Speckle Noise Removal in Ultrasound Images Using a Novel Hybrid De-Speckling Method Based on Dual Tree Complex Wavelet Transform and Improved Bilateral Total Variance Filtering Method

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Abstract

Noise reduction has turned into a fundamental errand in medicinal Ultrasound (US) imaging because of the presence of multiplicative (speckle) noise. As of late, there are a few denoising techniques such as median filter (MF), Bilateral filter (BF), Weiner filter (WF), Homomorphic filter (HF), etc., have been proposed to remove the Speckle Noise (SN). Notwithstanding, these denoising systems were found to stifle the speckle alongside with the original information of the image, which is now and then implied as over-sifting. In this way, it lessens the exactness of the acknowledgment procedure. So as to beat the over sifting, in this paper, a new hybrid filtering system is developed by consolidating Dual Tree Complex Wavelet Transform (DTCWT) and Improved Bilateral Total Variance (IBTV) channel. The DTCWT is performed on the image so as to acquire explicit coefficients describing these sorts of noise. At that point, these separated characteristics are expelled by thresholding and a reverse WT is applied so as to get the filtered image. At long last, so as to expel any residual noise present in the recreated image, IBTV is applied on the image. The reproduction results established that the DTCWT-IBTV system accomplishes better denoising execution on correlations with other sifting methods regarding Peak Signal to Noise Ratio (PSNR), Structural Similarity Index measure (SSIM), and Edge conservation Index (EPI).

Keywords: Speckle Noise, Dual Tree Wavelet Transform, Bilateral Filter, Ultra-sound image, Thresholding.

1. INTRODUCTION

The medicinal imaging gadgets to be specific X-ray, CT/MRI and ultrasound are producing plentiful images which are utilized by therapeutic professionals during the time spent analysis. The principle issue is the noise acquainted due with the outcome of the intelligent idea of the wave transmitted. Speckle is a complex phenomenon, which debases image quality with a backscattered wave appearance which begins from numerous infinitesimal diffused reflections that going through inside organs and makes it progressively hard for the spectator to segregate edge attributes of the images in diagnostic examinations. Consequently, denoising or diminishing these multiplicative noises from an uproarious image has turned into the prevalent advance in medicinal image processing. Multi-look procedure and spatial shifting are the two techniques of suppressing speckle noise. Multi-look procedure is utilized at the information procurement arrange while spatial shifting is utilized after the information is stored. Among these two methods, any technique can be utilized to expel the speckle noise, however they should preserve radiometric, edge, and spatial characteristics [1].

To meet the non-homogeneous areas, the improved and modified techniques were proposed, for example, refined Lee filter [2], weighting filter [3], hybrid sigma filter [4] and improved sigma filter [5] and so on. The authors of [6] introduces modified Lee filter, improved Kuan filter and enhanced Frost filter. These filtering methods can smooth the images, however somewhat to keep the image subtleties, but the image complexity is as yet decreased, that is, the edges are obscured. In [7], proposed a bilateral filtering (BF) of speckle noise. Since the filtering method considers the geometric closeness and dark worth likeness, it can adequately smooth the images, while safeguarding edges.

The wavelet and spatial filters could be used to lessen SN, Gaussian noise and salt and pepper noise in US images [8]. The joined wavelet thresholding and BF is used in order to stifle SN [9]. Total Variation (TV) regularization strategy was proposed in [10] in order to empty SN. In addition, a blend of TV, high-request TV and a Kullback–Leibler contrast system was proposed in [11] to expel trademark commotion. The Daubechies complex wavelet change is used to evacuate the SN [12], in which whimsical piece of complex scaling coefficient and shrinkage on complex wavelet coefficient are performed independently to recognize edges and non-edges of the image. Improved adaptable wavelet shrinkage was proposed in [13] subject to the relationship of the coefficients inside and over the goal's scales. DTCWT has the upside of inaccurate move invariance, extraordinary directional selectivity in two estimations, and perfect generation over the DWT [14]. Directly, complex wavelet change (CWT) has been developed to improve these DWT downsides, with the Dual-Tree CWT (DT-CWT) [15] transforming is a most suitable technique due to the effortlessness of its utilization.

Aims of this study

Because it was already recognised that the noises degenerate the image and regularly lead to wrong analysis and every one of these therapeutic imaging gadgets is influenced by various kinds of noise. For instance, the X-ray images are frequently adulterated by Poisson noise, while the ultrasound images are influenced by SN. The aim of this study is to evaluate the amount of noise produced and to reduce it by multi look procedure and spatial shifting.

2. SUBJECT & METHOD

Speckle Noise Model

Digital images are exaggerated by various types of noises such as gaussian noise, random noise, speckle noise etc. In this paper, only the speckle noise has been considered. The speckle noisy images show a granular pattern because of the scattering of the EM waves brought about by the transducer. When the waves pondered the unpleasant surface have an effect on said surface, they make obstructions which originates speckle noise in the enrolled image. These types of noise affect the quality of the original image, since it restricts the recognition of wounds, particularly in low-slung disparity images. To consummate the denoising strategies, it is critical to have an exact and solid model for conquering the SN. It is not a simple assignment; in any case, the accompanying model is viewed as a decent model for ultrasound images with SN.

$$S(x, y) = O(x, y) \cdot m(x, y) + a(x, y) \qquad (1)$$

Where, S(y, x) is the speckle noise ultrasound image, O(x, y) is the noiseless image, m(x, y) is the SN and a(x, y) is the additive noise components. In this paper, speckle noise alone has been considered. Therefore, the above equation can be written as

$$S(x, y) = O(x, y) \cdot m(x, y) \qquad (2)$$

Proposed Method

The block diagram of proposed method using DTCWT based Improved Bilateral Total Variation (IBTV) filtering is given in fig.1. Here, two stages of filtering process have been performed on the US images. In the first stage, US dataset has been applied on DTCWT. Then the transformed images are filtered by using soft thresholding with SURE estimation. The first stage filtered image is obtained after performing the inverse DTCWT operation. In this stage, not all the speckle noises are filtered, and the filtered images produces some blurring effects. In order to overcome these defects, second stage of filtering has been performed. In the second stage, IBTV based filtering process has been performed to eliminate the blurring effect, so that the de-speckled noise can be obtained.

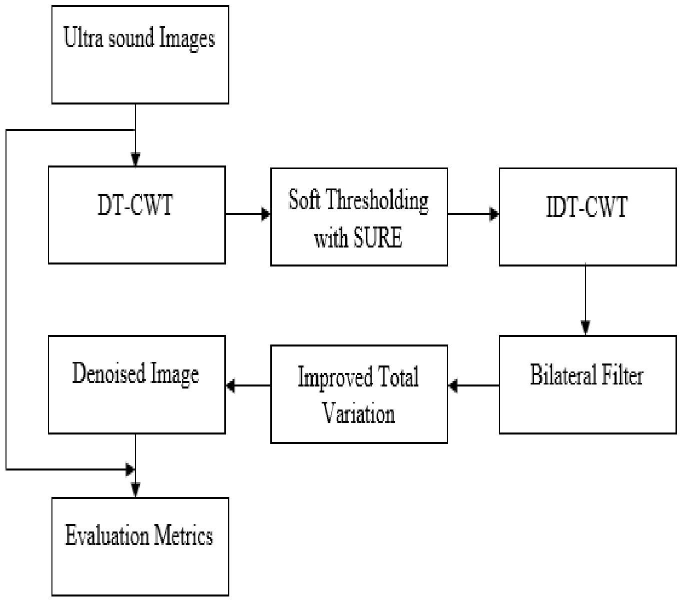

Fig.1 Hybrid de-speckling method based on DTCWT-IBTV Filter

DT-CWT

DTCWT is a type of DWT which produces complex quantities by utilizing a double tree of filters to acquire their real and unreal parts [21]. The dual tree (DT) employment of CWT has the attractive properties of inexact move invariance and great steering discernment. These characteristics are significant for some applications in image analysis and synthesis, image enhancement, watermarking, segmentation and classification. The filter bank structure of DTCWT is appeared in Fig.2. The way to get invariance from the DT structure lies in planning the filter delays at each stage, with the end goal that the low pass filter (LPF) yields in tree *b* are inspected at focuses halfway between the testing purposes of the comparable filters in tree *a*. This necessitates a delay refinement between the a and b LPF of 1 trial at tree level 1, and ½ trial at resulting measurements. At levels 1 any standard symmetrical or bi-symmetrical wavelet filters are used and produce the required delay move unimportantly by consideration or abrogation of unit delays, yet the further measurements the ½ test concede refinement is progressively problematic. In order to give the twofold tree improved symmetry and symmetry monied over the past structure, Q-move filters for level 2 and underneath are displayed. The DTCWT for 2-D image is acquired by discrete sifting along lines and afterward sections.

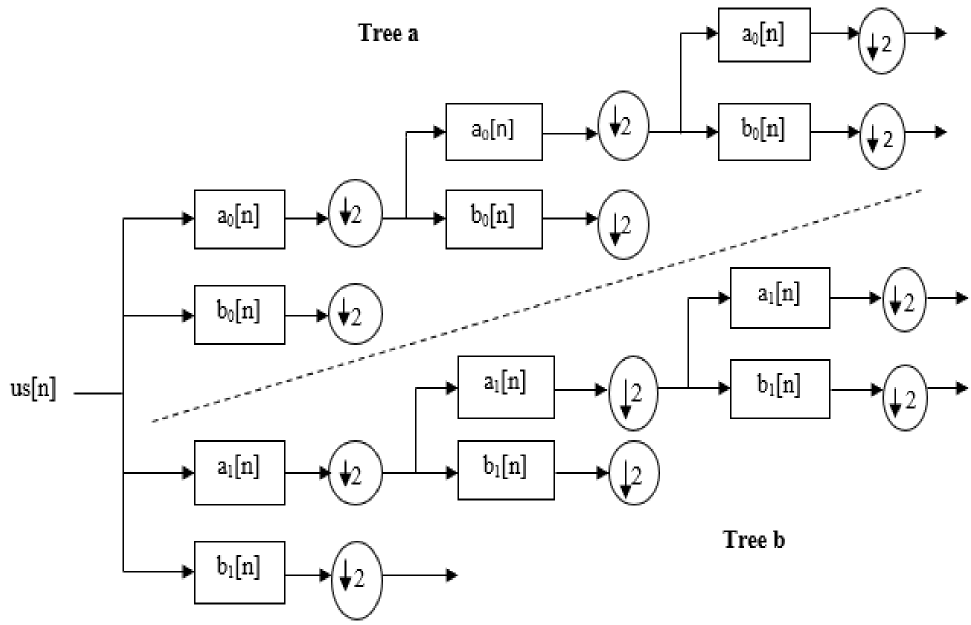

Fig.2 Analysis filter bank structure of DTCWT

The execution of 2-D DTCWT comprises of two stages. Initially, an image is disintegrated up to an ideal level by two distinct 2D DWT branches, tree a and b, whose channels are explicitly intended to meet the Hilbert pair necessity. Then, six high-pass bands are created at each level. HLa, LHa, HHa, HLb, LHb and HHb. Next, every two comparing sub bands which have a similar pass-bands are straightly joined by either averaging. Subsequently, sub groups of 2D DT-CWT at each level are attained as,

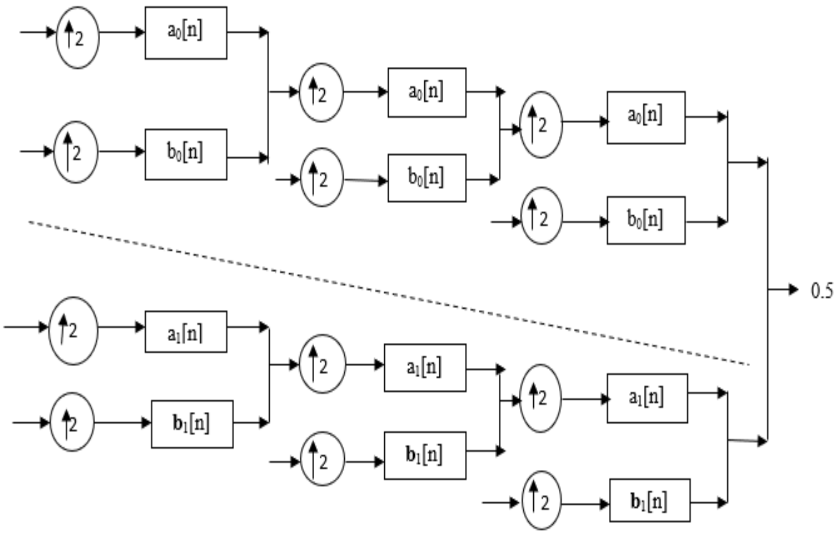

Fig.3 Synthesis filter bank structure of DTCWT

The synthesis filter bank structure of DTCWT is given in fig.3. It performs the reverse operation of DTCWT. The first stage de-speckled filtered image is obtained from the IDTCWT and this image used for further noise reduction. The image which are obtained from IDTCWT is little blurred and this blurring effect is eliminated by using IBF and total variation techniques.

Soft Thresholding with SURE Estimation

Minimax and SURE threshold value determination are increasingly moderate and would be progressively helpful when little subtleties of the image lie close to the noisy range. Therefore, to upgrade the denoising image for piecewise standard image, it is conceivable to utilize non-linear thresholding in a symmetrical wavelet premise which is represented as,

$$B = \{\psi_m\}_m \; Where, \psi_m \in R^N \qquad (3)$$

Here ψ_m is a wavelet element. The soft-thresholding estimator can be rewritten as,

$$h_\lambda(f) = \sum_m s_\lambda(\langle f, \psi_m \rangle)\, \psi_m \qquad (4)$$

Where, $s_\lambda(\alpha) = max\left(0,1 - \frac{\lambda}{|\alpha|}\right)\alpha$

It can be conveniently written as,

$$h_\lambda = W^* \, S_\lambda \, W \qquad (5)$$

Where, W and W^* are the forward and inverse DT-CWT

$$W(f) = (\langle f, \psi_m \rangle)_m \quad (6)$$

$$W^*(f) = \sum_m x_m \psi_m \quad (7)$$

S_λ is the diagonal soft thresholding operator

$$S_\lambda(x) = (S_\lambda(x_m))_m \quad (8)$$

Now, define the SURE operator, as a function of *f*, *h(f)*, *λ*.

$$E(\lambda) = SURE_\lambda(f) \; and \; E_o(\lambda) = \|f - h_\lambda(f)\|^2 \quad (9)$$

The denoised image is expressed as

Where,

$$\lambda^* = \underset{\lambda}{\operatorname{argmin}}\, SURE_\lambda\,(f) \quad (10)$$

Bilateral Filter

The intensity esteems at every pixel in a denoised image are supplanted by an average of pixel intensity esteems from neighboring pixels. This weight can be founded on Gaussian distribution. Vitally the weight does not only depend on Euclidean separation but depends on the radiometric distinction. These characteristics of bilateral filter preserves the sharp edges by efficiently circling through every pixel and modifying loads to the contiguous pixels accordingly. The objective function of bilateral function is expressed as,

$$B^{Filtered} = \sum_{x_i} DW(x_i k_r(\|DW(x_i) - DW(x)\|)k_s(\|x_i - x\|)$$

(11)

Where, $B^{Filtered}$ is the de-speckled image, DW is the filtered image using soft thresholding with SURE estimation, x is the co-ordinates of the current pixel to be filtered, k_r is the kernel range and k_s is the spatial kernel function for smoothing images.

Improved Total Variation

The improved total variation (TV), which is an enhancement for all out variety is connected to the picture so as to smooth the picture and expel the rest of the noise, particularly in high recurrence sub-groups. The TV minimization is characterized as,

$$min \frac{u-g^2}{2\lambda}+J(u) \quad (12)$$

where *u* is the noiseless image, *g* is the filtered image, λ is the Lagrange multiplier and *J*(*u*) is the TV as defined by the below equation:

$$J(u) = \sum_{i,j=1}^{N} |(\nabla u)_{i,j}| \quad (13)$$

The improved TV, which is dependent on double information, grants a fastest algorithm for minimizing the TV as a Euler equation given below:

$$u = g - \pi k_{\lambda}(g) \quad (14)$$

Here, $\pi k_r(g)$ is a non-linear orthogonal projection of g space.

3. Results

US dataset has been used for this experiment. It consists of two groups namely benign and malignant. Benign consists of 100 images and malignant contains 150 images. Therefore, this US dataset totally contains 250 ultrasound noisy images which are exaggerated by SN. In this experiment, SN is not additionally added, because the images itself contains SN. These images are directly utilized for the SN reduction process.

Here, various existing de-speckling filtering techniques and the proposed method using DTCWT based on IBTV have been applied on the speckled noisy ultrasound images. So that, the filtered US images are obtained and the various performance metrics are evaluated to find the effectiveness of the de-speckling method using DTCWT-IBTV. The simulation results of DTCWT-IBTV de-speckling method and the various present denoising methods for benign US image is given in fig.4-5 and the malignant US image is given in fig.6-7.

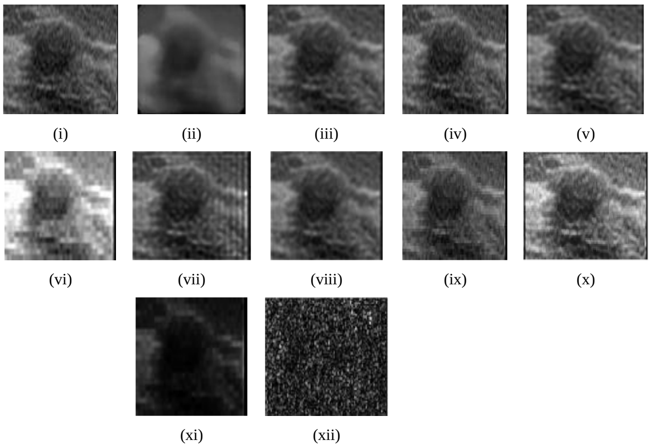

Fig.4 Simulation results of DTCWT-IBTV and various existing de-noising methods for Benign-01 US image

i) Input US Image ii) DTCWT-IBTV iii) BF iv) AWMF v) MF vi) WF vii) HAWMF viii) HIF ix) HBF x) HWF xi) ADMSS and xii) OBNLM

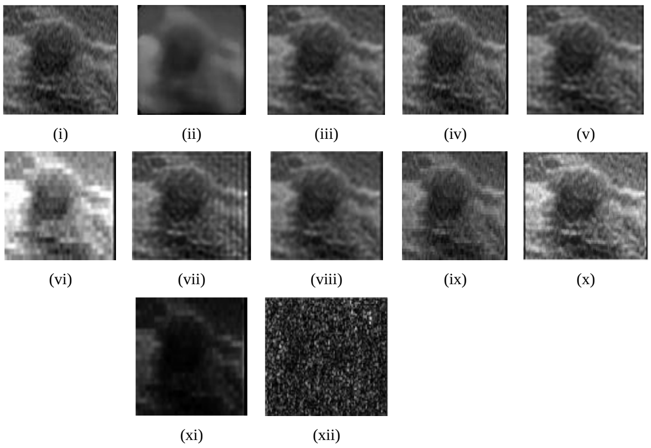

Fig.5 Simulation results of DTCWT-IBTV and various existing de-noising methods for Benign-02 US image

Input US Image ii) DTCWT-IBTV iii) BF iv) AWMF v) MF vi) WF vii) HAWMF viii) HIF ix) HBF x) HWF xi) ADMSS and xii) OBNLM

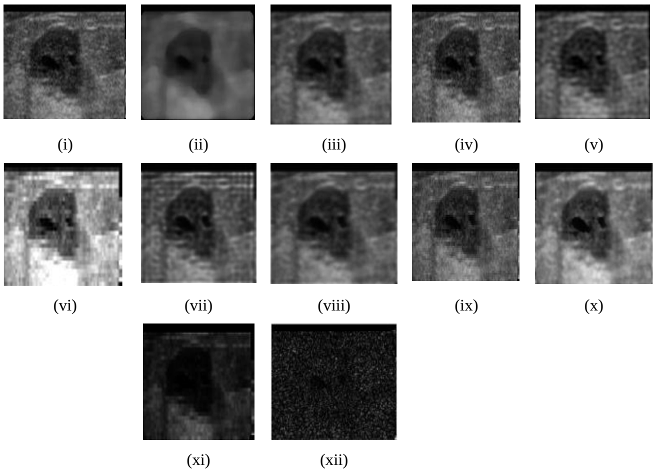

Fig.6 Simulation results of DTCWT-IBTV and various existing de-noising methods for Malignan-01 US image

i) Input US Image ii) DTCWT-IBTV iii) BF iv) AWMF v) MF vi) WF vii) HAWMF viii) HIF ix) HBF x) HWF xi) ADMSS and xii) OBNLM

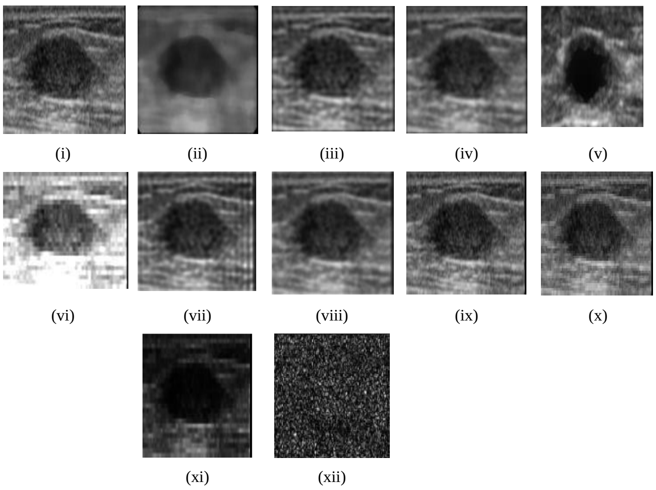

Fig.7 Simulation results of DTCWT-IBTV and various existing de-noising methods for Malignant-02 US image

i) Input US Image ii) DTCWT-IBTV iii) BF iv) AWMF v) MF vi) WF vii) HAWMF viii) HIF ix) HBF x) HWF xi) ADMSS and xii) OBNLM

From the visual examination of fig.4-7, it is noticed that, de-speckled images using the DTCWT with IBTV produces better results. ADMSS and OBNLM methods produces poor filtered images. After the proposed method, BF and AWMF and MF produces good performance.

4. Discussion

Performance of hybrid de-speckling method based on DTWT and improved bilateral filter can be assessed utilizing numerical proportions of image quality after the filtering method has been performed on the image. The presentation measurements are selected dependent on their processable contortion measures.

MSE and PSNR are the two most well-known proportions of image quality in image processing systems. In addition to these parameters, SSIM and EPI have also been evaluated to find the efficiency of hybrid de-speckling method. The PSNR and the MSE metrics are described by (15) and (16), correspondingly,

$$PSNR = 10log\frac{(255)^2}{MSE} \qquad (15)$$

$$MSE = \frac{\sum_{m=0}^{P-1}\sum_{n=0}^{Q-1}(x(m,n)-y(m,n))^2}{P\times Q}$$

The SSIM metric can be descried as,

$$SSIM(x,y) = \frac{(2\mu_x\mu_y+C_1)(2\sigma_{xy}+C_2}{(\mu_x^2+\mu_y^2+C_1)(\sigma_x^2+\sigma_y^2+C_2} \qquad (16)$$

Another parameter EPI can be determined by using the following equation, which is described as,

$$EPI = \frac{\sum(\Delta x-\overline{\Delta x})\sum(\Delta y-\overline{\Delta y})}{\sqrt{\sum(\Delta x-\overline{\Delta x})^2\sum(\Delta y-\overline{\Delta y})^2}} \qquad (17)$$

Where, x (m, n) represents the pixel values in the noise-free ultra sound image, y(m, n) denotes pixel esteems in the de-speckled image after the filtering process, P,Q represents the size of the image, and μ_x, μ_y, σ_x, σ_y and σ_{xy} are the local means, standard deviations and cross-variance respectively.

Table.1 Comparison of average value of performance metrics for various de-speckling methods for benign US image

Filter Type	PSNR	SSIM	EP1
DTCWT-IBTV	34.36	0.89	0.65
BF	33.83	0.84	0.62
AWMF	33.23	0.85	0.59
MF	32.87	0.82	0.58
WF	31.91	0.78	0.55
HAWMF	30.45	0.76	0.45
HIF	29.58	0.75	0.44
HBF	29.59	0.62	0.42
HWF	24.21	0.58	0.35
ADMSS	22.16	0.53	0.29
OBNLM	20.58	0.48	0.24

Table.2 Comparison of average value of performance metrics for various de-speckling methods for malignant image

Filter Type	PSNR	SSIM	EP1
DTCWT-IBTV	34.35	0.88	0.63
BF	33.22	0.82	0.62
AWMF	32.98	0.8	0.57
MF	32.54	0.79	0.56
WF	31.53	0.75	0.42
HAWMF	29.23	0.73	0.41
HIF	29.12	0.70	0.44
HBF	26.12	0.64	0.45

HWF	25.56	0.52	0.32
ADMSS	22.53	0.42	0.21
OBNLM	20.52	0.42	0.25

The performance metrics such as PSNR, SSIM and EPI of various de-noising methods are calculated and tabled in table.1 and table.2 for both benign and malignant images. From the above tables it is found that, the values of evaluation metrics are very low for ADMSS and OBNLM methods. DTCWT-IBTV and the BF produces better evaluation metrics values when compared with other various de-speckling techniques which includes AWMF, MF, WF, HAWMF, HIF, HBF and HWF methods.

5. Conclusion

This paper has concentrated on ultrasound images more explicitly, on the concealment techniques for the multiplicative noise. This work has contrasted with various denoising techniques utilized to suppress the SN in medicinal images acquired through US images. The simulation outcomes validated that, the hybrid de-speckling methodology based on DTWT and the improved bilateral filter performs better for the multiplicative noise concealment. This limit is significant and it moves the median filter, which is fair, into a considerably more competent channel. The wavelet filtering technique is unique. Here, in the images got subsequent to deteriorating, the situation of the recurrence coefficients corresponds to the pixels of the original image. With this information, filtering could be finished so that frequencies are disposed of as well as are treated in a legitimate manner, limiting or boosting, contingent upon whether they are a piece of the commotion or part of a zone of the edges which has a place with the image.

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