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Multiresolution Based Hybrid Filtering Technique for Despeckling Ultrasound Images

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Abstract : *Ultrasound imaging is the most commonly used imaging system for disease diagnosis. Speckle noise is an inherent property of medical ultrasound imaging. Since speckle may hinder the detection of image details it is typically regarded as noise and there is a strong need to remove speckle effectively for good and fast interpretation. Multiresolution analysis is the important tool in eliminating noise from images effectively. In this paper an algorithm is proposed that uses multiresolution analysis through which it is possible to distinguish noise and image information better than at one resolution level. The proposed algorithm combines the features of filtering techniques in multiresolution framework to combine the benefits that each one can contribute. This algorithm maintains a balance between speckle suppression and feature preservation. The result is shown to be promising and outperforms other despeckling approaches. Performance evaluations are performed by using statistical parameters like Mean Square Error (MSE), Signal to Noise Ratio (SNR), Peak Signal to Noise Ratio (PSNR), Speckle Index (SI) and Edge Preservation Index (EPI).*

Keywords: *Ultrasound imaging, Speckle noise, Multiresolution, PSNR, SI, EPI.*

I. Introduction

Ultrasonography is a powerful technique for imaging the internal anatomy of human body. A high frequency sound wave is transmitted and the reflected echoes are used to create the image. The advantage of ultrasound imaging over X-ray, Computed Tomography(CT), Magnetic Resonance Imaging (MRI) are reported as being painless, non-invasive, does not use ionizing radiation, is less expensive, can be performed real time, needs no special environment. An image is often corrupted by noise during its acquisition or transmission. In medical images noise suppression is delicate and difficult task. A tradeoff between noise reduction and preservation of actual image features has to be maintained.

The main disadvantage of using ultrasound imaging is the poor quality of image which is affected by speckle noise. Speckle is a kind of multiplicative noise. It is random interference pattern in an image formed with coherent radiation of a medium containing many sub resolution scatters. In case of medical literature, speckle noise is also known as texture. General model of speckle is represented as:

$$f(x,y) = g(x,y)\eta(x,y) \quad (1)$$

Where f(x,y) is the real noise image, g(x,y) is unobservable original image and η(x,y) is multiplicative noise component. The main need for despeckling is to improve human interpretation over ultrasound images and also speckle reduction makes the image cleaner with clearer boundaries.

Muhd Zain et al. [2] have reported the use of average, median, Wiener filtering techniques for speckle reduction from ultrasound images and concluded that Wiener filtering is better technique in reducing the speckle without fully eliminating edges. S.Sudha et al. [6] have reported the use of wavelet based thresholding scheme for noise suppression. The thresholding technique removes speckle effectively but the thresholding technique has difficulty in determining an appropriate threshold. K. Karthikeyan et al. [4] have reported the combination of anisotropic diffusion combined with speckle reduction anisotropic diffusion (SRAD) and Bayes shrink threshold gives better result in suppression of speckle noise. Irraivan Elamvazhuthi et al. [1] have reported the use of Dabechies and Wiener gave best result when combined with anisotropic diffusion filter. Bobby et al. [3] have reported about salt and pepper, Gaussian, speckle noise and various denoising filter and concluded that wavelet filter removes speckle noise effectively.

II. Filtering Algorithms

In this section several despeckling techniques such as Median, Average, Wiener, Anisotropic diffusion Ideal, Butterworth and Homomorphic filter are discussed.

A. Median Filter

It is a spatial domain filter. A median filter generally smoothens the image to reduce noise and at the same time it preserves edges. It replaces the middle pixel in the window with the median-value of its neighbors [9]. This filter does not create new pixel value. Instead it chooses the median value which is selected from the neighborhood. This will not affect other pixels significantly. Hence this filter preserves the edges.

B. Average Filter

This filter is a spatial domain filter. This filter acts on the image by smoothing it. It reduces the variation in terms of intensity between adjacent pixels. It replaces the middle pixel in the window with the average value of its neighbors [9].This filter removes the noise by smoothing but the edges are not preserved. This is because new pixel values are created which affects the other pixels significantly.

C. Wiener Filter

It is an adaptive filter which changes its characteristic according to the local statistics in the neighborhood of the current pixel. It generally uses small window size within each window the local mean and variance are calculated. This filter is based on the fact that if the variance over an area is high then smoothing is not done. If the variance over an area is low or constant then smoothing is done.
Local mean and variance for the mask is calculated using the formula given below:

$$\mu = \frac{1}{PQ}\sum_{n=0}^{Q-1}\sum_{m=0}^{P-1} f_b(m,n) \qquad (2)$$

$$\sigma^2 = \frac{1}{PQ}\sum_{n=0}^{Q-1}\sum_{m=0}^{P-1}\left(f_b^2(m,n) - \mu^2\right) \qquad (3)$$

Filtered image is obtained by using:

$$R(m,n) = \mu + \frac{\sigma^2 - v^2}{\sigma^2}\left(f_b(m,n) - \mu\right) \qquad (4)$$

Where V^2 is the user defined noise variance

D. Diffusion Techniques:

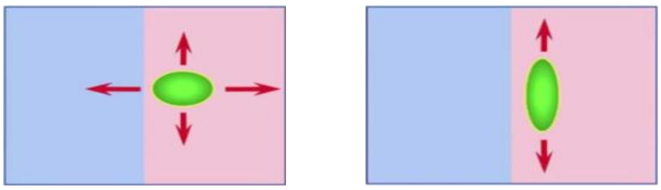
Diffusion is a physical process for balancing concentration changes. In image processing the image intensity can be seen as concentration. The noise can be modeled as little concentration inhomogeneity. This inhomogeneity could be smoothened by diffusion.

i. Isotropic diffusion:

It is like averaging an image that is diffusion of the pixel value all across the image. This result in blurring. Isotropic diffusion does not bother about the boundaries it smoothens the image all around (see fig. 1a.) Hence in isotropic diffusion edges are not preserved. According to the following PDE:

$$\frac{\partial I(x,y,t)}{\partial t} = div[c.\nabla I(x,y,t)] \qquad (5)$$

Where div is the divergence, c is diffusion constant. $\nabla I(x,y,t)$ is the gradient version of the image at time t.



a. isotropic diffusion b. anisotropic diffusion
Fig.1 diffusion techniques

ii. Anisotropic diffusion:

Smoothing is carried out depending on the image edges and their direction. It smoothens homogeneous image regions but retains image edges. The tool that we use to find the strength and direction of the edge is gradient. Based on this gradient value we perform smoothing. Generally in homogenous region the gradient is small. If the magnitude of the gradient is small then smoothing is done. Smoothing is stopped when the magnitude is high. This is called Persona- Malik Anisotropic Diffusion (PMAD).The PMAD is based on the following equation:

$$\frac{\partial I(x,y,t)}{\partial t} = div[g(\|\nabla I(x,y,t)\|)\nabla I(x,y,t)] \tag{6}$$

Where div is the divergence, t is the time parameter, I(x,y,t) gradient version of the image at time t, g(.) is the conduction function, $\nabla I(x,y,t)$ is the gradient version of the image at time t.The conduction function must satisfy the following two conditions:

$$\lim_{x\to 0} g(x) = 1 \tag{7}$$

$$\lim_{x\to \infty} g(x) = 0 \tag{8}$$

The conduction function says when to start and stop diffusion. The conduction function that satisfies the above two condition is given by:

$$g(x) = \frac{1}{1+\frac{x^2}{k^2}} \tag{9}$$

Where k is the gradient magnitude threshold parameter that controls the rate of diffusion.

E. Fourier filtering:

Fourier filtering is based on Fourier transforms properties. In despeckling, our objective is to find a filter or filtering function which will minimize Fourier transform's high frequency components. Blurring (smoothing) is achieved in the frequency domain by attenuating a specified range of high-frequency components. This task is performed through low-pass filtering. Once this is done, the output image will be obtained by means of the inverse Fourier transform. We will consider two types of filters.

i. **Ideal Low-pass Filter**

The ideal low-pass filter is one which satisfies the relation:

$$H(u,v) = \begin{cases} 1, \text{ if } D(u,v) \le Do \\ 0, \text{ if } D(u,v) > Do \end{cases} \tag{10}$$

$$D(u,v) = (u^2 + v^2)^{1/2} \tag{11}$$

Where D_0 is a specified non-negative quantity, D(u, v) is the distance from point (u,v) to the origin of the frequency plane. The filter is called ideal because all the frequencies inside the circle of radius D_0 are passed with no attenuation, whereas all frequencies outside this circle are completely attenuated [9]. The drawback of this filter function is a ringing effect that occurs along the edges of the filtered spatial domain image.

ii. **Butterworth Low Pass Filter**

The Butterworth low-pass filter is an approximation to the ideal filter without the step discontinuity. The transfer function of the Butterworth low-pass filter of order n and with cut-off frequency locus at a distance D_0 from the origin is defined by the relation:

$$H(u,v) = \frac{1}{1 + [D(u,v)/Do]^{2n}} \tag{12}$$

$$D(u,v) = (u^2 + v^2)^{1/2} \tag{13}$$

n is the order of the filter.

F. Wavelet Filtering

Wavelet filtering [9] exploits the decomposition of the image into the wavelet basis and zeros out the wavelet coefficients to despeckle the image. Wavelets are simply mathematical functions and these functions analyze data according to scale or resolution. We use a processing which is carried out without implementing very complex transform. It consists of eliminating certain frequencies in order to eliminate any existing noise. Since we know that in an image HH, LH and HL components contain most of the noise. We can eliminate noise by eliminating those components. This does not mean that all noise present in the image is eliminated. Some details in the image may also be lost.

G. Homomorphic Filter

These filters are used for image enhancement. It simultaneously normalizes the brightness across an image and increase contrast. Homomorphic filter is used to remove multiplicative noise. Natural log is taken to the input image which converts multiplicative noise into additive noise. Then a user defined filter is used and finally exponential operation is done (Fig.2).

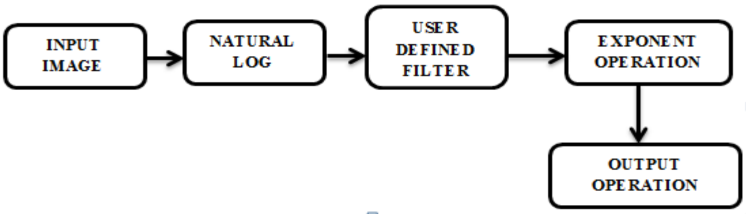


Fig. 2 Homomorphic Filtering

III. Proposed Algorithm

In the proposed system hybridization of various filtering technique are done to achieve optimal results. The hybridization is done in two different ways one is sequential and the other one is parallel hybridization.

Sequential hybridization:

In sequential hybridization we have a series of methods where the output of one will be the input of the next one. Several sequential combination of above mentioned filters are experimented. The combination that gave the best result is represented in the fig.3.

Fig.3 Sequential hybridization of Filters

Proposed Multiresolution Parallel hybridization:

Parallel hybridization is made up of several sequential combinations. Then the resulting images of each sequential combination are fused together. We try to complement the positive and negative aspects of each sequence with parallel hybridization. Since the defects of one side will be compensated with the advantages of the other side although each ones positive traits may also diminish. Thus to obtain best possible results a compromise will have to be made.

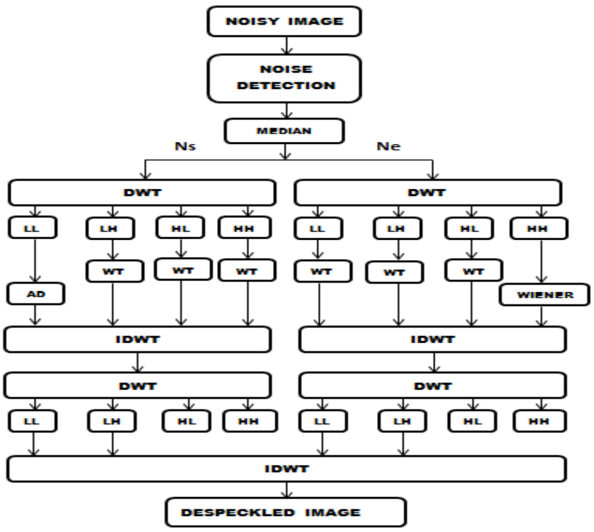


Fig.4 Proposed Multiresolution Parallel Hybridization

Key features of proposed algorithm:

A. **Multiresolution Framework:**

An two dimensional image after wavelet decomposition it gets decomposed into approximated band(LL) and detailed bands (see fig.4) The detailed bands comprises of horizontal (LH), Vertical (HL) and diagonal detail (HH). The main advantage of using multiresolution framework is that the coarse grain noise at the original level is difficult to identify and eliminate. But when the image is decomposed into different component the noise become fine grains and the noise can be eliminated more easily by processing at different bands.

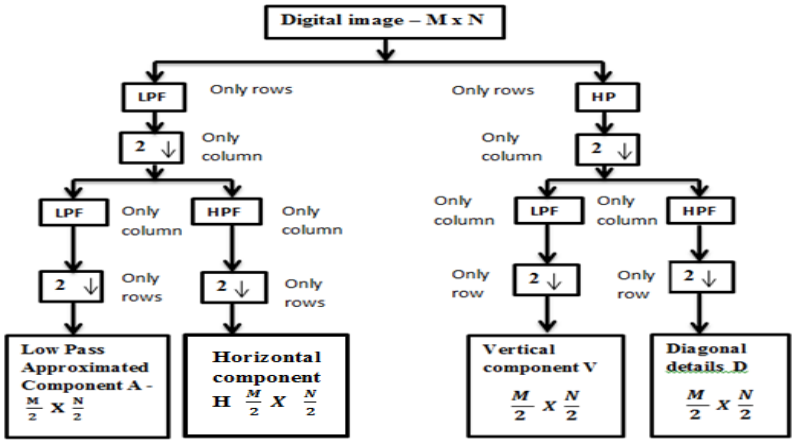


Fig.5 Two Dimensional Forward Discrete Wavelet Transform.

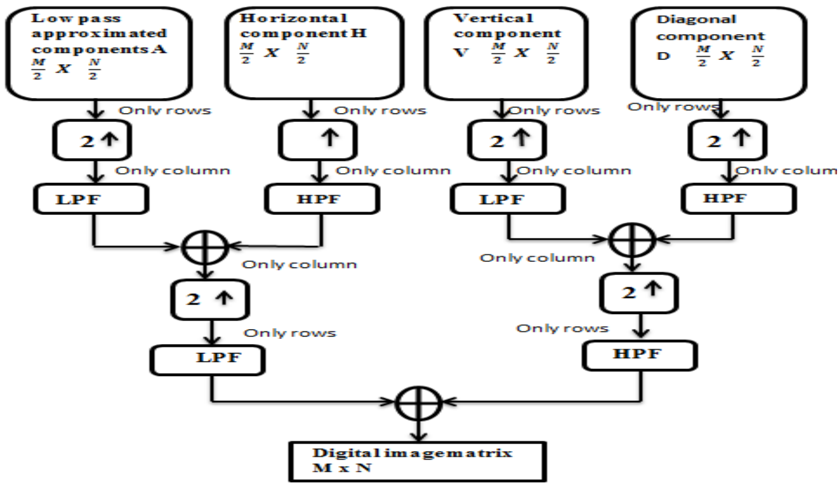


Fig.6 Two Dimensional Inverse Discrete Wavelet Transform

B. Noise Detection:

Generally for denoising an image the filtering techniques are directly applied on the entire image. In this case, the entire pixels in the image undergo filtering. This will affect the noise free pixels in the image. In order to avoid this, the proposed algorithm initially detects noise in an image before filtering. This will preserve the useful information.

Algorithm – Noise Detection:

Step1: Read a noisy image

Step2: Form a 3 x 3 window by neighborhood processing which involves defining a center point (x, y)

Step3: Estimate whether the center pixel is noisy or not

Step4: To differ the noisy pixel from the noise free pixel, calculate mean (M) and standard deviation (D) of the window. If the center pixel value is within the range of (M-D) and (M+D), then that pixel is noise free. Otherwise the center pixel is considered as noisy pixel.

Step5: After detecting the noise filtering is done. In the proposed system median filtering is applied for noisy pixel.

C. Wavelet Thresholding:

Wavelet thresholding removes the noise by killing coefficients that are insignificant, relative to some threshold value. Here the threshold value is calculated using band dependent optimal thresholding technique. In this technique, the threshold value depends on the band. The threshold value varies for each band depending upon the low and high frequency information corresponding to that particular band. Generally, in an image high frequency component contains more noise. In order to eliminate the existing noise, we threshold the high frequency components and retain the low frequency component from all the bands. Thus in order to extract low frequency component from those bands, we choose different threshold value for each band. Hence we can isolate low frequency components and eliminate high frequency components. Further the selected threshold in this method would be optimum which means the selected threshold value yields MSE which is very low.

Algorithm for proposed Multiresolution Parallel Hybridization:

Step1: Read the noisy image

Step2: Detect the noise by using the noise detection technique mention above

Step3: Process the noise detected image with two different filtering techniques each in a different multiresolution framework at the same time.
For processing the same noise detected image with two different techniques, let us consider one as Ns and other as Ne. By processing the Ns image the noise is effectively removed. Similarly By processing the Ne image the edge
details are preserved.

Step4: Decompose Ns and Ne into LL, LH, HL and HH component by using discrete wavelet transform.

Step5: To remove the noise efficiently from Ns, we use wavelet thresholding technique at LH, HL and HH band. Then the LL band is filtered using anisotropic diffusion filtering technique.

Step6: To preserve the edge details from Ne, we use wavelet thresholding technique at LL, LH and HL band. Then the HH band is filtered using homomorphic wiener filtering technique.

Step7: Finally the LH and HL bands from Ns and Ne are fused together by taking inverse discrete wavelet transform.

IV. Evaluation Metrics

Some common measurements that are needed to evaluate the performance of speckle reduction filters for ultrasound images are listed below

A. Mean Square Error

It indicates how different the images being compared are. It is given by:

$$MSE = \frac{1}{M.N}\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}[\,I(m,n) - \hat{I}(m,n)]^2 \tag{14}$$

Where I(m, n) is original image, $\hat{I}$(m,n) is filtered image, M is number of rows, N is number of columns. Therefore lower its value is the closer the estimated image to the original image.

B. Signal to Noise Ratio

It shows the relationship between the real image and estimated image. This ratio indicates how strong the noise corrupted the original image. It is given by:

$$SNR = 10\log_{10}\frac{\frac{1}{M.N}\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} I^2(m,n)}{MSE} \tag{15}$$

Where I is the original image, M is number of rows, N is number of columns. Here higher the value indicates an improvement.

C. Peak Signal to Noise Ratio

In PSNR we are interested in signal peak. This is more content specific than pure SNR.Here we say how high intensity regions of the image come through the noise and paying much less attention to low intensity regions. It is given by:

$$PSNR = 10\log_{10}(2^B - 1)^2 / MSE \tag{16}$$

Where B is number of bits used for representing each pixel, MSE is mean squared error. Here higher the value indicates an improvement.

D. **Speckle Index (SI)**

SI is a measure of speckle reduction in terms of average contrast of the image. Lower value of SI corresponds to improved image quality. The SI is defined as follow:

$$SI = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{\sigma(i,j)}{\mu(i,j)} \qquad (17)$$

σ(i,j) and μ(i,j) are the standard deviation and mean corresponding to neighbor domain.

E. **Edge Preservation Index**

EPI is used to evaluate the preservation of edges. In this case an increase of this parameter also indicates better performance quality. It is given by:

$$EPI = \frac{\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}[\,\Delta I(m,n) - \hat{\Delta}\, I].[\Delta\, \hat{I}(m,n) - \hat{\Delta}\hat{I}\,(m,n)]}{\sqrt{\sum_{n=0}^{N-1}[\Delta\, I(m,n) - \hat{\Delta}\, I]^{2}.\,[\Delta\, \hat{I}(m,n) - \hat{\Delta}\hat{I}\,(m,n)]^{2}}} \qquad (18)$$

Where Δ operator means applying a high pass filter to the image. To perform the filtering, the Laplacian operator is used in its 3 x 3 version. $\hat{\Delta}$ is the mean value of the image after operator is applied.

V. Experimental Results And Discussions

To compare the algorithms, we experiment those algorithms with the pancreas image in Fig.7a. Since we only have a noise corrupted image and the real noise-free image does not exist, conventional metrics cannot be used to indicate the quality obtained with filtering. So, from this image we have generated a noisy image (see Fig.7b).

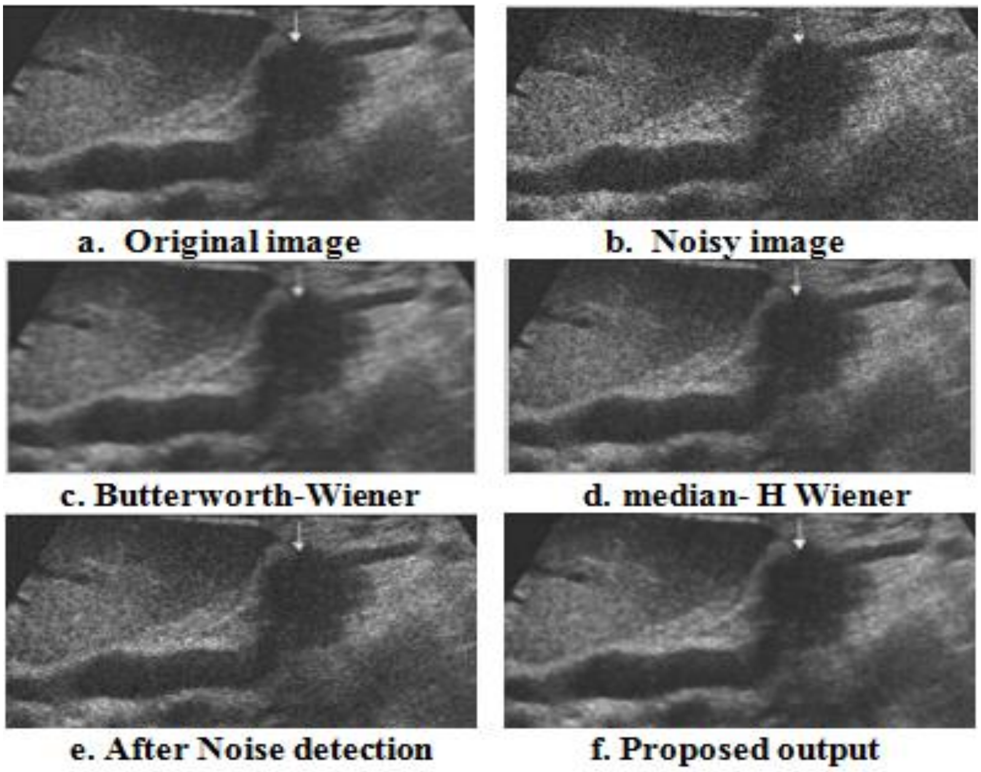


Fig.7 Results of sequential and parallel hybridization.

Table 1: Computed Performance Metrics of Various Filters
(Note: The SI value of original image is 1.86 e^-6)

Filters	MSE	SNR	PSNR	EPI	SIxe^-6
NOISY	4.02833	70.1986	72.0796	1400.52	2.15
AVERAGE	0.513252	79.1465	81.0275	1685.42	1.82
MEDIAN	0.552982	78.8227	80.7037	1550.34	1.83
WIENER	1.09943	75.8381	77.7191	1800.07	1.93
H-WIENER	0.611278	78.3874	80.2684	1879.21	1.88
IDEAL	0.540452	78.9223	80.8032	2359.45	1.86
BUTTERWORTH	0.410876	80.1127	81.9937	2057.58	1.83
WLET LH-HL-HH	1.12821	75.7259	77.6069	1806.7	1.92
ANISOTROPIC DIFFUSION	0.519228	79.0963	80.9772	1819.08	1.78
BTW-MED-60	0.395924	80.2737	82.1547	1935.18	1.82
MEDIAN-WIENER	0.561689	78.7549	80.6358	1722.54	1.86
HWIENER-AVG	0.435178	79.8632	81.7441	2061.58	1.84
WIENER-BTW-60	0.409719	80.125	82.0059	1981	1.82
MED-HWIENER	0.478799	79.4483	81.3293	1717.05	1.85
PROPOSED	0.170038	83.9444	85.8253	1840.97	1.81

In case of average filter different window sizes have been used such as 3x3, 5x5, and 7x7. According to the metrics (Table 1), average filter with 3 x 3 window size eliminates noise in such a way that we obtain a better quality image than the noisy image.

In case of median filter different window sizes have been used such as 3x3, 5x5, and 7x7. According to the metrics (Table 1), a median filter with 3 x 3 window size eliminates noise in such a way that we obtain a better quality image than the noisy image. We have also noticed that as the window size increases noise is reduced effectively but smoothing also increase which means that edges are not preserved, as the window size increase.

In case of Ideal and Butterworth filter evaluation is done by varying Cutoff frequency such as 30, 40, and 60.We have observed that in case of Ideal filter (IDL) some part of the background of the image is smoother but the object contours have become blurred and there is a wave like effect around the background. This wave effect decreases as the cutoff frequency increases. Hence an Ideal filter with cutoff frequency 60 gives best result.

In case of Butterworth filter (BTW), it tries to eliminate the wave effect which is introduced in Ideal filter. If the cutoff value is lowered even more, we would get greater smoothness but we would also lose sharpness in the image and the Gibbs effect may become more significant. That is why we do not lower the cutoff value more significantly. On the contrary, it is raised to 60 to avoid these damaging effects. Hence the Butterworth filter with cutoff frequency 60 gives best result.

In wavelet filtering (WLET) bands such as LH, HL, HH, LH-HH-HL, LH-HL, HL-HH, and LH-HH are eliminated separately and their evaluation metrics are calculated. Some those metrics are listed in Table1. By eliminating bands white spots is created in the image which is not present in the original image, this white spots is not that much prevalent when we remove LH-HH-HL together.

Wiener filtering preserved the edges reasonably well, but in this case the noise elements are visible. This is overcomed by using homomorphic Wiener filter.In relation to the images, noise in bright regions have higher variations and could be interpreted wrongly as features in the original image by Wiener filter. Thus, it is harder and more complicated to smooth the noise without degrading true image feature. Hence by using homomorphic Wiener filtering technique, noise in the brighter regions is also removed.

Homomorphic combination is tried with filters like Ideal (H-IDL), Butterworth (H-BTW), Wiener (H-Wiener), and Wavelet (H-WLET). Out of this homomorphic Wiener gave best result Table 1. Several hybrid combination of above mentioned filters are experimented. Some of the hybrid combination that gave best results is listed in Table 1.

We can notice from the chart (Fig.8) that proposed multiresolution filter removes noise effectively and also preserve edges. A single adjustable parameter is to balance the relevant image feature preservation and speckle noise suppression. The SI of the original image is 1.86 e^-6 whereas the SI of the hybrid filtered image is 1.81 e^-6. From this we can observe that the designed hybrid filter not only removes the noise we added but also removes the speckle noise that already exist in the original image.

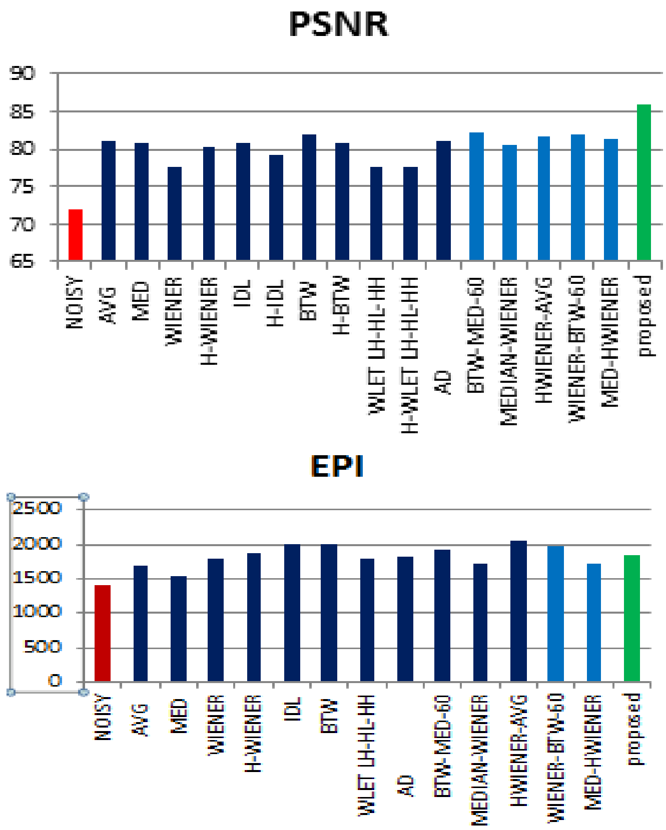


Fig.8 PSNR and EPI of individual and hybrid filters

VI. Conclusion

The current need of the healthcare industries is to preserve useful diagnostic information with minimum noise. Ultrasound images often suffer with a special type of noise called speckle. To help the medical practitioners to achieve correct diagnosis, the ultrasound images have to be despeckled. In this work, a multiresolution based parallel hybridization technique is proposed. The proposed system outperforms sequential hybridization techniques and maintains a balance between speckle suppression and feature preservation based on the performance metrics like MSE, SNR and PSNR, SI, EPI.

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