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Despeckling SAR Images using Complex Wavelet Transform

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Abstract: The presence of multiplicative speckle noises caused by the interference of backscattered coherent waves make the computer aided image processing and interpretation a difficult task. This speckle noise filtering is very much important for improving suitable conditions of post processing of images. This report covers the information regarding the nature of the speckle, its causes and possible methods to reduce them. In this work, speckle removal filters such as Lee filter, Gamma MAP filter, Spatially Adaptive MAP filter and Bivariate Cauchy MAP Estimation are discussed. Each filter is different from the other and removes speckle noise from SAR images using suitable algorithms. Images are filtered by using these filters and their results are formulated in terms of statistical parameter like PSNR, MSE and ENL for the image quality assessment.

Keywords: Complex wavelet transform, Gamma MAP filter, spatially adaptive MAP filter, Speckle Denoising

I. Introduction

The Synthetic Aperture Radar (SAR) image is generated by sending electromagnetic waves from a moving platform, spaceborne or airborne, towards the target surface, and coherently integrating the backscattered energy. It records both the amplitude and phase of the backscattered radiation. SAR systems take advantage of the long-range propagation characteristics of radar signals and the complex information processing capability of modern digital electronics to provide high resolution imagery. The motion of a ground-based moving target such as a car, truck, or military vehicle, causes the radar signature of the moving target to shift outside of the normal ground return of a radar image. One can even extract other target related information such as location, speed, size, and Radar Cross Section (RCS) from these target signatures. The Lee filter [1] uses a least-square approach to estimate the true signal strength of the center cell in the filter window from the measured value in that cell. The local mean brightness of all cells in the window and a gain factor is calculated from the local variance and the noise standard deviation. The filter assumes a Gaussian distribution for the noise values and calculates the local noise standard deviation for each filter window. The Lee filter calculation produces an output value close to the local mean for uniform areas and a value close to the original input value in higher contrast areas. More smoothing occurs in the more uniform areas, while maintaining edges and other fine details. The kaun filter [2] uses a maximum likelihood probability approach to estimate the true signal value for the center cell filter window. The filter assumes that the speckle noise has a negative exponential distribution, and maximizes a probability function involving the center cell value, the local mean and standard deviation. The kaun adaptive noise smoothing filter uses a minimum square error calculation to estimate the value of the true signal for center cell in the filter window from local statistics.

In [3], the filter performs a weighted average of the cell values in the filter window. With the weights for each cell being determined from the local statistics to minimizes the mean square error of the signal estimate. The filter weight of a cell assumes a negative exponential function of the standard deviation, and also decrease with distance from the center cell. The center cells are weighted heavily as the variance in the filter window increases. The filter therefore smoothes more in the homogeneous areas, but provides a signal estimate closer to the observed value in the center cell in heterogeneous areas. The Gamma-MAP [4] logic maximizes the a posteriori probability density function with respect to the original image. It combines both geometrical and statistical properties of the local area. The filtering is controlled by both the variation coefficient and the geometrical ratio operators. The Gamma-MAP logic maximizes the a posteriori probability density function with respect to the original image. MAP filter is analysed and improved by implementing more realistic a priori statistical models for the scene. In this method, the speckle is

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smoothed while fine details are not blurred. For vegetated areas, the Gamma MAP process is the more justified.

II. MATERIALS AND METHODS

A. Filter Design

Complex wavelets have not been widely used due to the difficulty in designing complex filters which satisfy perfect reconstruction property. The Dual Tree Complex Wavelet Transform uses two trees of real filters to generate the real and imaginary coefficients separately. The key to the successful operation of the DTCWT lies in designing the filter delays at each stage, such that the lowpass filter outputs in tree b are sampled at points midway between the sampling points of equivalent filters in tree a. This requires a delay difference between the tree a and b lowpass filters of 1 sample period at level 1, and of ½ sample period at subsequent levels. The figure shows the dual tree of real filters for the Q-shift complex wavelet transform, giving the real and imaginary parts of complex coefficients from tree a and tree b respectively.

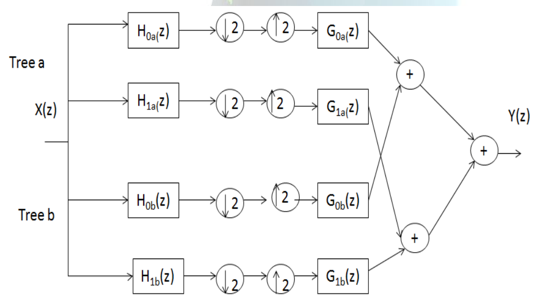


Figure.1. 1-level decomposition and reconstruction of Dual Tree Complex Wavelet Transform

Delay for each filter is indicated in brackets, where q=1/4. The figure shows the 1-level decomposition and reconstruction of complex dual tree. H_{0a}, H_{1a} and H_{0b}, H_{1b} are the analysis filters for tree a and tree b respectively. The reconstruction filters for tree a and b are obtained by reversing alternate coefficients of the analysis filters. The perfect reconstruction condition is given by

$$H(z)H(z^{-1})+H(-z^{-1})H(-z)=2 \qquad (1)$$

To achieve this perfect reconstruction property, H can be derived from a polyphase matrix, factorised into a cascade of orthonormal rotations $R(\theta_i)$, and delays z, such that

$$\begin{bmatrix} H(z) \\ z^{-1}H(-z^{-1}) \end{bmatrix} = R(\theta_i)ZR(\theta_{n-1})Z\dots R(\theta_1)\begin{bmatrix} 1 \\ z^{-1} \end{bmatrix} \qquad (2)$$

where

$$R(\theta_i) = \begin{bmatrix} \cos\theta_i & \sin\theta_i \\ -\sin\theta_i & \cos\theta_i \end{bmatrix}$$

$$Z = \begin{bmatrix} z & 0 \\ 0 & z^{-1} \end{bmatrix}$$

If H(z) is to have at least one zero at z=-1, the n rotations θ_i must sum to $\pi/4$. This leaves only n-1 angles to optimize, instead of 2n coefficients of H(z) and automatically satisfies the perfect reconstruction condition. The different range of filters for odd/ even and qshift Dual Tree Complex Wavelet Transform
are listed below.

A Type - (13,19) tap and (12,16) tap near orthogonal odd/even filter sets.

B Type - (13,19) tap near- orthogonal filters at level 1, 18- tap Q-shift filters at levels ≥2.

C Type - (13,19) tap near orthogonal filters at level 1, 14-tap Q-shift filters at levels ≥2.

D type - (9,7) tap biorthogonal filters at level1, 18-tap Q-shift filters at levels at levels≥2.

E Type - (9,7) tap biorthogonal filters at level 1, 6-tap Q-shift filters at levels≥2.

D Type -(5,3) tap biorthogonal filters at level 1,18-tap Q-shift filters at levels≥2.

B. MAP Estimator

The MAP estimator is natural and optimal choice when the pdf of the signal and noise are known as a priori. The wavelet coefficients of natural images have significant dependencies due to the following properties. 1) If a wavelet coefficient is large/small, the adjacent coefficients are likely to be large/small, and 2) large/small coefficients tend to propagate across the scales. The Cauchy PDF is used to model the the interscale and intrascale dependence of the dual tree complex wavelet transform coefficients. The dispersion parameter of the Cauchy PDF is estimated from the Maximum-likelihood estimator. The Cauchy distribution requires the accurate estimation of dispersion parameter. It calculates the dispersion parameters using the central moments of the noisy observation through mellin transform.

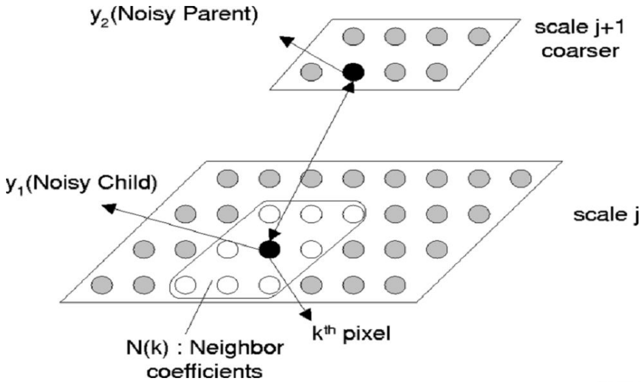


Figure.2. Illustration of neighbourhood coefficient

Figure.2. shows the dependency of wavelet coefficients across different scales. The noisy parent y_2 and noisy child y_1 are considered as the interscale dependency, that is the dependency between the child subband and its parent subband. Here N(k) is defined as all coefficients within a square-shaped window that is centered at the kth coefficient and it assumes a intrascale dependency, that is the dependency of a wavelet coefficient with neighbourhood pixels. The robust estimate of the noise standard deviation is obtained from the finest decomposition scale of the noisy wavelet coefficients. The noise standard deviation is obtained as,

$$\sigma_n = \frac{mad(d(k,l))}{0.6745}, \quad d(k,l) \in \text{HH subband} \qquad (3)$$

where mad signifies the median absolute deviation operator. Furthermore, it is considered that the speckle standard deviation remains the same for every scale j.

The dispersion parameter, is adopted as a simple prior for 41modelling the wavelet coefficients of the log-transformed reflectance image. It is to be noted that the Bayesian estimation in the wavelet domain with the Cauchy prior has been shown to provide an effective reduction of speckle in SAR images.

The dispersion parameter can be calculated by,

$$\Gamma = \sqrt{\left[m - \frac{\sigma_n^2}{4\pi}\right] \frac{\Gamma\left(\frac{3}{2}\right)}{\Gamma\left(\frac{-1}{2}\right)} 8\pi} \qquad (4)$$

where m be the first order central moment of the noisy wavelet coefficients,

$$m = \frac{1}{N} \sum_{i=1}^{N} d((k,l)^i) \qquad (5)$$

$d(k,l)^i$ represents the six directional subbands oriented in different directions. The dispersion parameter is calculated using equation (4). The term $|x_j|$ represents the interscale and intrascale dependency represented by

$$|x_j| = x_j^2 + x_{j+1}^2 \qquad (6)$$

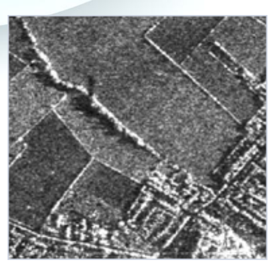
$|x_j|$ represents the dependency among the child x_j and parent x_{j+1} wavelet coefficients. The child subband represents the N- dependency reflectance matrix modelling the intrascale dependency among the dual tree complex wavelet coefficients at level j. It is defined as all coefficients within a square-shaped window of size n. Here n is taken as 3. N is the number of coefficients in the window.

$$x_j = \frac{1}{N} \sum_{i=1}^{N} d((k,l)^i) \qquad (7)$$

The modified noisy wavelet coefficients are reconstructed using inverse Dual tree Complex Wavelet Transform with suitable synthesis filters. Finally, logarithmic transformation can be removed by applying exponential transformation on inverse DTCWT. Thus the despeckled image is obtained using DTCWT and Maximum A Posteriori shrinkage rule.

III. RESULTS AND DISCUSSION

The performance of the proposed work based on despeckling using Dual Tree Complex Wavelet Transform with Maximum A Posteriori by considering inter scale and intrascale dependencies(for three level decomposition) is compared with Lee filter, gamma MAP filter, Spatially Adaptive Wavelet Based MAP(SAMAP) estimation and Bivariate Cauchy Maximum A Posteriori(BCMAP) estimation.This transform outsmarts with maximum A posterior considering inter scale and intra scale dependencies.


(a)


(b)

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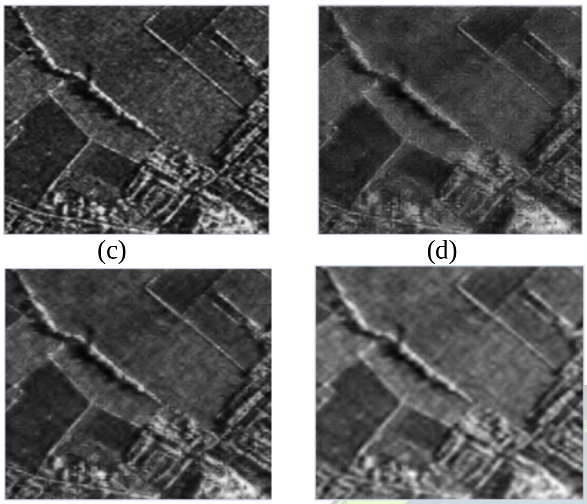

(c) (d) (e) (f)

Figure .3. Results obtained with different despeckling filters for the real time vegetaion image. (a) Original SAR image (b) Lee filter (c) Gamma MAP filter (d) SAMAP filter (e) BCMAP filter (f) Proposed work

IV. Conclusion

The presence of multiplicative speckle noises caused by the interference of backscattered coherent waves make the computer aided image processing and interpretation a difficult task. This speckle noise filtering is very much important for improving suitable conditions of post processing of images. This report covers the information regarding the nature of the speckle, its causes and possible methods to reduce them. In this work, speckle removal filters such as Lee filter, Gamma MAP filter, Spatially Adaptive MAP filter and Bivariate Cauchy MAP Estimation are discussed. Each filter is different from the other and removes speckle noise from SAR images using suitable algorithms. Images are filtered by using these filters and their results are formulated in terms of statistical parameter like PSNR, MSE and ENL for the image quality assessment.

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