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A Novel Block Merging Algorithm for Image Denoising using Dual Tree Complex Wavelet Transform

Sk.Umar Faruk | Dr J.Praveen Kumar

Department of Electronics & Communications, Teegala Krishna Reddy Engineering College ,Hyderabad, India.

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ABSTRACT

There has been a lot of research work dedicated towards image denoising. However, with the wide spread of image usage in many fields of our lives, it becomes very important to develop new techniques for image denoising. In the proposed method, the DTCWT is applied on the noisy image to produce the wavelet coefficients in different sub bands. A block including the denoising point in the particular sub band is used to split in order to get distinct sub blocks. The signal-variance in a sub-block is estimated by using median estimator. The coefficients of original decomposed image in wavelet domain are estimated using the minimum mean squared error (MMSE) estimator by means of the estimated signal variance.

I. INTRODUCTION

Image processing has got broad applications in multimedia communication, computer vision, television broadcasting, etc. that requires very good quality of images. The quality of an image degrades due to introduction of additive white Gaussian noise (AWGN) during acquisition, transmission/ reception and storage/ retrieval processes. It is very much necessary to suppress the noise in an image and to preserve the edges and fine details as far as possible. This procedure is traditionally performed in the spatial-domain or transform-domain by filtering. When image is contaminated with Gaussian noise, one method that has received considerable attention in recent years is wavelet thresholding or shrinkage: an idea of killing coefficients of low magnitude relative to some threshold. The different thresholding or shrinkage methods proposed in the literature are Visu Shrink [1][2], Sure Shrink [3][4], Bayes Shrink [5] etc. The windowing method such as locally adaptive window maximum likelihood (LAWML) estimation [6] is also available in the literature where the statistical relationship of coefficients in a neighbourhood is considered. The wavelet domain methods are suitable in retaining the detailed structures; However The Conventional Discrete Wavelet Transform (DWT) has several limitations, such as aliasing, shift sensitivity and poor directional selectivity [8]. Due to large changes in wavelet coefficients and down sampling, aliasing may happen in DWT. The inverse DWT eliminates this aliasing only if the wavelet and scaling coefficients are unchanged. Due to shift sensitivity, the small shifts in input signals can cause an irregular change in the distribution of energy between DWT coefficients at different scales. Because of poor directionality, DWT cannot differentiate between +45∘ and −45∘ spectral features. These DWT limitations can be resolved using complex wavelet transforms (CWT). CWT decomposes the signals into real and imaginary parts in the spectral domain. The real and imaginary coefficients are used to compute the amplitude and phase information. To overcome from the limitations of DWT, Kingsbury introduced the dual-tree complex wavelet transform, which allows perfect reconstruction. The dual-tree complex wavelet transform is enhanced version of DWT, with important additional properties: shift invariance and good directionality [17].

II. DUAL TREE COMPLEX WAVELET TRANSFORM

In recent The dual-tree complex wavelet transform (DTCWT) has received considerable importance in the wavelet domain, owing principally to its directional selective [7] and near-shift invariant [8] properties. It has been revealed that with two separate maximally decimated and dyadic decompositions [9] where filters are offset by a half sample, the resulting CWT wavelet bases form an approximate Hilbert transform pair [10]. It achieves this with a redundancy factor of only 2^d for d-dimensional signals, which is considerably lower than the un-decimated DWT. The multidimensional (M-D) dual-tree CWT is non-separable but is based on a computationally efficient, separable filter bank [11]. The dual tree complex wavelet transform allows the perfect reconstruction using short linear phase filters [12],also provide efficient order-N computation only twice the simple DWT for 1-D.

In formulation, the DTCWT [13] is a complex pair of real and imaginary discrete wavelet transforms trees. The schematic structure of Kingsbury's DTCWT implementation is shown in Fig. (1). Since the single tree wavelet structure is descent in required directional selectivity in two or multiple directions and due to its shift sensitivity, lack of phase information, the dual tree structure is proposed by Kingsbury. The analysis and synthesis filter banks used in the proposed DTCWT framework are Length-10 filters based on Farras wavelet implementation. A separate set of analysis and synthesis filter banks are used for first stage and higher stages. The filter coefficients used for real and imaginary trees are shown in table (1).

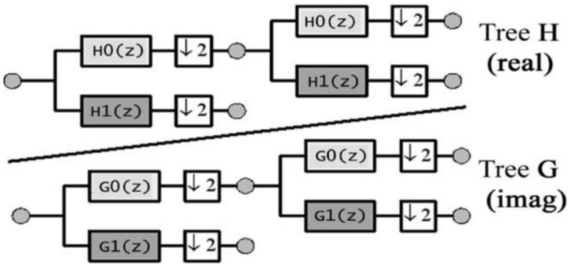

Fig 1: Kingsbury's dual-tree Complex Wavelet Transform

III. RELATED WORK

The proposed wavelet domain based on DTCWT method introduces an image denoising scheme with block merging approach. In the proposed technique, the Dual Tree Complex wavelet transform is applied on the noisy image to produce the wavelet coefficients (real and Imaginary) in different sub bands. A block incorporating denoising point in the particular sub band is partitioned in order to get distinct sub blocks. The signal-variance in a sub- block is estimated by using Donoho robust median estimator. It discriminates a sub-blocks with some rationally high ac signal power from a sub- block have negligible ac signal power. The sub- blocks containing considerable ac signal power are combined together to get a large homogenous block. However, if the sub- block incorporating denoising point has insignificant ac signal power, then this sub- block can be merged with other likelihood sub- blocks with insignificant ac signal power to obtain a homogenous region. Now, in wavelet domain based on DTCWT, in a substantial homogenous region, the signal variance is assessed with better precision. The coefficients of original decomposed image in wavelet domain are estimated using the minimum mean squared error (MMSE) estimator by means of the estimated signal variance.

In order to discover the denoised image it is fundamental to estimate the wavelet coefficients of the original decomposed image in wavelet domain. In estimating the coefficients of original decomposed image from the coefficients of noisy image the minimum mean squared error (MMSE) estimator plays an significant role . The MMSE estimator is defined as:

$$\hat{w}_k = \frac{\hat{\sigma}_k^2}{\hat{\sigma}_k^2+\sigma_n^2} y_k \qquad - \quad (1)$$

Here y_k and $\hat{w}_k$ are the well-known and estimated wavelet coefficients in a kth block of a particular sub band. σ_n^2 and $\hat{\sigma}_k^2$ are the noise variance and estimated signal variance respectively .

It is then significant to compute the signal variance in a block. However, this can be estimated from Donoho [1][6] relation proposed as

$$\sigma\ (\text{MAD}) = \text{median}\ \frac{\{\|w(i,j)\|\}}{0.6745} \quad - \quad (2)$$

Where, where w(i,j) represents the detail coefficients at the finest level.

In the proposed method, the noisy image experiences four levels of decomposition in wavelet domain to produce wavelet coefficients in different sub-bands. The 10-tap wavelet filter is used for the point of decomposition. After a decomposition process, Except LL (approximate) sub band, all the high pass sub bands are retained and only LL sub band is taken for further decomposition. In this way at each stage, three high pass sub bands will be obtained from real and imaginary trees. In a particular sub band, a square shaped 9×9 region is divided into distinct 3×3 sub-regions. So, in a large region nine distinct sub-regions are obtained. In each distinct sub-region, the signal variance is estimated using median estimator. Depending upon the ac power level, the sub-regions are merged to form a larger sub-region for better estimation of signal component. Then the MMSE algorithm is applied to this large sub-region to estimate the wavelet coefficients of original image. The BM-DTCWT algorithm is presented in Fig.2.

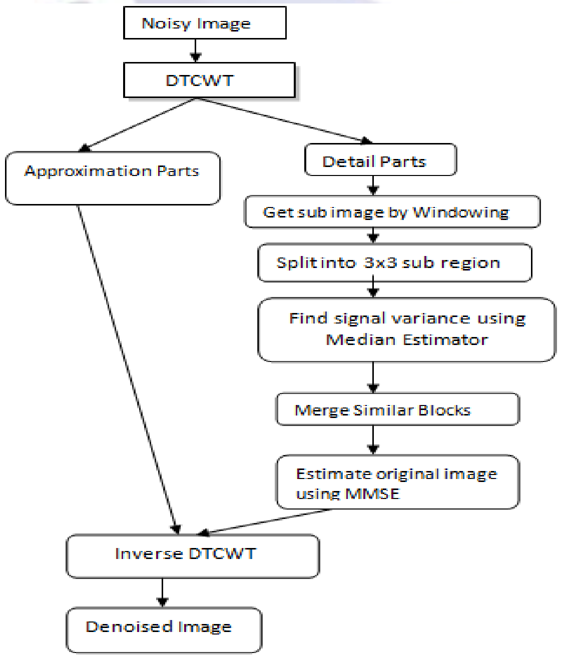

Fig 2: Proposed BM-DTCWT algorithm.

IV. EXPERIMENTAL RESULTS

The proposed technique, Block Merging based DTCWT is simulated in MATLAB Environment. The test images: Lena of sizes 512×512 corrupted with AWGN of standard deviation, σ = 10, 20, 30, 40, and 50 are used for simulation purpose. The performance of the proposed method is compared with those of conventional wavelet-domain techniques Visu Shrink, Sure Shrink, Bayes Shrink. The peak-signal-to noise ratio (PSNR), root-mean-squared error (RMSE), is taken as performance measures.

Table 1: Performance of BM and various algorithms in terms of PSNR operated on LENA image Under various noise conditions

Denoising Method	Standard deviation of AWGN				
	σ=10	**σ=20**	**σ=30**	**σ=40**	**σ=50**
Visu Shrink	39.17	33.95	32.67	32.29	31.76
Sure Shrink	39.65	34.59	33.97	33.14	32.14
Bayes Shrink	40.38	34.98	34.24	33.79	32.63
Proposed	**43.89**	**39.83**	**35.67**	**33.94**	**32..88**

Table 2: Table 1: Performance of BM and various algorithms in terms of RMSE operated on LENA image Under various noise conditions

Denoising Method	Standard deviation of AWGN				
	σ=10	**σ=20**	**σ=30**	**σ=40**	**σ=50**
Visu Shrink	3.01	5.16	5.69	6.53	6.42
Sure Shrink	2.72	5.37	5.17	5.89	5.97
Bayes Shrink	2.48	4.68	5.04	5.37	5.64
Proposed	**2.26**	**2.28**	**4.58**	**5.16**	**5.39**

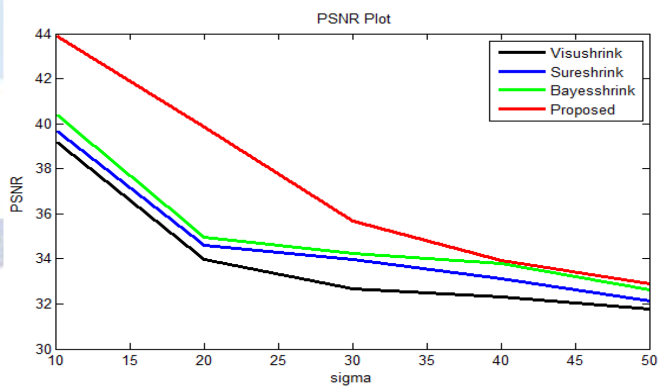

Fig 3. Performance comparison of various filters in terms of PSNR under different noise levels of AWGN on the images

The PSNR values of the different techniques for various images are given in the table-1. The largest PSNR value for a particular standard deviation of Gaussian noise is highlighted to show the best performance. The PSNR values under different noise conditions are graphically represented in Fig. 3. The RMSE values of different filters are given in the Table-2. The smallest RMSE value for a particular standard deviation of Gaussian noise is highlighted. The qualitative performance based on human visual system using BM-DTCWT for sigma 20 and 40 are shown in Fig 4.The proposed filters are compared with only some high performing filters.

Fig 4. Denoising illustration using BM-DTCWT for sigma = 20 and 40

V. CONCLUSION

In this paper, we have developed an image denoising method based on Block merging technique for denoising the images efficiently. This method removes a large amount of additive noise and preserves most of the edges and visual quality of the image. Our proposed method gives better performance than the Visu Shrink, Sure Shrink, and Bayes Shrink. A comparative analysis of denoising results is performed in tabular and graphical manner and provided to exploit the operational superiority of the proposed algorithm over the existing algorithms. It is observed from the tables that the proposed method BM-DTCWT is found to be the best in filtering smooth and complex regions with quite little distortion and giving the best visual quality among all filters compared here.

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