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An Adaptive Patch-based Image De-noising using Dual tree Complex Wavelet Transform

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Abstract: *Image de-noising is an important tool in computer vision and image processing applications. The conventional wavelet image de-noising methods not only does the smoothing but also suppresses the desired edges, corners and other sharp structures in an image. This degradation of edge features can be overcome by directional, shift invariant dual tree wavelet transform. In this paper, dual tree complex wavelet transform is used to decompose the noisy image and locally adaptive patch based thresholding have been implemented to de-noise the bench mark images which were suffered with white Gaussian noise. The proposed work implemented using MATLAB R2014a.*
Keywords: *Dual tree complex wavelet transform, local patch based thresholding, Image de-noising*

I. Introduction

In recent times, the influence of digital images on science and technology are tremendous. Image processing has become a critical component in modern science and technology. It became interdisciplinary subject involving many areas such as astronomy, computer vision, data compression, motion estimation and many other fields. However, images captured by modern digital cameras may often get corrupted by noise during the process of acquisition. This form of corruption may result in loss of visual appearance or quality of an image. Image de-noising is a preprocessing operation which is used to remove noise from the noisy image while retaining important image features like edges in an image without affecting the important image structure.

The standard Fourier transform is only localized in frequency where as wavelet is localized both in time and frequency [1]. The localized nature of the wavelet transforms in both time and frequency results in de-noising in coordination with edge preservation [2, 3]. Wavelet thresholding has been demonstrated to be one of the powerful methods for image de-noising. The procedure of wavelet thresholding consists of applying DWT to the noisy image, thresholding the wavelet coefficients other than approximate coefficients then inverse transforming the thresholded coefficients to obtain the de-noised image. Thresholding is a non-linear technique which operates on wavelet coefficients. In this process, each wavelet coefficient is thresholded by comparing with the calculated threshold value. Donoho & Johnstone [4] proposed many works on finding suitable threshold value based on the noise conditions. There are many methods for wavelet thresholding which rely on the selection of a threshold value such as VisuShrink [5,6], SureShrink [7,8] and BayesShrink [9]. The VisuShrink cannot deal with minimizing the mean squared error. The threshold selected using sure- Shrink depends upon Stein's Unbiased Risk Estimator [6].

The threshold selection is dependent on the sub band under consideration [4-9] but the noisy many vary from pixel to pixel in the sub band. To improve wavelet based de-noising, an adaptive threshold is determined in a neighborhood dependent manner to characterize noise and features of each pixel in an image. A locally adaptive patch-based (LAPB) threshold scheme [10] is proposed to threshold wavelet coefficients which are noisy while preserving edges.

The organization of the paper is as follow. Section 2 gives image de-nosing using multi level wavelet transform, section 3 deals with wavelet thresholding, section 4 discusses the proposed method of implementation and simulation results including a comparison with conventional wavelet thresholding. Finally section 5 deals with conclusions.

II. Image De-noising using multi level wavelet transform

The discrete wavelet transform (DWT) provides better spatial and spectral localization of the image being subject to it. The DWT decomposes the image $f(x, y)$ into four sub bands namely $LL, LH, HL\ and\ HH$ by passing it through a series of filter banks. The image is subjected to a low pass filter with impulse response $h_0(n)$ and high pass filter impulse response $h_1(n)$.The three sub bands $LH, HL\ and\ HH$ are called detail wavelet coefficients and LL is called approximation coefficients.

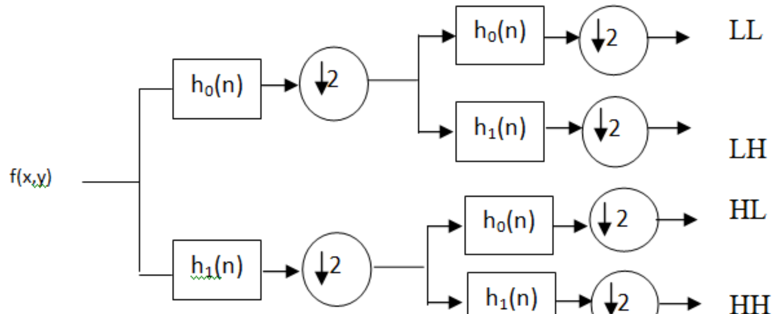
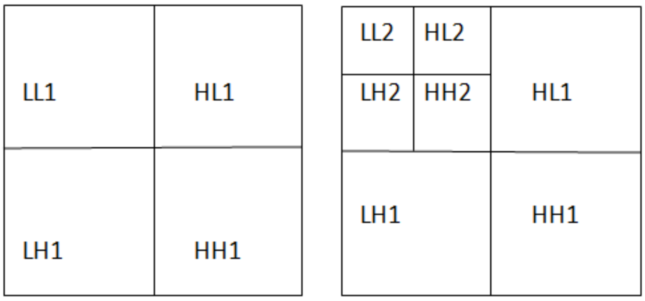


Fig. 1: Decomposition of an image using DWT

To obtain the next level of decomposition, approximation sub band $LL1$ is further decomposed into four sub bands labeled as $LL2, LH2, HL2$ and $HH2$ as shown in Fig. 2.



(a) One –Level (b) Two-Level

Fig. 2: 2D DWT with 1-Level and 2-Level decompositions

2.1 Dual tree complex wavelet transform (DT-ℂWT):

The dual tree complex wavelet transform is an enhancement to the DWT. The transform was proposed by Kingsbury [11] in order to gain two advantages over DWT namely, the shift invariance and good directionality. It achieves this with redundancy which is lower than the undecimated DWT [12]. The dual tree complex DWT of an image $f(x, y)$ is computed using two critically sampled DWTs in parallel on the same image is shown in Fig. 3. The upper tree of DWT is interpreted as real part of the complex wavelet transform and the lower tree as imaginary part. The obtained transform using this kind of structure is 2 time expansive than DWT and shift invariant. The filter sets in the first tree $h_{0a}(n), h_{1a}(n)$ and filter sets in the second tree $h_{0b}(n), h_{1b}(n)$ are forming a Hilbert transform pair. Let $h_{0a}(n), h_{1a}(n)$ denote the low pass/high pass filter pair of upper tree and $h_{0b}(n), h_{1b}(n)$ denote low pass/high pass filter pair of lower tree. Let $g_{0a}(n), g_{1a}(n)$ and $g_{0b}(n), g_{1b}(n)$ denote synthesis filters of upper and lower trees respectively. The filter coefficients of analysis and filter coefficients are shown in Table 1 &2.

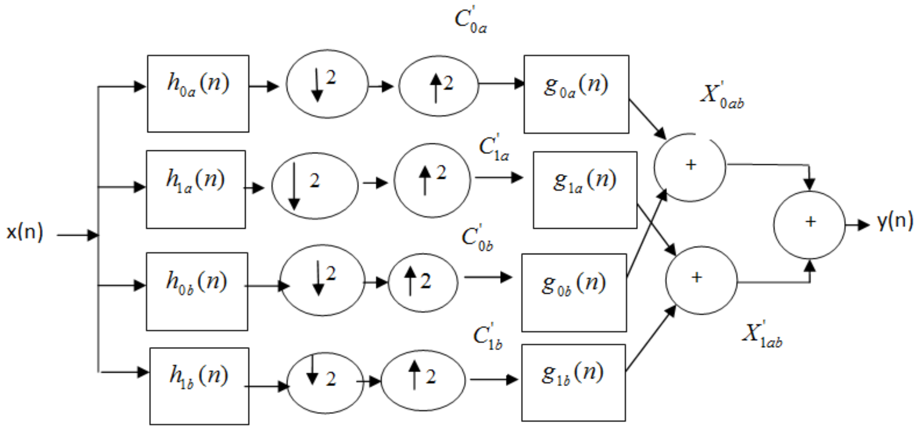


Fig. 3 Design implementation of one level DT- ℂWT

III. Wavelet Thresholding

In image de-noising procedure the selection of the threshold value plays a major role. During image transmission, the image $f(x, y)$ is corrupted by white Gaussian noise of different mean and standard deviation σ or Noise variance (σ^2). The selection of the threshold procedure is given below. The Noisy image $\eta(x, y)$ is first decomposed using wavelet transform to obtain wavelet sub band coefficients namely LL, LH, HL and HH and noise variance can be found in (1).

$$\sigma^2 = \left[\frac{median(median(|HH|))}{0.6745} \right]^2 \tag{1}$$

The universal threshold represented by T can be calculated using (2).

$$T = \sigma\sqrt{2\log M} \tag{2}$$

Where, M represent the number of pixels in the image.
There are mainly two types of thresholding methods are used known as hard thresholding and soft thresholding. In this implementation, soft thresholding method is used to threshold detail wavelet coefficients. Soft thresholding results in better image de-noising and less distortion than hard thresholding [13]. Soft thresholding of the DWT coefficients of details (LH, HL, HH) can be obtained as given in (3).

$$\begin{aligned} d_{ij} &= sign(d_{ij})(|d_{ij}| - \lambda) \qquad if \quad |d_{ij}| > T \\ &= 0 \qquad\qquad\qquad\qquad\quad if \quad |d_{ij}| \le T \end{aligned} \tag{3}$$

Where, d_{ij} are detail wavelet coefficients. Inverse DWT procedure is applied to reconstruct the de-noised image.

Table 1: Analysis dual tree complex wavelet coefficients

First Stage Real Coefficients		First Stage Complex Coefficients		Second Stage Real Coefficients		Second Stage Complex Coefficients	
LPF	HPF	LPF	HPF	LPF	HPF	LPF	HPF
0	0	0.011227	0	0.035164	0	0	-0.03516
-0.08839	-0.01123	0.011227	0	0	0	0	0
0.088388	0.011227	-0.08839	-0.08839	-0.08833	-0.1143	-0.1143	0.088329
0.69588	0.088388	0.088388	-0.08839	0.23389	0	0	0.23389
0.69588	0.088388	0.69588	0.69588	0.760272	0.587518	0.587518	-0.76027
0.088388	-0.69588	0.69588	-0.69588	0.587518	-0.76027	0.760272	0.587518
-0.08839	0.69588	0.088388	0.088388	0	0.23389	0.23389	0
0.011227	-0.08839	-0.08839	0.088388	-0.1143	0.088329	-0.08833	-0.1143
0.011227	-0.08839	0	0.011227	0	0	0	0
0	0	0	-0.01123	0	-0.03516	0.035164	0

Table 2: Synthesis dual tree complex wavelet coefficients

First Stage Real Coefficients		First Stage Complex Coefficients		Second Stage Real Coefficients		Second Stage Complex Coefficients	
LPF	HPF	LPF	HPF	LPF	HPF	LPF	HPF
0	0	0	-0.01123	0	-0.03516	0.035164	0
0.011227	-0.08839	0	0.011227	0	0	0	0
0.011227	-0.08839	-0.08839	0.088388	-0.1143	0.088329	-0.08833	-0.1143
-0.08839	0.69588	0.088388	0.088388	0	0.23389	0.23389	0
0.088388	-0.69588	0.69588	-0.69588	0.587518	-0.76027	0.760272	0.587518
0.69588	0.088388	0.69588	0.69588	0.760272	0.587518	0.587518	-0.76027
0.69588	0.088388	0.088388	-0.08839	0.23389	0	0	0.23389
0.088388	0.011227	-0.08839	-0.08839	-0.08833	-0.1143	-0.1143	0.088329
-0.08839	-0.01123	0.011227	0	0	0	0	0
0	0	0.011227	0	0.035164	0	0	-0.03516

IV. Proposed method of implementation

The conventional wavelet thresholding methods usually apply a universal threshold calculated using (1-2). However, this global threshold value not only suppresses noise but also eliminates sharp details such as lines and curves in an image. Therefore, single threshold value cannot be used to de-noise all the details coefficients in all sub bands. An adaptive threshold value is to be calculated based on patch size (3X3 or 5x5) in order to keep details intact.

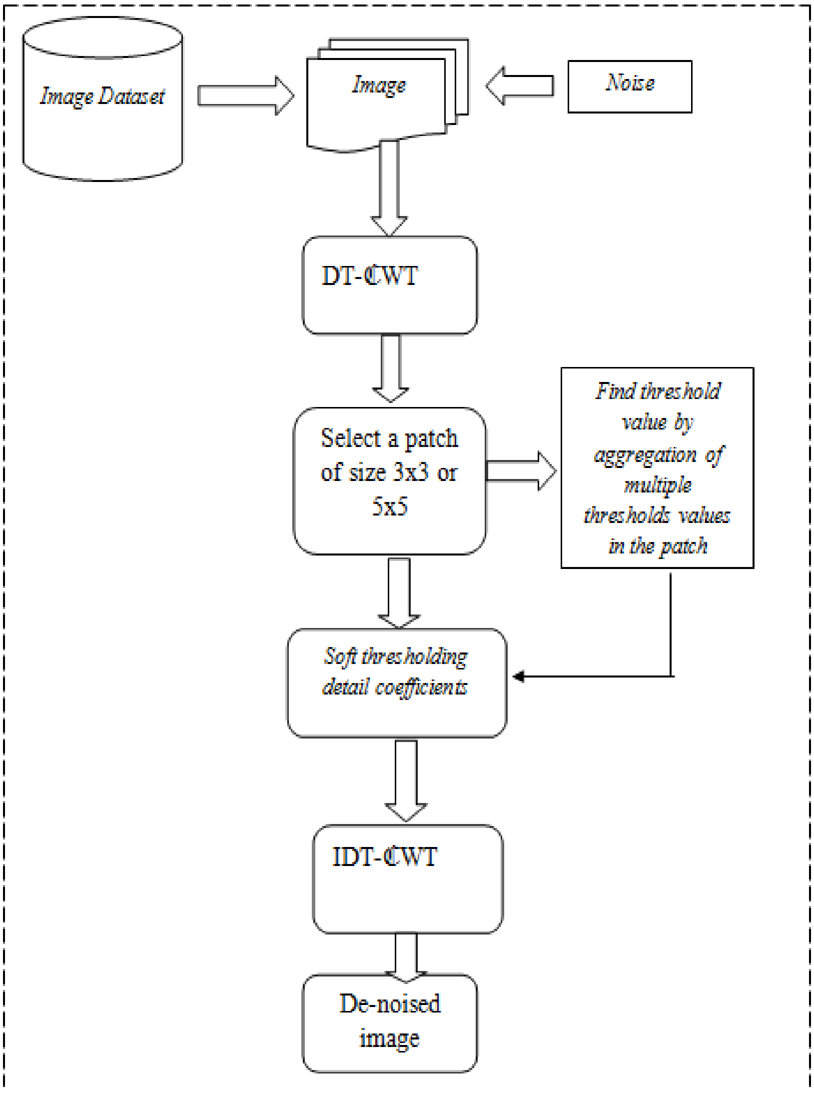


Fig. 4 Design of the proposed de-noising method

4.1 Adaptive threshold estimation:

The noisy image is first decomposed using the wavelet transform shown in Fig. 4. Local neighborhood shown in Fig. 5 is considered around center pixel and the threshold value is calculated using the formula given below

$$\sigma_{noise} = \frac{median(median(|HH|))}{0.6745} \tag{4}$$

$$\sigma_{image} = \sqrt{\sigma_{subimage}^2 - \sigma_{noise}^2} \tag{5}$$

$$T = \frac{\sigma_{noise}^2}{\sigma_{image}} \tag{6}$$

If $\sqrt{\sigma_{subimage}^2 - ceil(\sigma_{noise}^2)} > 0$ then $T_{th} = T\sqrt{2\log M}$

Else $T_{th} = \sigma_{noise}\sqrt{2\log M}$, where M is the size of the image and $\sigma_{subimage}^2$ is the variance of the subimage centered around the pixel and $ceil$ represents round the value towards plus infinity.

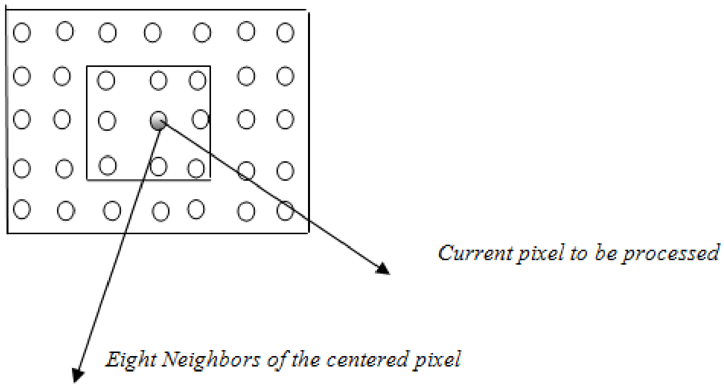


Fig. 5: Illustration of neighborhood

The above procedure is repeated for all the sub bands and the threshold values at each and every pixel will be obtained. The size of the threshold values matrix is also same as the size of the sub band into consideration. Now all the threshold values in a sub band are aggregated to get the resultant threshold value matrix. Now this matrix used to threshold each corresponding wavelet coefficient and the entire procedure is repeated for all the subbands in the consideration. The original image, corrupted image with noise standard deviation 20 and the de-noised images obtained using existing [10] using aggregation and proposed techniques for "cameraman.tif" image is shown in Fig. 6. Different simulations are conducted on bench mark images with noise standard deviation 10, 20 and 30 and the corresponding PSNR values are shown in Table 3 & 4.

4.2 Peak Signal to Noise Ratio (PSNR)

Here, the performance of the methods have evaluated by considering PSNR. The PSNR is that the quantitative relation between the most power and also the mean square error (MSE) between two images. PSNR is typically expressed in terms of decibels. Higher the value of the PSNR indicates higher the quality of the image. The MSE and PSNR calculated as

$$MSE = \frac{1}{MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}[f(x,y) - f^{'}(x,y)]^2 \tag{7}$$

$$PSNR = 10\log_{10}(255^2 / MSE) \tag{8}$$

Where $f(x,y)$ and $f^{'}(x,y)$ are original image and de-noised images of size MxN respectively.

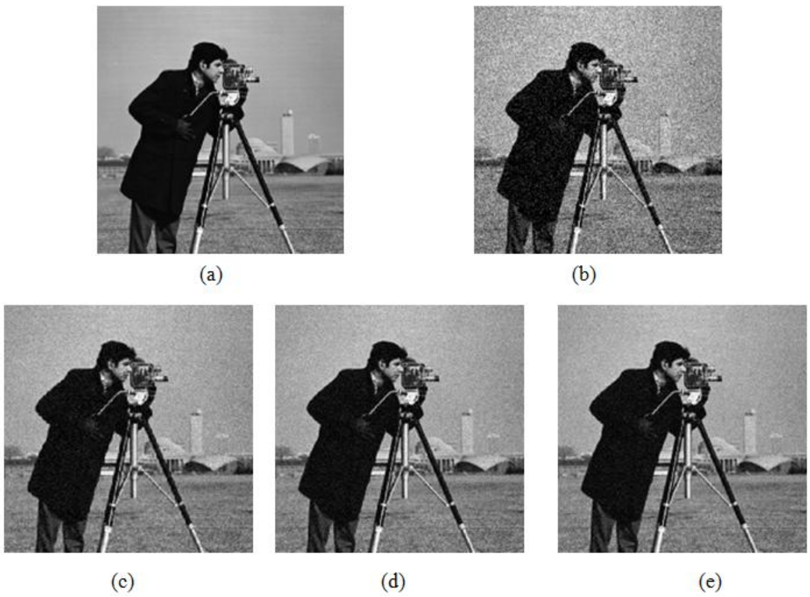


Fig. 6: (a) Original Image (b) Noisy image with standard deviation 20 (c) De-noised image obtained using Haar transform (d) De-noised image obtained by existing method using patch size of 3x3 and dual tree complex wavelet transform (e) De-noised image obtained by proposed technique using patch size of 3x3 and dual tree complex wavelet transform

Table 3: Comparison of existing and proposed techniques considering patch size of 3x3

Image Name	Noise standard deviation	Simple wavelet thresholding using Haar	Patch based wavelet de-noising using Haar	Proposed wavelet de-noising using Haar
Lena	10	30.82	30.41	**31.24**
Barbara	10	28.05	30.25	**30.4**
cameraman	10	32.88	33.01	**33.99**
Lena	20	26.48	26.31	26.61
Barbara	20	23.8	25.19	24.71
cameraman	20	26.71	26.88	27.04
Lena	30	23.91	23.48	23.93
Barbara	30	22.12	22.62	22.49
cameraman	30	24.01	23.63	24.06

Table 4: Comparison of existing and proposed techniques of patch size 3x3 and 5x5

Image Name	Noise standard deviation	Patch(3x3) based thresholding using dual tree wavelet transform	Patch(5x5) based thresholding using dual tree wavelet transform	Proposed Patch(3x3) based thresholding using dual tree wavelet transform	Proposed Patch(5x5) based thresholding using dual tree wavelet transform
Lena	10	28.82	28.92	30.46	30.7
Barbara	10	24.46	23.65	25.16	24.3
cameraman	10	32.47	33.28	33.78	33.68
Lena	20	27.51	27.95	**28.37**	28.3
Barbara	20	24.09	23.62	**25.21**	24.91
cameraman	20	28.3	28.81	**29.17**	29.12
Lena	30	24.92	25.29	**25.56**	25.49
Barbara	30	22.82	22.61	**23.55**	23.39
cameraman	30	25.17	25.6	**25.91**	25.85

V. Conclusion

In this paper, a new method of patch based image de-noising is proposed. The existing method using aggregation of threshold values in the neighborhood compared with the proposed de-noising scheme using Haar and dual tree wavelet transforms. Simulation results show that proposed method works better with Haar wavelet transform when the noise standard deviation is 10. The dual tree complex wavelet transform performs better with locally adaptive patch-based threshold selection when the image contains more noise. The proposed idea of thresholding can be extended with the help of real double density and complex double density dual tree complex wavelet transforms.

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