Investigation of various Speckle Noise Denoising Filters

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***Abstract*—In this paper, various ultra sound image denoising techniques are investigated and results are compared for various conditions. Synthetic Aperture radar images and ultra sound images are often corrupted by speckle noise. It is also known as granular noise. There are many methods for removal of speckle noise. The filters are developed for the removal of speckle noise. This paper reviews filters mostly used to remove speckle noise. Frequency analysis methods, various adaptive methods, temporal analysis methods are defined for the removal of speckle noises.**

Keywords—Speckle noise, denoising adaptive filter

I. INTRODUCTION

In Sonography, various medical images are analysed for short and long time diseases in which high frequency waves are used for deep viewing. The human internal organs can be viewed and it can be either movable or immovable. Even blood flow of the body and organs can be viewed in micro variations. Ultra sound imaging is as safe as no harmful radiation is used. Reflections of the waves are measured and the imaging is done. These are the sound waves in nature. The various ultrasound imaging are as follows – abdominal ultrasound, Fetal, Bone, Breast, Doppler, biopsies etc. Remove of noise from ultrasound is a challenging task though it is non invasive in nature [1].

Speckle noise occurs during image acquisition, due to environmental factors and it is very common in case of medical images, Radar images, SAR images etc. Waves emitted from sensor reflected out of phase from the target area as it is at different distance from the sensor. The noisy images are despeckled by filters as this noise may corrupt the original quality of the image.

The image of ultrasound is taken and speckle noises are concentrated for the removal in the part II. Segment III audits the distinctive channels utilized for dot clamor decrease as 1.Scalar channels and 2.Adaptive channels. Area IV audits execution measurements and segment V finishes up the survey.

II. SPECKLE MODEL

The speckle noise can be modelled as combination of discrete noise models.

$$s = \sum_{i=0}^{n} a^{\mathrm{i}} e^{j\varphi} \tag{1}$$

Where 'n' is the number of scatters, a_i is the amplitude, φ is the phase of the i^{th} scatter. Speckle noise is the visual noise that degrades the image as it is multiplicative in nature. Speckle noises are usually a multiplicative noise. Multiplicative Speckle noise [1] is expressed as in eqn. (1)

$$o(m,n) = p(m,n) * v(m,n) + \eta(m,n) \tag{2}$$

Where g(m,n) is corrupted image, v(m,n) is the speckle noise pattern and η(m,n) is the noisy component. In case of ultrasound additive noise has to be excluded (2)

$$o(m,n) = p(m,n) * v(m,n) + \eta(m,n) - \eta(m,n)$$

$$(x,y) = f(x,y) * u(x,y) \tag{3}$$

The Speckle noise has the gamma function and it is given as per the equation[7]

$$F(h) = \frac{g^{\varphi-1}}{(\varphi-1)!\alpha^{\varphi\alpha}} e^{\frac{-g}{\alpha}} \tag{4}$$

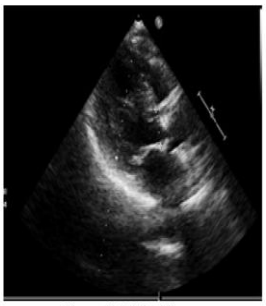


Fig. 1. Real Image

Fig. 2. Image with granular pattern

III. SPECKLE NOISE REMOVAL FILTERS

Speckle removal is a repetitive undertaking in pre-handling of pictures. Spot commotion contains high recurrence parts due to worldly development of organs as mind, heart and so on. Subsequently it's important to create low pass channel to dispose of the high recurrence commotion. To dispose of dot clamor from pictures until right now a few channels zone unit utilized. A few channels zone unit savvy in visual translation wherever as some zone unit shrewd in smoothing capacities and commotion decrease. A few examples of such channels region unit Mean, Median, Lee, Kuan, Frost, expanded Frost, Wiener and Gamma MAP channels. Some of these utilization window strategies to dispose of spot clamor, referred to as portion. This window size will change from 3-by-3 to 33-by-33 anyway it ought to be odd. To accomplish better outcome window size ought to be littler.

A. Scalar Filters

The statistical data for reducing the pixel values of the noisy image by gradual filtering process. Fundamental types of mean and median filters are as follows,

Geometric and harmonic Mean filter

The idea of mean filter is to replace the pixel with the average value of the neighbourhood pixels if it is noisy. It removes either uniform or Gaussian type of noises in images. Geometric type of mean filter removes the Gaussian type of noise and it is better for preserving edge information. Harmonic mean filter is better for removing positive outliers. Larger filter size gives best result. The mathematical equation for Mean filter is given by

$$r = \frac{r1 + r2 + r3 + \cdots \ldots \ldots + rn}{n} \qquad (5)$$

Mean Filter

It is basic and natural channel concocted by Pomalaza-Raez in 1984[2]. It doesn't oust spot disturbance at whole yet decreases at some grow. It tackles ordinary commence that is within pixel is displaced by the typical of the all pixels. Along these lines this channel gives darkening effect to the photos, so it is scarcest pleasing system to clear speck bustle as it results in loss of purposes of intrigue. Logical depiction is given in eqn. (4) for m×n window region. The mathematical equation [3] for Mean filter is given by

$$h(i,j) = \frac{1}{mn \sum_{k=m} \sum_{l=n} f(k,l)} \qquad (6)$$

Median Filter

It gives very preferred outcome over the mean channel. Here focus pixel is supplanted by the middle estimation everything being equal and thus delivers less blurring [4]. Because of this nature it is utilized to decrease imprudent spot clamour. Good position is it spares the edges. Drawback is extra time required for estimation of the centre an impetus for organizing N pixels, the common versatile quality is O (N log N). Centre channel takes after figuring as takes after:

- Take a 3 × 3 (or 5×5 and so forth.) area revolved around the pixel (I, j).
- Sort the force estimations of the pixels in the area into rising request
- Select the center an incentive as the new estimation of pixel (I, j).

B. Adaptive Filters

A couple of change procedures are proposed to achieve a prevalent result by fluctuating window size and besides to spare the features like edges. Channels that are having adaptable nature are discussed in following zones:

A. Frost filter

Planned by Frost in 1982, is straight, convolutional channel used to remove the multiplicative racket from pictures. At the point when appeared differently in relation to mean and center channel it has flexible nature and besides it is exponentially-weighted averaging channel. Ice channel tackles the introduce of coefficient of assortment which is the extent of neighborhood standard deviation to the close-by mean of the demolished picture. Inside the bit size of n-by-n then the center pixel regard is displaced by weighted whole of estimations of the region in piece. The weighting factor decrease as we leave from interested pixel and augmentation with contrast. It expect multiplicative noise. Ice channel pursues equation given by eqn. (7).

$$m = exp[-KC_y(t_0)|t|]\ C_y = \frac{\sigma_y}{y} \qquad (7)$$

Where K is the parameter, t_o represents point where the processed pixel is located, |t| represents the distance from pixel t_o.

B. Lee Filter

It is superior to above channels in edge conservation. It depends on multiplicative spot model and uses neighbourhood measurements to save points of interest. Lee channel takes a shot at the difference premise, i.e. in the event that difference of the region is low then it performs smoothing activity yet not for high change. That implies it can protect subtle elements in low and in addition in high difference consequently it has versatile nature.

$$I(i,j) = I_v + W * (C_v - I_v) \qquad (8)$$

I – filtered pixel value
Iv=mean strength(ntensity)
C_v=Center pixel
W=Filter window
Noisy pixels near edges is difficult for Lee filter to remove.

C. Kuan filter

The filter was designed by Kuan and Nathan and Kurlander[5]. Under multiplicative noise, the filter is linear, and it is minimum MSE filter. It is more. It is quite advanced than previously proposed filter like lee filters. The additive noise model is generated from this kuan filter instead of multiplicative noise. Weighted function of Kuan filter is

$$W = \frac{1 - \frac{Cu}{Ci}}{1 + Cu} \qquad (9)$$

Cu = estimated noise variation coefficient.
Ci = variation coefficient of image.

Enhanced Frost and Lee filter

Mean value is found when the threshold value is lesser than the coefficient value of the filter [6]. When the variance value obtained is in between the average value and identity value is taken. It is the multiplicative noise removal modelling filter and it is given by,

$$Zx_y = X_{u,v}.V_{u,v} \qquad (10)$$

where z ia an observed image, x is an processing image and v is an noisy image, respectively.

Riesz Wavelet transform

The strategy proposed applies 2d Riesz wavelet change to loud picture. The Riesz change is the characteristic multidimensional augmentation of the Hilbert change [7]. The 2d Riesz wavelet change is steerable pyramid wavelet change. The steerable pyramid is a multi-introduction, multi-scale picture deterioration which was produced by Simoncelli and others. It is a wavelet-like portrayal whose investigation capacities are widened and turned forms of a solitary directional wavelet. Steerability is characterized as the property that the fundamental wavelets can be pivoted to any introduction by shaping reasonable straight mixes of an essential arrangement of equiangular directional wavelet segments. This gives an intense component to adjusting the change to the neighborhood attributes of the picture by guiding the premise capacities toward maximal reaction. The monogenic controlling property of Riesz change is connected to loud picture with 8 introduction and 4 scales.

$$y(x) = w^T\Phi(x) + b \qquad (11)$$

Dual tree complex wavelet transform-based Levy Shrink algorithm (DTCWT)

The coefficients are modelled into sub tree band A and B where each wavelet subband modelled by heavy tailed Levy distribution[8]. The DTCWT coefficients of each subband are modelled using a heavy tailed Levy distribution. Here both trees A and B have same frequency response. Sub tree A is opposite of sub tree B.

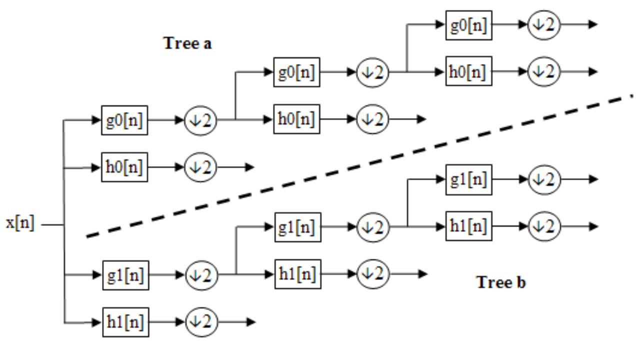


Fig. 3. Block diagram for a 3-level DTCWT

Adaptive singular value decomposition (SVD) based clutter filtering

The global value is obtained by adding the local special values where the signals are noise local stationary values. Singular value decomposition is the factorization of real or complex matrix. The MSE can be reduced by using SVD technique. The rectangular matrix A is formed by

$$A=U\wedge V^T \qquad (12)$$

$$A=U \times S \times V^T \qquad (13)$$

Where U is mxn unitary matrix, V^T is complex unitary matrix

D. Spatial Prediction Filtering

Frequency-space (F-X) prediction filtering (FXPF) is a filtering technique for reverberation and impulse noise is removed in medical ultrasound imaging [10]. The lower value for the parameter gives the lower filter values. The computational cost is too high. The forward prediction filter and backward prediction filter is obtained is obtained using $[x_0,x_1,....,x_n]$ in the LHS of equation (14). The normal of these two expectations is typically superior to simply forward forecast.

$$\begin{bmatrix} x_2 \\ x_3 \\ x_4 \\ . \\ . \\ x_{n+1} \\ 0 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} x_1 & 0 & x_1 & x_1 \\ x_2 & x_1 & x_2 & x_2 \\ x_3 & x_2 & x_3 & x_3 \\ . & . & . & . \\ . & . & . & . \\ x_n & x_{n-1} & x_{n-2} & x_{n-3} \\ 0 & x_n & x_{n-1} & x_{n-2} \\ 0 & 0 & x_n & x_{n-1} \\ 0 & 0 & 0 & x_n \end{bmatrix} \begin{bmatrix} f_1 \\ f_2 \\ f_3 \\ f_4 \end{bmatrix} \qquad (14)$$

E. Variational method based

The image is split into a domain using true value, intermediate value, false value [11]. The gamma distribution obtained in the filtering operation can be decreased by using regularization of the image which can be computed using the entropy of an indeterminate set as shown in the figure 4.

F. Gaussian wavelet based dynamic filtering (GWDF) method

The main wavelet can be split into sub wavelet which is known as daughter wavelet. The Neutrosophic variation of the filtering operation is performed and hence it is transformed into gray level domain. Thus the despeckled image would be obtained.

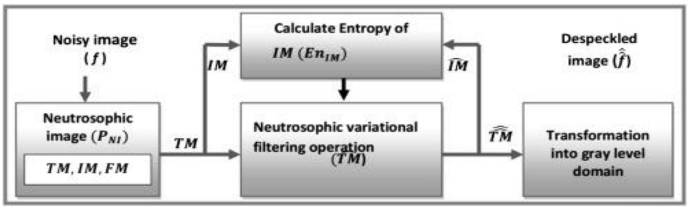


Fig. 4. Variation method based on Gamma distribution

Autocorrelation is the basis for estimation of the given depth of the received signal. The daughter wavelet is given by,

$$g_{n_0}(t) = \frac{1}{\sqrt{a}} g\left(\frac{t}{a}\right)$$

$$= \frac{1}{\sqrt{a}}\left(\frac{\partial}{\pi}\right)^{\frac{1}{4}} exp(-\frac{\partial}{2}\left(\frac{t}{a}\right)^2 cos(\omega_u \frac{t}{a}) \qquad (15)$$

SUSAN controlled anisotropic diffusion method

The filter strengthens the diffusion value based on the edge detector and it is known as SUSAN detector [13].

It discovers picture includes by utilizing neighborhood data from a pseudo-worldwide point of view. The new component locators depend on the minimization of this nearby picture area, and the noise decrease strategy utilizes this region as the smoothing neighborhood. The subsequent techniques are exact, commotion safe and quick. It utilizes roundabout veils to perform edge discovery. The partial differential equation for the SUSAN-AD model is denoted as,

$$\frac{\partial I}{\partial t} = dic[c(S = div[c(SUSAN(G(\sigma) * I)).\nabla I]] \qquad (16)$$

where, G(σ) denotes the Gaussian kernel function with a standard deviation σ and SUSAN( ) finds the intensity at the edge using the SUSAN edge detector.

IV. PERFORMANCE ANALYSIS PARAMETERS

The evaluation parameters for the speckle noise reduction techniques are SNR – Signal to Noise Ratio, Peak signal to noise ratio, Contrast to noise ratio, FOM, NQI, MSE, APSNR, VQM. The above parameters are discussed as follows

A. SNR

The average value of the pixels is measured and the noisy pixel is replaced with this averaged value of the image[14]. The speckle noise value is 1.91 for the maximum rate considered. WHeb the noise is higher the SNR will be high ao it is directly proportional.

$$SNR = 10\log\frac{{\sigma_g}^2}{{\sigma_e}^2} \qquad (17)$$

B. RMSE

The squared difference of the pixel value is done and it value is squared to get correct the noisy pixel value. The mask used can be either 3x3 or 5x5. 3x3 gives the better results. Smaller the mask greater the noise reduction[15]. Root mean square error is always negative, each error in RMSE is the squared value of the MSE and it is given by

$$RMSE = \sqrt{MSE} \qquad (18)$$

C. Peak Signal Noise Ratio and Average Peak Signal Noise Ratio

Peak Signal Noise Ratio is defined from Root Mean Square Error. If Root Mean Square Error value decreases the Peak Signal Noise Ratio value increases and if the RMSE value increases the Peak Signal Noise Ratio value decreases. For 256 gray levels, Peak Signal Noise Ratio is defined as

$$PSNR = 20Log\frac{255}{RMSE} \qquad (19)$$

A simple average of Peak Signal Noise Ratio per frame is called *Average Peak Signal Noise Ratio*

D. *D. Mean Absolute Error*

MAE is generally less demanding to comprehend than the square base of the normal of squared blunders. Moreover, every blunder impacts MAE in guide extent to the outright estimation of the mistake, which isn't the situation for RMSD

$$MAE(I_{filt}, I_{ref}) = \frac{1}{XY}\sum_{i=1}^{Y}\sum_{j=1}^{X}\left|I_{filt}(i,j) - I_{ref}(i,j)\right| \qquad (20)$$

E. *E. Pratt's FoM*

The Pratt measure requires a "best quality level" - that is, something that gives you immaculate or perfect edges for your pictures. You could utilize a standard edge location calculation for this reason if what you need to do is contrast another edge locator and the standard one. The "perfect edges" are, as you say, the edges from whatever standard you've picked.

$$FoM(I_{filt}, I_{ref}) = 1/max(N_{filt}, N_{ref})\ \sum_{i=1}^{N}\frac{1}{1+{d_i}^2\alpha} \qquad (21)$$

F. *F. CNR*

CNR proportion is the relationship of flag power contrasts between two areas, scaled to picture clamour[16]. Enhancing CNR builds view of the unmistakable contrasts between two clinical territories of intrigue. A complexity to clamor proportion is a rundown of SNR and difference. It is the distinction in SNR between two applicable tissue composes. (An and B): CNR = SNRA – SNRB.

This metric is calculated as

$$CNR = \frac{|\mu_1 - \mu_2|}{\sqrt{{\sigma_1}^2 + {\sigma_2}^2}} \qquad (22)$$

G. *G. SSIM*

The similarity values can be obtained here and it is reduced by the averaged value [17]. It is a universal quality index. CSSIM is frequently contrasted with different measurements, including more basic measurements, for example, MSE and PSNR, and other perceptual picture and video quality measurements. SSIM has been over and over appeared to essentially beat MSE and its derivates in exactness,

$$SSIM = 1/M\ \sum\frac{(2\mu_1\mu_2 + C_1)(2\sigma_{1,2} + C_2)}{({\mu_1}^2 + {\mu_2}^2 + C_1)({\sigma_1}^2 + {\sigma_2}^2 + C_2} \qquad (23)$$

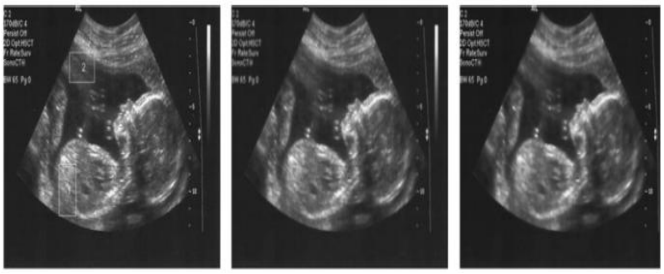
H. VQM

The discrete cosine transform is modified based on the property of the temporal (space) of the eye perception. VQM is a metric got in 1991 from Digital Video Quality (DVQ) and in light of Discrete Cosine Transform (DCT) coefficients that demonstrate a 95% connection to the emotional criteria [18]. The fundamental thought comprises in applying Spatial Contrast Sensitivity Function (SCSF) network for static edges and dynamic casings in a single step. The first and got/estimated pictures are changed to the

YUV shading space and thus changed to the DCT coefficients[19].

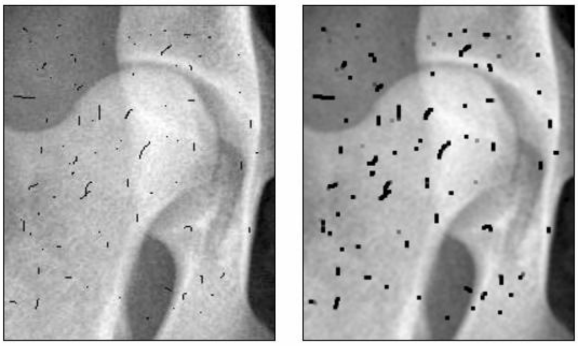
$$LC(i,j) = DCT(i,j)\frac{\left(\frac{DC}{1024}\right)^{0.65}}{DC} \qquad (24)$$

V. Result and Discussion



a b c

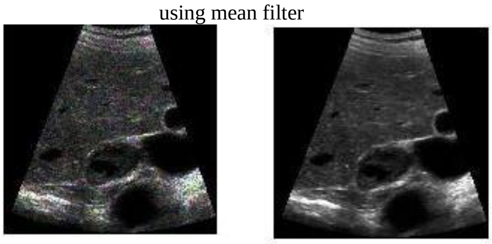
Fig. 5. Noise removal of baby image a. Real image b. LEE filter c. SRAD filter



a. Noisy image

b. Denoised image using mean filter for size 3

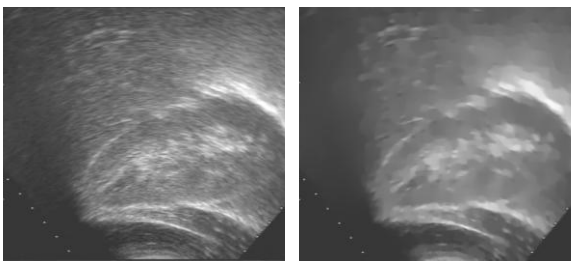
Fig. 6. Noise removal of various images a. Real Image b. Denoised image using mean filter



b. Noisy image

c. Denoised image using median filter

Fig. 7. Noise removal of various images a. Original image b. Denoised image using median filter



d. Noisy image

e. Denoised image using Frost filter

Fig. 8. Noise removal of various images a. Original image b. Denoised image using frost filter

TABLE 1. PSNR COMPARISON FOR LEE AND LEVY SHRINK FILTERS OF PHANTHOM IMAGES

Noise σ^2	Lee	Levy Shrink
0.1	21.75	26.37
0.2	26.905	32.153
0.25	27.436	32.742
0.5	28.32	33.844

TABLE 2. SSIM AND FOM COMPARISON OF VARIOUS FILTERS FOR KIDNEY IMAGE

Filter	SSIM	FOM
Kuan	0.2547	0.4880
Surelet	0.2719	0.4288
SRAD	0.2029	0.4677

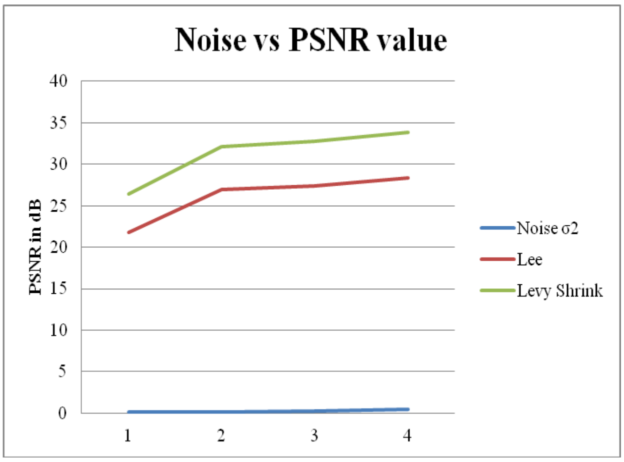


Fig.9. PSNR comparison for Lee and Levy Shrink filters of phanthom images

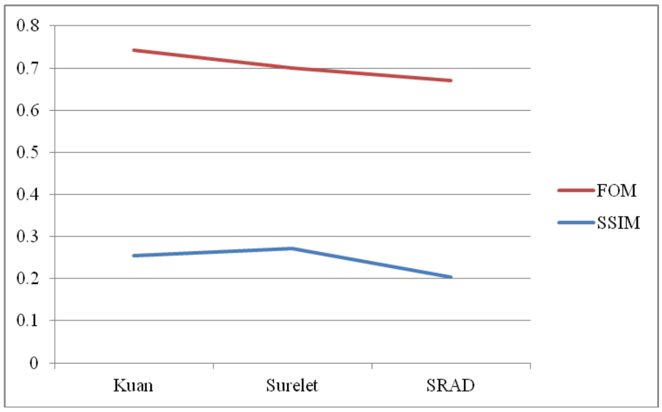


Fig.10. SSIM and FOM comparison of various filters for Kidney image

VI. Conclusion

The speckle filters are compared and various methods are analyzed by which each filter perform better in its own way. Adaptive filters are better for high frequency noise removal. An adaptive filter has a disadvantage of failing to protect the edge data of the image. The weighting function of the filter plays a vital role for the evaluation of computation time. For filters like mean, median, etc the computation time is large and mostly all adaptive filters take long computation time.

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