A Sub-Band Adaptive Visushrink in Wavelet Domain for Image Denoising

M. Laavanya, V. Vijayaraghavan

Abstract*—A novel sub-band adaptive Visushrink approach in wavelet domain for image denoising, is proposed. In the transformed noisy image, the variance of wavelet coefficients will not be same across the scale and mean value of noisy signal will be more. Hence a sub-band adaptive threshold using, noise and signal variance is computed. The proposed threshold is simple and adaptive to the decomposition scale. The wavelet transformed noisy image undergoes thresholding using the proposed threshold. Comparative PSNR evaluation shows that the projected approach is superior to other techniques by removing noise with protection of image edges.

***Keywords*— Adaptive threshold, DTCWT, Image denoising, PSNR, Visushrink**

I. INTRODUCTION

In day to day life, digital images plays a dynamic role. In digital image processing the visual appearance of images are improved. During capture, transmission and reception digital images are prone to noise. Hence image denoising is yet a challenging problem. Among various image denoising techniques, wavelet transform based denoising methods are better due to its sparse representation [2]. Donoho [3] proposed a threshold based approach, in which too many information bearing wavelet coefficients are killed. Following Donoho, various denoising techniques based on threshold value can be found in [1] [9]. The performances of these methods are improved by considering the neighboring wavelet coefficients, but leads to Gibbs phenomenon. This drawback can be overcome if statistical dependencies between wavelet coefficients are considered. One such method proposed by Sendur and Selesnick [16] [17] depend on the child parent relationship, gives better denoising performance. Denoising images by Gaussian adaptive filter designed based on the estimation of probability density function gives better denoising performance was proposed by Hajihashemi [8]. Feng [7] analyzed the strength and weakness of various wavelet based threshold methods and drawn Gaussian mixture model is superior to other approaches. Although in all these techniques increase in mean value of noisy signal is not considered and also, Discrete Wavelet Transform (DWT*)* does not detect the oriented singularities in the image. It also shifts the wavelet coefficient when there is a shift in input.

Kingsbury [12] proposed Dual Tree Complex Wavelet Transform (DTCWT), that exactly detects the curves and lines in the image along with shift invariant property. Shift invariance gives the accurate spectral energy along scale, space and orientation. Hence the total energy of wavelet sub-band coefficients is invariant to translation. The threshold value in soft thresholding approach, is calculated based on the wavelet coefficients mean, variance and median value, gives better noise reduction [9]. The bivariate model [18] of complex wavelet coefficients considers only the correlation between neighborhood coefficients using suitable window size but not the multi scale correlation between the wavelet coefficients.

Hence in this work a sub-band adaptive visushrink in wavelet domain is proposed for denoising the image. Here the variance is considered to be varying across the scales and accordingly threshold value is estimated. The suggested scheme removes the noise by maintaining the details of the image.

The structure of the paper is, describes the theory of DTCWT in section 2, section 3 explains about presented scheme, the section 4 shows the efficacy of new approach, is good at restoring the noisy image and section 5 describes the inference of works.

II. DUAL TREE COMPLEX WAVELET TRANSFORM

DTCWT provides multiresolution, sparse representation of image. Further it purveys shift invariance and directional selectivity [10] [11] [15]. Compared to DWT, the redundancy factor of DTCWT is 2^d for d dimension. The DTCWT uses two isolated real DWT to compute the complex coefficients. The real part of wavelet coefficients are given by first real DWT and the imaginary part of wavelet coefficients are given by second real DWT. Then the dual tree complex wavelet coefficients is given by Equation (1)

$$\psi_c(t) = \psi_r(t) + j\,\psi_i(t) \qquad (1)$$

In equation (1), the real wavelet $\psi_r(t)$ and the imaginary wavelet $\psi_i(t)$, are ninety degrees out of phase with each other. Then the complex wavelet coefficient is given in equation (2)

$$d_c(j,n) = d_r(j,n) + j\,d_i(j,n) \qquad (2)$$

Figure 1 shows the DTCWT structure for analysis filter bank and Figure 2 shows the DTCWT structure for synthesis filter bank [13] [14]. In Figure 1, $h_0(n)$ and $h_1(n)$ denotes the low pass and high pass filters of upper filter bank, $g_0(n)$ and $g_1(n)$ denotes the low pass and high pass filters of lower filter bank.

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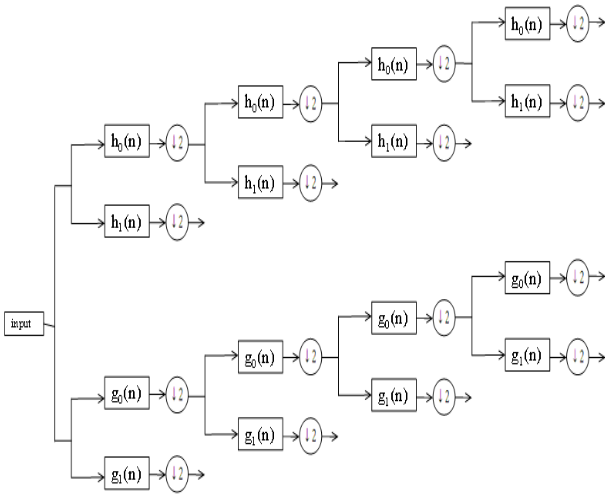

Figure 1. DTCWT Structure For Analysis FB

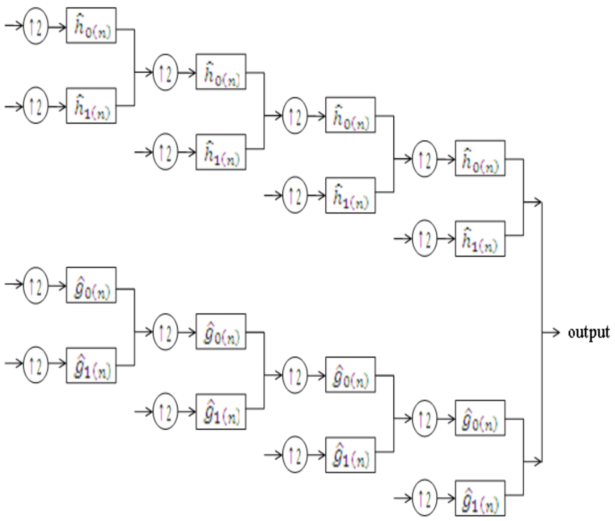

Figure 2. DTCWT Structure For Synthesis FB

III. DTCWT AND SUB-BAND ADAPTIVE VISUSHRINK

Image contaminated by additive white Gaussian noise is considered. DTCWT of an image is computed using a two real discrete wavelet transforms and the wavelet coefficients are stored in the form of cell array. The threshold value is estimated using a sub band adaptive Visushrink method. Donoho and Johnstone [4] introduced VisuShrink technique, generally it is based on universal threshold. The value of threshold is stated as

$$T = \sqrt{(\sigma_n^2 \log M)} \qquad (3)$$

In equation (3), noise variance is denoted by σ_n and number of pixels denoted by M in the given image. When number of pixels increases, probability approaches to one. This leads to kill many useful coefficients in the process. However, Visushrink does not consider about the increased mean value of signal power in the noisy image. Therefore, Visushrink produces an overly smoothed estimated.

Hence in the proposed method, the threshold is computed by considering both noise and signal variance. The noise variance is found by robust median estimator and it is given by

$$\sigma_n^2 = \frac{median(|y_i|)}{0.6745} \qquad (4)$$

Where, $y_i \in$sub-band, signal variance is computed by processing all scales of sub band separately in a loop using a window to have sub band adaptivity. Thus the new threshold function depending on both noise and signal variance is defined as

$$T = (\sqrt{(\sigma_n^2 \log M)}) - \sigma_s^2 \qquad (5)$$

In Equation (5), σ_s^2 is the signal variance. Thus the increase in mean value of noisy signal is removed by subtracting noise variance from signal variance. Thresholding is done by processing each sub band separately in a loop using Visushrink hard function. The noise free image is retrieved by taking inverse DTCWT.

IV. RESULTS AND DISCUSSION

The result obtained after noise reduction of the presented algorithm is presented in this section. A standard 8-bit grey scale Lena image of size 512×512 is used to verify the presented scheme. To evaluate the performance a standard indicator called PSNR is used. The noisy image at two different power levels (σ= [20 30]) is taken to evaluate the perfprmance. The projected scheme is compared with bivariate shrinkage function exploiting inter-scale dependency and bivariate model in wavelet domain [16] [18]. The proposed approach is also compared in contourlet domain [5] incorporating SURE shrink for image denoising and in curvelet framework integrating wiener filter for denoising images [6]. Table 1 summarizes the results attained for noisy Lena image. It is evident from the PSNR values, that the presented scheme is better than other existing methods, by approximately +0.4 dB of average gain at noise level 30.

TABLE I. Denoising results (psnr) for Lena with different denoising methods

σ_n	Sendur [16]	Ehsaeyan [5]	Ehsaeyan [6]	Zhang [18]	Visushrink	Proposed method
20	31.71	31.16	31.21	30.89	30.95	32.037
30	29.85	29.56	29.44	29.14	29.27	30.178

Figure 3, shows the noisy images for the noise level 20 and the noise level 30. Figure 4 shows how the proposed approach removes the noise significantly from the image for the noise level 20 and the noise level 30.

Figure 3. Noisy images of Lena for a) σ=20 b) σ=30

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Figure 4. Denoised images of Lena for a) σ=20 b) σ=30

V. CONCLUSION

One main issue addressed in this work is a sub-band adaptive threshold by modifying visushrink threshold for image denoising. The proposed scheme is not only compared in wavelet domain, but also in contourlet and curvelet domain. The outcomes of the presented sub-band adaptive threshold tackles the noise in the image in a better way than other existing techniques. This approach can be used for denoising all source of digital images.

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