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Denoising of Images using Double Density Complex DWT

Prof. Yogesh S Bahendwar*
Head of Dept. ETC Dept. SSTC SSEC
Bhilai, India

Shashank Kumar
Asst. Prof. SSTC SSGI
Bhilai, India

Abstract - Image denoising is a challenging work in the field of image processing nowadays. Although, various methods and algorithms has been proposed for denoising of an image.there have been proposed but, most of them have not attained the desirable results. There performance was not good and there was a loss of information while denoising. The wavelet theory is relatively very effective as compare to previous methods of denoising like Fourier Transform .The main aim of this paper is to study the extensions of wavelet Transform and examine its result on images of jpg and png format. In this paper we propose a double density CWT for removal of noise from an image. The double-density DWT is an improvement upon the critically sampled DWT with important additional properties:
(1) It employs one scaling function and two distinct wavelets, which are designed to be offset from one another by one half
(2) The double-density DWT is over complete by a factor of two.
(3) It is nearly shift-invariant.
The double-density complex DWT 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 other pair of wavelets form an approximate Hilbert transform pair. This Paper uses double density CWT for noise removal and calculates Peak Signal to noise ratio (PSNR) and Root mean square error (RMS).

Index Terms— Complex DWT, Denoising, Double Density DWT, Dual Tree DWT Introduction

I. INTRODUCTION

The wavelet transform is a powerful tool for processing of signal and image and now a days it is extensively used in the field of signal processing, image compression, computer graphics, and pattern recognition. Image Denoising means removal various unwanted signals from an image. Various methods are used for image denoising. In this method removal of noise and the actual reconstruction of image is very important. In image denoising, the standard DWT suffers the problems of shift invariance and directional selectivity. Because of this problem, the extensions of the DWT are used. A complex wavelet transform (CWT) is a tool which posses the solution of the shortcomings of the DWT. In Mallat-type algorithms there is problem of shift sensitivity. Kingsbury [4] defines a Dual-tree complex wavelet transforms which is nearly shift-invariant. A double-density dual-tree DWT is introduced by Selesnick [2]. This combined structure in this paper introduces the properties of both the double-density DWT and the dual-tree DWT. The main purpose of this paper is to uses the important properties of both the double-density DWT and dual-tree complex DWT for image denoising and compares its effect on jpg and images

II. DUAL TREE COMPLEX WAVELET TRANSFORM

The dual-tree CWT comprises of two parallel wavelet filter bank trees which contain filters of different delays to minimize the aliasing effects due to down sampling [4]. The Dual Tree Complex Wavelet Transform (DT-CWT) has been developed to use the important properties of Fourier transform. Here two wavelet trees are used, one is used for the real part of the complex wavelet coefficients and the other is used for the imaginary part of the complex wavelet coefficients .They are termed as real tree and imaginary tree . The most important properties of DT-CWT are shift invariance, directional sensitivity, Phase Information, Perfect Reconstruction (PR), Limited Redundancy. The Dual-Tree CWT of a signal x (z) is formed using two critically-sampled DWTs in parallel with the same data. The transform is two times expansive .The designing of filters are done in such a way that the sub-band signals of the upper DWT can be interpreted as the real part of a CWT and sub-band signals of the lower DWT can be interpreted as the imaginary part The orthogonal two-channel filter banks with analysis low pass filter given by the z-transform H0 (z), analysis high-pass filter H1(z) and with synthesis filters G0(z) and G1(z) is shown in Figure1.

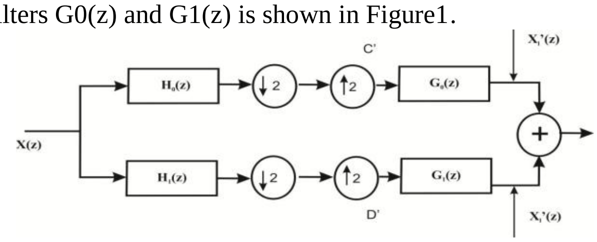

Figure 1 DWT Filter Bank

For an input signal X (z), the analysis part of the filter bank followed by up sampling produces the low-pass and the high-pass coefficients respectively and decomposes the input signal into a low frequency part X1'(z) and a high frequency part Xh'(z), the output signal comprises the sum of these two components. In order to obtain a shift invariant decomposition can be done by the addition of a filter bank with shifted analysis filters and synthesis filters and subsequently taking the average of the low-pass and the high-pass branches of both filter banks as shown in Figure 2.

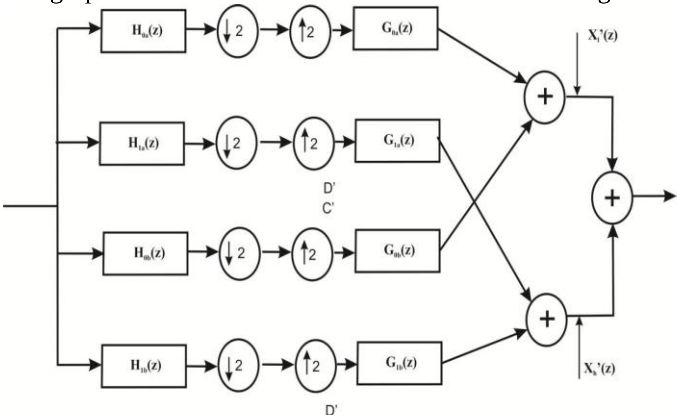

Figure 2 Complex Dual Tree

The implementation of DT-DWT is very straight forward. The decomposition of input image is done by two sets of filter banks, (H_0a, H_1a) and (H_0b, H_1b) separately, filtering the image horizontally and then vertically just as conventional 2D DWT does. After that eight sub bands are obtained: LLa, HLa, LHa, HHa , LLb , HLb , LHb and HHb . Each high-pass sub-band from one filter bank is combined with the corresponding sub-band from the other filter bank by simple linear operations: averaging or differencing. The size of each sub-band is the same as that of 2D DWT at the same level. But there are six high pass sub-bands instead of three high pass sub-bands at each level. The two low pass sub-bands, LLb and LLa, are iteratively decomposed up to a desired level within each branch. Dual Tree Complex DWT can be used to implement 2D wavelet transforms where each wavelet is oriented, which is very important for image processing. The Dual-Tree Complex DWT outperforms the critically-sampled DWT for applications like image denoising and enhancement

III. DOUBLE DENSITY WAVELET TRANSFORM

To implement the double-density DWT, we must first select an appropriate filter bank structure. The filter bank proposed in Figure 3 illustrates the basic design of the double-density DWT.

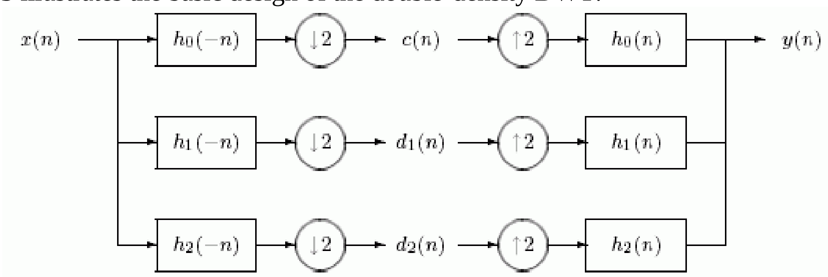

Figure 3: A 3-Channel Perfect Reconstruction Filter Ban

The analysis filter bank consists of three analysis filters—one lowpass filter denoted by h0 (-n) and two distinct highpass filters denoted by h1(-n) and h2(-n). As the input signal x(n) travels through the system, the analysis filter bank decomposes it into three subbands, each of which is then down-sampled by 2. From this process we obtain the signals c(n), $d_1(n)$, and $d_2(n)$, which represent the low frequency subband, and the two high frequency subbands, respectively. The synthesis filter bank consists of three synthesis filters—one lowpass filter denoted by $h_0(n)$ and two distinct highpass filters denoted by $h_1(n)$ and $h_2(n)$—which are essentially the inverse of the analysis filters. As the three subband signals travel through the system, they are up-sampled by two, filtered, and then combined to form the output signal y(n). One of the main concerns in filter bank design is to ensure the perfect reconstruction (PR) condition. That is, to design h0(n), h1(n), and h2(n) such that y(n)=x(n).

The Double Density discrete wavelet transform is based on a single scaling function and two distinct wavelets where the two wavelets are designed to be offset from one another by one half, the integer translates of one wavelet fall midway between the integer translates of the other wavelet. In this way, the Double Density DWT approximates the continuous wavelet transform (having more wavelets than necessary gives a closer spacing between adjacent wavelets within the same scale). The Double Density DWT is two-times expansive regardless of the number of scales implemented potentially much less than the Undecimated DWT. The Double Density DWT has twice as many coefficients as the critically sampled DWT. A separable 2D Double Density DWT can be obtained by alternating between rows and columns as is usually done for 2D separable DWTs. The corresponding filter bank, illustrated in figure 4, is iterated on the low pass branch (the first branch). While the 1D Double-Density DWT is redundant by a factor of 2, the corresponding 2D version is redundant by a factor of 8/3, not by 2 or 4 as one might initially expect. In the oversampled filter bank for the 2D case, the 1D oversampled filter bank is iterated on the rows and then on the columns. This gives rise to 9 2D branches. One of the branches is a 2D low pass scaling filter, while the other 8 make up the 8 2D wavelet filters. Like the Dual Tree DWT of Kingsbury, the overcomplete DWT described above is less shift-sensitive than an orthonormal wavelet basis and in the 2D case has fewer rectangular artifacts.

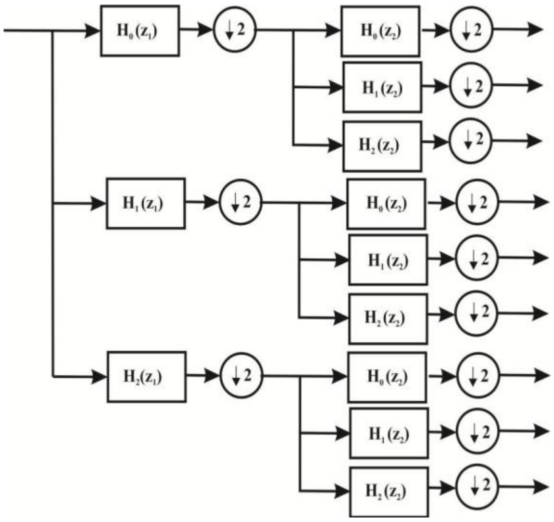

Figure 4 An over sampled Filter Bank

IV. COMPLEX DOUBLE DENSITY DUAL TREE WAVELET TRANSFORMS

We proposed the Double-Density complex DWT which is designed to simultaneously possess the properties of the Double-Density discrete wavelet transform and the Dual-

Tree CWT. The Double-Density DWT and the Dual-Tree CWT are similar in several respects like they are both overcomplete by a factor of two, they are both nearly shift-invariant, and they are both based on FIR perfect reconstruction filter banks, but there exist a difference between them . Both wavelet transforms can outperform the critically sampled DWT for several signal processing applications. By using the important properties of both the dual tree CWT and double density DWT a single wavelet transforms is designed.

The Double-Density complex DWT is proposed which is designed to simultaneously possess the properties of the Double-Density DWT and the Dual-Tree DWT is based on two distinct scaling functions and four distinct wavelets where the two wavelets are offset from one another by one half and where the two wavelets form an approximate Hilbert transform pair. One pair of the four wavelets are designed to be offset from the other pair of wavelets so that the integer translates of one wavelet pair fall midway between the integer translates of the other pair. Simultaneously, one pair of wavelets are designed to be approximate Hilbert transforms of the other pair of wavelets so that two complex (approximately analytic) wavelets can be formed. Therefore, they can be used to implement complex and directional wavelet transforms. The design procedure for the Double-Density CWT is based on the flat-delay filter, spectral and factorization filter bank completion.

The Double-Density Complex DWT proposed in this paper is based on using two oversampled DWTs. The filter bank structure corresponding to the Double-Density complex DWT consists of two oversampled iterated filter banks operating in parallel similar to the Dual-Tree DWT. The oversampled filter bank is illustrated in figure 5.

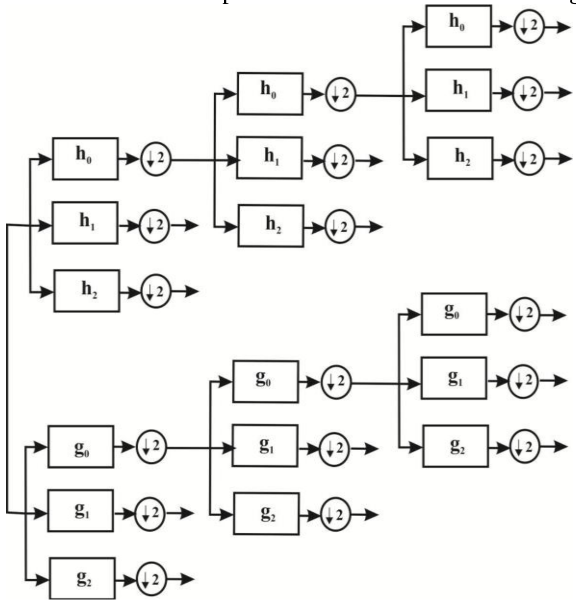

Figure 5 Iterated Filter Bank for Double Density Complex DWT

The iterated oversampled filter bank corresponding to the implementation of the Double-Density Dual-Tree is illustrated in figure We will denote the filters the first filter bank by hi(n) and the filters in the second filter bank by gi(n), for i=0,1,2 4.

V. EXPERIMENTAL RESULTS

This work utilizes Matlab as the software program as it gives multi-paradigm Numerical computing environment. It has the capabilities of data visualization and analysis along with algorithm development.

For JPEG image

(i) In the table 1 for different noise variance and different thresholding points the calculated Peak signal to noise ratio (PSNR) and root mean square error (RMSE) are given.

Table 1 PSNR Values and RMS Error For jpeg image

Method	**Method**	**Double density CWT**	**Double densityCWT**
Noise variance	**Threshold value**	**PSNR Value**	**RMS Error**
10	10	37.4215	73.1496
20	20	37.7945	72.2246
30	30	38.0896	71.4986
40	40	38.3589	70.8408
50	50	38.4789	70.5482
60	60	38.6005	70.2532
70	70	38.7271	69.9466
80	80	38.8126	69.7403
90	90	38.8423	69.6687
100	100	39.1091	69.2434

(ii). For constant noise variance of 40 and different thresholding point the double density Complex DWT results for PSNR and RMS errors are shown in Table

Table 2 For Constant noise variance PSNR value and RMS Error

Method	**Double density CWT**	**Double densityCWT**
Threshold value	**PSNR Value**	**RMS Error**
0	34.0611	81.8501
10	36.4113	75.6949
20	37.5019	72.9495
30	38.0307	71.6433
40	38.3589	70.8405
50	38.5079	70.4777

(iii) For constant noise variance of 50 and different thresholding point the double density CWT results for PSNR and RMS errors are shown in Table 3

Table 3 For Constant noise variance PSNR value and RMS Error

Method	**Double density CWT**	**Double densityCWT**
Threshold value	**PSNR Value**	**RMS Error**
0	32.6947	85.5857
10	35.6111	77.7532
20	37.0828	73.9965
30	37.8088	72.1894
40	38.2366	71.1387
50	38.5079	70.4777

(iv)The original image along with its histogram representation, noisy image along with its histogram representation and the denoised or image along with its histogram representation is given

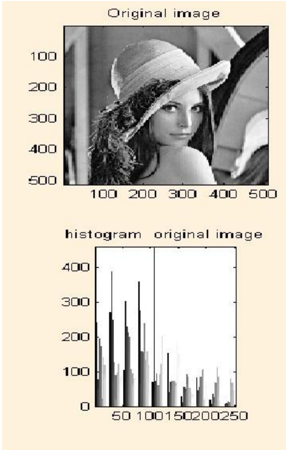

Figure 6Original image with its histogram

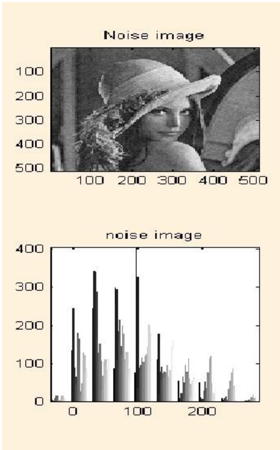

Figure 7 noisy image with its histogram

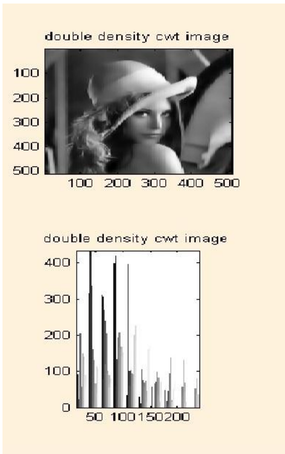

Figure 8 DDCDWT image with its histogram

For png image

(i) In the table 4 for different noise variance and different thresholding points the calculated Peak signal to noise ratio (PSNR) and root mean square error (RMSE) are given

Table 1 PSNR Values and RMS Error For jpeg image

Method	**Method**	**Double density CWT**	**Double densityCWT**
Noise variance	**Threshol d value**	**PSNR Value**	**RMS Error**
10	10	30.846	90.8287
20	20	31.2143	89.7661

Method	Method	Double density CWT	Double densityCWT
30	30	31.412	89.1995
40	40	31.5269	88.8714
50	50	31.6564	88.5027
60	60	31.6742	88.4519
70	70	31.723	88.3132
80	80	31.7499	88.237
90	90	31.8521	88.0238
100	100	31.9469	87.6792

(ii). For constant noise variance of 40 and different thresholding point the double density Complex DWT results for PSNR and RMS errors are shown in Table

Table 2 For Constant noise variance PSNR value and RMS Error

Method	**Double density CWT**	**Double densityCWT**
Threshold value	**PSNR Value**	**RMS Error**
0	27.9773	99.421
10	29.9409	93.4787
20	30.9119	90.638
30	31.3351	89.4196
40	31.5249	88.8771
50	31.6272	88.5858

(iii) For constant noise variance of 50 and different thresholding point the double density CWT results for PSNR and RMS errors are shown in Table 3

Table 3 For Constant noise variance PSNR value and RMS Error

Method	**Double density CWT**	**Double densityCWT**
Threshol d value	**PSNR Value**	**RMS Error**
0	26.9019	102.971
10	29.1957	95.717
20	30.5541	91.6775
30	31.2043	89.7949
40	31.4744	89.0212
50	31.6118	88.6296

(iv)The original image along with its histogram representation, noisy image along with its histogram representation and the denoised or image along with its histogram representation is given

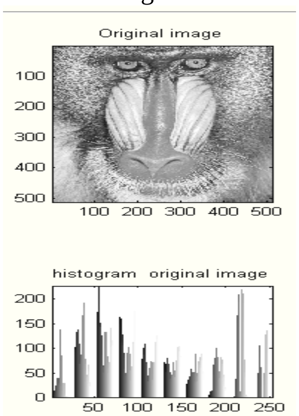

Figure 9 Original image with its histogram

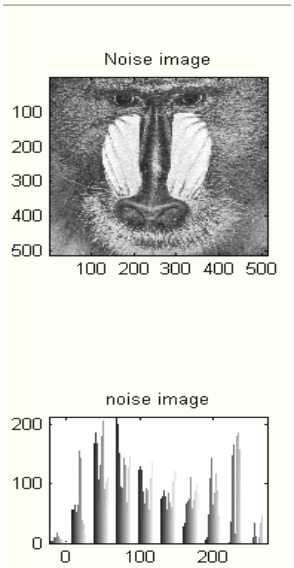

Figure 10 Noisy image with its histogram

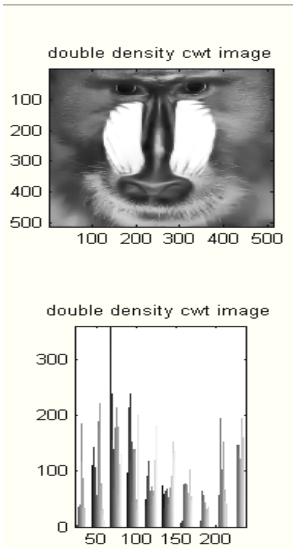

Figure 11 DDC DWT image with its histogram

The shift invariance and directionality properties of complex wavelet Transform are used in various areas of image processing like denoising, object segmentation ,feature extraction and image classification. Here we are considering the Double Density Complex DWT for denoising and consider its effect on jpeg and png images , different thresholds points and noise variance were selected are used on these images . But optimal thresholds points gives the minimum root mean square error from the original image and we get more PSNR value for less noise variance, showing a great effectiveness in removing the noise compared to the classical discrete wavelet transform.
The images are corrupted with different noise variance .Initially the Gaussian noise present in form of additive noise is removed. The various results in form of PSNR and RMS error are shown in the table above along with its histogram representation.

VI. CONCLUSION AND FUTURE SCOPE

A. Conclusion: The wavelet transforms which has the excellent property of spatial localization and multi-resolution, which are similar to the theoretical models of the human visual system isused for removal of noise. In image denoising DWT is very effective tool, The compaction property of DWT i.e. having only a small number of large coefficients and large number of small coefficients is used. But discrete wavelet transform performance is not good in some of signal processing tasks due to strong shift dependence, lack of directional selectivity, aliasing and oscillations of the coefficients. The solution to this entire problem is complex discrete wavelet transform method Here we are proposing a hybrid model of Double Density CWT for removal of noise and to obtain a significantly high peak signal to noise ratio. The experimental results demonstrated on above image shows the Double Density Dual complex DWT is better method as compare to other wavelet transform method.

B. Future Scope These future research directions of double density complex DWT is the analysis of 3D images and medical images , image segmentations, Texture synthesis and imaging radar etc.

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