DENOISING OF HIGH RESOLUTION REMOTE SENSING DATA USING STATIONARY WAVELET TRANSFORM

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ABSTRACT

An image is often corrupted by a noise in its acquisition and transmission. A high resolution remote sensing data will be seen more roughly if it is corrupted by a noise. Wavelet is one of the fascinating denoising manners that will be used to solve this problem. The main application of the Stationary Wavelet Transform (SWT) is denoising. The principle is the average of several denoised signals. Each of them is obtained by using the usual denoising scheme, but it is applied to the coefficients of a ε-decimated DWT. The stationary wavelet transform (SWT) is to make the wavelet decomposition time invariant. This improves the power of wavelet in the signal denoising. In this research, we apply the SWT method to preprocess the remote sensing data for removing the noise. The Worldview-1 satellite data is used in this research. The sensor resolution is 0.55 meters and Ground Sample Distance (GSD) at 20^{o} off-nadir. The Area of Interest (AoI) is Monas, Jakarta and the acquisition of the data was done on March 13^{th}, 2008. For the data analysis, the Worldview-1 satellite data is added by the noise. The result of this research is that the noise can be removed by SWT method. By using structural similarity index (SSIM), the quality of the denoised images by SWT, Wavelet Transform 2D and Wavelet Packet 2D are 0.2666, 0.1912, and 0.1927, respectively. Thus, the SWT provides a better performance in denoising the remote sensing data than Wavelet Packet 2 D and Wavelet 2D methods.

Keyword: *Denoising, Remote sensing data, Stationary wavelet transform*

ABSTRAK

Suatu citra sering mengalami gangguan yang disebabkan oleh *noise* pada saat akuisisi dan transmisi. Resolusi tinggi data penginderaan jauh akan terlihat lebih kasar jika mendapat gangguan oleh *noise*. Wavelet adalah salah satu cara *denoising* menarik yang akan digunakan untuk menyelesaikan masalah ini. Aplikasi utama dari *Stationary Wavelet Transform* (SWT) adalah *denoising*. Prinsipnya adalah rata-rata beberapa sinyal yang di *denoising*. Masing-masing diperoleh dengan menggunakan skema *denoising* biasa, tetapi diterapkan pada koefisien DWT dari *ε-decimated*. *Stationary Wavelet Transform* (SWT) adalah metode untuk membuat *time* dekomposisi wavelet invarian. Hal ini meningkatkan kekuatan sinyal wavelet di *denoising*. Dalam penelitian ini, kami menerapkan metode *preprocess* SWT data penginderaan jauh untuk menghilangkan *noise* dengan menggunakan data satelit the Worldview-1. Data satelit he Worldview-1. Resolusi sensor adalah 0,55 meter *Ground Sample Distance* (GSD) di 20^{o} *off-nadir*. *Area of Interest* (AOI) diambil di Monas, Jakarta dan akuisisi data pada tanggal 13 Maret 2008. Untuk analisis data, Worldview-1 data satelit ditambahkan oleh *noise*. Hasil penelitian ini adalah *noise* dapat dihilangkan dengan metode SWT. Menggunakan indeks kesamaan struktural (SSIM), kualitas gambar *denoised* oleh SWT, Wavelet Transform 2D dan Wavelet Packet 2D masing-masing adalah 0,2666, 0,1912, dan 0,1927. Jadi, SWT memberikan kinerja *denoising* pada data penginderaan jauh yang lebih baik bila dibandingkan dengan Wavelet Packet 2 D dan 2D metode Wavelet.

Kata kunci: *Denoising, Data penginderaan jauh, Stationary wavelet transform*

1 INTRODUCTION

Fourier transform based spectral analysis is the dominant analytical tool for frequency domain analysis. However, Fourier transform cannot provide any information of the spectrum changes with respect to time. Fourier transform assumes the signal is stationary, but not every signal is always stationary. To overcome this deficiency, a modified method-short time Fourier transform allows to represents the signal in both time and frequency domain through time windowing function. The window length determines a constant time and frequency resolution. Thus, a shorter time windowing is used in order to capture the transient behavior of a signal; we sacrifice the frequency resolution. So, an alternative mathematical tool-wavelet transform must be selected to extract the information from a signal. In the meantime, we can improve the signal to noise ratio based on prior knowledge of the signal characteristics.

An image is often corrupted by noise in its acquisition and transmission. Image denoising is used to remove the additive noise while retaining as much as possible the important signal features. In the recent years there has been a fair amount of research on wavelet thresholding and threshold selection for signal denoising (D.L. Donoho, 1993; D.L. Donoho and I. M. Johnstone, 1995; M. Lang, H. Guo and J.E. Odegard, 1995; S. Grace Chang, Bin Yu and M. Vattereli, 2000) because wavelet provides an appropriate basis for separating noisy signal from the image signal. The motivation is that as the wavelet transform is good at energy compaction, the small coefficients are more likely due to noise and large coefficient due to important signal features (Maarten Jansen, 2001).

In this research, we proposed an approach based on wavelet method to provide an enhanced approach for eliminating such noise source and ensure better gene expression. It is well known that wavelet transform is a signal processing technique which can display the signals in both time and frequency domain. Wavelet transform is superior approach to other time-frequency analysis tools because its time scale width of the window can be stretched to match the original signal, especially in image processing studies. This makes it particularly useful for non-stationary signal analysis, such as noises and transients. For a discrete signal, a fast algorithm of discrete wavelet transform (DWT) is multi-resolution analysis, which is a non-redundant decomposition (S. Mallat, 1989). The drawback of non-redundant transform is their non-invariance in time space, i.e., the coefficients of a delayed signal are not a time-shifted version those of the original signal. The stationary wavelet transform (SWT) is to make the wavelet decomposition time invariant (J. C. Pesquet, H. Krim, and H. Carfantan, 1996). This improves the power of wavelet in signal denoising. In this research, we apply the SWT method to preprocess the remote sensing data for removing the random noises. We also compare this method with two other methods, namely Wavelet 2D and Wavelet Packet 2D, to validate the enhanced characteristics of this method.

2 BASIC PRINCIPLES OF SWT

The basic principles of the SWT method are presented in this section. The SWT method is described as follows in summary. At each level, when the high-pass and low-pass filters are applied to the data, the two new sequences have the same length as the original sequences. To do this, the original data is not decimated. However, the filters at each level are modified by padding them out with zeros.

Supposing a function $f(x)$ is projected at each step on the subset $V_j(.....\subset V_3 \subset V_2 \subset V_1 \subset V_0)$. This projection is defined by the scalar product $c_{j,k}$ of $f(x)$ with the scaling function $\phi(x)$ which is dilated and translated

$$c_{j,k} = \left\langle f(x), \phi_{j,k}(x) \right\rangle \quad (2\text{-}1)$$

$$\phi_{j,k}(x) = 2^{-j}\phi(2^{-j}x - k) \quad (2\text{-}2)$$

where $\phi(x)$ is the scaling function, which is a low-pass filter $c_{j,k}$ is also called a *discrete approximation* at the resolution 2^j. If $\varphi(x)$ is the wavelet function, the wavelet coefficients are obtained by

$$\omega_{j,k} = \left\langle f(x), 2^{-j}\varphi(2^{-j}x - k) \right\rangle \quad (2\text{-}3)$$

$\omega_{j,k}$ is called the *discrete detail signal* at the resolution 2^j. As the scaling function $\phi(x)$ has the following property:

$$\frac{1}{2}\phi\left(\frac{x}{2}\right) = \sum_n h(n)\phi(x-n)$$

$c_{j+1,k}$ can be obtain by direct computation from $c_{j,k}$.

$$c_{j+1,k} = \sum_n h(n-2k)c_{j,n} \text{ and}$$

$$\frac{1}{2}\varphi\left(\frac{x}{2}\right) = \sum_n g(n)\phi(x-n) \quad (2\text{-}4)$$

The scalar products $\left\langle f(x), 2^{-(j+1)}\varphi(2^{-(j+1)}x - k) \right\rangle$ are computed with

$$\omega_{j+1,k} = \sum_n g(n-2k)c_{j,n} \quad (2\text{-}5)$$

The equations (2-4) and (2-5) are the multi-resolution algorithm of the traditional DWT. In this transform, a down-sampling algorithm is used to perform the transformation. That is, one point out of two is kept during transformation. Therefore, the whole length of the function $f(x)$ will reduce by half after the transformation. This process continues until the length of the function becomes one.

However, for stationary or redundant transform, instead of down-sampling, an up-sampling procedure is carried out before performing filter convolution at each scale. The distance between samples increasing by a factor of two from scale j to the next $c_{j+1,k}$ is obtained by

$$c_{j+1,k} = \sum_l h(l)c_{j,k+2^j l} \quad (2\text{-}6)$$

And the discrete wavelet coefficients

$$\omega_{j+1,k} = \sum_l g(l)c_{j,k+2^j l} \quad (2\text{-}7)$$

This redundancy of this transform facilities the identification of salient features in a signal, especially for recognizing the noises. For two dimensional image, we separate the variables x and y, the following wavelets are

- Vertical wavelet: $\varphi^1(x,y) = \phi(x)\varphi(y)$
- Horizontal wavelet: $\varphi^2(x,y) = \phi(x)\varphi(y)$
- Diagonal wavelet: $\varphi^3(x,y) = \phi(x)\varphi(y)$

Thus, the detail signal is contained in three sub images

$$\omega^1_{j+1}(k_x,k_y) = \sum_{l_z=-\infty}^{+\infty}\sum_{l_y=-\infty}^{+\infty} g(l_x)h(l_y)c_{j,k+2^j(l_x,l_y)} \quad (2\text{-}8)$$

$$\omega^2_{j+1}(k_x,k_y) = \sum_{l_z=-\infty}^{+\infty}\sum_{l_y=-\infty}^{+\infty} h(l_x)g(l_y)c_{j,k+2^j(l_x,l_y)} \quad (2\text{-}9)$$

$$\omega^3_{j+1}(k_x,k_y) = \sum_{l_z=-\infty}^{+\infty}\sum_{l_y=-\infty}^{+\infty} g(l_x)g(l_y)c_{j,k+2^j(l_x,l_y)} \quad (2\text{-}10)$$

3 ALGORITHM OF SWT FOR IMAGE

The idea to restore the translation invariance, which is a desirable property lost by the classical DWT is to average some slightly different DWT, called ε-decimated DWT, to define the stationary wavelet transform (SWT). This property is useful for several applications such as breakdown point detection.

The main application of the SWT is denoising. The principle is to average several denoised signals. Each of them is obtained using the usual denoising scheme, but applied to the coefficients of a ε-decimated DWT.

The SWT algorithm is very simple and is close to the DWT one. More precisely, for level 1, all the ε-decimated DWT (only two at this level) for a given signal can be obtained by convolving the signal with the appropriate filters as in the DWT case but without down-sampling. Then the approximation and detail coefficients at level 1 are both of size N, which is the signal length.

The algorithm for the stationary wavelet transform for image is visualized in the following figure.

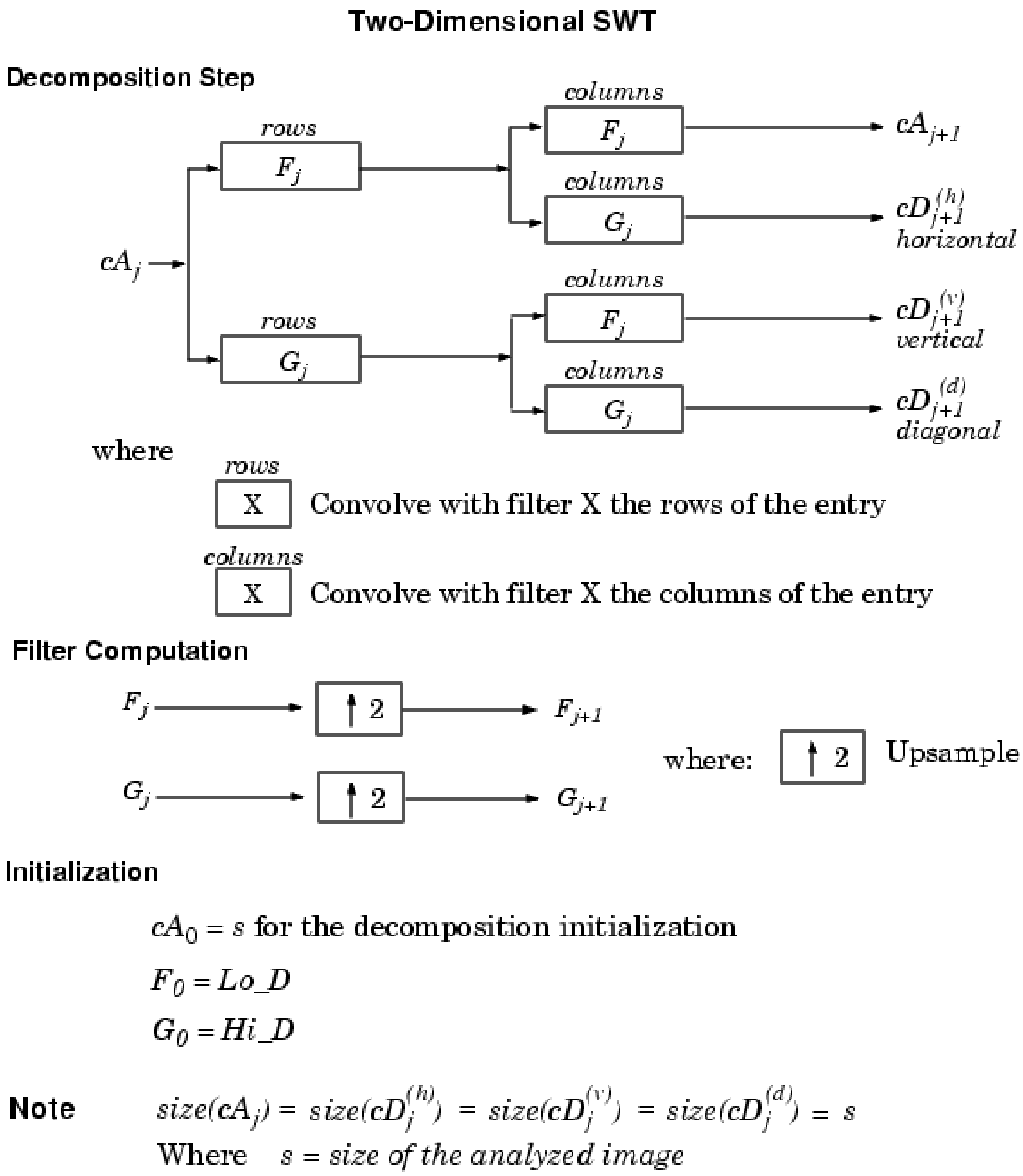


Figure 3-1: Two-Dimensional SWT

4 THE SWT IMPLEMENTATION IN DENOISING OF HIGH RESOLUTION REMOTE SENSING DATA

The Worldview-1 satellite data is used in this research. The acquisition of the data is March 13th, 2008. The Area of Interest (AoI) is Monas, Jakarta. For analysis data, the Worldview-1 satellite data is added by noise. The code in this research is written in M-file using Matlab. The characteristic of Worldview-1 is described below.

The implementation issue of the SWT method for denoising high resolution remote sensing image is described in this section. A comparative analysis of this method with other methods is presented to validate the results obtained. The wavelet denoising is achieved via thresholding. The wavelet thresholding procedure removes noise by thresholding only the wavelet coefficient of the detail sub bands, while keeping the low resolution coefficients unaltered.

There are two thresholding methods frequently used, soft-thresholding and hard-thresholding functions. The soft-thresholding rule is normally chosen over hard-thresholding in denoising. There are several reasons for this. First, soft-thresholding has been shown to achieve near-optimal minimax rate. Second, the optimal soft-thresholding estimator yields a smaller risk thanks the optimal hard-thresholding estimator.

Finally, in practice, the soft-thresholding method yields more visually enhanced images over hard-thresholding because the latter is discontinuous and yields abrupt artifacts in the recovered images, especially when the noise energy is significant. The general soft-thresholding function is defined by

$$\eta_T(x) = sng(x).\max(x - T, 0) \qquad (4\text{-}1)$$

Its function is also illustrated in Figure above and compared with the hard thresholding.

By the soft thresholding, the general denoising procedure involves three steps, including:

- **Decompose**

Choose a wavelet, choose a level N. Compute the wavelet decomposition of the signal S at level N.

- **Threshold detail coefficients**

For each level from 1 to N, select a threshold and apply soft thresholding to the detail coefficients. Soft and hard are two kinds of threshold. Hard thresholding is the simplest method. Soft thresholding has nice mathematical properties. Hard thresholding can be described as the usual process of setting to zero the elements whose absolute values are lower than the threshold. Soft thresholding is an extension of hard thresholding, first setting to zero the elements whose absolute values are lower than the threshold, and then shrinking the nonzero coefficients towards 0.

Table 4-1:CHARACTERISTIC OF WORLDVIEW-1 SATELLITE

Worldwiew-1	Information
Orbit Altitude	496 km
Orbit Inclination	Sun-synchronous
Swath Width	17.6 km at nadir
Resolution	0.55 meters GS Dat 20° off-nadir (note that imagery must be re-sampled to 0.5 meters for non-US Government customers)
Sensor Band	Panchromatic
Geolocation Accuracy	With registration to GCPs in image: 2.0 meters (6.6 feet)

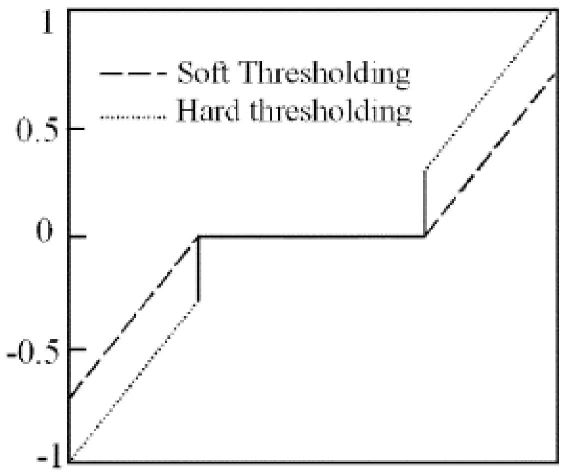


Figure 4-1: Soft and hard thresholding

- **Reconstruct**

Compute wavelet reconstruction using the original approximation coefficients of level N and the modified detail coefficients of levels from 1 to N. The graphical interface tools feature a denoising option with a predefined thresholding strategy. This makes it very easy to remove noise from a signal.

In the three steps, a signal is first decomposed by the wavelet transform. Then the decomposition coefficients are thresholded by the thresholding rule. After the thresholding, a new coefficient is obtained. This new coefficient is then reconstructed to a new signal. This is filtered signal by wavelet transform.

5 RESULTS

First, we do denoising to the data using the SWT method. We will see the results then do analyzing of the results. Then, we compare some wavelet methods in this research.

Through the thresholding, the noise sources in detail images are eliminated at each level. After the denoising, the denoised detail images and the approximation image are reconstructed and the result is shown in Figure 5-2(b). In de-nose stage, we used soft penalize high for threshold method with soft threshold. For the comparison, the original image is also displayed in Figure 5-2(a). Wavelet Transform 2D and Wavelet Packet 2D are also performed following the above procedure using same wavelet, decomposition level, and thresholding function. The results of the denoised image using Wavelet Transform 2D and Wavelet Packet 2D are shown in Figure 5-2(c) and 5-2(d).

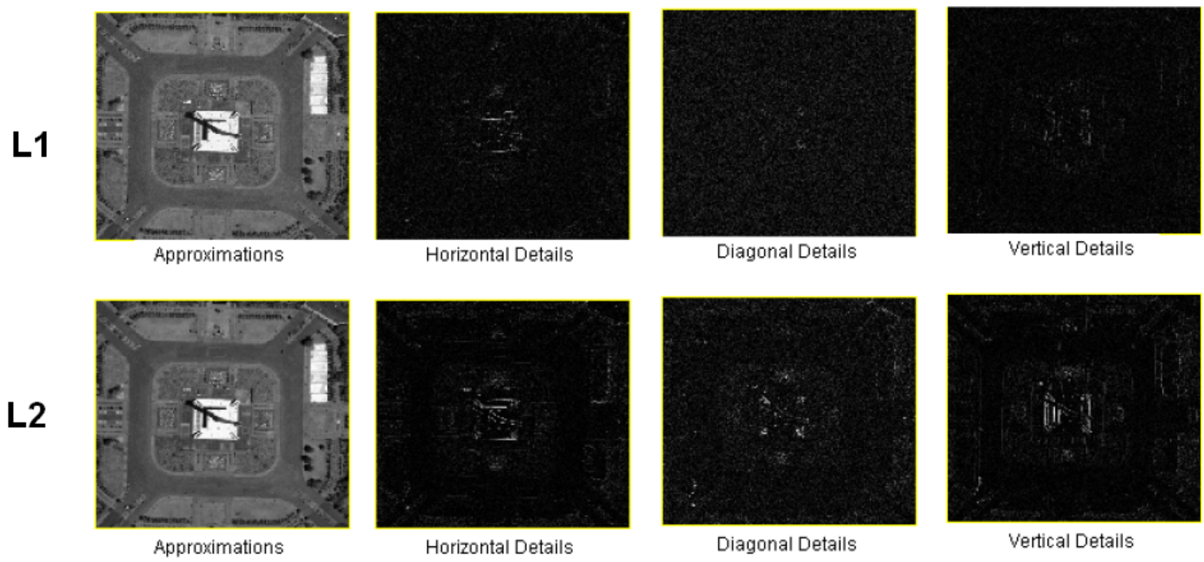
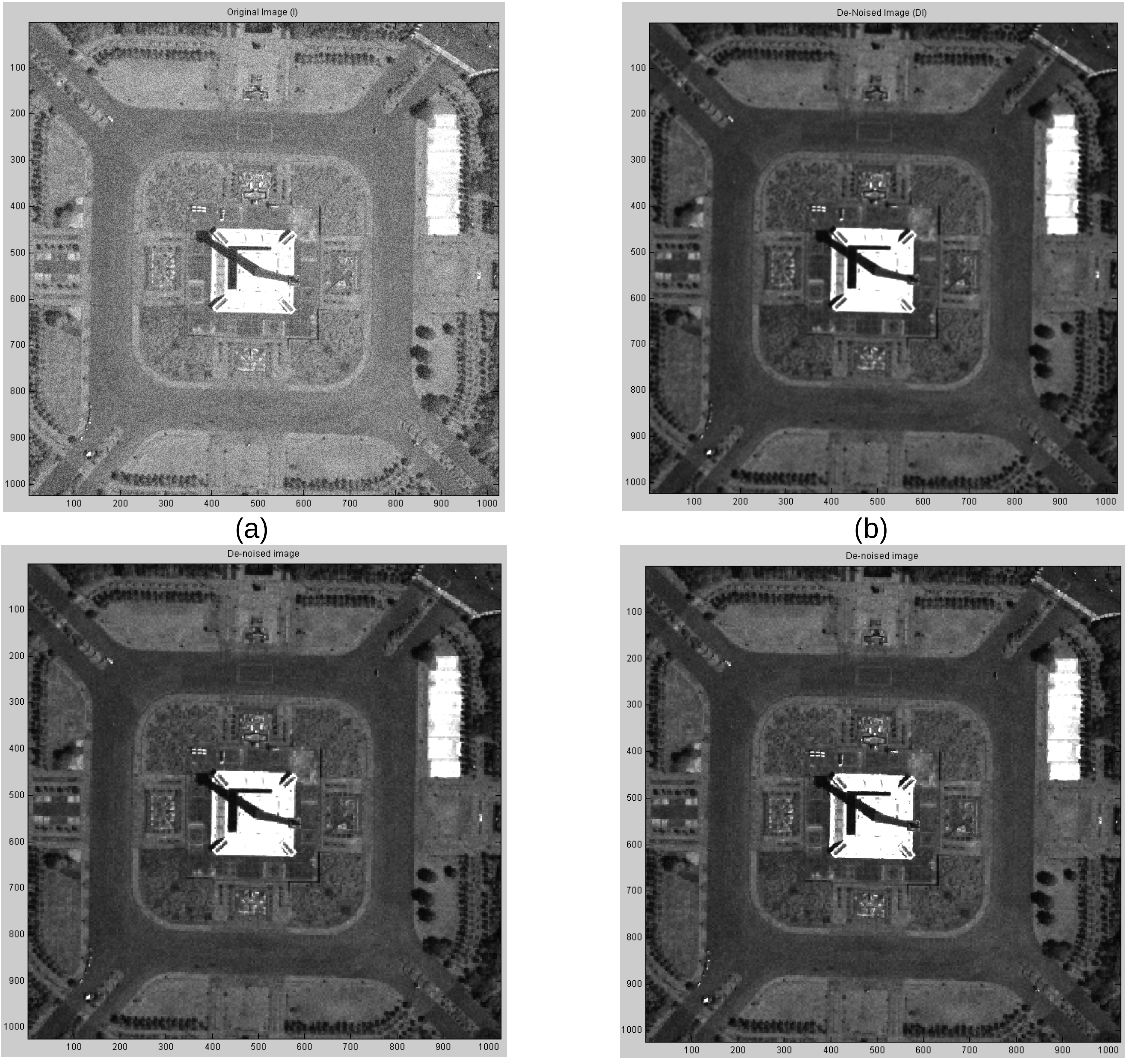


Figure 5-1: Decomposition of SWT at Level 2



(c) (d)

Figure 5-2:(a) Original image after added by noise, (b) The result of denoising used SWT Denoising 2D, (c) The result of denoising used Wavelet Packet 2-D, and (d) The result of denoising used Wavelet 2D

In order to provide a quantitative measure of the resultant images, the universal index proposed in (Z. Wang and A. Bovik, 2002) is presented here. This is defined as

$$Q = \frac{4\sigma_{xy}\,\bar{x}.\bar{y}}{\left(\sigma_x^2 + \sigma_y^2\right)\left[\left(\bar{x}\right)^2 + \left(\bar{y}\right)^2\right]} \quad (5\text{-}1)$$

Where $\left(\bar{x}\right) = \left(\frac{1}{N}\right)\sum_{i=1}^{N} x_i,\ \bar{y} = \left(\frac{1}{N}\right)\sum_{i=1}^{N} y_i$

$$\sigma_x^2 = \frac{1}{N-1}\sum_{i=1}^{N}\left(x_i - \bar{x}\right)^2$$

$$\sigma_y^2 = \frac{1}{N-1}\sum_{i=1}^{N}\left(y_i - \bar{y}\right)^2$$

$$\sigma_{x.y} = \frac{1}{N-1}\sum_{i=1}^{N}\left(x_i - \bar{x}\right)\left(y_i - \bar{y}\right)$$

Using this index, the quality of the denoised images by SWT, Wavelet Transform 2D and Wavelet Packet 2D are 0.2666, 0.1912, and 0.1927, respectively. From Table 5-1, it is clear that the SWT denoising achieves a better image quality than Wavelet Transform 2D and Wavelet Packet 2D if the decomposition level and thresholding rules keep the same.

Table 5-1: THE SRUCTURAL SIMILARITY INDEX (SSIM) OF THE DENOISED IMAGES FROM EACH METHOD

No.	Denoising Method	Structural SIMilarity (SSIM) index
1	Stationary Wavelet Transform (SWT)	0.2666
2	Wavelet Transform 2D	0.1912
3	Wavelet Packet 2D	0.1927

6 CONCLUSION

In this research, the SWT applied to deal with denoising of high resolution remote sensing data analysis is presented. The SWT method can be applied to preprocess the high resolution remote sensing data for removing the random noises. Using structural similarity index, the quality of the denoised images by SWT, Wavelet Transform 2D and Wavelet Packet 2D are 0.2666, 0.1912, and 0.1927, respectively. Thus, the SWT provides a better performance in denoising of high resolution remote sensing data than Wavelet Packet 2 D and Wavelet 2D methods.

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