An Extension of a Complete Model-Based Decomposition of Polarimetric SAR Data Postprint

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Abstract

The model-based decomposition that originated from Freeman-Durden three-component decomposition (FDD) has been widely applied in polarimetric synthetic aperture radar (PolSAR) data processing for its clear physical interpretation and easy implementation. Numerous improvements have been proposed to settle the twomain drawbacks of FDD, i.e., the incomplete utilization of the polarimetric information in the coherency matrix and the negative scattering power problem. Recently, Cui et al. proposed a complete model-based three-component decomposition which successfully settled the two aforementioned drawbacks. However, the three scattering components' powers are not totally derived using scattering models, and the remaining coherency matrix (RCM) obtained by subtracting the volume scattering component from the coherency matrix is not consistent with the models of surface and double-bounce scattering components. As an extension of Cui' s method, this letter is dedicated to develop a novel method to discriminate the surface and double-bounce scattering components both using scattering models. With the orientation angle (OA) variation and helix angle (HA) variation compensated for the RCM, the RCM is automatically consistent with the models of surface and double-scattering components. The OA variation and HA variation compensation for the RCMis done by unitary transformations of the eigenvectors of the RCM. The powers of surface and double-bounce scattering components are positive. The effectiveness of the proposedmethod is demonstrated by processing the real PolSAR data.

Full Text

Preamble

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Abstract– The model-based decomposition originated from Freeman-Durden three-component decomposition (FDD) has been widely applied in polarimetric synthetic aperture radar (POLSAR) data processing for its clear physical interpretation and easy implementation. Numerous improvements have been proposed to settle the two main drawbacks of FDD, i.e., incomplete utilization of the polarimetric information in the coherency matrix and the negative scattering power problem. Recently, Cui et al. proposed a complete model-based three-component decomposition of POLSAR coherency matrix data which has successfully settled the two aforementioned drawbacks. However, the three scattering components' powers are not totally derived using scattering models, and the remained coherency matrix (RCM) obtained by subtracting the volume scattering component from the coherency matrix is not consistent with the models of surface scattering and double-bounce scattering components. As an extension of Cui' s method, this letter is dedicated to develop a novel method to discriminate the surface scattering and double-scattering components from the RCM both using scattering models. With the orientation angle (OA) variation and helix angle variation compensated for the RCM, the RCM is automatically consistent with the models of surface scattering and double-scattering components. The OA variation and helix angle variation compensation for the RCM is done by unitary transformations of the eigenvectors of the RCM. Then the compensated RCM is used to derive the powers of surface scattering and double-scattering components using scattering models. The powers of surface scattering and double-bounce scattering components are positive. The effectiveness of the proposed method is demonstrated by processing POLSAR data.

Index Terms– Freeman-Durden three-component decomposition, helix angle variation, nonnegative eigenvalue decomposition, orientation angle variation, polarimetric synthetic aperture radar.

I. Introduction

Polarimetric target decomposition plays an important role in target identification, target classification, and geophysical parameters retrieval. Huynen pioneered the work of target decomposition. He decomposed the distributed target into a single target and the target "noise" [?]. The instability, non-uniqueness, as well as the preference for symmetry and regularity, made the Huynen decomposition not widely used. Nowadays, target decomposition research mainly concentrates on two categories: the Cloude-Pottier eigenvalue/eigenvector decomposition and the model-based decomposition originated from Freeman-Durden three-component decomposition (FDD). For the Cloude-Pottier eigenvalue/eigenvector decomposition, the polarimetric coherency matrix is decomposed into three orthogonal eigenvectors which represent three orthogonal single targets, respectively [?], while for the FDD, the coherency matrix is decomposed into three scattering components: surface scattering component, double-bounce scattering component, and volume scattering component [?].

We only focus on model-based decompositions in this letter. Because reflection symmetry (RS) is assumed, FDD only accounts for five of nine independent parameters of the coherency matrix; the cross-polarization elements of the coherency matrix are not used, and thus polarimetric information loss is unavoidable. Due to the volume scattering component, the negative power of surface scattering or double-bounce scattering component may occur in FDD. In fact, numerous improvements [?] have been achieved to solve these two problems. Yamaguchi et al. [?] added a helix component to account for the off-diagonal elements of the coherency matrix, and six independent parameters are accounted for. The negative power problem is also alleviated to some degree as the helix component also accounts for some cross-polarization power. An et al. [?] and Lee et al. [?] introduced deorientation operation to the coherency matrix to mitigate the negative power problem and reduced the independent parameters from nine to eight. The Yamaguchi four-component decomposition with deorientation operation can account for six out of eight parameters [?]. Based on RS assumption, nonnegative eigenvalue decomposition (NNED) was proposed by van Zyl et al. [?, ?] to avoid the negative power problem, but the polarimetric information is still not fully utilized.

Recently, Cui et al. [?] proposed a complete model-based three-component decomposition. The volume scattering component is determined by the NNED without RS assumption, and thus full utilization of polarimetric information is guaranteed. In [?], two algorithms are introduced for discriminating the second and third components, i.e., surface scattering and double-bounce scattering components. In the first algorithm, the powers of these two components are derived as the eigenvalues of the remained coherency matrix (RCM) after interpreting the scattering mechanisms of the de-oriented eigenvectors of the RCM. However, the powers are not derived using scattering models as mentioned by Lee et al. [?]. In the second algorithm, the RCM is first de-oriented, and from which a maximum single scatterer—surface scatterer or double-bounce scatterer—is derived using scattering model as the second scattering component. However, the third component is not derived using scattering model, and the derivation procedure is complex and ambiguous in physical meaning as mentioned by An et al. [?]. An et al. [?, ?] considered that the (3,3) element of the coherency matrix of the third scattering component should be zero, because for a pure surface scatterer or double-bounce scatterer the (3,3) element is zero, which can be verified by the models of surface scattering and double-bounce scattering components:

$$T_S = \begin{bmatrix} 1 & \beta^* & 0 \\ \beta & |\beta|^2 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \quad |\beta| < 1$$

$$T_D = \begin{bmatrix} |\alpha|^2 & \alpha^* & 0 \\ \alpha & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \quad |\alpha| < 1$$

The RCM, $T' = T - P_V T_V$, contains two single scatterers: the surface scatterer and the double-bounce scatterer. Cui et al. proposed two methods to discriminate these two single scatterers, which will be briefly reviewed in the following.

A. The Algorithm 1

The first algorithm is based on eigenvalue/eigenvector decomposition of the RCM. The RCM is decomposed as $T' = \lambda_1 k_1 k_1^H + \lambda_2 k_2 k_2^H$, where the superscript H denotes the complex conjugate transpose. The eigenvectors are then de-oriented and finally discriminated as surface scattering mechanism or double-bounce scattering mechanism based on co-polarized phase. The corresponding eigenvalues are assigned as the powers of the corresponding scattering mechanisms.

B. The Algorithm 2

The second algorithm tries to fit a maximum power single surface (or double-bounce) scatterer with azimuth slope modulation to the RCM. The RCM can be represented as $T' = P_S R(\theta) T_S R(\theta)^H + P_D R(\theta) T_D R(\theta)^H$, where $R(\theta)$ is the OA rotation matrix:

$$R(\theta) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos 2\theta & \sin 2\theta \\ 0 & -\sin 2\theta & \cos 2\theta \end{bmatrix}$$

The value of OA θ can be derived by maximizing P_S or P_D. The RCM is rotated as $R(\theta)^H T' R(\theta)$. The scattering mechanism of the power-maximized single scatterer is determined by the value of the parameter β or α. A power-maximized rotated surface scatterer is fitted to the RCM when $|\beta| < 1$, and a power-maximized rotated double-bounce scatterer is fitted when $|\alpha| < 1$. The last scattering component is determined using the coherency matrix $T' - P_S R(\theta) T_S R(\theta)^H$ or $T' - P_D R(\theta) T_D R(\theta)^H$, whose corresponding scattering matrix is calculated, then de-oriented, and at last the scattering mechanism is determined based on co-polarized phase.

It can be seen that the powers of surface and double-bounce scatterers are derived from eigenvalues and eigenvectors for Algorithm 1, not from scattering models. For Algorithm 2, although the second scattering component is derived using scattering model, it is not the case for the third scattering component derivation, and the derivation procedure is complicated and ambiguous in physical meaning [**?**].

III. The Proposed Method

As an extension of Cui' s method, the proposed method is devoted to discriminating the surface scattering and double-bounce scattering components from the RCM. First, the volume scattering power is derived using Cui' s method, and then the RCM is decomposed as shown in (6). Then, the OA variation and helix angle variation are compensated for the RCM, i.e., the two eigenvectors are individually compensated for their OA and helix angle. The eigenvectors are modeled by co-diagonalization of the scattering matrix [?, ?]. The compensated eigenvector has the form:

$$k_i' = \begin{bmatrix} \cos 2\tau_i & \sin 2\tau_i \\ -\sin 2\tau_i & \cos 2\tau_i \end{bmatrix} \begin{bmatrix} \cos 2\theta_i & \sin 2\theta_i \\ -\sin 2\theta_i & \cos 2\theta_i \end{bmatrix} k_i$$

We can see that the cross-polarization element of the eigenvector is zero now after OA and helix angle compensations.

The compensated RCM can be synthesized by combining the two compensated eigenvectors together as:

$$T_c' = \sum_{i=1}^{2} \lambda_i k_i' k_i'^H$$

where λ_i are the eigenvalues. It is interesting to see that not only the (3,3) element of the compensated RCM is zero now, but also the (1,3), (3,1), (2,3), and (3,2) elements are all zero. It is noteworthy that T_c' is consistent with (1) and (2), and can be used to derive the surface and double-bounce scattering components' powers using scattering models of (1) and (2).

The OA compensation for k_i is carried out by $k_i' = R(\theta_i)k_i$, where $R(\theta_i)$ is the OA rotation matrix. The OA can be easily derived as:

$$\theta_i = \frac{1}{2}\tan^{-1}\left(\frac{2\text{Re}(k_{i,2}k_{i,3}^*)}{|k_{i,2}|^2 - |k_{i,3}|^2}\right)$$

The helix angle compensation is carried out as $k_i'' = U(\tau_i)k_i'$, where $U(\tau_i)$ is the unitary transformation matrix for helix angle. The helix angle is derived from:

$$\tau_i = \frac{1}{2}\tan^{-1}\left(\frac{2\text{Im}(k_{i,2}'k_{i,3}'^*)}{|k_{i,2}'|^2 - |k_{i,3}'|^2}\right)$$

The proposed extension of Cui's method is presented as Algorithm 1 below.

Algorithm 1: An Extension of Cui's Method

1. Input T and T_V
2. Solve cubic equation: $\det(T - P_V T_V) = 0$
3. Select the minimum root to be the value of P_V
4. Obtain the RCM: $T' = T - P_V T_V$
5. Implement eigendecomposition: $T' = \lambda_1 k_1 k_1^H + \lambda_2 k_2 k_2^H$
6. For $i = 1$ to 2 do

- Obtain OA θ_i with (12)
- Implement OA compensation for k_i with (13)
- Obtain helix angle τ_i with (15)
- Implement helix angle compensation for k_i' with (16)
- Obtain OA and helix angle compensated k_i''

7. End for
8. Obtain compensated RCM: $T_c' = \sum_{i=1}^{2} \lambda_i k_i'' k_i''^H$
9. If $T_c'(1,1) > T_c'(2,2)$ then
   - $\alpha = \sqrt{T_c'(1,1)/T_c'(2,2)}$
   - $P_S = T_c'(1,1) + T_c'(2,2)$
   - $P_D = 0$
10. Else then
    - $\beta = \sqrt{T_c'(2,2)/T_c'(1,1)}$
    - $P_D = T_c'(1,1) + T_c'(2,2)$
    - $P_S = 0$
11. End if
12. Output: P_S, P_D, P_V

IV. Experimental Results

In this section, the decomposition results of Cui' s Algorithm 1 and the proposed method on RADARSAT-2 dataset of San Francisco area are presented and compared. As the performances of Cui' s Algorithms 1 and 2 are similar [**?**], the decomposition results of Cui' s Algorithm 2 are omitted here for saving space.

The used RADARSAT-2 C-band data of San Francisco area were acquired on April 9, 2008 in a fine-beam and quad-polarization mode. The original data are in single-look complex scattering matrix format, and the azimuth and ground range resolutions are about 4.82 m and 4.73 m, respectively. The data were then 6-look processed both in azimuth and ground range directions to get the coherency matrix data, after which they have a dimension of 2402×470 pixels. There are ocean, park, and built-up areas in the scene. Color-coded decomposition results of Cui' s Algorithm 1 and the proposed decomposition are shown in Fig. 1 [Figure 1: see original paper]. We only present a portion of the whole scene. The surface scattering, double-bounce scattering, and volume scattering contributions are color coded in blue, red, and green, respectively. It can be seen from Fig. 1 that the color of ocean areas, which are surface scattering dominant areas, is blue as expected. The color of park area, which is volume scattering dominant area, is green. The color of built-up areas, which are double-bounce scattering dominant areas, is red in general. However, in some largely oriented built-up areas, the color is yellow or even green, which means that the volume scattering contribution is still over-estimated even with the proposed method and Cui' s method implemented.

The average span normalized P_S and average normalized P_D by the proposed method for the whole image are computed, and are 6.59% and zero on the whole image, respectively. As pointed out in [?, ?], the (3,3) element of the RCM, i.e., the cross-polarization power of surface scattering and double-bounce scattering components represented by (1) and (2), respectively, should be zero, which has been achieved by the proposed method.

To specifically demonstrate the different characteristics between the proposed method and Cui' s Algorithm 1 further, three typical patches are selected for detailed processing. The selected three patches are ocean area, built-up area, and central park area as shown in Fig. 1(b). The surface scattering, double-bounce scattering, and volume scattering power proportions are shown in Table I . As can be seen from Table I, the power proportions by the two methods are similar generally, because of which the visual effects of the decomposition results by the two methods of Fig. 1 are similar generally. As can be seen from Table I, the surface scattering, double-bounce scattering, and volume scattering contributions are dominant in ocean area for patch 1, in built-up area for patch 2, and in park area for patch 3, respectively. One difference between the proposed method and Cui' s Algorithm 1 is that the proposed method gets a little higher surface scattering power, which is because further helix angle compensation is adopted by the proposed method. Comparing the formulations, we can find that the cross-polarization element becomes zero after further helix angle compensation is implemented, and the corresponding power of the cross-polarization will be transferred from $T_c'(3,3)$ to $T_c'(1,1)$ of the coherency matrix. The $T_c'(1,1)$ element represents the surface scattering contribution in a sense. Thus, the surface scattering power obtained from the proposed method is a little higher.

In reality, it is still a problem to verify which method' s result is consistent with the ground truth. Hence, we just compare the performances of the proposed method and Cui' s Algorithm 1 here to demonstrate the characteristics of the two methods and the effectiveness of the proposed method.

V. Discussion

A. The Necessity of Helix Angle Variation Compensation

In [?], Huynen used one parameter F to represent the helicity of a distributed target, and the helicity is a kind of global shape twist of the target. In [?], Yamaguchi et al. introduced helix scattering component as the fourth component of the scattering contribution from a target. In [?, ?], Huynen and Touzi both used helix angle to characterize the asymmetry of the target. Thus, the helicity is an inherent characteristic of the target.

When using scattering models to discriminate the surface scattering and double-bounce scattering components from the RCM, the models of (1) and (2) are not consistent with the RCM [?, ?]. However, if we use the proposed method with OA variation compensation and further helix angle variation compensation for the RCM, then the compensated RCM is just consistent with the models (1) and (2). Actually, except for OAs of the surface scatterer and the double-bounce scatterer, the helix angles of the surface scatterer and the double-bounce scatterer also contribute to the cross-polarization, which can be demonstrated by the helix scattering component of the Yamaguchi four-component decomposition [?]. When (1) and (2) were being modeled in [?], any OA and helix angle were not considered. Thus, OA variation and helix angle variation of the RCM must be compensated for before it is used to discriminate the surface scattering and double-bounce scattering components.

In addition, the helix angle of the whole image is generally small. Thus, the effect on the decomposition results of helix angle compensation is not so obvious, but the proposed method has necessarily accommodated the RCM to the scattering models.

B. Interpretation of the Two Eigenvectors

Questions may be raised about how to interpret the two eigenvectors and which one is of surface or double-bounce scattering mechanism. It is noteworthy that we do not interpret the scattering mechanisms of the two eigenvectors. The two orthogonal eigenvectors can be considered as the projections of all the surface scatterers and double-bounce scatterers in one resolution cell to the orthogonal axes expanded by the two orthogonal eigenvectors. We just compensate for the OA variation and helix variation via Cloude' s eigenvalue/eigenvector decomposition of the RCM, and combine the two compensated eigenvectors together as (18) to get the compensated RCM which is used to derive the powers of surface and double-bounce scattering components. The compensated RCM is also a positive semi-definite Hermitian matrix and physically realizable.

C. Future Work

As shown in the results, although with the proposed method and Cui' s method implemented, the scattering mechanism is still misinterpreted in some largely oriented built-up areas. The reason may be that the used volume scattering models do not fit all the scattering cases. The adaptive volume scattering model fitting all the scattering situations needs further study.

VI. Conclusion

As an extension of Cui' s complete model-based decomposition, a novel method to discriminate the surface and double-bounce scattering components via compensating the OA and helix angle variation for the RCM using scattering models is proposed in this letter. As an alternative to Cui' s method, it accommodates the RCM to the models of surface scattering and double-bounce scattering components. Its effectiveness is verified on the real POLSAR data.

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TABLE I

AVERAGE SCATTERING PROPORTIONS OF SURFACE SCATTERING, DOUBLE-BOUNCE SCATTERING, AND VOLUME SCATTERING COMPONENTS IN SELECTED THREE PATCHES

Algorithm	PS/SPAN (Patch 1)	PD/SPAN (Patch 1)	PV/SPAN (Patch 1)	PS/SPAN (Patch 2)	PD/SPAN (Patch 2)	PV/SPAN (Patch 2)	PS/SPAN (Patch 3)	PD/SPAN (Patch 3)	PV/SPAN (Patch 3)
Proposed method	94.38%	2.52%	11.02%	31.49%	57.49%	48.11%	36.66%	15.23%	11.02%
Cui' s Algorithm 1	94.35%	2.55%	11.02%	29.19%	59.79%	48.11%	35.57%	16.32%	11.02%

Fig. 1. Decomposition results on RADARSAT-2 data of San Francisco by (a) Cui' s Algorithm 1 and (b) the proposed method.

Note: Figure translations are in progress. See original paper for figures.

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