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An Algorithm for Remote Sensing Image Denoising Based on the Combination of the Improved BiShrink and DTCWT

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Abstract

By considering the strong correlation between wavelet coefficients of the actual image, while bivariate model is only a statistical model for the interscale dependency of wavelet coefficient with parent coefficient, without taking into account the correlation of adjacent coefficient. Therefore, based on the shift-invariance and better directionality of the dual-tree complex wavelet transfer (DTCWT)， and incorporating neighboring wavelet coefficients with BiShrink, a novel BiShrink threshold and DTCWT remote sensing image denoising method is presented. Experimental results show the proposed algorithm gets better PSNR than other methods mentioned，observably. In terms of visual quality，the proposed algorithm can get the images with more details，smooth profiles and aliasing is restricted.

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Keywords: Dual Tree Complex Wavelet Transfer(DTCWT)，BiShrink threshold，Neighboring coefficients，Remote sensing image denoising

1. Introduction.

Within the remote sensing imaging and image transmission, the image quality will decline due to the unavoidable noise influence, which seriously affects the analysis and understanding for remote sensing image. So the remote sensing image needs pre-processing before used and then follow-up other deal.

In order to overcome shortcomings of the discrete wavelet transform (DWT), the Complex Wavelet Transform (CWT)[1-2], which is proposed by Kingsbury in 1998, has received special attention for its important properties: nearly shift invariant and directionally selective with low computational complexity in two or higher dimensions. But the CWT has also drawbacks. Bacause the input of CWT more than one

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layer decomposition is plural, it is very difficult to reconstruct.Furthermore, Kingsbury presented the Dual Tree Complex Wavelet Transform (DTCWT)[3-5], which preserves the usual properties of perfect reconstruction and computational eciency with well-balanced frequency responses. Each DTCWT wavelet has a unique direction, oriented at ±15° ,±45° ,and ±75° ,respectively.

In addition, because of the strong correlation between wavelet coefficients of the actual image, choosing a good statistical model for a wavelet coefficient can achieve better denoising perpormance[6]. Experimental results in[7]show that BiShrink is better than BayeShrink and hidden Markov model (HMT).While bivariate model is only a statistical model for a wavelet coefficient and its parent, lack of consideration of the correlation of adjacent coefficient, it is unable to enhance the denoising effect futher[8-9]. Therefore, based on the shift-invariance and better directionality of the dual-tree complex wavelet transfer(DTCWT)，and incorporating neighboring wavelet coefficients with BiShrink, a novel BiShrink threshold and DTCWT remote sensing image denoising method is presented．Experimental results show the proposed algorithm gets better PSNR than other methods mentioned，observably. In terms of visual quality，the proposed algorithm can get the images with more details，smooth profiles and aliasing is restricted．

2. Basic concepts

1.1. Dual tree complex wavelet transfer(DTCWT)

The DTCWT is implemented by two independent and parallel real DWT. The same data is parallelly operated by two filter banks pair. It employs two real DWTs; the first DWT gives the real part of the transform while the second DWT gives the imaginary part. The two real DWTs use two different sets filters, with each satisfying the perfet reconstruction conditions. The two sets of filters are jointly designed so that the overall transform is approximately analytic.

1.2. Bivariate shrinkage

Bivariate shrinkage (BiShrink) is a denoising method using Bayesian MAP estimation which uses bivariate model as prior distribution of joint coefficient-parent. The theoretical basis of bivariate model is the interscale dependency of wavelet coefficients, in detail, the coefficient-parent dependency.

We consider the denoising of an image corrupted by additive white Gaussian noise, AWGN, with variance σ_n^2 . In order to exploit the interscale dependency of the wavelet coefficients, let w_2 represent the parent of w_1. The parent is located at the same geometrical coordinates like the child, but at the successive scale. We can write:

$$y_k = w_k + n_k, \quad k = 1,2,\ldots, m \tag{1}$$

where $y_k = (y_{1k}, y_{2k}), w_k = (w_{1k}, w_{2k}), n_k = (n_{1k}, n_{2k}),$ and m is the total number of wavelet coefficients.

The MAP estimation of w , realized using the observation y , is given by the following MAP filter equation:

$$\hat{w}(y) = \arg\max_w [\log(p_n(y-w)) + \log(p_w(w))] \tag{2}$$

The bivariate shrinkage can be written as

$$\hat{w}_1(\underline{y}) = \left(1 - \frac{\sqrt{3}\,\sigma_n^2 / \sigma}{\sqrt{y_1^2 + y_2^2}}\right)_+ \cdot y_1 \tag{3}$$

where

$$(g)_+ = \begin{cases} 0, & \text{if } \; g < 0 \\ g, & \text{otherwise} \end{cases} \tag{4}$$

3.Proposed algorithm

After DTCWT decomposition, there are strong correlations between current, parent and adjacent coefficients. The traditional BiShrink is a denoising method based on the interscale dependency of wavelet coefficient with parent coefficient, without taking into account the correlation of adjacent coefficient. In this method, a threshold denoising formula based on incorporating neighboring wavelet coefficients with BiShrink is constituted to restrain noise interference.

Chen and Bui[10] proposed incorporating neighboring wavelet coefficients as

$$S_{j,k} = \sum_{(i,l)\in B_{j,k}} y_{i,l}^2 \tag{5}$$

Given that $y_{j,k}$ is the set of wavelet coefficients of the observed image.For every $y_{j,k}$ of our interest, we need to consider a neighborhood window $B_{j,k}$ around it, which can be window sizes of 3×3, 5×5, or others. Fig.1.illustrates an 5×5 neighborhood window centered at the waveletcoefficient to be denoising.

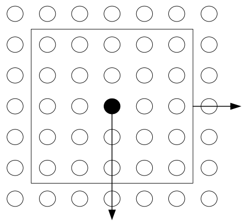


Fig.1. Illustration of the neighborhood window centered at the denoising wavelet coefficient.

To apply neighboring wavelet coefficients to BiShrink threshold Function in(3), we need to calculate the average value of parent and child coefficients within the neighborhood window:

$$S_{j,k} = \frac{\sum_{(i,l)\in B(j,k)} ((y_1)_{i,l}^2 + (y_2)_{j,l}^2)}{k^2} \tag{6}$$

Where k is here the neighborhood window size in one dimension.Then, we propose to use (3) and (6) to reduce noise within image by using new threshold function as

$$\hat{w}_{j,k} = \left(1 - \frac{2\times(\sqrt{3}\sigma_{nj,k}^2/\sigma_{j,k})^2}{S_{j,k}}\right)_+ y_{1j,k} \tag{7}$$

To estimate the standard deviation of the noise from the noise wavelet coefficients, a robust median estimator[11] is used from the finest scale wavelet coefficients (HH1 subband), such as the formula(8). The formula(9) is the fine-tuning factor.

$$\hat{\sigma}_{nj,k} = median(|y_{j,k}|)/0.6745 \; , y_{j,k} \in \text{subband HH} . \tag{8}$$

$$\hat{b}_{nj,k} = mean\,(y_{j,k}|_{i=1}^{n/2}) - mean\,(y_{j,k}|_{i=n/2}^{n}) \tag{9}$$

Where yj,k is the wavelet high-frequency coefficients of the level j, n is high-frequency coefficients points, median yj,k is the median amplitude of all the wavelet coefficients yj,k of the level j.

Combined with correlation of DTCWT neighborhood coefficient, $\sigma_y^2 = \sigma_w^2 + \sigma_n^2$, the variance σ_y^2 of the noisy signal can be estimated[12] as (10), where M is the neighborhood window Bj,k size. The original signal variance $\sigma_{j,k}$ can be estimated such as the formula (11) below.

$$\sigma_y^2 = \frac{1}{M}\sum_{(i,j)\in B(j,k)} y_{i,l}^2 \tag{10}$$

y

$$\hat{\sigma}_{j,k} = \sqrt{(\hat{\sigma}_y^2 - \hat{\sigma}_{nj,k}^2)_+} \tag{11}$$

According to the above research result, the steps of the proposed algorithm are as follows.

a. Compute the 2D dual-tree complex wavelet transform of the noisy image to obtain the multiresolution of the noisy image.

b.Estimate the standard deviation $\hat{\sigma}_{nj,k}$ of the noise using the high-frequency wavelet coefficients.

c.Estimate the original signal variance $\hat{\sigma}_{j,k}$.

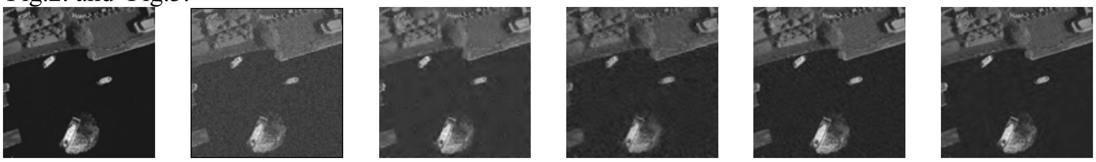
d.Calculate the average value of parent and child coefficients within the neighborhood window.

e.Apply the proposed method in each scale and orientation for noise removal.

f.Implement the inverse 2D-DTCWT transform on the denoising coefficients to obtain the restoration image.

4. The result of simulation and comparison

In this paper, two city remote sensing images of 256×256 pixels are employed for performance evaluation. Each image is corrupted by an additive white Gaussian noise with σn= 10, 15, 20, 25, 30. In order to illustrate the performance of the proposed scheme, it is compared with wavelet hard-thresholding, contourlet thresholding and wavelet-BiShrink. Comparing the PSNR values of different denoising methods on remote sensing images are tabulated in Tab.1. As to visual quality, comparing the performance of the denoising schemes on remote sensing image_1 and image_2 with σn=20 are showed in Fig.2. and Fig.3.



(a)Original image (b)Noisy image (c) WT (d) CT (e) BiShrink_WT (f) proposed method

Fig.2. Comparing the performance of the denoising schemes on remote sensing image_1 with σ_n=20.

(a)Original image (b)Noisy image (c) WT (d) CT (e) BiShrink_WT (f) proposed method

Fig.3. Comparing the performance of the denoising schemes on remote sensing image_2 with σn=20.

Tab.1.Comparing the PSNR Values of different denoising methods on remote sensing images.

Test images	σn	Noisy	WT	CT	BiShrink WT	Proposed
Image_1	10	28.19	30.89	29.36	32.96	34.59
	15	24.62	28.56	27.49	30.87	32.18
	20	22.10	26.92	26.22	29.09	30.61
	25	20.17	25.79	25.43	28.10	29.48
	30	18.65	24.98	24.73	27.23	28.53
Image_2	10	28.17	28.13	26.84	29.86	31.31
	15	24.64	25.72	24.87	27.72	29.12
	20	22.14	24.18	23.56	25.91	27.66
	25	20.20	22.97	22.58	24.88	26.50
	30	18.63	22.09	21.78	23.69	25.51

From the experiment results, we can draws the following conclusions:

(1)From the Tab.1, we find that the proposed sheme achieves higher PSNR than other denoising schemes. Comparing to WT, CT, BiShrink WT, the PSNR values of the proposed method is improved about 3.5dB, 4.2dB, 1.5dB for both images.

(2)In Fig.2 and Fig.3, we illustrate a set of denoising results of remote sensing image_1 and image_2. It is observed that the perpormance of the proposed is better than WT, CT and BiShrink WT in the visual quality. The proposed algorithm can get the images with more details, smooth profiles and aliasing is restricted. From the surface of the water, the outline of the ship in the de-noised image_1, and the texture of the buildings in de-noised image_2, we can clearly see that fully reflects the denoising algorithm proposed in the superiority of the performance.

5. Conclusions

Based on the shift-invariance and better directionality of the dual-tree complex wavelet transfom (DTCWT), and incorporating neighboring wavelet coefficients with BiShrink, a novel BiShrink threshold and DTCWT remote sensing image denoising method is presented. Experimental results show the proposed algorithm gets better PSNR than other methods mentioned, observably. In terms of visual quality, the proposed algorithm can get the images with more details, smooth profiles and aliasing is restricted. This provides a sound image basis for remote sensing image feature extraction, pattern recognition and so on.

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