A FILTERING ALGORITHM BASED ON POLARIZATION DECOMPOSITION FOR BETTER PRESERVING POLSAR IMAGE SCATTERING FEATURES

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ABSTRACT

The polarimetric synthetic aperture radar (PolSAR) image filtering is an essential step before the quantitative inversion. However, the existing filtering algorithms often change the scattering features of the original PolSAR images. This leads to a performance decrease for the subsequent quantitative inversion. In order to combat such drawback, we adopted a novel filtering algorithm preceding the quantitative inversion. This algorithm adopted the idea of “classify first, filter later”. By utilizing the hybrid four-component polarization decomposition (HPD) method to pre-classify the pixels, and implementing non-local means lee (NLM-Lee) filtering only between the same ground object points, the scattering features are well-protected. The experiment results show that the proposed algorithm can not only effectively reduce the speckle and preserve the structural features of the image, but is far superior in preserving the scattering features of the images. Hence, when the PolSAR image filtering is carried out by the proposed algorithm, the performance of the quantitative inversion will be improved.

Index Terms—polarimetric synthetic aperture radar (PolSAR), filter, non-local means (NLM), polarization decomposition

1. INTRODUCTION

Quantitative inversion of polarimetric synthetic aperture radar (PolSAR) images is of great significance for crop yield estimation [1] and soil parameter extraction[2]. Owing to the coherent superposition of all basic scatterer responses in the same resolution unit, speckle noise appears in SAR images, which covers the original information of the image. In order to obtain the real information of the PolSAR image, speckle filtering becomes a necessary step for the preprocessing of the PolSAR image. However, the existing filtering algorithms cannot protect the scattering features of the image well, and the accuracy of subsequent quantitative inversion will decrease [2].

From previous research, we conclude that PolSAR image filtering should strive to keep the image structure and scattering characteristics unchanged as far as possible while reducing speckles. In order to ensure the accuracy of quantitative inversion, the ability of the filtering algorithm to preserve the scattering features becomes the focus of this paper. First, the hybrid four-component polarization decomposition (HPD) polarization decomposition is employed to obtain the scattering eigenvector of each pixel. Then, we need to find the pixels which have the same scattering mechanism as the center Pixel i . Finally, non-local means lee (NLM-Lee) algorithm is applied between these pixels. The NLM-Lee filter as explained in Section 2.3 combines the non local means algorithm and the Lee filter algorithm. In the experiment, Radarsat-2 PolSAR data is selected to verify the algorithm's preservation of scattering features. Finally, it is found that the algorithm can maintain scattering features better than other algorithms. Hence, when using this algorithm for quantitative inversion, the accuracy of the result will be improved.

2. METHODOLOGY

2.1 HPD decomposition algorithm

Literature [3]proposed an improved hybrid four-component polarization decomposition (HPD) speckle suppression algorithm by combining Yamaguchi decomposition[4][11] with Pauli decomposition. In order to avoid classification errors caused by Freeman-Durden decomposition hypothesis, the algorithm first conducts de-orientation processing on the original coherence matrix of the polSAR image. Formulae (1)-(3) shows the process of de-orientation, where T and T^0 represent the original and de-orientated polarization covariance matrix respectively, and θ represents the angle.

$$T = \begin{bmatrix} T_{11} & T_{12} & T_{13} \\ T_{21} & T_{22} & T_{23} \\ T_{31} & T_{32} & T_{33} \end{bmatrix} \tag{1}$$

$$Q=\begin{bmatrix}1 & 0 & 0\\ 0 & \cos 2\theta & \sin 2\theta\\ 0 & -\sin 2\theta & \cos 2\theta\end{bmatrix} \tag{2}$$

According to literature[5], we can obtain the HPD polarization decomposition vector from the matrix T^0, and the expression of vector is shown in formula (4). The P_s, P_d, P_v and P_c denote surface scattering power, double-bounce scattering power, volume scattering power and helix scattering power separately[4]. P_v and P_c is calculated by Formulae (5)-(7).

$$T^0=QTQ^T=\begin{bmatrix}T_{11}^0 & T_{12}^0 & T_{13}^0\\ T_{21}^0 & T_{22}^0 & T_{23}^0\\ T_{31}^0 & T_{32}^0 & T_{33}^0\end{bmatrix} \tag{3}$$

$$V_{HPD}=[P_s,P_d,P_v+P_c]^T=[T_{11}^0,T_{22}^0,P_v+P_C]^T \tag{4}$$

When $T_{33}^0<T_{11}^0+T_{22}^0+2\operatorname{Re}(T_{12}^0)$, there is

$$P_v=\begin{cases}\frac{15}{4}\left(T_{33}^0-\left|\operatorname{Im}(T_{23}^0)\right|\right) & |r|>2\\ 4(T_{33}^0-\left|\operatorname{Im}(T_{23}^0)\right|) & |r|\le 2\end{cases} \tag{5}$$

$$r=10\times\log\left(\frac{T_{11}^0+T_{22}^0-2\operatorname{Re}(T_{12}^0)}{T_{11}^0+T_{22}^0+2\operatorname{Re}(T_{12}^0)}\right) \tag{6}$$

Where $\operatorname{Re}(.)$ and $\operatorname{Im}(.)$ represent the real and imaginary parts of the complex number respectively.

When $T_{33}^0\ge T_{11}^0+T_{22}^0+2\operatorname{Re}(T_{12}^0)$ or $P_v<0$, there is:

$$\begin{cases}P_v=4T_{33}^0\\ P_c=0\end{cases} \tag{7}$$

2.2 The polarization similarity

The algorithm in our paper assumes that if the polarization decomposition vectors of two pixels are the same, then the two pixels belong to the same ground object. We can learn from Fig. 1 that if the directions of the vectors (V_{HPD-i} and V_{HPD-k}) or the lengths of vectors (V_{HPD-i} and V_{HPD-j}) are unequal, then the polarization decomposition vectors are not equal. Therefore, the pixels corresponding to the vectors do not belong to the same ground object.

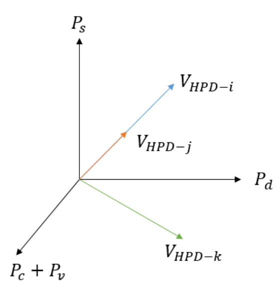

Fig. 1 The vector space constituted by the V_{HPD} polarization decomposition vectors of each pixel

In order to determine the polarization similarity between vectors, we first assume V_{HPD-i} and V_{HPD-j} represent the HPD decomposition vectors of pixel i and j respectively, and then we define the similarity degree of direction and module length of the two vectors as S_S and S_p, respectively[6]. Then, judgment conditions of polarization similarity between two pixels is defined as formula (10). Theoretically, if V_{HPD-i} and V_{HPD-j} are equal, then $S_{psp}(i,j)=1$. However, in fact, two exactly equal HPD decomposition vectors do not exist, so the polarization similarity threshold Th_{psp} is given in Literature [5].

When $S_{psp}\ge Th_{psp}$, it can be considered that two pixels have the same polarization characteristics, that is, they belong to the same object.

$$S_s(i,j)=\frac{\left|V_{HPD-i}^T\cdot V_{HPD-j}^T\right|}{\left\|V_{HPD-i}\right\|\cdot\left\|V_{HPD-j}\right\|} \tag{8}$$

$$S_p(i,j)=\min\left(\frac{P_i}{P_j},\frac{P_j}{P_i}\right) \tag{9}$$

$$S_{psp}(i,j)=S_s(i,j)\cdot S_p(i,j) \tag{10}$$

$$\begin{aligned}Th_{psp}=&\left(\left(0.1530e^{-0.1052L}+0.1193\right)\alpha-\left(0.0633e^{-0.1189L}+0.0273\right)\right)e^{-p}\\&+\left(-\left(0.5897e^{-0.1515L}+0.4141\right)\alpha+\left(\frac{1}{0.9236+0.5738e^{-1.3812L}}\right)\right)\end{aligned} \tag{11}$$

After determining that two pixels belong to the same object, it is necessary to quantitatively describe the degree of similarity between them. Now, we define the similarity parameter $k(i,j)$ between two pixels as formula (12) [6]. where $V_S(\cdot)$ and $V_N(\cdot)$ represent the variance of the original SAR image SPAN data and noiseless image data respectively.

$$k(i,j)=\left|\frac{V_N(i\cup j)-\frac{V_N(i)+V_N(j)}{2}}{V_S(i\cup j)-\frac{V_S(i)+V_S(j)}{2}}\right| \tag{12}$$

2.3 NLM—Lee filter

Based on the multiplicative noise model of SAR images, Lee proposed a filtering algorithm using the simplest form of minimum mean square error estimation[7]. Mathematically, the degraded pixels of the multiplicative noise model are described as $z(i,j)=x(i,j)u(i,j)$.

After assuming the filter window size as t , and the expression of Lee filtering operation is as formula 13.

$$x_{lee}(t) = \bar{z}(t) + k(t)\left[z(t) - \bar{z}(t)\right] \tag{13}$$

Where $x_{lee}(t)$ represents the image value after image denoising, $\bar{z}(t)$ represents the mathematical expectation of the filter window. The NLM filtering algorithm can keep the edge features of image relatively well. It can replace the similarity between single pixels by using the similarity between image blocks. The NLM-Lee filter, which combines NLM algorithm and Lee filter algorithm. The non-local mean value of pixel i in the search domain is calculated, which is defined as formula (14) [6].

$$\bar{C}_{NLM}(i) = \sum_{j \in S(i)} w(i,j) C(j) \tag{14}$$

$$w(i,j) = \begin{cases} \frac{1}{Z_i} \exp\left(-\frac{\ln H(i,j)}{\ln H}\right) & \ln H(i,j) > \ln H \\ 0 & \ln H(i,j) \le \ln H \end{cases} \tag{15}$$

Combining Formula 13 and 14 can be given as follows:

$$C_{lee}(i,j) = C(j) + k(i,j)\left(C(i) - C(j)\right) \tag{16}$$

$$C_{NL-Lee}(i) = \sum_{j \in S(i)} w(i,j) C_{lee}(i,j) \tag{17}$$

where $C_{NL-Lee}(i)$ is the estimated polarization covariance matrix after NLM-Lee processing.

2.4. The steps of proposed algorithm

In this paper, we employ the HPD polarization decomposition method and polarization similarity judgment condition to roughly classify the images, and then filter between the same ground object points. And then, NLM-Lee denoising algorithm was used to reduce speckles. The steps of the proposed algorithm are as follows.

Step1: Enter the image and deorient the image.

Step2: The polarization covariance matrix C_3 and the polarization coherence matrix T_3 of each pixel are obtained.

Step3: Use HPD decomposition algorithm to get the scattering eigenvector V_{HPD} of each pixel.

Step4: According to the polarization similarity judgment conditions, the pixels that have the same scattering features as the central pixel in the search domain are found, and the pixels form the set $S(\cdot)$ of same ground objects.

Step5: The similarity $w(i,j)$ of neighborhood blocks of two pixels is calculated.

Step6: Calculate NLM-Lee filtering results in $S(\cdot)$.

3. EXPERIMENTAL RESULTS

Three parameters: equivalent number of looks (ENL) [8], edge presentation index (EPI) [9] and root mean square error (RMSE), are selected as the assessments of the ability of different algorithms in reducing speckles, maintaining structural features and scattering features, respectively.

The definition of RMSE is as formula (18),

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left|DN_{(filter,j)} - DN_{(original,j)}\right|}, j \in \{R,G,B\} \tag{18}$$

Where $DN_{(original,j)}$ and $DN_{(filter,j)}$ respectively refer to the digital number of the j band after Pauli decomposition of the PolSAR image before and after filtering, and n represents the size of the image. According to the concept of Pauli decomposition [10], when J is R, G, B in turn, RMSE respectively indicate the ability of filtering algorithms to maintain odd scattering power, maintain dihedral scattering power with 0° rotation angle and maintain dihedral scattering power with 45° rotation angle.

In this paper, Radarsat-2 fully polarized SAR image is selected as the experimental data, and in order to verify the performance of the filtering algorithm, we select the sub-regions in the image with rich types of ground object features, complex texture information, and complicated edge features. We compare the proposed algorithm with box filter, gauss filter and mean_shift filter and refined_lee filter provided by the commercial software PIE-SAR. After speckles reduction by filtering algorithm, we use Pauli decomposition to obtain the energy of the PolSAR image under different scattering mechanisms. Finally, the digital number values of all experimental images are converted to $[0,255]$. Fig. 2 shows Pauli decomposition of the original PolSAR image and different filtering algorithms.

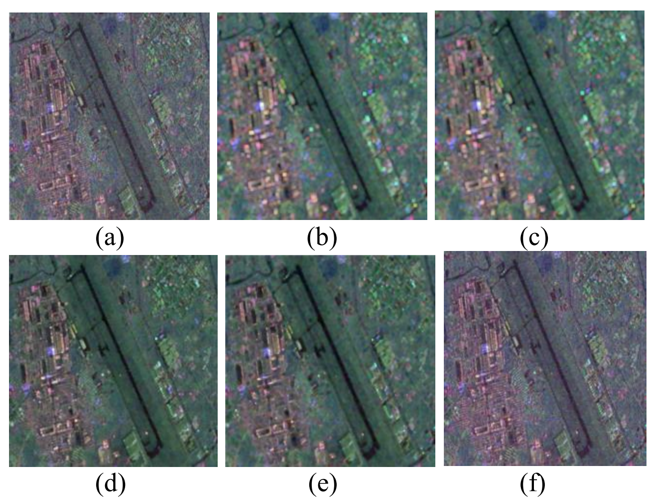

Fig. 2 Pauli decomposition images after filtering in Region2 (a)original;(b)box filter; (c) gauss filter;(d) mean_shift filter; (e) refined_lee filter ;(f) the proposed algorithm

The experimental data in Table 1 show that the improved algorithm in this paper can better filter out the speckles and maintain the edge characteristics, and it performs very well in maintaining the scattering characteristics of the image.

Table1 Comparison the proposed algorithm with other filter algorithm by the commercial software PIE-SAR

box filter	ENL		11.5677
	EPI		0.4427
	RMSE	odd scattering	17.5431
		0°dihedral scattering	22.0442
		45°dihedral scattering	16.5224
gauss filter	ENL		12.0287
	EPI		0.5719
	RMSE	odd scattering	14.4632
		0°dihedral scattering	17.4537
		45°dihedral scattering	13.7257
mean_shift filter	ENL		11.7037
	EPI		0.6104
	RMSE	odd scattering	22.1851
		0°dihedral scattering	25.7174
		45°dihedral scattering	17.1750
refined_lee filter	ENL		11.8906
	EPI		0.4920
	RMSE	odd scattering	20.2345
		0°dihedral scattering	24.2890
		45°dihedral scattering	17.3986
the proposed algorithm	ENL		16.5347
	EPI		0.9677
	RMSE	odd scattering	3.0400
		0°dihedral scattering	2.0535
		45°dihedral scattering	1.1785

4. CONCLUSIONS

This paper presented a filtering algorithm for the quantitative inversion of PolSAR images, based on the idea of "classify first, filter later". This algorithm combines the Hybrid Phase Discriminator (HPD) polarization scattering model based on non-local means Lee filtering, which makes the filter applicable for all different sources of PolSAR images.

The proposed algorithm can not only effectively reduce the speckle and preserve the structural features of the image, but also significantly improve the ability to preserve the scattering features. Therefore, when the PolSAR image filtering is carried out by this algorithm, the performance of the subsequent quantitative inversion will be improved.

5. ACKNOWLEDGEMENT

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