnitude, *cof* (*x*) is the diffusion coefficient and I0 the initial image. They give two diffusion coefficients, which are given as

$$cof(x) = \left(\frac{1}{1+\left(\frac{x}{k}\right)^2}\right) \text{ and } \quad (8)$$

$$cof(x) = exp\left[\left(-\frac{x}{k}\right)^2\right] \quad (9)$$

ix) Entropy Map Filter

Information entropy is described as the log2 (number of possible outcomes for a message).It filters the data by replacing every value by the entropy value in the area covered by neighborhood. For a given neighborhood in an image local entropy is deals with the complexity commonly defined by a structuring element.

x)Log Compress Filter

For log compressed ultrasound images, the speckle index C is shows as [24]:

$$C = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{\sigma_{i,j}^2}{\mu_{i,j}} \quad (10)$$

It is the mean of the speckle noise present in the image area with size Mover the entire image. It depends on the intensity, mean, and variance σ^2 of the whole image. Larger the value of C shows that the observed neighborhood belongs to an edge.

xi) Lee Diffusion Filter

Ideally Lee filter operates in a 7×7 moving window. In Lee diffusion filter we choose the filter window as {(i-1,j), (i,j-1), (i+1,j), (i+1,j)} at an interior site. Lee filter can be describes as a discrete isotropic diffusion.

III. Image Quality Metrics

i) Mean Square Error (MSE)

Mean Square error is the mean of squared amplitude of the given input image and the enhanced output image pixels and is described as:

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(g_{i,j} - f_{i,j})^2 \quad (11)$$

It is a broadly used quality parameter, for an M×N window it computes the variation in quality between the given input and processed image [25]. Mean square error is directly proportional to image degradation. The value of MSE reached to zero shows better quality of de-speckled image. So, more value of MSE depicts low quality of image.

ii) Root Mean Square(RMSE)

Root Mean Square error is the average of square root of the squared error over an MxN window [2] is described as:

$$RMSE = \sqrt{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(g_{i,j} - f_{i,j})^2} \quad (12)$$

RMSE is considered as the best error estimator. Lower value of RMSE again depicts excellent quality images.

iii) Peak Signal-to-Noise Ratio (PSNR) and Signal-to-Noise ratio (SNR)

PSNR is the ratio between the maximum considerable power of a signal and the power of corrupting noise that affects the fidelity of its representation. PSNR is a mathematical measurement of image quality. The SNR evaluation is computed as the pixel difference between original input and restored images [26]. Higher the value of PSNR leads to higher quality images. PSNR is defined as in

$$\mathrm{PSNR} = -10 * \log 10 \frac{MSE}{g_{max}^2} \quad (13)$$

The PSNR is generally the SNR where all pixel values are equal to the maximum possible value. If value of Signal to Noise Ratio:

SNR <16 dB = not acceptable image quality
25 dB>SNR > 16 dB=average image quality
34 dB > SNR > 25 dB = good image quality
SNR > 34 dB = excellent image quality
The standard value of PSNR is 35 to 40 db.

iv) Universal Image Quality Index

In 2002, Wang and Bovik describes UIQI [27]. It divides the comparison between original and degraded image as: luminance, contrast, and structural comparisons. UIQI is a quality measure that counts on first order and second order statistic of the original and degraded images. It is a kind of unstable measure which is not correlate with subjective assessment. In structural similarity index metric the values of UIQI lies between 1 and -1.

v)Structural Similarity Index (SSIN)

The structural similarity index between two images [1], is given by:

$$SSIN(x,y) = \frac{(2\mu_x\mu_y+c_1)(2\sigma_{xy}+c_2)}{(\mu_x^2+\mu_y^2+c_1)(\sigma_x^2+\sigma_y^2+c_2)} \quad (14)$$

vi) Geometric Average Factor (GAE)

GAE is a image quality measure, used to analyze the quality of the despeckled image. It is used to replace or complete the RMSE and is computed as:

$$\mathrm{GAE} = \left(\pi_{i=1}^{M}\pi_{j=1}^{N}\sqrt{g_{i,j} - f_{i,j}}\right)^{\frac{1}{MN}} \quad (15)$$

The value of GAE is depends on the difference between the pixel values of original and restored despeckled image. If the difference is smaller the value of GAE approaching to zero. If the every pixel value is different of both original and despeckled image than the GAEs value is positive. GAE could be used as a replacement of RMSE. GAE is zero for all the filters we have mentioned here, therefore, it is categorized as excellent.

iii) Maximum Difference

Maximum difference is used to find the correspondence between input original and despeckled image [1]. Maxi- mum difference can be showed using Minkowski Metric. It is defined as the summation of error. [1]:

$$\mathrm{Err} = \left(\frac{1}{RC}\sum_{i=1}^{R}\sum_{j=1}^{C}|g_{i,j} - f_{i,j}|^{\beta}\right)^{\frac{1}{\beta}} \quad (16)$$

Here the size of the image is RxC. For β = 3 (Err3) and β = 4 (Err4). For β = 2, the RMSE is computed as in (eq. 12), the absolute difference can be calculated with $\beta = 1$ and maximum difference is computed at $\beta =$. The value of maximum difference must be low for high quality image results.

Average Difference (AD): The average difference between the original and restored image is defined as [24]:

$$AD = \sum_{i=1}^{M}\sum_{j=1}^{N}|g_{i,j} - f_{i,j}| \quad (17)$$

where $g_(i,j)$, $f_(i,j)$ are original and restored despeckled image. Above technique is used in object detection and recognition applications in image processing applications where we evaluate the average difference between dual images. The value of average difference must be keeping low to obtain high quality images.

iv) Structural Content (SC):

The structural content is used to predict the perceived quality of digital video and images mainly for television and cinema pictures. It is an improved version of PSNR and MSE, used to measure similarity between two images and defined as:

$$\mathrm{SC} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} g_{i,j}^{2}}{\sum_{i=1}^{M}\sum_{j=1}^{N} f_{i,j}^{2}} \quad (18)$$

Higher the values of SC indicate images with poor quality. When two images are similar its value is 1.

IV Experiment and Results

To quantify the results we have applied 12 various despeckling filtering techniques and evaluated their performance on various parameters on 200 random images. The performance is compared among Linear Scale, Entropy Map, Hybrid Median, Kuan, Lee, Lee Diffusion, Anisotropic Diffusion, Log Compress, Local Enhancement, Median, SRAD Filter, and Wavelet Filter in terms of various quality measuring parameters of noise reduction. The algorithms experiment is implemented on the MATLAB R2014a on an Intel core i3 processor with 3 GB RAM. Total 200 images have been randomly selected from the dataset of 5500 images of nerves called the Brachial Plexus (BP) in ultrasound images. A screenshot of matlab implementation is shows in figure 1.

Algorithm 1 shows detail steps for selection of filters.

Description for algorithm 1 is as follows.

STEP 1: The input images are taken and speckle noise having different standard deviation (σ) has been introduced.

STEP 2: Noisy images are filtered by using filters like Anistropic Diffusion, Entropy Map, Hybrid median, Lee, Kuan, Lee Diffusion, Linear Scale, Log Compress, Median, Speckle, Local Enhancement, Wavelet and SRAD.

STEP: 3: Noisy and despeckled images are saved for estimation of statistical measures.

STEP 4: Aforementioned performance parameters are calculated for the resulting image obtained from each filter with respect to original image.

STEP: 5: Step 4 is applied for all the resulting images obtained from all the filters.

STEP: 6: Best filter is selected for every parameter.

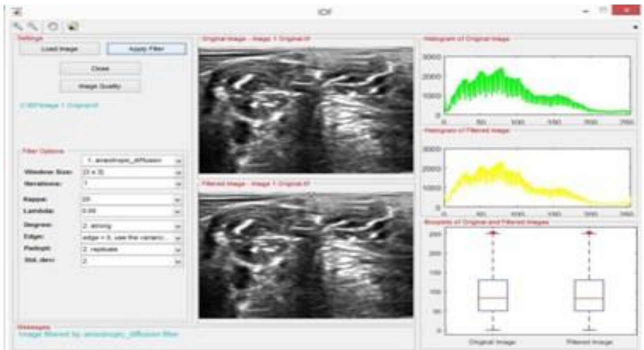


Fig. 1. Implementation of Anistropic diffusion filter

Algorithm 1 Algorithm for filter selection

Step 1: Procedure Comparefilter
Require: input: US_Image Im[i], filter_image j[i], QP[k]
$i \leftarrow 1$
$j \leftarrow 1$
$k \leftarrow 1$
for i=1 to 10 **do**
  Step 2:
  select Im[i]
  Introduce speckle noise with standard deviation $\sigma = 0.01$ into Im[i]
  for j=1 to 11 **do**
    Step 3:
    select filter [j]
    apply filter j[i] to Im[i]
    save result in $j[i]$
    for k=1 to 11 **do**
      Step 4:
      calculate QP[k] for each
      Im[i] and J[i] pair & PDF level 0.01
      $k \leftarrow k+1$
    end for
    $J \leftarrow J+1$
  end for
  $i \leftarrow i+1$
end for

Speckle noise of variance 0.01, 0.02 and 0.05 respectively has been introduced to the US test image. Table 1 and Table 2 show the comparative study of various filters based on different quality parameters of image 1[fig 2] and image 2[fig 3] respectively. 200 images have been selected from the dataset of 5500 images [28].

Table 1, 2 show the values of selected image quality matrices. The value of GAE is 0 for all the filters. It means the information between original and filtered images do not changed. The quality metrics for the linear filter, smaller values of the same metrics were observed. It is shown by the graph that the quality parameters RMSE value of SRAD filter is higher than the companion filters. SRAD filter removes considerable amount of noise along with

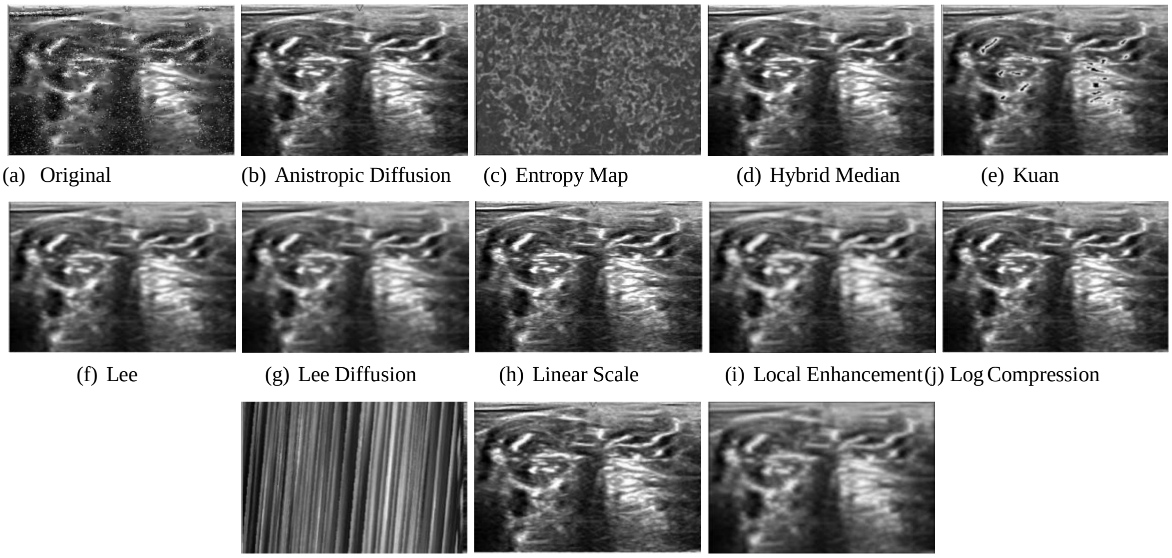
International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-8 Issue-2, July 2019

preserving the image details and edges.

Speckle Reducing Anisotropic Diffusion filter (SRAD) is better than other commonly used filters including Mean, Lee, Kuan, and median filter in terms of speckle reduction and detail retention of original structure of the image.

Table 1. Comparative study of various filters on image 1

Feature	Anistropic Diffusion	Entropy Map	Hybrid Median	Kuan	Lee	Lee Diffusion	Linear scale	Local Enhancement	Log Compress	Median	SRAD	Wavelet
No. of Iterations	4	10	3	3	3	4	4	3	3	3	40	20
GAE	0	0	0	0	0	0	0	0	0	0	0	0
MSE	12435.44	12435.44	12435.44	12435.44	12435.44	12435.44	12435.44	12435.44	12435.44	12435.44	12435.44	12435.44
SNR	13.35	7.79	30.45	17.33	20.62	20.18	17.06	20.4112	18.7	6.98	5.23	23.54
SRMSE	33.29	57.88	4.73	20.96	14.48	15.23	21.72	14.8291	18.31	67.14	73.96	10.47
PSNR	20.69	15.89	37.65	24.71	27.93	27.49	24.4	27.7188	25.89	14.6	13.76	30.75
UIQI	0.42	0.02	0.94	0.83	0.65	0.6	0.49	0.65179	0.75	0.01	0	0.82
SSIM	0.45	0.22	0.95	0.85	0.73	0.69	0.63	0.7306	0.78	0.13	0.23	0.83
AD	4.23	10.52	0.13	2.54	0.68	0.29	0.2	0.71891	-1.56	5.65	24.79	0.04
SC	1.08	1.62	1.01	1.1	1.06	1.06	1.08	1.0594	1	1.24	2.14	1.01
MD	255	215	126	255	155	126	187	150	201	246	228	131



(a) Original (b) Anistropic Diffusion (c) Entropy Map (d) Hybrid Median (e) Kuan

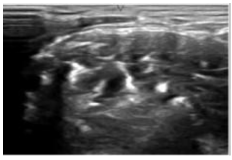
(f) Lee (g) Lee Diffusion (h) Linear Scale (i) Local Enhancement (j) Log Compression

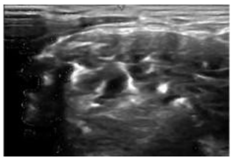
(k) Median (l) SRAD (m) Wavelet

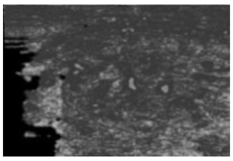
Fig. 2. Results of Various Filters for Image1

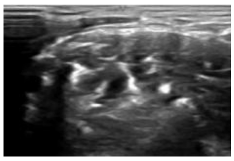
Table 2. Comparative study of various filters on image 2

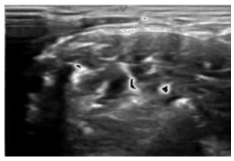
Feature	Anistropic Diffusion	Entropy Map	Hybrid Median	Kuan	Lee	Lee Diffusion	Linear scale	Local Enhancement	Log Compress	Median	SRAD	Wavelet
No. of Iterations	1	1	1	1	1	1	1	1	1	1	1	1
GAE	0	0	0	0	0	0	0	0	0	0	0	0
MSE	8377.504	8377.504	8377.504	8377.504	8377.504	8377.504	8377.504	8377.504	8377.504	8377.504	8377.504	8377.504
SNR	22.4384	5.3256	36.2773	20.3173	26.6401	27.0362	23.152	26.5383	24.5006	5.1632	1000000	33.848
SRMSE	9.7293	64.6697	1.9842	12.4068	5.99948	5.7308	8.9775	6.0651	7.7092	70.9921	0	2.6267
PSNR	31.3795	14.9271	45.1893	29.2679	35.5856	35.9766	32.078	35.4844	33.4009	14.1169	1000000	42.753
UIQI	0.83173	0.01406	0.97992	0.93252	0.88719	0.88979	0.76545	0.67657	0.95289	0.043392	1	0.93748
SSIM	0.88728	0.25816	0.98848	0.96323	0.92549	0.92711	0.85143	0.92643	0.95887	0.19217	1	0.97086
AD	0.69178	1.1492	0.083756	0.61853	0.1745	0.9337	-0.59715	0.19461	-0.30131	0.40742	0	0.00211
SC	1.0193	1.4254	1.0057	1.0239	1.0214	1.0191	1.0122	1.0217	1.0003	1.0254	1	1.0025
MD	253	199	125	255	106	104	110	89	118	253	0	19

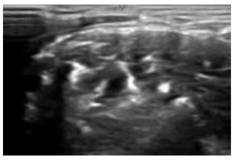

(a) Original

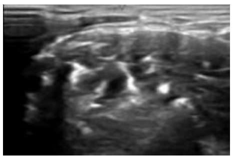

(b) Anistropic Diffusion

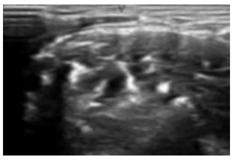

(c) Entropy Map

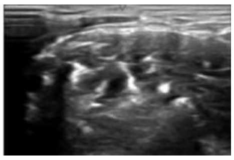

(d) Hybrid Median

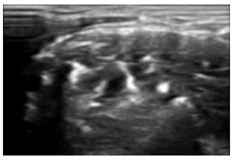

(e) Kuan

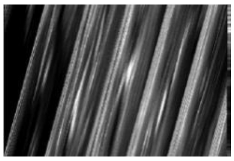

(f) Lee

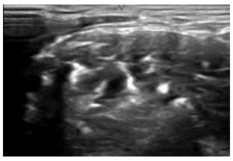

(g) Lee Diffusion


(h) Linear Scale


(i) Local Enhancement


(j) Log Compression


(k) Median


(l) SRAD

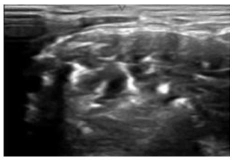

(m) Wavelet

Fig. 3. Results of Various Filters for Image2

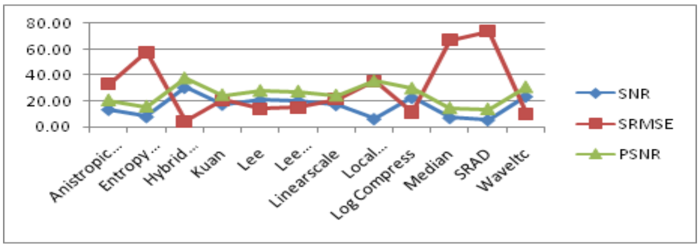


Fig. 4. Comparison of filters using SNR, SRMSE, PSNR

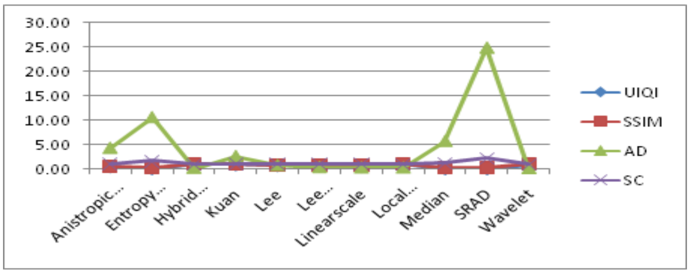


Fig. 5. Comparison of filters using UIQI, SSIM, AD, SC

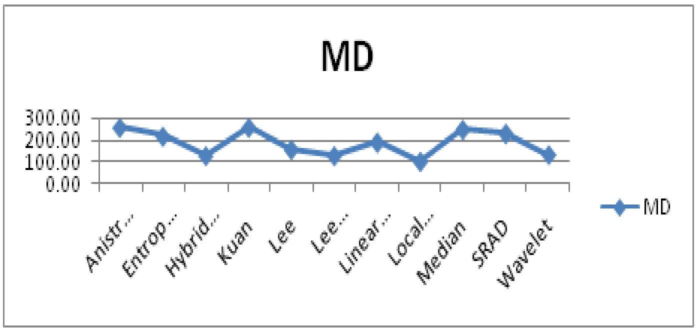


Fig. 6. Comparison of filters using MD

Retrieval Number: B1631078219/19©BEIESP
DOI: 10.35940/ijrte.B1631.078219
Journal Website: www.ijrte.org

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

Table 3. Quality Parameter for Image 1

PARAMETERS	QUALITY PARAMETERS LOW/AVERAGE/GOOD/EXCELLENT											
	Hybrid Median	Kuan	Lee	Median	SRAD	Wavelet	Anistropic Diffusion	Entropy Map	Linear Scale	Local Enhacement	Log Compress	Lee Diffusion
Geometric Average Error (GAE)	EXCELLENT	EXCELLENT	EXCELLENT	EXCELLENT	EXCELLENT	EXCELLENT	EXCELLENT	EXCELLENT	EXCELLENT	EXCELLENT	EXCELLENT	EXCELLENT
Mean Square Error (MSE)	LOW	LOW	LOW	LOW	LOW	LOW	LOW	LOW	LOW	LOW	LOW	LOW
Signal to Noise Ratio (SNR)	GOOD	AVERAGE	AVERAGE	LOW	LOW	AVERAGE	LOW	LOW	AVERAGE	AVERAGE	AVERAGE	AVERAGE
Square Root of the Mean Square Error (SRMSE)	EXCELLENT	AVERAGE	GOOD	LOW	LOW	GOOD	AVERAGE	LOW	AVERAGE	GOOD	GOOD	GOOD
Peak Signal to Noise Ratio (PSNR)	EXCELLENT	AVERAGE	AVERAGE	LOW	LOW	GOOD	AVERAGE	AVERAGE	AVERAGE	AVERAGE	AVERAGE	AVERAGE
Universal Quality Index (UIQI)	EXCELLENT	GOOD	AVERAGE	LOW	LOW	GOOD	LOW	LOW	LOW	AVERAGE	AVERAGE	AVERAGE
Structural Similarity Index (SSIN)	EXCELLENT	GOOD	AVERAGE	LOW	LOW	GOOD	LOW	LOW	AVERAGE	AVERAGE	AVERAGE	AVERAGE
Average Difference (AD)	EXCELLENT	AVERAGE	GOOD	LOW	LOW	EXCELLENT	AVERAGE	LOW	EXCELLENT	GOOD	AVERAGE	GOOD
Structural Content (SC)	GOOD	GOOD	GOOD	AVERAGE	LOW	GOOD	GOOD	AVERAGE	GOOD	GOOD	EXCELLENT	GOOD
Maximum Difference (MD)	AVERAGE	LOW	LOW	LOW	LOW	AVERAGE	LOW	LOW	LOW	AVERAGE	LOW	AVERAGE

As per the graph the SNR value is the best one in median filter as compared with others filters. Linear despeckled filter performs best in terms of UIQI and SSIM ap-plied to the whole. It is found on the basis of values of parameters shown in table 1,2 that linear filter has best performance when applied to a region of interest, followed by hybrid median filter. As per values of quality parameters in table 1,2 Maximum Difference (MD) gives better results to analyzed the blurred image. From Image 1 the maximum difference is lower in local enhancement which leads to better quality. Like MD, AD is also much sensitive for noisy blurred image. The iterations. On increasing the neighborhood size the MSE remains relatively ineffective while the SNR is reduced considerably. Median filter preserves the mean, decreases slightly the variance, while decreases the speckle index. It conserves the edges and can be used to preserve and enhance edges of different organs in US images. Mean and median are preserved, the variance is reduced, and PSNR, quality index, and SSIM are high. Anisotropic diffusion filter preserves the mean and median, reduces the standard deviation, contrast and speckle index of the image. The PSNR, quality index, and SSIN are high while AD and MD are low. Wavelet filter preserves the mean, median, and variance but lowers skewness and contrast of the image. The values for quality index and SSIN are high. Best results were found for the Linear Scale, Wavelet, and Hybrid Median with higher SNR. Best values for the UIQI, and SSIN were obtained for Linear Scale and Hybrid Median filters. The SC was best for the Linear Scale Filter. The smallest MD values were given for the Linear Scale filter and Hybrid Median filter. Here we used a table 3 that divided the quality measurement parameters in four categories Low, Average, Good and Excellent to summarize the observation.

V. CONCLUSION

In this paper comparison of various filters for filtering of speckle noise from ultrasound images of Brachial plexus. To perform the comparison a framework has been designed and performance of 12 filters on the basis of 10 quality metrics have been measured both qualitatively and quantitatively. The results are shown in tabular and graphical format along with resulting filtered images of sample images. It has been observed that some filters perform well in some particular criteria and no filter works well in all parameters. Further the performance of all selected filters in various criteria has been summarized in various categories such as low, average, good and excellent. In future this review helps to design new filters for ultrasound images compare their performance with existing filters based on various parameters.

REFERENCES

1. Zhou Wang, Alan C Bovik, Hamid R Sheikh, and Eero P Simoncelli. Image quality assessment: from error visibility to structural similarity. *IEEE transactions on image processing*, 13(4):600–612, 2004.
2. K Bala Prakash, R Venu Babu, and B Venu Gopal. Image independent filter for removal of speckle noise. *International Journal of Computer Science Issues (IJCSI)*, 8(5):196, 2011.
3. V Shrimali, RS Anand, V Kumar, and RK Srivastav. Medical feature based evaluation of structuring ele- ments for morphological enhancement of ultrasonic images. *Journal of medical engineering & technology*, 33(2):158–169, 2009.
4. Savita Gupta, RC Chauhan, and SC Sexana. Wavelet-based statistical approach for speckle reduction in medical ultrasound images. *Medical and Biological Engineering and computing*, 42(2):189–192, 2004.
5. Suresh Sudha, GR Suresh, and R Sukanesh. Speckle noise reduction in ultrasound images by wavelet thresh- olding based on weighted variance. *International journal of computer theory and engineering*, 1(1):7, 2009.
6. Alin Achim, Anastasios Bezerianos, and Panagiotis Tsakalides. Novel bayesian multiscale method for speckle removal in medical ultrasound images. *IEEE transactions on medical imaging*, 20(8):772–783, 2001.
7. Khaled Z Abd-Elmoniem, A-BM Youssef, and Yasser M Kadah. Real-time speckle reduction and coherence enhancement in ultrasound imaging via nonlinear anisotropic diffusion. *IEEE Transactions on Biomedical Engineering*, 49(9):997–1014, 2002.

8. Yongjian Yu and Scott T Acton. Speckle reducing anisotropic diffusion. *IEEE Transactions on image pro- cessing*, 11(11):1260–1270, 2002.
9. Yongjian Yu, Janelle A Molloy, and Scott T Acton. Three-dimensional speckle reducing anisotropic diffusion. In *Signals, Systems and Computers, 2004. Conference Record of the Thirty-Seventh Asilomar Conference on*, volume 2, pages 1987–1991. IEEE, 2003.
10. Karl Krissian, Carl-Fredrik Westin, Ron Kikinis, and Kirby G Vosburgh. Oriented speckle reducing anisotropic diffusion. *IEEE Transactions on Image Processing*, 16(5):1412–1424, 2007.
11. Louıc Denis, Florence Tupin, Je´roˆme Darbon, and Marc Sigelle. Sar image regularization with fast approxi- mate discrete minimization. IEEE Transactions on Image Processing, 18(7):1588–1600, 2009.
12. Alessandro Sarti, Cristiana Corsi, Elena Mazzini, and Claudio Lamberti. Maximum likelihood segmenta- tion of ultrasound images with rayleigh distribution. *IEEE transactions on ultrasonics, ferroelectrics, and frequency control*, 52(6):947–960, 2005.
13. Gregorio Andria, Filippo Attivissimo, Anna ML Lanzolla, and Mario Savino. A suitable threshold for speckle reduction in ultrasound images. *IEEE Transactions on Instrumentation and Measurement*, 62(8):2270–2279, 2013.
14. Yanhui Guo, Yuedong Wang, and T Hou. Speckle filtering of ultrasonic images using a modified non local- based algorithm. *Biomedical Signal Processing and Control*, 6(2):129–138, 2011.
15. Guodong Wang, Jie Xu, Zhenkuan Pan, and Zhaojing Diao. Ultrasound image denoising using backward diffusion and framelet regularization. *Biomedical Signal Processing and Control*, 13:212–217, 2014.
16. Bhabesh Deka and Prabin Kumar Bora. Removal of correlated speckle noise using sparse and overcomplete representations. *Biomedical Signal Processing and Control*, 8(6):520–533, 2013.
17. Christos P Loizou and Constantinos S Pattichis. Despeckle filtering algorithms and software for ultrasound imaging. *Synthesis lectures on algorithms and software in engineering*, 1(1):1–166, 2008.
18. Christos P Loizou, Constantinos S Pattichis, Christodoulos I Christodoulou, Robert SH Istepanian, Marios Pantziaris, and Andrew Nicolaides. Comparative evaluation of despeckle filtering in ultrasound imaging of the carotid artery. *IEEE transactions on ultrasonics, ferroelectrics, and frequency control*, 52(10):1653–1669, 2005.
19. T Elatrozy, A Nicolaides, TH Tegos, AZ Zarka, et al. The effect of b-mode ultrasonic image standardisation on the echodensity of symptomatic and asymptomatic carotid bifurcation plaques. *International Angiology*, 17(3):179, 1998.
20. Jong-Sen Lee. Digital image enhancement and noise filtering by use of local statistics. *IEEE Transactions on Pattern Analysis & Machine Intelligence*, (2):165–168, 1980.
21. Venkata Rukmini and MD Singh. *Filter selection for speckle noise reduction*. PhD thesis, 2008.
22. D Sasikala and M Madheswaran. Speckle noise filtering for ultrasound images of common carotid artery: A review. *ICTACT Journal on Image & Video Processing*, 4(4), 2014.
23. Pietro Perona and Jitendra Malik. Scale-space and edge detection using anisotropic diffusion. *IEEE Trans- actions on pattern analysis and machine intelligence*, 12(7):629–639, 1990.
24. VS Vora, AC Suthar, YN Makwana, and SJ Davda. Analysis of compressed image quality assessments, m. *Tech Student in E &C Dept, CCET, Wadhwan-Gujarat*, 2010.
25. Tzong-Jer Chen, Keh-Shih Chuang, Jay Wu, Sharon C Chen, Ming Hwang, and Meei-Ling Jan. A novel image quality index using moran i statistics. *Physics in Medicine & Biology*, 48(8):N131, 2003.
26. Thanasis Loupas, WN McDicken, and Paul L Allan. An adaptive weighted median filter for speckle suppres- sion in medical ultrasonic images. *IEEE transactions on Circuits and Systems*, 36(1):129–135, 1989.
27. Zhou Wang and Alan C Bovik. A universal image quality index. *IEEE signal processing letters*, 9(3):81–84, 2002.
28. Ultrasound nerve segmentation — kaggle.