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A New Method for Medical Image Denoising using DTCWT and Bilateral Filter

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Abstract: ***The quality of digital medical images plays vital role in Non-invasive imaging techniques, which are suitable for medical diagnosis and treatment. Removal of noise from a noisy image without losing the diagnostic details in medical image is still a challenging task even though several denoising methods have been proposed since past years. The wavelet thresholding approach has been reported to be a highly successful method for image denoising. However, the main problem experienced in wavelet thresholding is smoothening of edges. In order to retain original texture while denoising medical images, several methods have been reported in literature. In this paper, we proposed, a new method based on combination of dual-tree complex wavelet transform (DTCWT) and bilateral filters for denoising of medical images. The proposed models are experimented on standard medical images, like MRI image of knee contaminated with Rician noise, CT Scan image of brain contaminated with Gaussian noise, Ultrasound image of liver contaminated with Speckle noise. The results have shown that denoised images using the proposed approach have better performance in terms of smoothness and accuracy compared with existing methods. To assess quality of denoised images the quality metrics, the standard Signal to Noise Ratio (SNR), Universal Image Quality Index (UQI) Mean square error (MSR), and Structural Similarity Index (SSIM) are employed.***

Keywords: ***Image denoising, DTCWT, Bilateral filter, Quality metrics, Wavelet thresholding.***

I. INTRODUCTION

The medical imaging techniques like Computer Tomography (CT), Magnetic Resonance Imaging (MRI), Endoscopy, Positron Emitted Tomography (PET), X-ray radiography, Fluoroscopy, Medical ultrasonography or ultrasound, Elastography, Tactile imaging are useful to diagnose illness non-invasively. High quality image (High SNR) is an essential for proper treatment and diagnosis. Removal of noise (denosing) from a noisy image without losing the diagnostic details in medical image is still a challenging task even though several denosing methods are found in literature such as Wiener filter, bilateral filtering [1], total variation method [2] , wavelet thresholding [3], anisotropic filtering [4] and non-local methods [5]. The development of algorithms for image denoising is an important task because removal of noise from the medical image should be done without destroying particular textures of image that are important for medical diagnosis and treatment. However, most algorithms reported in literature have not yet attained a desirable level of quality. In this work, we proposed, a new model based on the hybridization of dual-tree complex wavelet transform (DTCWT) and bilateral filters for denoising of medical images. Bilateral filtering is very effective approach for removing the noise of low frequency sub bands [6], where as noise of high frequency subbands is effectively eliminated by thresholding [7]. The DTCWT and Bilateral filters are combined such that, noise of low frequency sub bands is removed by bilateral filter and noise of high frequency sub-bands is removed by DTCWT. The proposed models are experimented on MRI CT, and Ultrasound images which corrupted with Riciannoise, Gaussian noise, Speckle noise respectively. The performance of proposed algorithms are estimated by calculating various quality metrics and by comparing with existing algorithms. This paper is organized as follows: Section 2 describes Noise removal by Bilateral. Section 3 outline dual-tree complex wavelet transform (DTCWT) denoising techniques and various thresholding, Section 4 describes proposed hybrid approach method. Finally, simulated results and conclusions are presented in Section 5 and 6 respectively.

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II. BILATERAL FILTER

Tomasi and Manduchi [8] developed Bilateral filter, which is suitable to remove additive noise in images. It is a non-linear method and the process is non-iterative, local, and simple. Bilateral filtering does the spatial averaging without smoothening the edges. The weights of the filter depends totally on the spatial distance (geometric distance) and the gray-level distance (photometric distance) with respect to the center pixel.

The geometric distance between any location of arbitrary pixel (x_1, y_1) with respect location of center pixel (x, y) is given by equation (1)

$$d_d = \sqrt{(x_1 + x)^2 + (y_1 + y)^2} \quad (1)$$

And, sub kernel defined as

$$W_d = \exp\left(-\frac{1}{2}\left(\frac{d_s}{\sigma_d}\right)^2\right) \quad (2)$$

Where, σ_d : Standard deviation of w_d

The photometric distance between intensity value $g(x_1.y_1)$ of any arbitrary pixel at location $(x_1, y_1)$with respect to intensity value g(x, y) of its center pixel at location (x, y)is given by equation (3)

$$d_g = [|g^2(x_1 + y_1) + g^2(x + y)|]^{\frac{1}{2}} \quad (3)$$

And, sub kernel is defined as

$$w_g = \exp\left(-\frac{1}{2}\left(\frac{d_g}{\sigma_g}\right)^2\right) \qquad (4)$$

Where, σ_g : standard deviation of w_g

The Bilateral Kernel is achieved by multiplying sub kernel of geometric and photonic distances i.e. equation (2) and (4)

$$w_{bl} = w_d w_g \qquad (5)$$

Where w_{bl} is Kernal of Bilateral filter.

The estimated output at location (a, b) of filter after moving the mask over entire noisy image is given by equation (6)

$$\hat{f}(x, y) = \frac{\sum_{s=-a}^{a}\sum_{t=-b}^{b} g(x+s, y+t)}{\sum_{s=-a}^{a}\sum_{t=-b}^{b} w_{bl}(s,t)} \qquad (6)$$

The bilateral filter has been proposed as non-iterative method and best suited for denoising images, though images degrade quickly as noise level increase.

III. DTCWT (DUAL TREE COMPLEX WAVELET TRANSFORM)

Designing complex filters which satisfy a perfect reconstruction property for Complex wavelets are difficult. The dual-tree complex wavelet transform (DTCWT) is proposed by Kingsbury, which is nearly shifted invariant and directionally selective in two and higher dimensions [9]. These properties are important for post image processing approaches including deblurring, super resolution, watermarking, segmentation and classification. DTCWT generates the separate set of imaginary and real parts of the wavelet coefficients by using two trees of real filters. Among two trees,

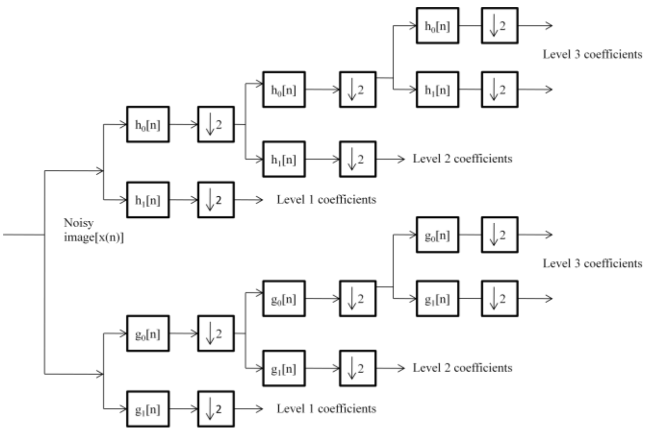


Figure 1: Structure of one Dimensional CDWT

first one is used to generate real part of the complex wavelet coefficients of real tree and second one generates an imaginary part of the complex wavelet of coefficients of an imaginary tree. The dual-tree complex WT of a signal x(n) is shown in Figure 1 in which sub bands of upper DWT is represented as real part of CWT and the lower tree as imaginary part. The transform is shift invariant and expansive by factor 2 [10].

IV. WAVELET THRESHOLDING

Denoising of images by thresholding in wavelet domain is proposed by Donoho et al [11, 12]. In case of wavelet domain, Small coefficients correspond to the noise; where as small ones represent the signal. The selection of threshold is one of key parameter in denoising process without disturbing the edges of the denoised image. Wavelet thresholding methods are broadly classified into two categories [13]:

1. Hard thresholding
2. Soft thresholding

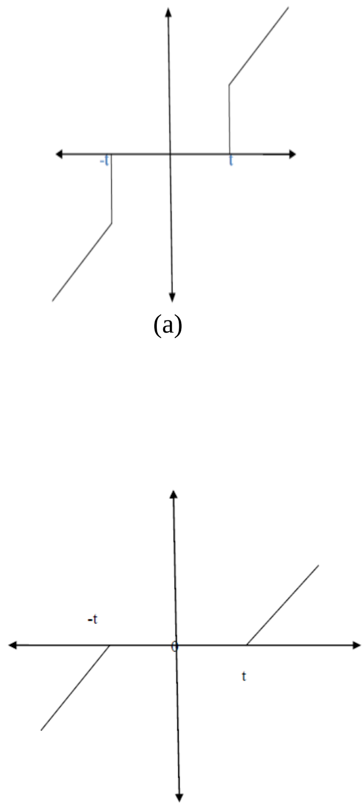
The hard thresholding is defined as

$$T_H = \begin{Bmatrix} x & \text{for } |x| > t \\ 0 & \text{for other regions} \end{Bmatrix} \qquad (7)$$

The graphical representation of equation (7) is shown in Figure 2(a). From Figure 2(a) it should be noted that, magnitude of all coefficients varies with respect to threshold value (t), whose magnitude is greater than't' are remains same and the others are set to zero. Soft thresholding is also known as Shrinks function. In this, the coefficients whose magnitude is less than the threshold value are set to zero and others shrinks towards zero. The soft thresholding is defined as [13, 14]

$$T_S = \begin{Bmatrix} \mathrm{Sign}(x)(|x| - t) & \text{for } |x| > t \\ 0 & \text{in other regions} \end{Bmatrix} \qquad (8)$$

The graphical representation of equation (8) is shown in Figure 3



(a)

(b)

Figure 2: (a) Hard Thresholding, (b) Soft Thresholding

In practice, the continuity of soft thresholding has some advantages over hard thesholding since hard method is discontinuous and yields abrupt artifacts in the recovered images. Based on the selection of threshold value,

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wavelet thresholding methods for denoising image are classified into different categories namely Oracle Shrink, Visu Shrink, Neigh shrink, Bayes Shrink, Smooth Shrink, Sure Shrink, and Fuzzy based Shrink

V. PROPOSED METHOD

As we discussed in sections 2 and 3 bilateral filter is very effective approach for removing the noise of low frequency sub bands [6], where as noise of high frequency sub-bands is effectively eliminated by thresholding [7].

The existing hybrid denoising models based on wavelet, bilateral are depicted in Figure 4 and Figure 5 respectively [7, 15]

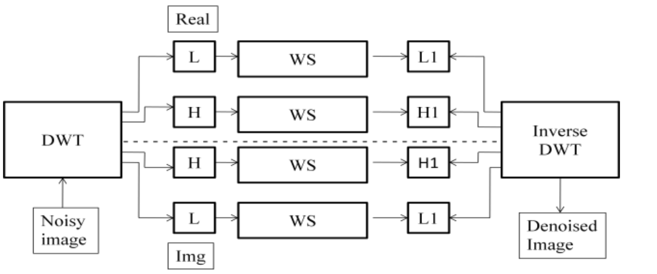


Figure 4: Hybrid image denoising method using wavelet shrinkage and DWT

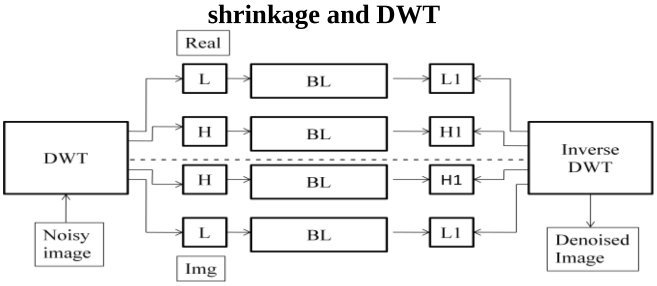


Figure 5: Hybrid image denoising method with Bilateral and DWT

In wavelet based model the input noisy image is sub divided into four sub bands namely L, H, L, H using DWT .Then, soft thresholding technique is applied on all the decomposed sub bands. Finally, output image is reconstructed by applying inverse DWT. It is capable to remove noise in high frequency sub bands only. In Bilateral filtering method, the input noisy image is decomposed into four sub bands namely L, H, L, H using DWT and bilateral filtering is applied on these sub bands. The resultant components are again recombined into one image by using inverse discrete wavelet transform (IDWT).The advantage of this model is noise removal took place with preserving the edges. On the other hand, it is unable to remove the noise in the texture part of the image. Therefore, by taking advantages of both methods, we have proposed a hybrid image denoising method illustrated in Figure 6. The dual-tree complex wavelet transform (DTCWT) is directionally selective, nearly shift invariant in two, and higher dimensions [9]. In post image processing methods like classification and segmentation, these properties will influence the quality of image. The proposed method combines the features of dual-tree complex wavelet transform (DTCWT) and bilateral filtering to get the benefit from both the methods. In this process, input image is decomposed into various levels and sub bands using dual-tree complex wavelet transform, then the low frequency sub band and high frequency details coefficients are modified using bilateral filtering (BL) and wavelet thresholding or shrinkage (WS) respectively. After the filtering process, inverse dual-tree complex wavelet transform (IDTCWT) is applied to reconstruct denoised image. It leads the noise present in the low frequencies and high frequency sub bands are removed with edge preserving feature, which is very useful for medical diagnostic.

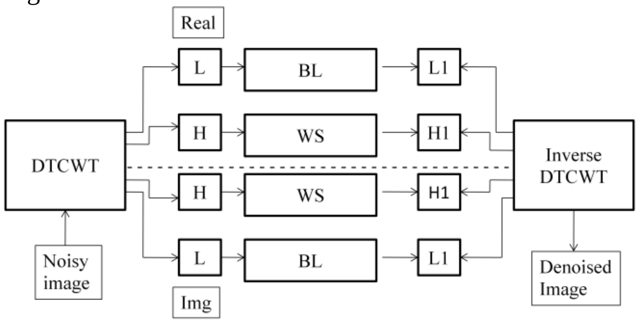
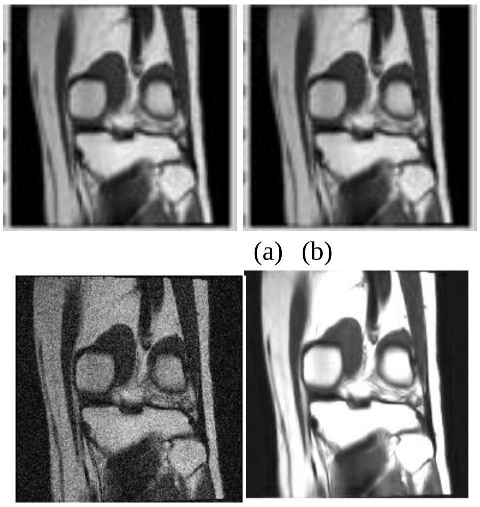


Figure 6: Proposed hybrid image denoising method using Bilateral Filter and DTCWT

VI. RESULTS AND DISCUSSION

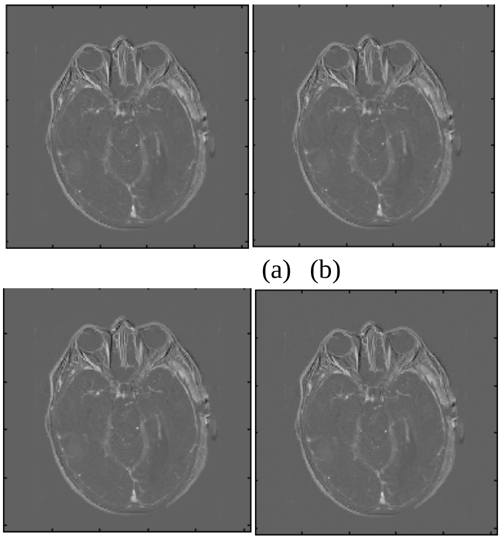
The experimental study has been performed on MRI, CT, and Ultrasound images which are corrupted with Rician noise, Gaussian noise, Speckle noise respectively. Initially noise is added over these images to make them noisy and then these noisy images are denoised using proposed scheme. CT scan image of brain and MRI image of knee are corrupted by the additive zero-mean Gaussian noise with different noise levels: 0, 5, 10, 15, 20, 25 and 30, whereas ultrasound image of liver is corrupted with different noise levels varies from 0 to 0.1 with increment of 0.01.The two low frequency sub-bands of the image is denoised first with bilateral filtering. Then soft thresholding method is employed on two high frequency sub-bands. The thresholding values varied from 0.001 to 0.1 and the suitable thresholding result is found as 0.01 using db8 filters. The reconstructed images are obtained for the existing and proposed approach for the medical image depicted in Figures 8, 9 and 10. From Figures, it can be seen that the image for hybridization of DTCWT and bilateral filter shows the best quality of perceptual image with better in preservation of many local structures. To evaluate the performance of proposed model, the standard quality metrics like Signal to Noise Ratio (SNR), Mean square error (MSE), Universal Image Quality Index (UQI) and Structural Similarity index (SSIM) are computed. The Computed values of quality metrics used for performance evaluation are tabulated in Tables 1,2 and 3 .It can seen that, SSIM value is good compared to existing methods. The Structural Similarity Index Measure (SSIM) [16] is quality metric which compare patterns of pixel intensities on the basis of the contrast and local luminance. Better value of SSIM leads images are denoised without losing the useful information such as edges and textures with minimum amount of redundancy. From Tables, it is observed that the proposed approach gives more enhanced results in comparison to existing schemes. The performance results of proposed approach are evaluated for low and high noise condition. Therefore, the denoising capability of proposed approach is better than Bilateral and DWT methods.



(a) (b)

(c) (d)

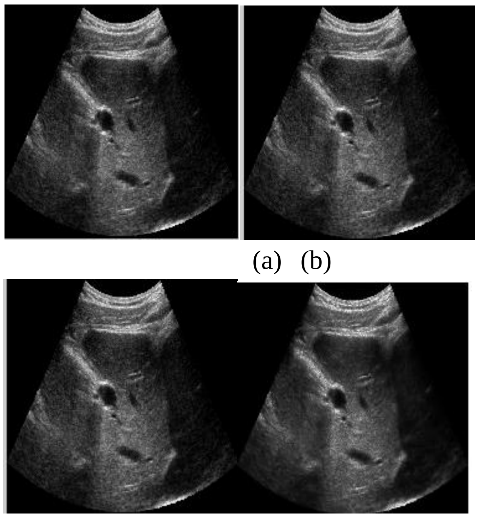
Figure 8: Denoised images of MRI Image of Knee (a) Noisy image (σ=20), (b) Using Bilateral, (c) Using DWT (soft), (d) Using Proposed method



(a) (b)

(c) (d)

Figure 9: Denoised images of CT scan image of Brain (a) Noisy image (σ=20) , (b) Using Bilateral , (c) Using DWT(soft), (d) Using Proposed method.



(a) (b)

(c) (d)

Figure 10: Denoised images of Ultrasound image of Liver (a) Noisy image (σ=0.05) , (b) Using Bilateral, (c) Using DWT(soft), (d) Using Proposed method.

Table 1: Computed quality metrics for MRI Image of Knee

	MSE			SNR			UQI			SSIM		
σ	BL	DWT	Proposed	BL	DWT	Proposed	BL	DWT	Proposed	BL	DWT	Proposed
0	0	16.21	31.9	156.82	35.92	32.98	0.99	0.77	0.7	1	0.94	0.9
5	27.7	388.24	71.3	33.61	2.1	29.48	0.75	0.39	0.58	0.83	0.54	0.75
10	113.8	1099.35	133.89	27.48	17.63	26.75	0.62	0.3	0.51	0.67	0.45	0.66
15	260.98	2242.82	214.51	23.89	14.66	24.7	0.53	0.24	0.46	0.54	0.39	0.61
20	464.19	3920.71	315.42	21.42	12.44	23.04	0.45	0.19	0.43	0.45	0.34	0.57
25	726.62	6118.17	436.52	19.5	10.77	21.64	0.39	0.16	0.41	0.38	0.31	0.54
30	1055.32	8913.88	576.17	17.92	9.45	20.45	0.35	0.13	0.39	0.32	0.28	0.52

Table 2: Computed quality metrics for CT scan image of Brain

σ	MSE			SNR			UQI			SSIM		
	BL	DWT	Proposed	BL	DWT	Proposed	BL	DWT	Proposed	BL	DWT	Proposed
0	0	0.6	1.4	181.53	45.34	41.68	0.77	0.58	0.49	1	0.99	0.98
5	25.02	5.26	6.03	53.51	35.93	35.34	0.61	0.38	0.39	0.87	0.95	0.96
10	100.16	11.05	10.76	47.48	32.71	32.82	0.54	0.32	0.35	0.7	0.92	0.93
15	224.05	17.05	15.14	43.99	30.82	31.34	0.5	0.29	0.33	0.59	0.9	0.92
20	400.97	24.24	19.48	41.46	29.3	30.24	0.46	0.27	0.32	0.51	0.88	0.9
25	625.89	30.51	23.49	39.53	28.3	29.43	0.43	0.25	0.31	0.46	0.86	0.88
30	901.99	36.86	26.91	37.94	27.47	28.84	0.4	0.24	0.3	0.42	0.85	0.87

Table 3. Computed quality metrics for Ultrasound image of Lever

σ	MSE			SNR			UQI			SSIM		
	BL	DWT	Proposed	BL	DWT	Proposed	BL	DWT	Proposed	BL	DWT	Proposed
0	0	5.04	8.13		37.11	28.8	1	0.67	0.62	1	0.99	0.96
0.01	31.12	24.51	22.21	23.02	23.02	24.43	0.93	0.59	0.56	0.93	0.92	0.91
0.02	61.42	38.37	34.48	20.09	20.24	22.52	0.88	0.55	0.52	0.88	0.87	0.88
0.03	92.53	51.06	46.65	18.33	18.6	21.2	0.84	0.5	0.49	0.84	0.83	0.86
0.04	122.92	62.22	57.68	17.12	17.4	20.29	0.81	0.47	0.47	0.81	0.8	0.84
0.05	153.71	73.39	68.61	16.16	16.53	19.54	0.78	0.44	0.45	0.79	0.78	0.82
0.06	182.27	83.52	80.1	15.43	15.77	18.87	0.76	0.42	0.43	0.76	0.75	0.81
0.07	212.83	94.29	90.7	14.78	15.14	18.33	0.74	0.4	0.41	0.74	0.73	0.79
0.08	243.09	103.88	101.86	14.22	14.63	17.83	0.72	0.38	0.4	0.73	0.72	0.78
0.09	273.15	114.27	111.67	13.73	14.17	17.43	0.7	0.37	0.38	0.71	0.7	0.77
0.1	300.98	122.87	123.41	13.34	13.74	17	0.69	0.35	0.37	0.7	0.69	0.76

VII. CONCLUSION

A new hybrid method based on bilateral filters and dual-tree complex wavelet transform (IDTCWT) has been proposed for image denoising of medical images. The proposed method is designed such that, it make use of advantages of both Bilateral filters and wavelet methods. The experimental study has been performed on MRI, CT, and Ultrasound images which are corrupted with Rician noise, Gaussian noise, Speckle noise respectively. The comparative study of denoising performance is made with the help of quality metrics like Signal to Noise Ratio (SNR), Universal Image Quality Index (UQI), Mean square error (MSE), and Structural Similarity index (SSIM). It is found that, SSIM value is good compared to existing methods. Better value of SSIM leads images are denoised without losing the required data such as textures and edges with minimum amount of redundancy. It is observed that Hybrid method has shown better performance than the existing denoising methods. Moreover, the proposed model is more capable in denoising all the images as compared to other methods.

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