SPECKLE NOISE REDUCTION FILTERS ANALYSIS

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Abstract— Speckle noise reduction from echocardiographic images is essential to study them for medical analysis point of view. But it has been remain a challenging task for the medical world. Speckle noise gets introduced to them at the time of acquiring such images and also due to the nature of acquiring system. To reduce the speckle noise from echo images image processing filters such as Median, Lee, Frost, Kuan, Enhanced Lee and Frost, Weiner, Gamma Map are used. But they have different behavior on different variance of the speckle noise. This paper is the analysis of above mentioned filters with quality metrics against speckle variance. Quality metrics used are SNR, PSNR, ASNR, FOM, CNR, SSIM, MSE.

Index Terms— Echocardiographic Images, Speckle Noise, Speckle Filters, SNR, PSNR, APSRR, FOM, SSIM, CNR, MSE.

I. INTRODUCTION

Echocardiographic and ultrasound images are usually noisy images. As they are taken from far distance or from far internal organs of body as heart, brain, kidneys etc. Hence they get corrupted because of speckle noise. Speckle noise has granular pattern and it is tedious to remove. Classical filters give more accurate reduction of noise from echo images [1].

Two basic models of noise are Additive and Multiplicative. Additive noise is systematic and can be modelled, hence can be removed easily but multiplicative noise is image dependent, it is hard to model and hence cannot be removed easily. When the multiplicative noise is generated due to de-phased echoes it is called as Speckle noise. Speckle is the result of diffuse scattering [2]. Speckle noise has standard variance of 0.04 and as it increases speckle noise also increases [3]. Hence filters behave differently for different variance factor. Mathematically speckle noise can be modelled as in eqn. (1) [4]. Where $g(m,n)$ is image with noise, $u(m,n)$ is multiplicative component and $\eta(m,n)$ is the additive component of speckle noise.

$$g(m,n) = f(m,n) * u(m,n) + \eta(m,n) \qquad (1)$$

This work gives the analysis of such filters over different variance with the qualitative measurement of quality metrics such as SNR, PSNR, ASNR, FOM, CNR, SSIM, MSE [1]. In this work eight filters and seven different quality metrics are used for five variance values. This work is arranged in the paper as following. Section II describes algorithms for speckle filters. Section III contains quality metrics details. Section IV discusses on the result analysis and section V concludes the discussion.

II. SPECKLE FILTERS

Basically speckle filters can be classified as scalar (mean and median) and adaptive filters (Lee, Frost, Kuan etc). Both types of filter use a moving window [5]. The main difference between them is that the adaptive filters usually include a multiplicative model and the use of the local statistics. The Frost filter is an adaptive filter, and convolves the pixel values within a fixed size window with an adaptive exponential impulse response. The Lee filter performs a linear combination of the observed intensity and the local average intensity value within the fixed window [6]**.** In this section some of them are explained with their respective algorithms.

A. Median Filter

In median filter operation centre pixel is replaced by the median value of all pixels and hence produces less blurring and it preserves the edges.

Algorithm: 1. Take a 3 × 3 (or 5×5 etc.) region cantered around the pixel (i, j).

2. Sort the intensity values of the pixels in the region into ascending order.

3. Select the middle value as the new value of pixel (i, j).

B. Frost Filter

The Frost filter reduces speckle noise and preserves important image features at the edges.

Algorithm: $K = e^{(- B * S)}$

Where $B = D * (L_V / L_M * L_M)$

S : Absolute value of the pixel distance from the centre pixel to its neighbors in the filter window

D : Exponential damping factor (input parameter),

L_M : Local mean of filter window

L_V : Local variance of filter window.

The resulting gray-level value of the filtered pixel is

R = (P1 * K1 + P2 * K2 + ... + Pn * Kn) / (K1 + K2 + .. + Kn)

Where P1,P2,...Pn are gray levels of each pixel in the filter window. K1,K2,...Kn are weights (as defined above) for each pixel.

C. Lee Filter

This filter reduces speckle noise by applying spatial filter to each pixel.

Algorithm: $L_M + K * (P_C - M * L_M)$

Where, K(weighting function)= $M * L_V / ((L_M * L_M * MV)(M * M * L_V))$

Where MV = 1/NLooks

P_C : Centre pixel value of window

L_M : Local mean of filter window

L_V : Local variance of filter window

M : Multiplicative noise mean (input parameter)

MV : Multiplicative noise variance (input parameter)

Nlooks : Number of looks (input parameter)

D. Weiner Filter

It reduces noise from image by comparing desired noiseless image. Weiner filter works on the basis of computation of local image variance.

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

Where, $H(u,v)$ = Degradation function

$G(u,v)$ = Degraded image

$Sn(u,v)$ = Power spectra of noise

$Sf(u,v)$ = Power spectra of original image.

E. Kuan Filter

Applies a spatial filter to each pixel in an image, filtering the data based on local statistics of the centered pixel value.

Algorithm: The resulting filtered pixel value is:

$$R = P_C * K + L_M * (1 - K)$$

Where, $C_U = 1 / \mathrm{sqrt}(NLooks)$: Noise variation coefficient

$C_I = \mathrm{sqrt}(L_V) / L_M$: Image variation coefficient

$K = (1 - ((C_U * C_U) / (C_I * C_I))) / (1 + (C_U * C_U))$

P_C : Centre pixel value of window

L_M : Local mean of filter window

L_V : Local variance of filter window

Nlooks : Number of looks

F. Enhanced Lee Filter

The enhanced Lee filter is an altered version of the Lee filter reducing the speckle noise effectively by preserving image sharpness and detail.

Algorithm: Value of smoothed centre pixel:L_M for $C_I <= C_U$

$L_M * K + P_C * (1 - K)$ for $C_U < C_I < C_{max}$

P_C for $C_I >= C_{max}$

where P_C : Center pixel value of window

L_M : Local mean of filter window

SD : Standard deviation in filter window

Nlooks : Number of looks (input parameter)

D : Damping factor (input parameter)

C_U = 1 / square root (NLooks)(Noise variation coef.)

C_{max}=srt(1+2/NLooks)(Max.noise variation coef.)

$C_I = SD / L_M$(Image variation coefficient)

$K = e^{(- D (C_i - C_U) / (C_{max} - C_I))}$

G. Enhanced Frost Filter

Algorithm: $W(x,y) = e^{-kfunc\left(C_I(x',y')\right)|(x,y)|}$
Where $func\left(C_I(x',y')\right)$ is a hyperbolic function of $C_I(x',y')$ defined as follows.

$$func(C_I) = \begin{cases} 0 & for\ C_I(x',y') < C_B \\ \frac{[C_I(x',y'-C_B]}{[C_{max}-C_I(x',y')]} & for C_B \leq C_I(x',y') \leq C_{max} \\ \infty & for\ C_I(x',y') > C_{max} \end{cases}$$

H. Gamma Map Filter

Based on the application of maximum a posteriori (MAP) approach, which required the a priori knowledge of the probability density function (PDF) of the image.

Algorithm:

$$U(x',y') = \begin{cases} I'\ (x',y') & C_I(x',y') < C_B \\ \frac{(\alpha-L-1)(x',y')+\sqrt{I^2(x',y')(\alpha-L-1)+4\alpha LI'(x',y')}}{[C_{max}-C_I(x',y')]} & for C_B \leq C_I(x',y') \leq C_{max} \\ I(x',y') & for\ C_I(x',y') > C_{max} \end{cases}$$

Where L is the number of looks,

$C_{max}(x',y') = \sqrt{2C_B}$

And $\alpha = \frac{1+C_B{}^2}{C_I{}^2(x',y')-C_B{}^2}$

III. QUALITY METRICS

For the quantitative assessment seven quality metrics are used on both noisy and filtered images. Quality metrics that are used in this work are signal to noise ratio (SNR), peak signal-to-noise ratio (PSNR), average peak signal-to-noise ratio (APSNR), Pratt's figure of merit (FoM), contrast-to-noise ratio (CNR), structural similarity (SSIM), edge-region mean square error (MSE). These are explained in following sections.

A. SNR

This is fundamental parameter to measure level of noise. It is widely used. It is the ratio of mean to the standard deviation of pixel amplitudes in an image. Image having maximum speckle noise has SNR 1.91. There is indirect proportion between speckle noise and SNR [14].

$$\mathrm{SNR} = 10\log_{10}\frac{\sigma_g{}^2}{\sigma_e{}^2}$$

B. PSNR:

PSNR is defined from RMSE and quantifies the ratio between the possible power of a signal and the power of corrupting noise [15]. For a gray level image with 256 gray levels, PSNR is defined as,

$$PSNR = 20log_{10}(\frac{255}{RMSE})$$

Where, $\mathrm{RMSE} = \sqrt{\mathrm{MSE}}$

$$\mathrm{MSE}(\mathrm{I_{filt,}I_{ref}}) = \frac{1}{\mathrm{XY}}\sum_{i=1}^{Y}\sum_{j=1}^{X}\left(\mathrm{I_{filt}(i,j)} - \mathrm{I_{ref}(i,j)}\right)^2$$

C. APSNR:

A simple average of PSNR per frame is called APSNR [15]

D. FOM:

FoM is an estimator for quantifying the edge pixel displacement between the edge masks of filtered and reference images, and is defined as [16],

$$FoM(I_{filt}, I_{ref}) = \frac{1}{\max(N_{filt}, N_{ref})}\sum_{i=1}^{N}\frac{1}{1+d_i{}^2\alpha}$$

Where, di = Euclidean distance between the ith detected edge pixel and the nearest original edge pixel, and

α = constant and set to 0.1

E. CNR

This metric operates on a single image and exploits levels of contrast between two different regions of images [8]. One region is a region of interest (ROI) and the other can be a part of the background. This metric is calculated as

$$\mathrm{CNR} = \frac{|\mu 1-\mu 2|}{\sqrt{\sigma 1^2+\sigma 2^2}}$$

Where, $\mu 1$ and $\sigma 1$ are mean and variance of ROI and $\mu 2$ and $\sigma 2$ are mean and variance of background.

F. SSIM:

Index is another metric for measuring the similarity between two images. This metric has much better consistency with the qualitative appearance of the image [1].

$$SSIM = \frac{1}{M}\sum\frac{(2\mu 1\mu 2 + C1)(2\sigma_{1,2} + C_2)}{(\mu_1{}^2 + \mu_2{}^2 + C_1)(\sigma_1{}^2 + \sigma_2{}^2 + C_2)}$$

Where, $\mu 1$ and $\mu 2$ are the means and and $\sigma 1\ and\ \sigma 2$ are the standard deviations of the images being compared. $\sigma_{1,2}$ is the covariance between them. SSIM has value between 0 and 1, when it is equal to 1 images are structurally equal.

G. MSE:

This measures the average absolute difference between two images [17].

$$MSE\left(IE_{filt}, IE_{ref}\right) = \frac{1}{XY}\sum_{i=1}^{Y}\sum_{j=1}^{X}\left(IE_{filt}(i,j) - (i,j)\right)^2$$

Where IE_{filt} and IE_{ref} are edges of filtered and reference images respectively. The edge-region MSE measures the average differences in edge regions.


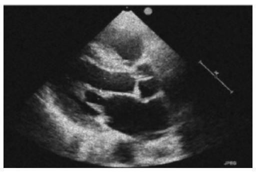

Fig. (a) noisy image Fig. (b) Lee Filtered Image

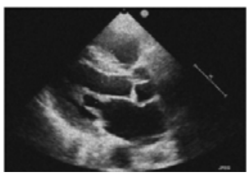
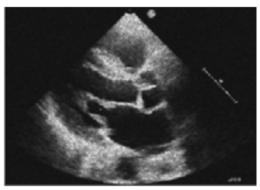

Fig. (c) Frost Filtered Image Fig. (d) Weiner Filtered Image


Fig.(e) Mean Filtered Image Fig.(f) Median Filtered Image

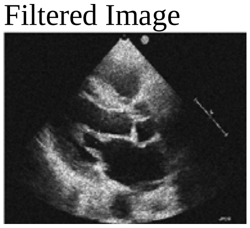


Fig.(e)Adv. Lee Filtered Image Fig.(f) Adv. Frost Filtered Image


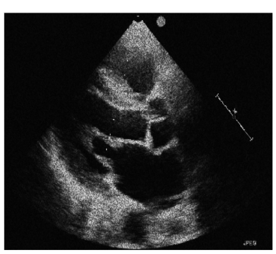

Fig.(e) Kuan Filtered Image Fig.(f) Gamma Map Filtered Image

IV. EXPERIMENTAL RESULTS AND ANALYSIS

To remove speckle noise from echo images nine filters (Lee, Frost, Mean, Median, Kuan, Advanced Lee and Frost, Gamma Map and Wiener) are used in this work. This filtering is done for five values of variances (0.02, 0.04, 0.06, 0.08 and 0.1). Results are shown in following figures. Figure (a) is noisy image having variance 0.08. Figures (b) to (j) are filtered images.

Result analysis is done by measuring seven quality metrics (SNR, PSNR, ASNR, FOM, CNR, SSIM, MSE.) Following tables shows comparative analysis of nine filters for five different variance value.

V. CONCLUSION

This work filters the speckle noise with the help of nine different filters. Filtering analysis is done by using the seven different quality metrics for five variance values. As speckle variance increases noise also increases. For higher values of speckle variance filter performance reduces slightly. In tables bold value shows the more correct value for that variance. Adaptive filters such as Lee, Frost, Advanced Lee and Frost and wiener gives more appropriate results.

Table 1. Quality metrics readings for speckle variance 0.02

Quality Metrics	SNR	PSNR	ASNR	FOM	CNR	SSIM	MSE
Mean	14.06	22.71	0.055	0.13	0.04	0.73	635.7
Median	17.15	25.69	**0.03**	0.14	0.02	0.74	222.1
Lee	**18.59**	**26.08**	0.031	0.13	0.02	**0.77**	211.3
Frost	17.15	24.72	0.32	**0.18**	0.02	0.74	279.4
Kuan	6.17	14.68	0.36	0.13	0.33	0.6	3688
Adv. Lee	17.15	25.04	0.031	0.11	0.02	0.73	234.1
Adv. Frost	0.032	6.43	1.42	0.06	**1.42**	0.04	1887
Wiener	18.58	26.19	0.031	0.11	0.02	**0.77**	**178.5**
GMap	0.032	6.43	1.43	0.08	1.4	0.04	1909

Table 2. Quality metrics readings for speckle variance 0.04

	SNR	PSNR	ASNR	FOM	CNR	SSIM	MSE
Mean	13.61	22.2	0.07	0.13	0.05	0.69	700.6
Median	15.6	24.17	**0.042**	0.14	0.02	0.68	307.8
Lee	**17.31**	**24.98**	0.05	0.13	0.03	**0.73**	**279.4**
Frost	16.41	24.19	0.05	**0.17**	0.02	0.71	330.2
Kuan	6.009	14.52	0.37	0.13	0.34	0.54	3813
Adv. Lee	13.96	22	0.05	0.12	0.02	0.64	469.2
Adv. Frost	0.032	6.429	1.42	0.06	1.42	0.04	1889
Wiener	15.76	23.69	0.05	0.11	0.02	0.70	314.5
GMap	0.032	6.429	1.43	0.07	**1.43**	0.04	1909

Table 3. Quality metrics readings for speckle variance 0.06

Quality Metrics	SNR	PSNR	ASNR	FOM	CNR	SSIM	MSE
Mean	13.22	21.78	0.08	0.13	0.06	0.67	766.7
Median	14.48	23.09	**0.05**	0.13	0.04	0.65	392.4
Lee	**16.36**	**24.19**	0.06	0.13	0.04	**0.70**	**348.7**
Frost	15.9	23.71	0.06	**0.18**	0.04	**0.70**	383.8
Kuan	5.843	14.38	0.38	0.13	0.35	0.50	3924
Adv. Lee	12.7	20.19	0.06	0.10	0.04	0.58	712.5
Adv. Frost	0.032	6.429	1.42	0.08	1.42	0.04	1889
Wiener	14.02	22.08	0.06	0.10	0.04	0.66	457.9
GMap	0.032	6.429	1.43	0.06	1.43	0.04	1909

Table 4. Quality metrics readings for speckle variance 0.08

Quality Metrics	SNR	PSNR	ASNR	FOM	CNR	SSIM	MSE
Mean	12.81	21.37	0.09	0.13	0.07	0.65	844.1
Median	13.58	22.22	**0.06**	0.12	0.04	0.62	482.7
Lee	**15.47**	**23.38**	0.07	0.13	0.05	**0.68**	**424**
Frost	15.31	23.26	0.07	0.15	0.05	**0.68**	443
Kuan	5.6	14.22	0.38	0.13	0.36	0.47	4035
Adv. Lee	10.73	18.9	0.07	0.10	0.05	0.53	964.2
Adv. Frost	0.030	6.429	1.42	**0.16**	1.42	0.04	1889
Wiener	12.71	20.89	0.07	0.11	0.05	0.62	608.2
GMap	0.030	6.429	1.43	0.06	**1.43**	0.04	1909

Table 5. Quality metrics readings for speckle variance 0.1

Quality Metrics	SNR	PSNR	ASNR	FOM	CNR	SSIM	MSE
Mean	12.44	20.95	0.10	0.12	0.08	0.63	911.5
Median	12.97	21.52	**0.06**	0.12	0.05	0.59	563.1
Lee	14.8	22.77	0.07	0.14	0.05	0.66	494.1
Frost	**14.86**	**22.86**	0.07	0.15	0.06	**0.67**	498.4
Kuan	5.56	14.11	0.38	0.13	0.36	0.44	4133
Adv. Lee	9.73	17.9	0.07	0.10	0.06	0.49	1209
Adv. Frost	0.03	6.429	1.42	**0.18**	1.42	0.04	1889
Wiener	11.74	19.95	0.07	0.11	0.06	0.59	**755.4**
GMap	0.03	6.429	1.43	0.06	**1.43**	0.04	1909

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