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Image Denoising using Dual-Tree Complex DWT and Double-Density Dual-Tree Complex DWT

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***Abstract*- Non-stationary signal processing applications use standard non-redundant DWT (Discrete Wavelet Transform) which is very powerful tool. But it suffers from shift sensitivity, absence of phase information, and poor directionality. To remove out these limitations, many researchers developed extensions to the standard DWT such as WP (Wavelet Packet Transform), and SWT (Stationary Wavelet Transform). These extensions are highly redundant and computationally intensive. Complex Wavelet Transform (CWT) is also an impressive option, complex-valued extension to the standard DWT. There are various applications of Redundant CWT (RCWT) in an image processing such as Denoising, Motion estimation, Image fusion, Edge detection, and Texture analysis. In this work, the focused application is the image denoising using two innovative techniques and the images are considered which are corrupted by a random noise. In this paper, first two sections explain about introduction to the topic and regarding wavelet transform domain. Third section gives an idea about basics concepts of the system. Forth section illustrates the proposed systems. Last section gives results and discussion. Here promising results are compared with DWT extensions namely, Dual-Tree Complex DWT (DTCWT) and Double-Density Dual-Tree Complex DWT (DDDTCWT).**

***Index Terms*- CWT, DWT, Dual-Tree Complex DWT, Double-Density Dual-Tree Complex DWT.**

I. Introduction

Image denoising is a technique which removes out noise which is added in the original image. Noise reduction is an important part of image processing systems. An image is always affected by noise. Image quality may get disturbed while capturing, processing and storing the image. Noise is nothing but the real world signals and which are not part of the original signal. In images, noise suppression is a particularly delicate task. In this task, noise reduction and the preservation of actual image features are the main focusing parts.

The wavelet transform provides a multiresolution representation using a set of analyzing functions that are dilations and translations of a few functions (wavelets). It overcomes some of the limitations of the Fourier transform with its ability to represent a function simultaneously in the frequency and time domains using a single prototype function (or wavelet) and its scales and shifts [2].

The wavelet transform comes in several forms. The critically-sampled form of the wavelet transforms provides the most compact representation; however, it has several limitations.

It lacks the shift-invariance property, and in multiple dimensions it does a poor job of distinguishing orientations, which is important in image processing. For some applications, improvements can be obtained by using an expansive wavelet transform in place of a critically-sampled one [1]. A denoising method is used to improve the quality of image corrupted by a lot of noise due to the undesired conditions for image acquisition. The image quality is measured by the peak signal-to-noise ratio (PSNR) or signal-to noise ratio (SNR). Traditionally, this is achieved by linear processing such as Wiener filtering [3]. Recently introduced Dual-Tree Complex DWT and Double-Density Dual-Tree Complex DWT can give best results in image denoising applications.

II. Wavelet Transform Domain

A Fourier Transform (FT) is only able to retrieve the global frequency content of a signal, the time information is lost.

A multi-resolution analysis becomes possible by using wavelet analysis. The Wavelet Transform (WT) retrieves frequency and time content of a signal. The basic types of wavelet transform are namely, i) Continuous Wavelet Transform (CoWT) ii) Discrete Wavelet Transform (DWT) iii) Complex Wavelet Transform (CWT). A multi-resolution analysis is not possible with Fourier Transform (FT) and Short Time Fourier Transform (STFT) and hence there is a restriction to apply these tools in image processing systems; particularly in image denoising applications. The multi-resolution analysis becomes possible by using wavelet analysis. A Continuous Wavelet Transform (CoWT) is calculated analogous to the Fourier transform (FT), by the convolution between the signal and analysis function. The Discrete Wavelet Transform uses filter banks to perform the wavelet analysis.

A. Complex wavelet transform

This is a newly introduced technique of DWT. Orthogonal wavelet decompositions, based on separable, multirate filtering systems have been widely used in image and signal processing, largely for data compression. Kingsbury introduced a very elegant computational structure, the Dual-Tree complex wavelet transform [5], which displays near-shift invariant properties. Other constructions can be found such as in [6]. Kingsbury [3] pointed out the problems of Mallat-type algorithms. These algorithms have the lack of shift invariance.

Complex wavelets have not been used widely in image processing due to the difficulty in designing complex filters which satisfy a perfect reconstruction property. To overcome this, Kingsbury proposed a Dual-Tree implementation of the CWT (DT CWT) [7], which uses two trees of real filters to generate the real and imaginary parts of the wavelet coefficients separately. The DWT suffers from the following two problems.

1] Lack of shift invariance - this results from the down sampling operation at each level. When the input signal is shifted slightly, the amplitude of the wavelet coefficients varies so much.

2] Lack of directional selectivity - as the DWT filters are real and separable the DWT cannot distinguish between the opposing diagonal directions.

The first problem can be avoided if the filter outputs from each level are not down sampled but this increases the computational costs significantly and the resulting undecimated wavelet transform still cannot distinguish between opposing diagonals since the transform is still separable.

To distinguish opposing diagonals with separable filters the filter frequency responses are required to be asymmetric for positive and negative frequencies. A good way to achieve this is to use complex wavelet filters which can be made to suppress negative frequency components. The Complex DWT has improved shift-invariance and directional selectivity than the separable DWT [6]-[7].

III. Basic Concepts Of The System

A filter bank plays an important role in wavelet transform applications. It consists of two banks namely, analysis filter bank and synthesis filter bank. The one dimensional filter bank is constructed with analysis and synthesis filter bank which is shown in Fig. 1.

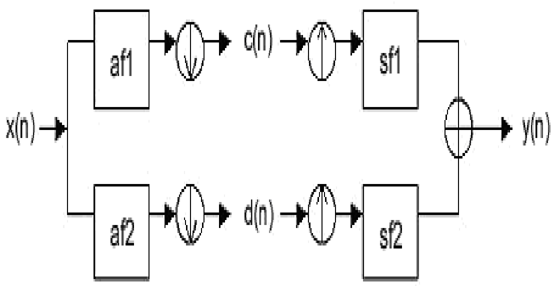

Fig. 1 One dimensional filter bank

The analysis filter bank decomposes the input signal x(n) into two sub band signals, c(n) and d(n). The signal c(n) represents the low frequency part of x(n), while the signal d(n) represents the high frequency part of x(n). It uses filter banks to perform the wavelet analysis. The DWT decomposes the signal into wavelet coefficients from which the original signal can be reconstructed again. The wavelet coefficients represent the signal in various frequency bands. The coefficients can be processed in several ways, giving the DWT attractive properties over linear filtering.

A. *A block schematic of wavelet based image denoising technique*

Image denoising means usually compute the soft threshold in such a way that information present in image is preserved. A block schematic of Wavelet based image denoising technique is shown in Fig. 2.

Here the basic steps of wavelet based image denoising are given below.

1. Decompose corrupted image by noise using wavelet transform.
2. Compute threshold in wavelet domain and apply to noisy coefficients.
3. Apply inverse wavelet transform to reconstruct image.

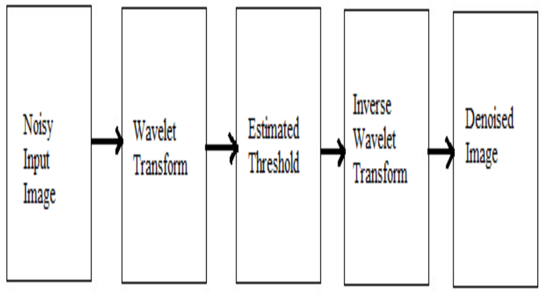

Fig. 2 A block schematic of wavelet based image denoising technique

B. *Basic differences between the two DWT extensions*

The basic differences between the Dual-Tree DWT and Double-Density DWT are given below.

1] The Dual-Tree and Double-Density DWTs are implemented with totally different filter bank structures.

2] The Dual-Tree DWT can be interpreted as a complex-valued wavelet transform which is useful for signal modeling and denoising (the Double-Density DWT cannot be interpreted as such).

3] For the Dual-Tree DWT there are fewer degrees of freedom for design, while for the Double-Density DWT there are more degrees of freedom for design.

4] The Dual-Tree DWT can be used to implement two-dimensional transforms with directional wavelets, which is highly desirable for image processing [8].

IV. Proposed Systems

By introducing Complex wavelet transforms (CWT) concept, we can achieve Dual-Tree Complex DWT system. Also combining the Double-Density DWT and Dual-Tree Complex DWT, we can achieve the Double-Density Dual-Tree Complex DWT system. Complex wavelet transforms (CWT) use complex-valued filtering (analytic filter) that decomposes the real/complex signals into real and imaginary parts in transform domain. The real and imaginary coefficients are used to compute amplitude and phase information.

A. Dual-Tree Complex DWT (DTCWT)

Kingsbury's complex Dual-Tree DWT is based on (approximate) Hilbert pairs of wavelets [8]. Kingsbury found that the Dual-Tree DWT is nearly shift-invariant when the lowpass filters of one DWT interpolate midway between the lowpass filters of the second DWT [9].

The Dual-Tree Complex DWT can be implemented using two critically-sampled DWTs in parallel as shown in the Fig. 3. This transform gives 2N DWT coefficients for an N-point signal. Hence this transform is known as 2-times expansive.

Here the filters are designed in such a way that the subband signals of the upper DWT can be interpreted as the real part of a CWT and subbands signals of the lower DWT can be interpreted as the imaginary part. For specially designed sets of filters, the wavelet associated with the upper DWT can be an approximate Hilbert transform of the wavelet associated with the lower DWT. In this manner, the designed DTCWT is nearly shift-invariant than the critically-sampled DWT [1]-[4].

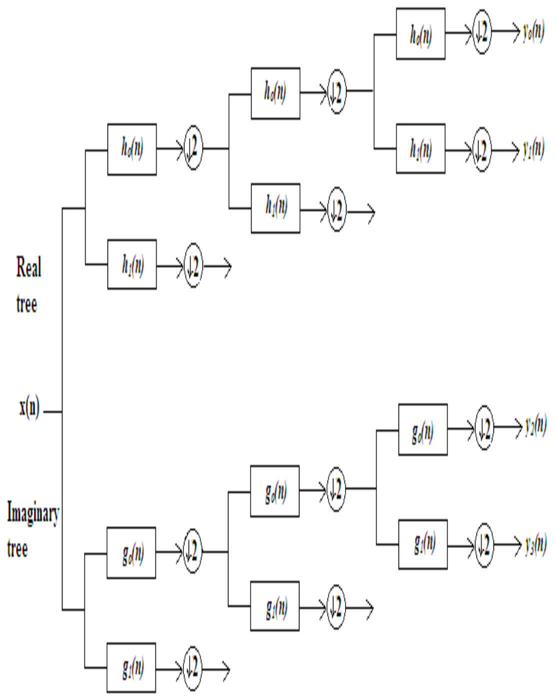

Fig. 3 Design implementation of Dual-Tree Complex DWT

The DTCWT gives wavelets in six distinct directions. In each direction, there are two wavelets. In each direction, one of the two wavelets can be interpreted as the real part and the other wavelet can be interpreted as the imaginary part of a complex-valued two dimensional (2D) wavelet. The DTCWT is implemented as four critically sampled separable 2D DWTs operating in parallel. However, different filter sets are used along the rows and columns [1]-[4]. Fig. 4 indicates that a flowchart of Dual-Tree Complex DWT. This illustrates the steps of implementation of DTCWT.

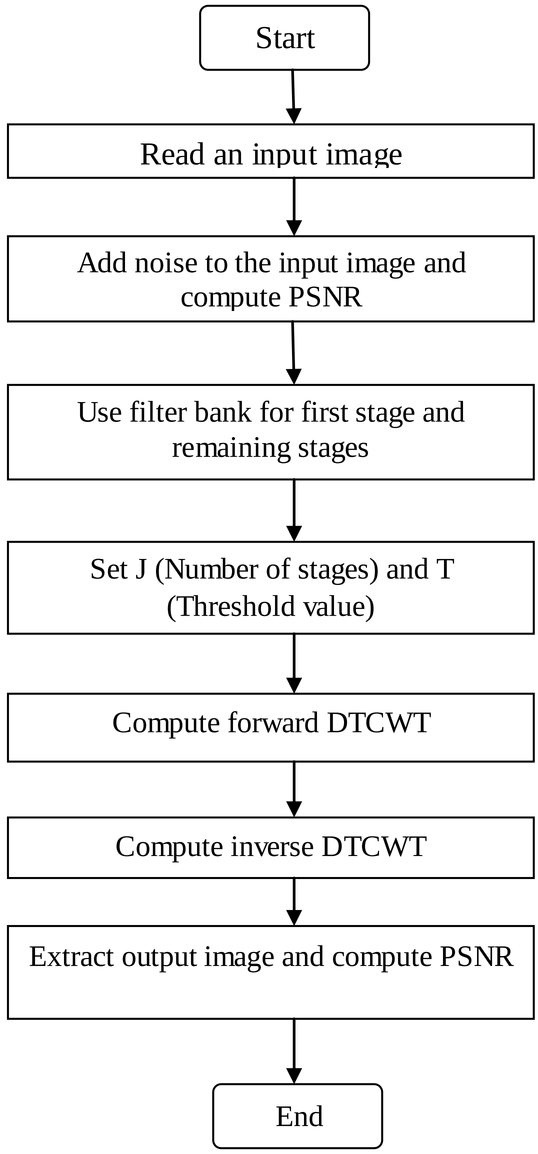

Fig. 4 Flowchart of Dual-Tree Complex DWT

B. Double-Density Dual-Tree Complex DWT (DDDTCWT)

Double-Density DWT performs superior than the standard DWT in terms of enhancement In two dimensions. But here all of the wavelets are not directional. Though the Double-Density DWT utilizes more wavelets, some lack a dominant spatial orientation, which prevents them from being able to isolate those directions [9]. A solution to this problem is provided by the Double-Density Dual-Tree Complex DWT, which combines the characteristics of the Double-Density DWT and the Dual-Tree DWT. The DDDTCWT is based on two scaling functions and four distinct wavelets, each of which is specifically designed such that the two wavelets of the first pair are offset from one other by one half, and the

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other pair of wavelets form an approximate Hilbert transform pair [9]. The DDDTCWT is 4-times expansive. It yields two wavelets in the same dominating orientations [11].

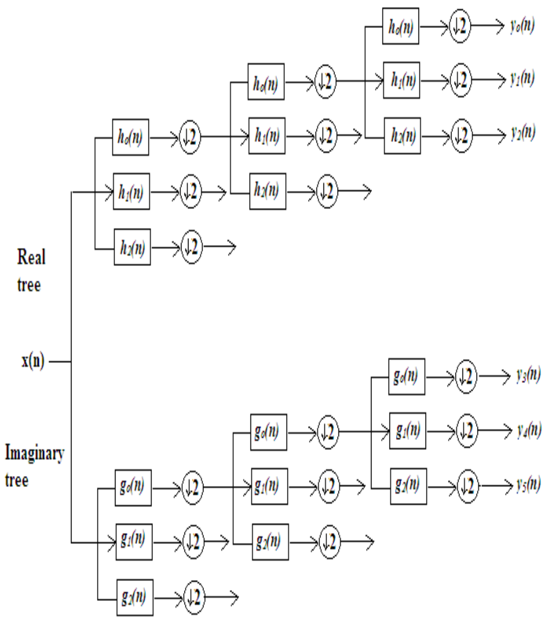

Fig. 5 Design implementation of the Double-Density Dual-Tree Complex DWT

For each of the directions, one of the wavelets can be interpreted as the real part and the other can be interpreted as the imaginary part. This transform is implemented by applying four 2D Double-Density DWTs in parallel with distinct filter sets for the rows and columns. Then the sum and difference of the subband images is carried out. This operation gives the 32 oriented wavelets [10].

Fig. 5 shows that design implementation of Double-Density Dual-Tree Complex DWT. The DDDTCWT is an over complete discrete wavelet transform (DWT) designed to simultaneously possess the properties of the Double-Density DWT and the Dual-Tree DWT [7]. Fig. 6 shows that a flowchart of Double-Density Dual-Tree Complex DWT. This illustrates the steps of implementation of DDDTCWT.

V. Results And Discussion

The implementation of this work has performed in MATLAB (7.9) software. A Table I illustrates the results for Tooth.jpg image with T=35. A Table II illustrates the results for Tooth.jpg image with Noise variance of 30. The performance of both the image denoising methods can be compared by comparing PSNR (Peak-Signal-to-Noise Ratio) value of each method. Here as noise increases, Double-Density Complex DWT gives better result than Dual-Tree Complex DWT. Fig. 7 shows that plot of PSNR versus Noise variance. Fig. 8 shows that plot of PSNR versus Threshold value.

Fig. 9 and Fig. 10 indicate output of DTCWT and DDDTCWT. Fig. 9(a) shows that original image which is corrupted by a noise with variance of 30 which is shown in Fig. 9(b). This corrupted image is applied to DTCWT and DDDTCWT. Fig. 9(c) depicts output denoised image using DTCWT and Fig. 9(d) output denoised image using DDDTCWT.

Similarly Fig. 10 shows that output images for noise variance of 50.

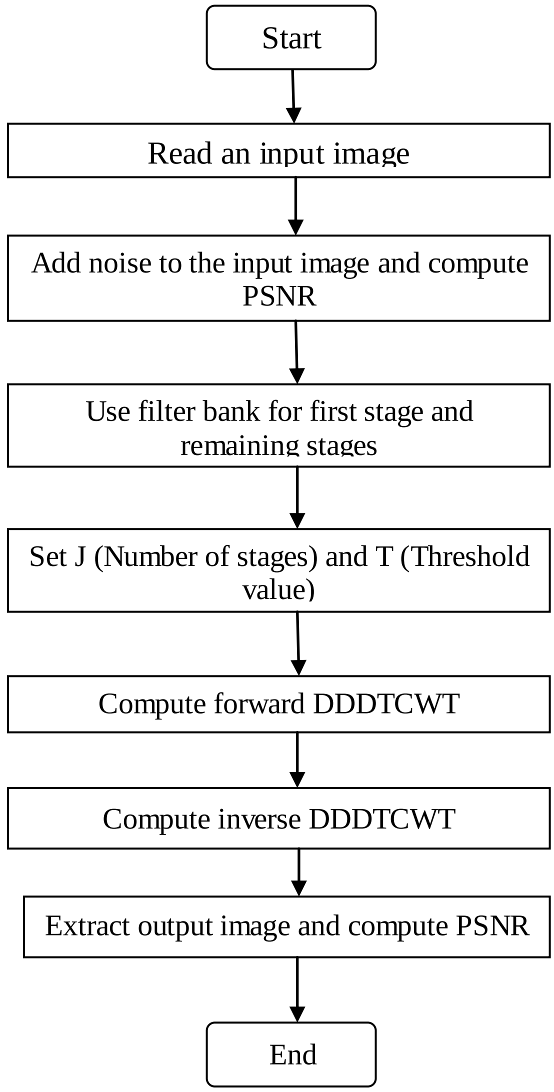

Fig. 6 Flowchart of Double-Density Dual-Tree Complex DWT

VI. Conclusion

The newly invented extensions of the DWT perform best in image processing applications. In this paper, the concept focused is wavelet based image denoising methods of an image which is corrupted by additive Gaussian noise. The techniques used are Dual-Tree Complex DWT and Double-Density Dual-Tree Complex DWT. These techniques give high performance as compared to the existing basic DWT methods. As noise increases Double-Density Dual-Tree Complex DWT works superior than Dual-Tree Complex DWT. The future work will be in the form of application of both the methods to audio and video signals.

Table I Results for Tooth.jpg image with T=35

Noise	PSNR (decibel)		
	Noisy Image	DTCWT	DDDTCWT
20	22.1360	31.5635	31.9626
25	20.2017	30.6586	31.7062
30	18.6247	29.5062	31.2922
35	17.2793	27.9968	30.5743
40	16.1089	26.3338	29.6936
45	15.1042	24.6170	28.6060
50	14.1952	22.9787	27.3532
55	13.3578	21.3644	25.8019
60	12.6091	19.9846	24.4681
65	11.8981	18.6467	22.9719
70	11.2730	17.5295	21.6661

Table II Results for Tooth.jpg image with Noise variance of 30

Threshold value (T)	PSNR (decibel)		
	Noisy Image	DTCWT	DDDTCWT
10	18.6347	22.4953	25.0989
15	18.6138	24.6411	28.1653
20	18.6297	26.6771	30.1356
25	18.6197	27.9968	30.5743
30	18.5950	29.0488	31.2199
35	18.6260	29.4638	31.2290
40	18.6087	29.5744	31.1469
45	18.6408	29.6180	31.0597
50	18.6304	29.5533	30.9814
55	18.6234	29.4834	30.8574
60	18.6296	29.5253	30.8638

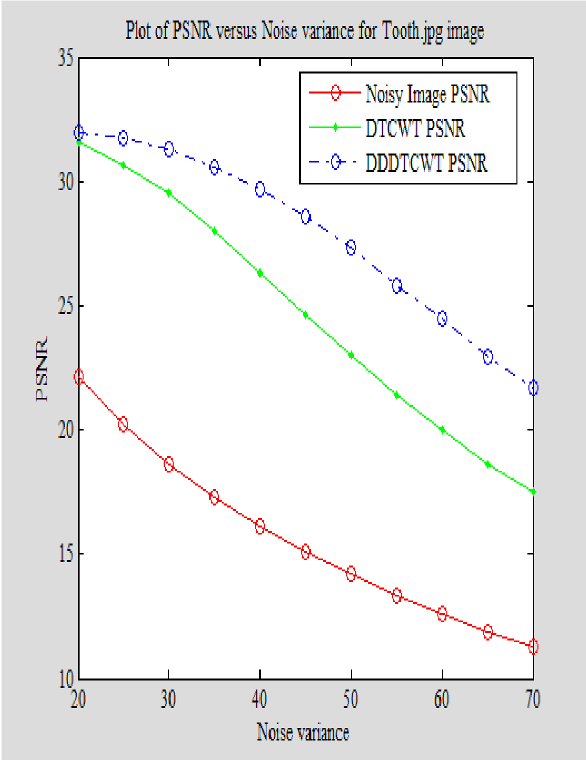

Fig. 7 Plot of PSNR versus Noise variance

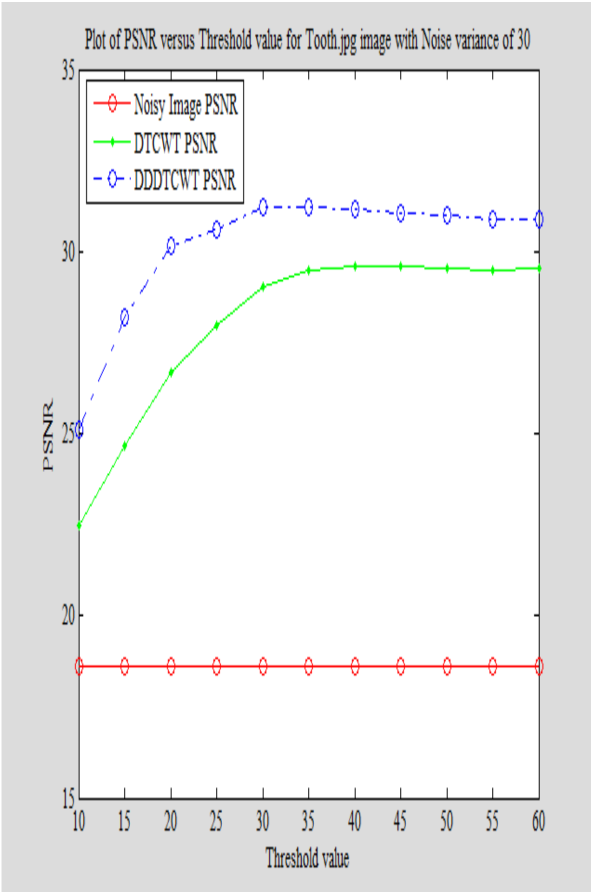

Fig. 8 Plot of PSNR versus Threshold value

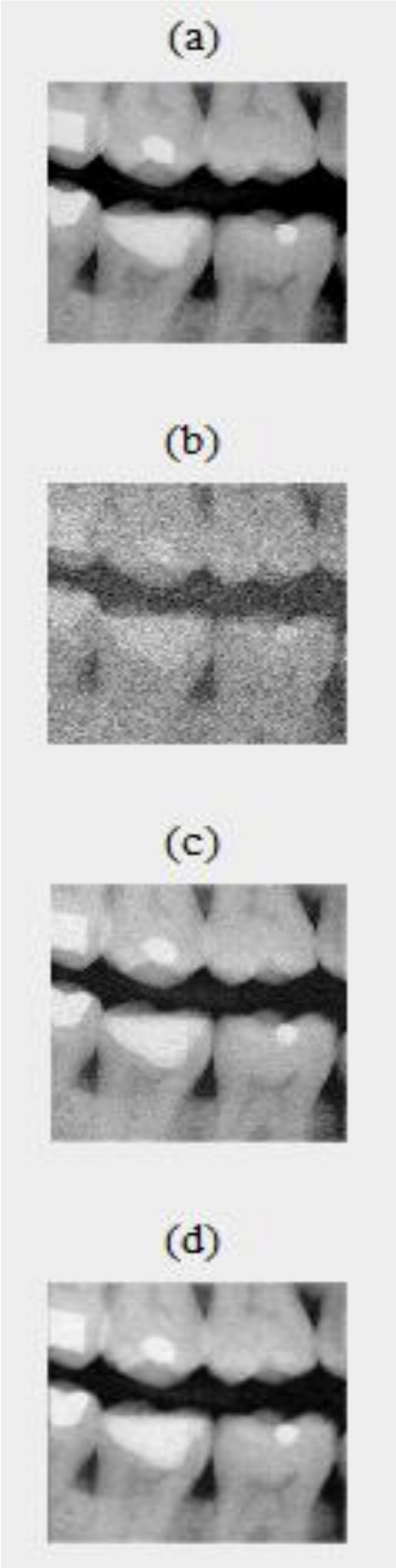

Fig. 9 Output for noise variance = 30
(a) Original image, (b) Noisy image, (c) Denoised image by DTCWT and (d) Denoised image by DDDTCWT

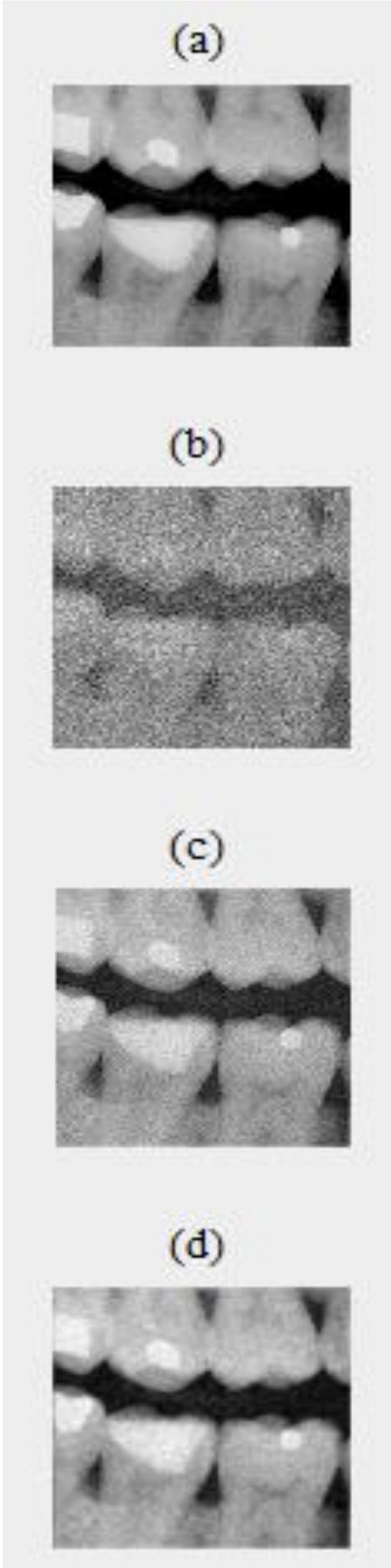

Fig. 10 Output for noise variance = 50
(a) Original image, (b) Noisy image, (c) Denoised image by DTCWT and (d) Denoised image by DDDTCWT

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REFERENCES

[1] I. W. Selesnick, R. G. Baraniuk, and N. G. Kingsbury, "The dual-tree complex wavelet transform—A coherent framework for multiscale signal and image processing," *IEEE Signal Procesin. Mag.*, vol. 22, no. 6, pp. 123–151, Nov. 2005.

[2] Shan Lal, Mahesh Chandra, Gopal Krishna Upadhyay, Deep Gupta, "Removal of Additive Gaussian Noise by Complex Double Density Dual Tree Discrete Wavelet Transform" *MIT International Journal of Electronics and Communication Engineering*, Vol. 1, No. 1, pp. 8-16 Jan 2011.

[3] Devanand Bhonsle and Sandeepa Dewangan "Comparative Study of dual-tree complex wavelet transform and double density complex wavelet transform for Image Denoising Using Wavelet-Domain" *International Journal of Scientific and Research Publications*, vol. 2, Issue 7, pp. 1-5,July 2012.

[4] I. Bayram and I. W. Selesnick, "A simple construction for the M-band dual-tree complex wavelet transform," in *Proc. 12th IEEE DSP Workshop*, pp. 596–601, 2006.

[5] N. G. Kingsbury, "The dual-tree complex wavelet transform: a new technique for shift invariance and directional filters", *Proceedings of the IEEE Digital Signal Processing Workshop*, 1998.

[6] J. Neumann and G. Steidl, "Dual–tree complex wavelet transform in the frequency domain and an application to signal classification", *International Journal of Wavelets, Multiresolution and Information Processing IJWMIP*, 2004.

[7] N. G. Kingsbury, "A dual-tree complex wavelet transform with improved orthogonality and symmetry properties," in *Proc. IEEE Int. Conf. Image Process. (ICIP)*, 2000.

[8] I. W. Selesnick, "The design of approximate Hilbert transform pairs of wavelet bases," *IEEE Transaction on Signal Processing*, vol. 50, no. 5, pp. 1144–1152, May 2002.

[9] I. W. Selesnick, "Hilbert transform pairs of wavelet bases," *IEEE Signal Process. Letter*, vol. 8, no. 6, pp. 170–173 Jun. 2001.

[10] G. Sandhya, K. Kishore, "Denoising of Images corrupted by Random noise using Complex Double Density Dual Tree Discrete Wavelet Transform", *International Journal of Engineering Research and Applications*, vol. 2, Issue 3, pp.079-087, May-Jun 2012.

[11] I. W. Selesnick, "The double-density dual-tree DWT", *IEEE Trans. on Signal Processing*, 52(5): pp. 1304-1314, May 2004.

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