WAVELET SPECKLE REDUCTION FOR SAR IMAGERY BASED ON EDGE DETECTION

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ABSTRACT:

This paper introduces a wavelet transform speckle reduction algorithm for Synthetic Aperture Radar (SAR) imagery based on edge detection. Existing speckle algorithm can efficiently reduce the speckle effect but unfortunately also, to some degree, smear edges and blur images. In this paper, the original image is firstly logarithmic transformed and decomposed with multi-scale wavelet transform. For each pyramid level, edge cross points are detected by using the wavelet transform modulus maximum. The multi-scale and edge fusion strategy enables to detect only edge crossings and ignore the local oscillations. Then local wavelet soft-threshold filter is applied to the area that there is no edge crossing point. Repeat it through the image pyramid levels, and the despeckled image is reconstructed. The experiments have been carried out to verify the method proposed in this paper and the results is elaborately analyzed. The results have shown that our method can not only filter the speckle noise efficiently, but well preserve the image detail in the SAR imagery

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1. INTRODUCTION

Synthetic Aperture Radar (SAR) is a kind of high resolution imaging system. It generates imagery which does not depend on time and weather conditions. It has the ability to penetrate through some depth of the soil or vegetation. SAR imagery is used in many fields, such as agriculture, forestry, geology, hydrology and so on (Fetter et al., 1994). Due to the coherent nature of the imaging system, it is inevitably that speckle exists. The presence of speckle reduces the radiometric resolution of the image and the detectability of the image feature. It is usually desirable to reduce the speckle noise prior to image applications, and speckle reduction is becoming a commonly used routine process.

Speckle in SAR imagery is multiplicative noise. As a consequence, a number of filtering algorithms dealing with multiplicative noise have been proposed. The most notable include the Lee (Lee, 1980), Kuan (Kuan, 1987), and Frost (Frost, 1982) filters. These filters, aims at minimizing the mean square error (MSE), are derived from the speckle model, i.e., assuming speckle is a multiplicative noise random variable, with mean of one. By examining the derived formulas, however, the Lee and Kuan filters can be considered as adaptive-mean filters, and the Frost filter is an adaptive-weighted-mean filter. Meanwhile other filters not derived from speckle models, such as the mean filter, median filter, geometric filter (Crimmins, 1986), and wavelet transform filter (Dong et al, 1998) have also been applied for SAR speckle reduction. Compared with the traditional statistical speckle filter, wavelet transform filter have several characteristics: (i) they preserve high frequency information; (ii) the balance between speckle reduction and detail preservation can be adjusted; (iii) they require no knowledge of the standard deviation of speckle.

Existing speckle filtering algorithms can efficiently reduce the speckle level. However, these algorithms also, to some degree, smear edges and blur images. Smoothing uniform areas while preserving and/or enhancing edges is difficult to accomplish. In the frequency domain, the former requires abandonment of high frequency components while the later needs the preservation of high frequency components. Adaptive filters take account of speckle distribution models and compute local statistics within a moving window and assign new values accordingly, leading to better results.

This paper introduces a new algorithm, which incorporates the wavelet transform filter and edge detection altogether, to achieve the goal of smoothing uniform areas and preserving the edges. The experiments have been carried out to verify the method proposed in this paper and the results is elaborately analyzed. Although the derivation of the algorithm is not based on the speckle model, by applying logarithmic transform to the original image, the algorithm is also applicable to the multiplicative speckle filtering.

2. OVERVIEW OF ALGORITHM

A wavelet transform speckle reduction algorithm based on edge detection is proposed in this paper. It implements as follows: with consideration of the particularity of speckle noise, firstly we apply logarithmic operation on SAR imagery to convert multiplicative noise into the additive noise model. And decompose the image into several levels by wavelet transform. In each level, before the filtering, the edge information is acquired. Firstly, the edge information from the higher level is projected to the current level. Then Wavelet Transform Modulus-Maximum Algorithm is applied to detect the candidate edge points in current level. By fusing them, the final edge information in this level is obtained,

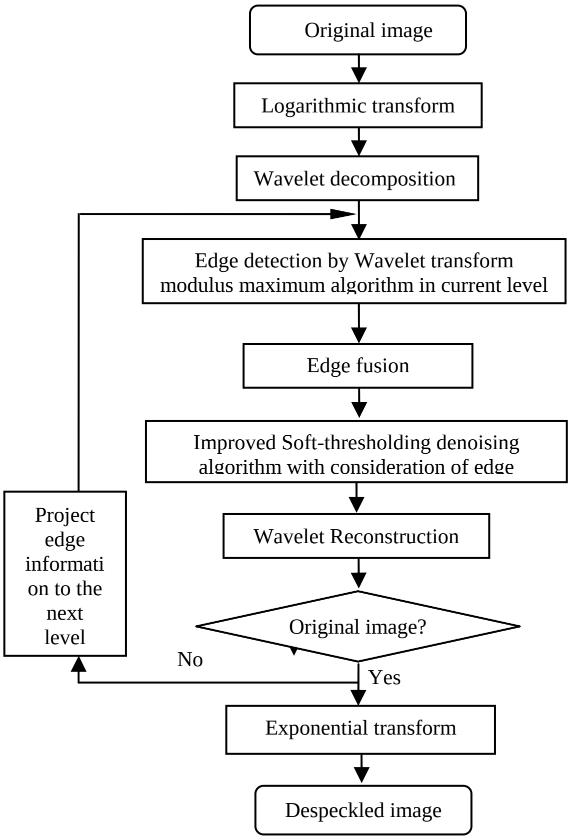


Fig.1 The workflow of proposed algorithm

which is considered as the auxiliary information for the following filtering. The non-linear improved local Wavelet soft-threshold algorithm is applied to filter the high frequency wavelet coefficients respectively with preservation at those pixels marked as edge points. Repeat it through the levels and after reconstruction and exponential transform, the final denoising image is produced.The workflow of proposed algorithm is shown in Fig. 1.

3. IMPLEMENTATION OF ALGORITHM

3.1 Wavelet Transform Modulus-Maximum Algorithm for Edge Detection

Mallat has established the mathematical relationship between wavelet transform and the local singularity of function, and it is expressed with the Lipschitz index. According to the study of Mallat, for edge points, which performances as step signal, its wavelet transform modulus value does not change with the scale; otherwise for white noise, which is regarded as random process of almost everywhere singularity, its modulus value will decrease with the increase of scale (Mallat et al, 1992). Therefore, the Wavelet transform modulus maximum algorithm can efficiently eliminate the noise disturbance and detect the genuine edge points.

At each step in the decomposition procedure, the signal $f_{2^{j+1}}(x,y)$ is decomposed into four independent and spatially oriented channels, producing four sub-images $f_{2^j}(x,y)$, $d^1_{2^j}(x,y)$, $d^2_{2^j}(x,y)$, $d^3_{2^j}(x,y)$, and only a coarse approximation image $f_{2^j}(x,y)$ is decomposed in the next step (Gupta, 2007).

We define the wavelet transform modulus and angle as:

$$\mathrm{M_s}\, f(x,y) = \sqrt{n_1^{\,2} + n_2^{\,2}} \tag{1}$$

$$\mathrm{A_s}\, f(x,y) = \mathrm{artan}(\frac{n_2}{n_1}) + \begin{cases} 0 & (n_1 > 0, n_2 \geq 0) \\ \pi & (n_1 < 0) \\ 2\pi & (n_1 > 0, n_2 < 0) \end{cases} \tag{2}$$

Where n_1 and n_2 are gradient in horizontal and vertical direction respectively. $\mathrm{M_s}\, f(x,y)$ is the modulus of the wavelet transform at the scale s. $\mathrm{A_s}\, f(x,y)$ is the modulus angle, which indicates the direction where the signal has the sharpest variation.

After getting the $\mathrm{M_s}\, f(x,y)$ and $\mathrm{A_s}\, f(x,y)$, the edge point is the one that has the locally maximum modulus along the direction $\mathrm{A_s}\, f(x,y)$. After that, a threshold is applied, the edge point modulus below it will be eliminated, and this can eliminate many false edge points.

3.2 Edge Fusion

To get the robust edge information in each level, it is realized by fusion the edge projected from the higher level and the edge detected by the Wavelet transform modulus-maximum algorithm in current level. Because the edge detection operator responds to the same edge differently in different scales, the edge position varies with the scale. If we just add the edge of two levels together to fuse the edge, this will lead to edge redundancy and cannot suppress the noise. In this paper, the edge fusion consists of two steps: one is edge correlation and the other is edge growth.

We firstly project the edge points of higher level into the current scale level, and for each point a neighborhood is defined, which we call it correlation domain. In the correlation domain, searching the modulus maxima point in current level with similar edge direction, if the edge direction difference is below a certain threshold, we assume the edge points of two levels are correlated, and the projected edge point's information is updated. Through edge correlation, the edge from higher level is transferred to the current level.

Because the edge correlation is only performed in a small correlation domain, this will cause a problem that the edge is incomplete. To overcome it, edge growth is used and implemented as follows. $B_{s,s+1}$ is the results of edge correlation of the level s and s+1, rewritten as $B^0{}_{s,s+1}$. $I_{s,s+1}$ and $A_{s,s+1}$ is the corresponding modulus and angular information, rewritten as $I^0{}_{s,s+1}$, $A^0{}_{s,s+1}$ respectively. M_s is the modulus maxima image of level s. the *k*th iteration results of edge growth is expressed as $B^k{}_{s,s+1}$ $(k \geq 1)$. The correlation between the pixel (i,j) in M_s and pixels of $B^{k-1}{}_{s,s+1}$ is depicted as $D_s^{k-1}(i,j)$. If $D_s^{k-1}(i,j) = 1$, it means the pixel (i,j) in M_s is correlated with the pixels of $B^{k-1}{}_{s,s+1}$, and vice versa. The value of $D_s^{k-1}(i,j)$ is determined as follows:

$$D_s^{k-1}(i,j)=\begin{cases}1 & \exists(m,n)\in B_{s,s+1}^{k-1}, s.t.\left|A_s(i,j)-A_{s,s+1}^{k-1}(m,n)\right|\le\alpha\\ or & \left|A_s(i,j)-A_{s,s+1}^{k-1}(m,n)\right|\ge 360^0-\alpha\\ 0 & else\end{cases} \quad (3)$$

The relationship between $B^{k-1}{}_{s,s+1}$ and $B^k{}_{s,s+1}$ is:

$$B^k{}_{s,s+1}=B1^k{}_{s,s+1}\cup B2^k{}_{s,s+1} \quad (4)$$

Where,

$$B1^k{}_{s,s+1}=\left\{(i,j)\in M_s \mid D_s^{k-1}(i,j)=1\right\}$$

$$B2^k{}_{s,s+1}=\left\{(m,n)\in B_{s,s+1}^{k-1} \mid \forall(i,j)\in M_s, D_s^{k-1(i,j,m,n)}=0\right\}$$

$$I_{s,s+1}^k(i,j)=\begin{cases}I_{s,s+1}^{k-1}(i,j),(i,j)\in B2_{s,s+1}^{k-1}\\ I_s(i,j), else\end{cases}$$

$$A_{s,s+1}^k(i,j)=\begin{cases}A_{s,s+1}^{k-1}(i,j),(i,j)\in B2_{s,s+1}^{k-1}\\ A_s(i,j), else\end{cases}$$

In the equation, $D_s^{k-1(i,j,m,n)}$ represents the correlation between the point (i,j) in M_s and the point (m,n) of $B^{k-1}{}_{s,s+1}$. $D_s^{k-1}(i,j,m,n)=1$ that means the two points are correlated with each other and vice versa.

If (i,j) is the point of $B^0{}_{s,s+1}$, through above iteration, it can be extended to the whole edge. With the step of edge fusion, it can be assumed that we have gotten the robust and accurate edge information in current level, which is then used as auxiliary information for the speckle filtering.

3.3 Improved Local Wavelet Soft-threshold with Edge Preservation

With consideration that for different levels and different wavelet sub-bands, the coefficients of them differ a lot. So it is inappropriate to use a universal threshold to filter the high frequency. The threshold Thr used in this paper for each wavelet sub-bands is derived by itself information, that is:

$$Thr=\sigma\sqrt{\frac{2}{n}\log(n)} \quad (5)$$

Here $\sigma\cong\hat{\sigma}=MAD/0.6745$ is given by Donoho (Donoho, 1995) and MAD is media absolute deviation of wavelet coefficients.

And to preserve the detail in the images, filtering is only applied to the pixels that are not marked by the edge points, that is:

$$\eta_T=\mathrm{sgn}(\omega)(|\omega|-T)=\begin{cases}|\omega|-T & \omega>Thr\\ 0 & |\omega|<Thr\\ |\omega|+T & \omega<-Thr\end{cases} \quad (6)$$

Here ω is the wavelet coefficient of the point not marked as edge and η_T is the filtered wavelet coefficient.

4. PERFORMANCE EVALUATION

In this paper, the performance of our filter was evaluated and compared with several the most widely used self-adaptive filter based on the spatial domain, including the Median, Lee, Frost and Gamma filter.

To quantitative evaluate of a filter, several criteria such as equivalent number of looks, relative standard deviation, edge preservation, texture preservation, are used.

4.1 Image Variance (IV)

$$IV=\frac{1}{N}\sum_i\sum_j(X_{ij}-E(\boldsymbol{X}))^2 \quad (7)$$

Where N is the total number of pixel, $\boldsymbol{X}$ is the matrix of pixel intensity, $E(\boldsymbol{X})$ is mean value.

4.2 Mean Square Error (MSE)

MSE indicates the average difference of the pixels throughout the image. A higher MSE indicates a greater difference between the original and denoising image. This means that there is a significant speckle reduction. Nevertheless, it is necessary to be very careful with the edges. The formula for the MSE calculation is given as:

$$MSE=\frac{1}{N}\sum_i\sum_l(X_{ij}-v_{ij})^2 \quad (8)$$

Where N is the size of the image, X is the denoising image, and v is the original image.

4.3 Relative Standard Deviation (RSD)

The reduction of the RSD is a good measure of the efficiency for a filter when the image mean varies little. The relative standard deviation is given as:

$$RSD=\sqrt{IV}\,/\,E(\boldsymbol{X}) \quad (9)$$

Where $E(\boldsymbol{X})$ is image mean value.

4.4 Equivalent Number of Looks (ENL)

The ENL is used to measure the speckle level in a SAR image over a uniform image region. A large value of ENL reflects better quantitative performance of the filter. The value of *ENL* depends on the size of the tested region. The equivalent number of looks is given as:

$$ENL=\left(E(\boldsymbol{X})/\sqrt{IV}\right)^2 \quad (10)$$

Method	Window size 3×3				Window size 5×5				Window size 7×7			
	IV	*MSE*	*SNR*	*PSNR*	*IV*	*MSE*	*SNR*	*PSNR*	*IV*	*MSE*	*SNR*	*PSNR*
Original image	540.04				540.04				540.04			
Lee	540.04	105.60	17.076	27.076	540.04	170.81	14.932	25.806	540.04	198.36	14.249	25.156
Gamma	540.04	110.20	16.874	27.709	540.04	181.74	14.656	25.536	540.04	212.92	13.945	24.849
Median	540.04	120.34	16.384	27.327	540.04	201.56	14.006	25.087	540.04	237.36	13.228	24.377
Frost	540.04	104.14	17.175	27.955	540.04	162.65	15.188	26.018	540.04	190.25	14.487	25.337

Table 1. Evaluation indices for standard filter

4.5 Peak Signal-to-Noise Ratio (PSNR)

$$PSNR = 10 \cdot \log_{10}\left(\frac{N * 255^2}{\sum_i \sum_j (X_{ij} - v_{ij})^2}\right) \tag{11}$$

PSNR is used for quantitative comparison.

4.6 Signal-to-Noise Ratio (SNR)

$$SNR = 10 \cdot \log_{10}\left(\frac{\sum_i \sum_j X_{ij}{}^2}{\sum_i \sum_j (X_{ij} - v_{ij})^2}\right) \tag{12}$$

4.7 Edge Preservation Index (EPI)

$$EPI = \frac{\sum\left(\left|p_s(i,j) - p_s(i+1,j)\right| + \left|p_s(i,j) - p_s(i,j+1)\right|\right)}{\sum\left(\left|p_o(i,j) - p_o(i+1,j)\right| + \left|p_o(i,j) - p_o(i,j+1)\right|\right)} \tag{13}$$

Here $p_s(i, j)$ is the denoising image, $p_o(i, j)$ is the original image. $p_s(i, j)$ and $p_s(i, j)$ are the pixel intensity of detected edges. The range of *EPI* is [0, 1].

5. EXPERIMENT AND RESULT ANALYSIS

To verify the method proposed in this paper, experiments have been performed. The original image used is the airborne SAR image of one place in China, whose size is 512×512 pixels.

In order to compare the optimal filtering results of each traditional filter, three different window sizes are used, and the obtained value of *IV, MSE, SNR* and *PSNR* is shown in the Table 1.From the results of Table 1, we can easily find that: firstly, the image variance of the denoising image does not vary in all the filters. The increase in window size deteriorates the *SNR* and *PSNR*, which means the worse image quality. Secondly, the optimal filtering results of all traditional filters are obtained when the window size is 3×3. So later, the results of filtering algorithm proposed in this paper is compared with them.

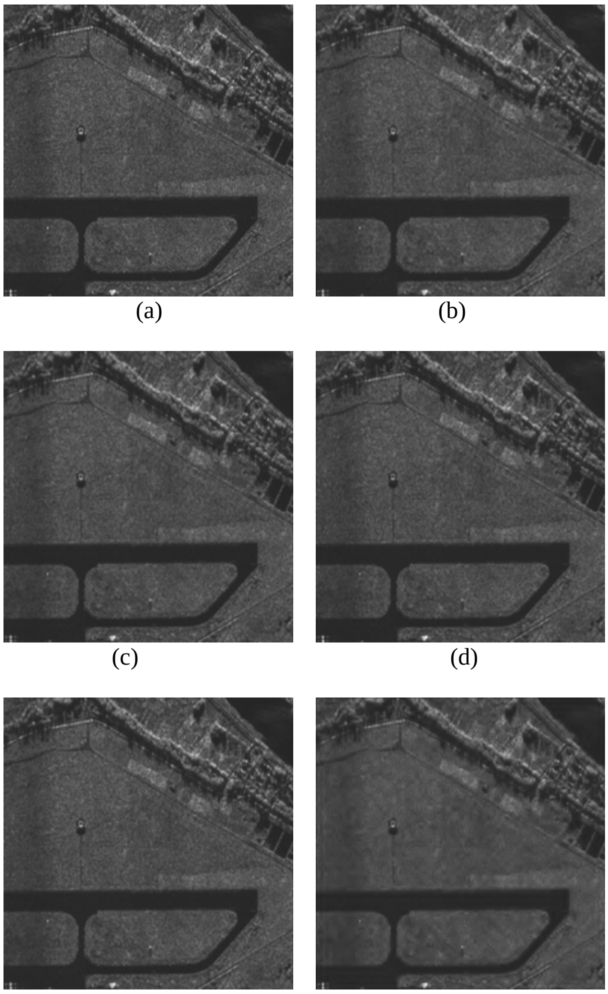
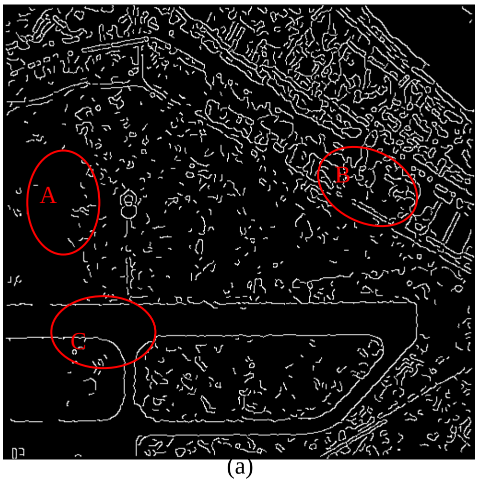


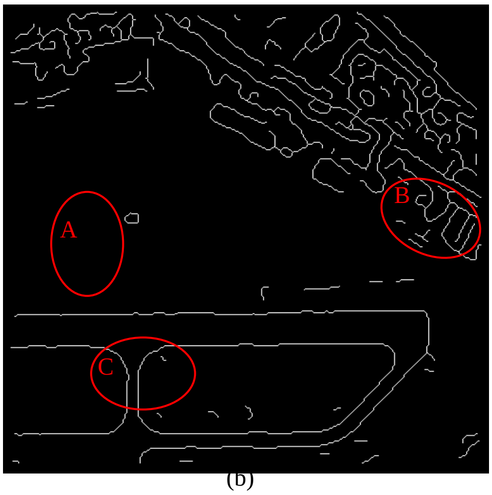
Fig.2 (a) Original imagery of airborne SAR with 512×512 pixels (b)-(f) filtered images by Lee, Gamma, Median, Frost and our filter respectively.

To evaluate the speckle reduction ability as well as the ability of edge preservation, index like mean value, standard variance, *RSV, ENL, PSNR* and *EPI* are calculated for comparison. The result of our filter and other traditional filters is shown in the Table 2. The filtered images by the Lee, Gamma, Median, Frost and our filter are shown in Fig.2 (b)-(f).

The edge detection result of original image and the image filtered by our algorithm is shown in the Fig.3. The pseudo-edges have disappeared (see region marked by A), while the true edge features have been efficiently preserved and the false edges are eliminated (see regions marked by B and C).



(a)



(b)

Fig.3 The edge detection result of original image (a) and the image filtered by our algorithm (b)

Through analyzing the results in Table 2, we can go to the following conclusion:

1) The standard deviation, RSD of our filter is obviously smaller than the traditional filters. The standard deviation, *RSD* of our filter is obviously smaller than the traditional filters. This means the ability of denoising is better than that of them.

2) The *PSNR* value maintains the same level with other filters, which represents the quality of filtered image is similar. But the *ENL*, *EPI* of proposed method is obviously better than the other filters. It means that our filter can not only efficiently reduce the speckle noise but well preserve the detail in the image. The main reason is that in our method before filtering we acquire the robust edge information through wavelet transform modulus maximum algorithm and edge fusion, which is then used as guidance for speckle reduction.

3) Fig.3 is the edge detection results in original and filtered image. It can easily find that by speckle reduction by our method many false edges have been disappeared while the main structures of the objects in the image are retained. It can also express that our method can efficiently reduce the speckle and well preserve the edge in the image.

6. CONCLUSION

Existing speckle filters can effectively reduce speckle effects but unfortunately also lose image details. In this paper, we propose a wavelet transform speckle reduction algorithm for SAR imagery based on edge detection. Through wavelet transform modulus maximum algorithm and edge fusion, this guarantee the edge information obtained is robust. This is then used to preserve the edge while filtering. Experiments have been performed and the filtering results of our filter and other traditional filters have been elaborately analyzed. From the results, we go to the conclusion that our method can not only efficiently reduce the speckle noise but well preserve the edges in the image.

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Images	*Mean*	*Deviation*	*RSD*	*ENL*	*PSNR* (dB)	*EPI*
Original image	70.9431	23.2387	0.3276	9.3196	—	1
Proposal method	69.859	18.366	0.2629	14.469	28.230	0.6149
Lee	70.826	19.210	0.2712	13.638	27.076	0.5502
Gamma	70.709	19.113	0.2703	13.778	27.709	0.5420
Median	69.793	19.041	0.2728	13.882	27.327	0.5736
Frost	71.067	19.573	0.2754	13.183	27.955	0.6082

Table 2. Comparison results of our filter with other traditional filters

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