Journal of Engineering and Applied Sciences 3 (7): 587-590, 2008
ISSN: 1816-949X

SAR Image Denoising Based on Dual-Tree Complex Wavelet Transform

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Abstract: Wavelet techniques can be successfully applied in various signal and image processing methods, namely in image denoising, segmentation, classification and motion estimation. Complex Discrete Wavelet Transform (CDWT) has significant advantages over real wavelet transform for certain signal processing problems. CDWT is a form of discrete wavelet transform, which generates complex coefficients by using a dual tree of wavelet filters to obtain their real and imaginary parts. In this study, we have illustrated the example of the application of complex wavelets for the denoising of SAR images, showing a great effectiveness in removing the noise compared to the classical DWT.

Key words: SAR, denoising, dual tree, complex wavelet transform

INTRODUCTION

Active radar sensing is often a prime source of inventory information about remote and cloud-covered areas of the world. Due to its high penetration power, Synthetic Aperture Radar (SAR) acquires high resolution images in almost all atmospheric conditions. However, the automatic interpretation of SAR images is often extremely difficult due to speckle noise. Appearing as a random granular pattern, speckle seriously degrades the image quality and hampers the interpretation of image content (Ali *et al*., 2007).

All SAR images inherently contain noise, whether due to the hardware or to stray radiation from other sources or to the phenomenon known as speckle. Speckle manifests itself in the image as the apparently random placement of pixels, which are conspicuously bright or dark. It arises from the requirement that a SAR image be formed using coherent radar--radar that can provide a Doppler resolution (Achim *et al*., 2003).

Speckle is caused by the interference between waves reflected from microscopic scattering through the terrain, in the particular case of SAR images. This kind of noise can be modeled in terms of a random walk in the complex plane and, in the case of a large number of scatters within the resolution cell (fully developed speckle), the real and imaginary parts of the resulting complex field are Gaussian random variables.

It has been experimentally verified in several works that over homogeneous areas, the standard deviation of the signal is proportional to its mean. This fact suggests the use of the multiplicative model for the speckle (Mansourpour *et al*., 2006).

It is well known that speckle in SAR images is problematic. Often, it is important to reduce noise before trying to extract scene features. Many filters have been developed to improve image quality by conserving what is thought to be intrinsic scene features and texture. Recently, there has been considerable interest in using the wavelet transform as a powerful tool for recovering SAR images from noisy data. It nevertheless suffers from the following 2 problems (Kingsbury, 2001):

- Lack of shift invariance-this results from the downsampling operation at each level. When the input signal is shifted slightly, the amplitude of the wavelet coefficients varies so much.
- Lack of directional selectivity-as the DWT filters are real and separable the DWT cannot distinguish between the opposing diagonal directions.

These problems hinder the use of wavelets in other areas of image processing. The 1st problem can be avoided if the filter outputs from each level are not downsampled but this increases the computational costs significantly and the resulting undecimated wavelet transform still cannot distinguish between opposing diagonals since, the transform is still separable. To distinguish opposing diagonals with separable filters the filter frequency responses are required to be asymmetric for positive and negative frequencies. A good way to achieve this is to use complex wavelet filters which can be made to suppress negative frequency components.

Complex wavelets have not been used widely in image processing due to the difficulty in designing complex filters which satisfy a perfect reconstruction property. To overcome this, Kingsbury (1998) proposed a dual-tree implementation of the CWT (DT CWT) which uses 2 trees of real filters to generate the real and imaginary parts of the wavelet coefficients separately.

DUAL-TREE COMPLEX WAVELET TRANSFORM

The Dual Tree Complex Wavelet Transform (DTCWT) has been developed to incorporate the good properties of the Fourier transform in the wavelet transform. As the name implies 2 wavelet trees are used, one generating the real part of the complex wavelet co-efficients tree $\Re e$ and the other generating the imaginary part tree $\Im m$ (Selesnick *et al*., 2005).

The dual-tree CWT comprises of 2 parallel wavelet filter bank trees that contain carefully designed filters of different delays that minimize the aliasing effects due to downsampling (Kingsbury, 1998). The dual-tree CDWT of a signal is implemented using 2 critically-sampled DWTs in parallel on the same data. The transform is 2 times expansive because for an N-point signal it gives 2N DWT coefficients. If the filters in the upper and lower DWTs are the same, then no advantage is gained. So, the filters are designed in a specific way such that the subband signals of the upper DWT can be interpreted as the real part of a complex wavelet transform and subband signals of the lower DWT can be interpreted as the imaginary part. When designed in this way, the DT CDWT is nearly shift invariant, in contrast to the classic DWT.

The structure is illustrated in Fig. 1. It should be noted that there are no links between the 2 trees, which makes it easy to implement them in parallel. Also the filters in the 2 trees are different and the filters in the first stage of each tree are different from the filters in all the later stages. Further there is no complex arithmetic involved in any of the trees. The complex coefficients are simply obtained as (Selesnick *et al*., 2005):

$$d_j^C(k) = d_j^{\Re e}(k) + i\ d_j^{\Im m}(k) \quad (1)$$

and the complex wavelet basis functions are given by

$$\psi_{j,k}^C(n) = \psi_{j,k}^{\Re e}(n) + i\ \psi_{j,k}^{\Im m}(n) \quad (2)$$

The inverse DTCWT is calculated as 2 normal inverse wavelet transforms, one corresponding to each tree and the results of each of the 2 inverse transforms are then averaged to give the reconstructed signal. Again, there is no complex arithmetic needed, since, the $d_j^C(k)$ coefficients are split up into $d_j^{\Re e}(k)$ and $d_j^{\Im m}(k)$, before they are used in the corresponding inverse transforms.

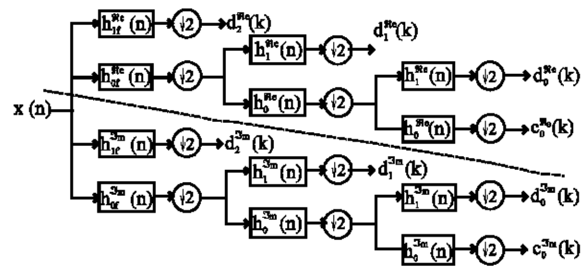

Fig. 1: Iterated filter bank for the dual-tree complex wavelet transform

In one dimension, the so-called dual-tree complex wavelet transform provides a representation of a signal x (n) in terms of complex wavelets, composed of real and imaginary parts which are in turn wavelets themselves. In fact, these real and imaginary parts essentially form a quadrature pair.

To extend the transform to higher-dimensional signals, a filter bank is usually applied separably in all dimensions. In case of real 2D filter banks the 3 highpass filters have orientations of 00, 450 and 900, for the complex filters the 6 subband filters are oriented at ±150, ±450 and ±750.

THE PROPOSED ALGORITHM

Denoising can also be considered as a separation problem. Usually there will be a desired signal, which is corrupted by other signals considered as the noise. In order to retrieve the desired signal, the noise needs to be decreased or preferably completely removed. To do that you need to separate the desired signal from the noise, so that they can be processed differently.

In our method, the logarithmic function is first applied on the image gray levels to convert the multiplicative noise into the case of additive noise. The multilevel dual-tree complex wavelet decomposition is then performed and the soft-thresholding on all highpass subbands is used to reduce the speckle noise.

The dual-tree CDWT uses length-10 filters, the Table 1 of coefficients of the analyzing filters in the first stage (Table 1) and the remaining levels (Table 2) are shown. The reconstruction filters are obtained by simply reversing the alternate coefficients of the analysis filters.

The thresholding method of SAR image using dual-tree CDWT can now be described using the following steps:

- Logarithmically transform the SAR image i.e., compute the intensity SAR image.

Table 1: First level DT CDWT coefficients

Tree $\Re e$		Tree $\Im m$	
h_0^{Re}	h_1^{Re}	h_0^{Im}	h_1^{Im}
0	0	0.01122679	0
-0.08838834	-0.01122679	0.01122679	0
0.08838834	0.01122679	-0.08838834	-0.08838834
0.69587998	0.08838834	0.08838834	-0.08838834
0.69587998	0.08838834	0.69587998	0.69587998
0.08838834	-0.69587998	0.69587998	-0.69587998
-0.08838834	0.69587998	0.08838834	0.08838834
-0.01122679	-0.08838834	-0.08838834	0.08838834
-0.01122679	-0.08838834	0	0.01122679
0	0	0	-0.01122679

Table 2: Remaining level DT CDWT coefficients

Tree $\Re e$		Tree $\Im m$	
h_0^{Re}	h_1^{Re}	h_0^{Im}	h_1^{Im}
0.03516384	0	0	-0.03516384
0	0	0	0
-0.08832942	-0.11430184	-0.11430184	0.08832942
0.23389032	0	0	0.23389032
0.76027237	0.58751830	0.58751830	-0.76027237
0.5875183	-0.76027237	0.76027237	0.58751830
0	0.23389032	0.023389032	0
-0.11430184	0.08832942	-0.08832942	-0.11430184
0	0	0	0
0	-0.03516384	0.03516384	0

- Perform the 2D dual-tree CDWT, to level J. During each level the dual-tree DWT filter bank is applied to the rows first and then to the column of the image as in the basic DWT. This operation results in 6 complex high-pass subbands at each level and 2 complex low-pass subbands on which subsequent stages iterate in contrast to 3 real high-pass and one real low-pass subband for the real 2D transform.
- Compute the threshold value for each sub-band.
- Apply thresholding to the complex high-pass subbands coefficients at each level.
- Perform the inverse dual-tree CDWT and exponential operation in order to acquire the final SAR image with an improvement in its radiometric quality.

EXPERIMENTS RESULTS

In this study, we present simulation result obtained by processing several SAR images using our proposed method. An example is given in Fig. 2. At first, the natural logarithm was taken for each pixel value of the original San Diego SAR image, which is shown in Fig. 2a. Then the logarithmic image was decomposed by a 2-level dual-tree CDWT. A threshold value was estimated and used for the soft-thresholding, which was performed on all the high frequency subimages. The exponential function was applied to the reconstructed logarithmic image in order to get back the conventional pixel values of the filtered image, as shown in Fig. 2b. We also chose to apply it on the Foster City image as shown in Fig. 3.

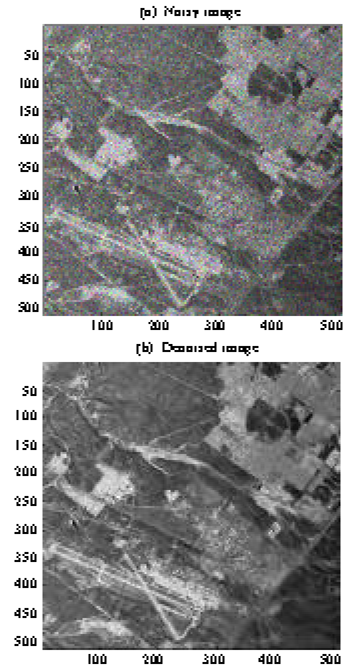

Fig. 2: San Diego SAR Image (a) Noisy Image with MSE = 34.5410, SNR = 11.9801 (b) Denoised Image with MSE= 14.8361, SNR= 19.0084, PSNR= 18.2088

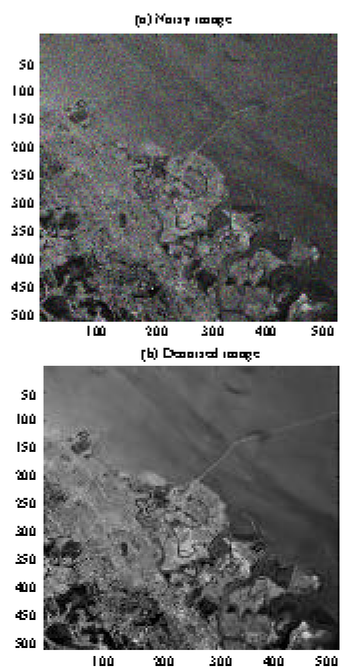

Fig. 3: Foster city image (a) Noisy image with MSE = 32.1916, SNR= 11.8433 (b) Denoised Image with MSE= 11.9778, SNR= 20.1060, PSNR= 18.6735

The quantitative measures for 2D denoising, namely MSE (mean square error) and PSNR (Peak signal to noise ratio) are determined as:

$$MSE=\frac{1}{NM}\sum_{1}^{N}\times\sum_{1}^{M}\left[s(n,m)-y(n,m)\right]^2$$

$$PSNR=10Log_{10}\left(\frac{255}{\sqrt{MSE}}\right)$$

where,

s = The original image.
y = The recovered image from the noisy image x.

CONCLUSION

Complex discrete wavelet transforms (DWTs) provide three significant advantages for signal processing applications: they have reduced shift sensitivity with low redundancy, improved directionality and explicit phase information.

The dual tree complex wavelet transform can provide a good basis for multiresolution image denoising and de-blurring.

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