

A FRAMEWORK OF POLARIMETRIC SAR FILTER BASED ON INDEPENDENCY OF INTENSITY AND POLARIMETRIC INFORMATION

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ABSTRACT:

The usual polarimetric speckle filters optimally combine the polarization channels into a single-channel image or only restore the radiometric information. The phase differences and the polarization channel correlation coefficients are lost. Though simple boxcar filter and extended Lee filter for covariance matrix can be used to preserve polarimetric information without changing the data form, the results are not satisfying enough. In this study, we proposed a new framework for polarimetric SAR filter in which phase and intensity information are filtered independently based on the independence of intensity and polarimetric information. Firstly, polarimetric covariance matrix is divided into the product of a scalar z and a matrix C_0 . The sum of diagonal elements in C_0 is 1 and z denotes the sum of diagonal elements in covariance matrix which is also called total power or SPAN. SPAN z and C_0 include intensity or texture information and polarimetric information respectively which both are relatively independent. Secondly, SPAN image is filtered as singly polarized imagery, for example using Lee filter. To preserve the polarimetric information, the boxcar filter is applied to C_0 , which can be considered as averaging pixels in a moving window using equal weights for each pixel. Also, the filtered C_0 must be normalized by dividing each element by the sum of its diagonal elements. Finally, the filtered result is obtained by multiplying the filtered SPAN and filtered C_0 . Experiment results show that the proposed filter is valid, and polarimetric information is well preserved. And compared with extended Lee filter, the performance of the proposed method is better.

1. INTRODUCTION

Synthetic aperture radar (SAR) is an active radar imaging system working on microwave band and can be operated under all weather condition without daylight. Thus it is now widely used as a tool of earth observation. However, for its coherent imaging mechanism, SAR images are inevitably corrupted by speckle noises (Lee, 2009). Speckle noise makes it more difficult to recognize terrain target and classify land cover than other remote sensing images. It is necessary and useful to suppress speckle noise before application. In recent years, many methods have been developed to reduce speckles in SAR images. For example, Lee, Frost, Kuan filters are effective in speckle suppression (Lee, 1980; Frost, 1982; Kuan, 1987). In order to preserve edges, lines or point targets, many new adaptive methods were proposed, and worked well. However, most of them are only fit for singly polarized real images.

On the other hand with the development of airborne and spaceborne radar, users can obtain fully polarized SAR (PolSAR) images more conveniently. The same as non-fully polarized images, the application of PolSAR data is also restricted for its speckle. There are several speckle filters which are often applied to PolSAR images. Polarimetric whitening filter proposed by Novak is often used to detect targets (Novak, 1990). And Multi-texture polarimetric whitening filter was developed by G.Q. Liu (Liu, 1995). The disadvantage of these methods is that the data form is changed to single- or multi-real channels. So the phase difference disappears, and polarimetric information is not well preserved. Another filter frequently used is optimal weighting filter developed by J.S. Lee. It requires that

the input data is real by which it is impossible to preserve phase difference. In order to keep the data form, assembling averaging and many improved assembling averaging method such as sigma filter are applied. Lee filter is also extended to polarimetric images. Other preferable filter is intensity driven adaptive neighbourhood filter (Vasile, 2006). Using these methods, speckle is well suppressed when data form is kept. Nevertheless the result is unstable in heterogeneous areas; especially there are some point targets in the neighbourhood. The filtered covariance matrix of centre pixel is often predominated by these point targets. So is the polarimetric information. That is the problem which exists in most filters developed before.

In this study, we assume that all information in PolSAR images is made of intensity and polarimetric information or phase difference expressed by a covariance matrix of which the sum of diagonal elements is 1. Both are relatively independent. The filtering is based on this assumption model. The intensity image and polarimetric information are filtered respectively. Finally, combining the filtered two parts, we obtain the speckle suppressed image with the same data form as the input image.

2. FRAMEWORK OF POLARIMETRIC FILTER

2.1 Model of PolSAR data

A fully polarized synthetic aperture radar measures both amplitude and phase of the four polarized backscattered signal

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HH, HV, VH VV, producing a 2x2 complex matrix or Sinclair matrix:

$$S = \begin{bmatrix} S_{HH} & S_{HV} \\ S_{VH} & S_{VV} \end{bmatrix} \quad (1)$$

where $S_{HH}, S_{HV}, S_{VH}, S_{VV}$ = complex backscattering coefficients of HH, HV, VH, VV polarization channel respectively.

In the reciprocal backscattering case, $S_{HV} = S_{VH}$. The Sinclair matrix can be transformed to a three dimensional vector:

$$y = [S_{HH} \quad S_{HV} \quad S_{VV}]^T \quad (2)$$

where T = the transpose of a vector.

In order to describe the polarimetric information more explicitly, the polarimetric data is usually converted to a 3x3 covariance matrix from polarimetric vector (Lee, 2009):

$$C = yy^H \quad (3)$$

where C = covariance matrix
Y = backscattering vector
H = the conjugate transpose of a complex vector.

The PolSAR data expressed by (1) contains two kinds of information. One is the information of the three intensities which is the diagonal elements of covariance matrix in (3), and the other one is the information of the three phase differences between the three polarized channels which are included in the non-diagonal elements of the covariance matrix. Actually there are two independent differences because:

$$\arg(C_{12}) + \arg(C_{23}) = \arg(C_{13}) \quad (4)$$

where $\arg(\cdot)$ = argument of a complex number
 C_{12} = complex covariance of S_{HH} and S_{HV}
 C_{23} = complex covariance of S_{HV} and S_{VV}
 C_{13} = complex covariance of S_{HH} and S_{VV} .

We consider that the PolSAR imagery in the form of covariance matrix is made of two parts:

$$C = zC_0 \quad (5)$$

where z = total power of backscattering coefficients (SPAN)
 C_0 = normalized covariance matrix (or polarimetric information part, or phase differences part)
C = observation of covariance matrix.

The first part z is a scalar, denoting the intensity or the total power and is the sum of the diagonal elements of C as $z = C_{11} + C_{22} + C_{33}$.

The total power z also called SPAN includes the information of texture. The other part C_0 is a matrix denoting the phase differences between the three polarimetric channels, including polarimetric information. The sum of diagonal elements in C_0 is 1. When each element of covariance matrix is divided by z, C_0 is obtained.

As depicted above, backscattering from a target is made of two parts, the intensity and polarimetric information. And because different targets may have different intensity, and the polarimetric information may be different, that is to say, the two aspects have no definite correlations, and both can be considered independent from each other. The filter proposed in this paper is based on this product model. The filtered covariance matrix is also made up by two part, SPAN and normalized covariance matrix.

2.2 Filter Framework Based on Independency of Intensity and Polarimetric Information

In unfiltered PolSAR images, not only intensity is degraded by speckle, but also the polarimetric information is degraded by speckle. In section 2.1, we know that intensity and polarimetric information or phase differences in PolSAR data are independent. Therefore, the two parts could be filtered separately.

2.2.1 Filter for intensity image. For intensity image, the distribution was discussed in many articles in detail, and many filters are developed based on the probability density function of clutters. Lee, Kuan, gamma and sigma filter are very useful. In order to preserve details, for example lines, edges and point targets, refined filters were developed, and the performance was improved. In a word, all filters which could be applied to singly polarized SAR intensity images could also be used for the filtering of the intensity part.

In this study, J.S. Lee filter was selected for the filtering of intensity part for its good adaptability. Lee filter is based on Statistic in a moving window:

$$\hat{x} = (1-b)\bar{Z} + bZ \quad (6)$$

Where \hat{x} = the estimation of true value for backscattering intensity
Z = the observation in window centre
 \bar{Z} = the mean of the intensity in the moving window.

Coefficient b in (6) can be calculated (Lee, 1980):

$$b = \frac{1 - \sigma_v^2 \bar{Z}^2 / \text{var}(Z)}{1 + \sigma_v^2} \quad (7)$$

where $\text{var}(Z)$ = the variation of Z in the moving window
 σ_v^2 = the variation of ideal speckle based on multiplicative model. For single look complex

(SLC) SAR images, $\sigma_v^2 = 1$.

2.2.2 Filter for polarimetric information. Polarimetric information is mainly included by the covariance matrix. There are two primary factors. One is phase difference between different polarized channels. The other one is the modulus of complex covariance of different polarized channels. Actually, both are also represented in the normalized covariance matrix C_0 of which the SPAN is considered as 1.

To make the description above more understandable, SPAN could be considered as a weight. In C_0 , the weight is set to 1 while in original covariance matrix the weight is the total power, SPAN. Apparently, It is more reasonable to assuming that the weight of each pixel for polarimetric information are equal to 1 than equal to SPAN if polarimetric information is primarily concerned. Therefore, Normalized covariance matrix is preferable comparing with original covariance matrix when polarimetric information preservation is considered as one of the most indexes of performance for PolSAR filter.

In homogeneous areas, each matrix for a resolution unit represents polarimetric information with equal weight. So the boxcar filter has top-priority. However, actually for SAR images, pixels in the neighbourhood are not always homogeneous. If we use origin covariance directly again as the polarimetric boxcar filter and extended J.S. Lee filter, the intensity plays a real role as weight actually, and the mechanism of strong targets such as points is magnified. Therefore polarimetric information is confused, and errors may be brought to the results. That is why the improvement was limited although many adaptive techniques were introduced.

But when the representation of polarimetric information, covariance matrix is normalized and averaged with equal weight, the influence of pixels with mechanisms different from centre pixel is restricted. In other words, polarimetric mechanisms for different pixels are assigned the same weight in the boxcar filter of normalized polarimetric covariance matrix.

Thus, in homogeneous or heterogeneous areas, the normalized boxcar filter for polarimetric information in the data form of covariance is better. In this step, we only need to apply boxcar filter to the normalized covariance matrix. In addition, after boxcar filtering, the filtered covariance matrix \hat{C}_0 should also be normalized divided by the sum of its diagonal elements:

$$\hat{C}_0 = \bar{C}_0 / (\bar{C}_{011} + \bar{C}_{022} + \bar{C}_{033}) \quad (8)$$

where \bar{C}_0 = the mean of C_0 in the moving window
 \hat{C}_0 = estimation of normalized covariance matrix
 \bar{C}_{0ii} = the diagonal elements of C_0 at Colum i and Row i .

So that, each pixel of filtered normalized covariance matrix has the same intensity, or the same weight as the input normalized covariance matrix.

2.2.3 Combination for the filtered two parts. According to the model represented in section 2.1, multiplying the filtered

intensity \hat{x} by filtered normalized covariance matrix \hat{C}_0 , we get the final filtering result for PolSAR images:

$$\hat{C} = \hat{x}\hat{C}_0 \quad (9)$$

where \hat{C} = estimation of polarimetric covariance matrix
 \hat{x} = estimation of SPAN (or intensity)
 \hat{C}_0 = estimation of normalized covariance matrix (or polarimetric information).

2.3 General Steps for Filter based on Intensity and Polarimetric Information

Generally speaking, there are three primary steps in the framework for filter based on the independence of the intensity and polarimetric information which are described in Figure 1. Now we discuss the sequences of the general three steps as follows:

- 1) Calculate intensity and normalized covariance matrix from Sinclair matrix according to (5), as the top of Figure 1.
- 2) Apply filters to intensity image and normalized covariance matrix respectively according to (6) and (8). For Intensity image, filters such as Lee, Kuan, sigma and gamma are compatible. For Normalized covariance matrix, in order to preserve polarimetric information, the mean filter with equal weight is the best. This step is described in the middle of Figure 1.
- 3) Combine the two filtered results obtained in step 2, and then get the final filtered PolSAR images as (9) and the bottom of Figure 1 which also contains the texture and polarimetric information with the same data form as the input data.

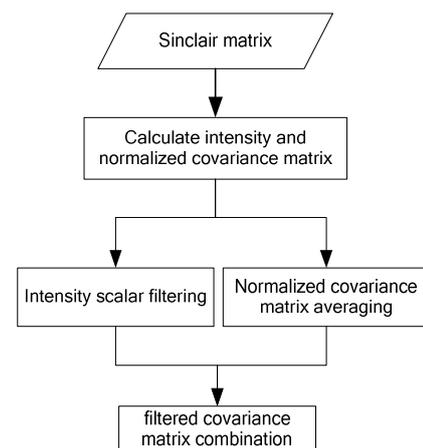


Figure 1. The follow chart of filtering based on intensity and phase difference model

2.4 Some Improvement for the Filter in the Framework

Although there is some disadvantages for polarimetric information preservation in the filter proposed above. Some improvements are possible and necessary.

In order to preserve textures or other details, techniques which are used in singly polarized intensity images to preserve textures or edges can also be extended to this filter framework. One method is changing the pixel set in neighbourhood or the moving window shape adaptively in which statistics are calculated. Taking refined Lee filter for example, firstly we need to determine which one of the eight non-square sub-windows the centre pixel belongs to, and then we calculate the statistics in the non-square sub-windows, finally we obtain the filtered covariance matrix as (9).

In addition, point target preservation is another index for the performance of a filter. A const false alarming rate (CFAR) method can be applied to the SPAN image to detect point targets firstly. Then in the process of filtering, the covariance matrix of point target is remained the same as that of the input. At the same time, point target is excluded from the neighbourhood where the local mean and variance is calculated in both intensity and normalized covariance matrix.

SPAN is usually assumed to have a gamma distribution, the CFAR used in this paper is based on this distribution. The threshold T is obtained by solving the equation (Gigly, 2002):

$$p_{fa} = 1 - \int_0^T \frac{1}{\Gamma(n)} \left(\frac{n}{\sigma}\right)^n t^{n-1} \exp\left(-\frac{nt}{\sigma}\right) dt \quad (10)$$

where p_{fa} = the false alarming rate,
 n = the number of looks, for SLC data $n=1$
 σ = normalized standard derivation in a moving window, $\sigma = \sqrt{\text{var}(Z)/E(Z)}$.

For a const false alarming rate, for example $p_{fa} = 0.005$, the centre pixel of which the intensity is larger than T is determined as point targets.

3. EXPERIMENTAL RESULTS

3.1 Data Description

The single look C band Radarsat 2 PolSAR image used in this study was acquired in 2007 over some suburb. The image is in the form of Sinclair matrix with the size of 512 by 512 pixels with a spatial resolution of about 10 meters.

For PolSAR imagery, Pauli decomposition is usually used to produce a colour image because this decomposition can be used to visualize PolSAR data based on the three primary scattering mechanisms (Lee, 2009). Pauli decomposition can be described as:

$$k = [S_{HH} + S_{VV} \quad S_{HH} - S_{VV} \quad 2S_{HV}] \quad (11)$$

where k = coherent polarimetric vector

$S_{HH}, S_{HV}, S_{VH}, S_{VV}$ = complex backscattering coefficients of the four polarized channel respectively.

Using the three elements of the polarimetric vector as red, green and blue channel, for example, Red = $|S_{HH} + S_{VV}|$, Green = $|S_{HH} - S_{VV}|$, Blue = $|S_{HV}|$ where $|\cdot|$ denotes calculating the modulus of a complex, we can obtain a colour image based on Pauli decomposition.

Figure 2 shows the original PolSAR image based on Pauli decomposition.



Figure 2. Original PolSAR image with Red = $|S_{HH} + S_{VV}|$, Green = $|S_{HH} - S_{VV}|$, Blue = $|S_{HV}|$

3.2 Experimental Results and Analysis

In the experiment, we use a 11×11 window with the const false alarming rate 0.005 to detect point target, and then apply the proposed method with a 7×7 window. Finally, filtered covariance matrix is obtained.

Covariance matrix can be transformed to coherent matrix of which the diagonal elements are the intensities of elements in polarimetric vector k . Therefore we also can obtain a colour image using Pauli decomposition. Figure 3 shows the filtered PolSAR image with Pauli decomposition colour composition where speckle is reduced greatly, and colour remains very similar to that in figure2.

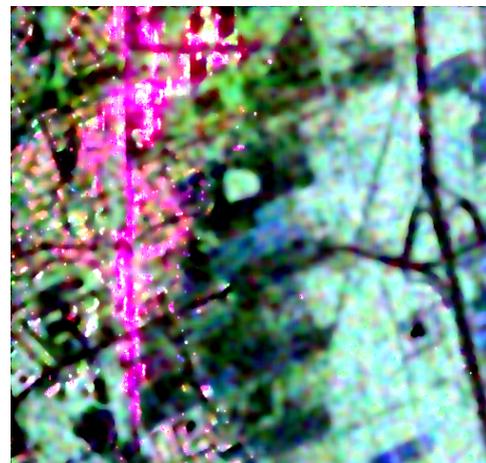


Figure 3. Filtered image using filtered proposed in this paper with Red = $|S_{HH} + S_{VV}|$, Green = $|S_{HH} - S_{VV}|$, Blue = $|S_{HV}|$

In order to test the validity of the proposed method, J.S. Lee filter is compared. Table 4 shows the mean, variance and the equivalent number of looks (ENL) for original, J.S. Lee filter and proposed filter in this paper. Both methods have similar performance for mean preservation and speckle reduction.

filter	original	J.S. Lee	proposed
mean	0.4928	0.4564	0.4876
variance	0.2880	0.0203	0.0262
ENL	0.84	10.27	9.06

Table 4. Mean and variance for intensity

The extent of preservation for polarimetric information is another important index for polarimetric filter. The ratio of different polarized channel is one of the most important polarimetric information indexes. In this study, in order to determine whether the proportion of each polarized channel is changed we use the percentage of each channel in SPAN to substitute the channel ratio. Table 5 shows the comparisons between original image and the two images filtered using J.S. Lee filter and the proposed filter. It shows that both methods can preserve the ratio between different polarizations. But the ratio for the proposed filter is closer to original ratio than that for J.S. Lee filter. It is demonstrated that polarimetric information is better preserved.

Ratio	E(HH/SPAN)	2×E(HV/SPAN)	VV/SPAN
original	30.86%	37.17%	31.97%
J.S. Lee	31.97%	37.59%	30.44%
proposed	31.23%	37.22%	31.54%

Table 5. Percentage for each channel in SPAN

4. CONCLUSIONS

A new filter framework for PolSAR imagery has been proposed in this paper. This algorithm is based on the multiplicative model of SPAN and polarimetric information for PolSAR data. SPAN and normalized covariance matrix are filtered respectively, and finally is combined to be the restored covariance matrix. Experimental results show that this method has the performance of speckle reduction similar to extended J.S. Lee filter and polarimetric information preservation better than extended J.S. Lee. Nevertheless, more studies to preserve edges, details in PolSAR filters propose in this paper are necessary.

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