A novel deorientation method in PolSAR data processing: Postprint

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Abstract

Deorientation plays an important role in polarimetric synthetic aperture radar (PolSAR) target decomposition, terrain classification, and geophysical parameters retrieval. The existing deorientation method roughly rotates the target by an average/mixed orientation angle (OA) about the line of radar sight. However, regarding the complex high-entropy mixed scatterer, which usually comprises several comparable sub-scatterers with different OAs, the average/mixed OA is obviously insufficient to account for the diverse OAs' reality. To address this, a novel PolSAR data deorientation method is proposed in this letter. The proposed method deorients a mixed scatterer by reconstructing the underlying sub-scatterers using the eigenvalue-based Cloude–Pottier decomposition first, and then compensates the OA of each reconstructed sub-scatterer using Huynen' s desying operation, respectively. One important feature of the proposed method is that it is consistent with Huynen' s desying operation that the real part of the (1, 3) element of the deoriented coherency matrix should be zero. The proposed method provides a fine deorientation for mixed targets, and is especially suitable for the extraction of oriented urban regions. Comparative experiments with the existing method on RADARSAT-2 PolSAR data demonstrate the excellent deorientation performance of the proposed method.

Full Text

Preamble

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Abstract

Deorientation plays an important role in PolSAR target decomposition, terrain classification, and geophysical parameter retrieval. Existing deorientation methods roughly rotate the target by a single average or dominant orientation angle (OA) about the radar line of sight. However, for complex high-entropy mixed scatterers—which typically comprise several comparable sub-scatterers with different OAs—this single OA is clearly insufficient to account for the diverse orientation reality. To address this limitation, we propose a novel PolSAR data deorientation method that first reconstructs the eigenvalue-based Cloude-Pottier decomposition and then compensates the OA of each reconstructed sub-scatterer individually using Huynen' s desying operation. A key feature of the proposed method is its consistency with Huynen' s desying operation, which requires that the real part of the (1, 3) element of the de-oriented coherency matrix be zero. The proposed method provides fine deorientation for mixed targets and is particularly suitable for extracting oriented urban regions. Comparative experiments using excellent RADARSAT-2 PolSAR data demonstrate the superior performance of the proposed method compared to existing approaches.

Keywords: deorientation; orientation angle compensation; orientation angle variation; PolSAR; target decomposition

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1. Introduction

Deorientation plays a crucial role in polarimetric synthetic aperture radar (PolSAR) target decomposition, terrain classification, and geophysical parameter estimation. Without proper deorientation, scattering mechanisms may be misjudged in target decomposition and terrain classification, leading to inaccurate geophysical parameter estimates. The most widely used deorientation method (the existing method) rotates the coherency matrix by a single orientation angle (OA) about the line of sight (LOS) [?, ?]. Lee et al. (2000) estimated the OA based on the circular polarization covariance matrix, while An et al. (2010) derived the OA by minimizing cross-polarization power.

However, recent studies have shown that even with the existing method applied, strongly oriented urban regions are still misclassified as volume scattering dominant areas [?]. The OA employed in the existing method represents a mixed OA of all sub-scatterers within a resolution cell. For high-entropy regions such as oriented urban areas not aligned along the track direction, the scattering mechanism is highly complex, potentially containing roofs with different azimuth slopes, oriented walls, and oriented dihedrals within a single cell [?]. These sub-scatterers exhibit diverse OAs, making a single OA inadequate for proper characterization.

Using Cloude-Pottier decomposition as an example [?]: in low-entropy situations, the dominant eigenvector effectively describes the target; in medium-entropy cases, the two dominant eigenvectors are required; while in high-entropy situations, all three eigenvectors must be used because they are comparable in magnitude. Similarly, a single OA may suffice for low-entropy scenarios but fails for high-entropy cases. This letter proposes a new deorientation method that accounts for OA variation to better handle high-entropy situations.

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2. Review of the Existing Deorientation Method

2.1 The Existing Deorientation Method

In coherent scattering cases, the scattering matrix contains the polarimetric scattering information about the target and can be expressed as:

$$S = \begin{bmatrix} S_{HH} & S_{HV} \\ S_{VH} & S_{VV} \end{bmatrix}$$

where the subscript HV denotes vertical polarization transmission and horizontal polarization reception. When expressed in the Pauli basis, the scattering vector becomes:

$$k = \frac{1}{\sqrt{2}}[S_{HH} + S_{VV},\ S_{HH} - S_{VV},\ 2S_{HV}]^T$$

where the superscript T denotes matrix transposition. In incoherent scattering cases, the coherency matrix is obtained as:

$$T = \langle k \cdot k^H \rangle = \begin{bmatrix} T_{11} & T_{12} & T_{13} \\ T_{12}^* & T_{22} & T_{23} \\ T_{13}^* & T_{23}^* & T_{33} \end{bmatrix}$$

where $\langle \cdot \rangle$ denotes time or spatial averaging and * denotes complex conjugation. The coherency matrix is positive semi-definite and thus physically realizable.

The existing deorientation method rotates the coherency matrix by an OA about the LOS [**?**, **?**]:

$$T_c = R(\theta) \cdot T \cdot R(\theta)^H$$

where T_c is the de-oriented coherency matrix from the existing method, and the superscript H denotes complex conjugate transposition. The rotation matrix is:

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

A noteworthy feature of the existing method is that the real part of the $T_c(2,3)$ element becomes zero.

2.2 Another Interpretation of the Existing Method

This subsection presents an alternative interpretation of the existing method. Using Cloude-Pottier' s eigen-decomposition, the coherency matrix can be decomposed into three orthogonal single targets [**?**]:

$$T = \sum_{i=1}^{3} \lambda_i k_i k_i^H = \sum_{i=1}^{3} T_i$$

where λ_i, k_i, and T_i (i=1,2,3) are the eigenvalues, eigenvectors, and single targets, respectively, with $\lambda_1 \geq \lambda_2 \geq \lambda_3$ assumed. This eigen-decomposition enables a statistical interpretation of the mixed/distributed target T in terms of three orthogonal single targets T_1, T_2, and T_3. All sub-scatterers in a resolution cell are projected onto these three single targets, which collectively represent all sub-scatterers in the cell.

Thus, the existing method of (4) can be rewritten as:

$$T_c = R(\theta) \cdot T \cdot R(\theta)^H = \sum_{i=1}^{3} R(\theta) \cdot T_i \cdot R(\theta)^H$$

The three single targets representing all sub-scatterers are de-oriented with the same OA θ and then combined to form the de-oriented mixed target represented by T_c. In other words, all sub-scatterers in the cell are rotated by identical OAs. As previously noted, for low-entropy situations where one dominant scatterer effectively describes the mixed target, a single OA may suffice. However, for high-entropy situations where the scattering powers of T_1, T_2, and T_3 are comparable and have different OAs, a single OA cannot effectively account for the situation. Motivated by this limitation, we developed a novel deorientation method that de-orients T_1, T_2, and T_3 separately using their own OAs rather than a common OA.

3. The Proposed Deorientation Method

3.1 The Proposed Method

The coherency matrix is first decomposed into three single targets via Cloude-Pottier' s eigen-decomposition as in (6). The proposed method can then be expressed by slightly modifying (7) as:

$$T_p = \sum_{i=1}^{3} R(\theta_i) \cdot T_i \cdot R(\theta_i)^H$$

where T_p is the de-oriented coherency matrix from the proposed method, and θ_i is the OA of each single target T_i or eigenvector k_i. The core idea is to reconstruct the underlying sub-scatterers using eigen-decomposition to obtain three eigenvectors and then de-orient each eigenvector separately with its own OA rather than a common OA.

We now detail the derivation of OA θ_i, which is based on Huynen' s desying operation. First, the eigenvector k_i is modeled using Kennaugh-Huynen' s co-diagonalization of the scattering matrix [**?**, **?**]. The corresponding scattering matrix S_i of eigenvector k_i can be parameterized as:

$$S_i = R(\theta_i) \cdot R_s(\tau_i) \cdot S_{di} \cdot R_s(\tau_i)^T \cdot R(\theta_i)^T$$

where S_{di} is the diagonal matrix whose diagonal elements are the complex con-eigenvalues x_{i1} and x_{i2}, respectively, and θ_i and τ_i are the OA and helix angle of S_i, respectively. The two unitary transformation matrices are:

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

and

$$R_s(\tau_i) = \begin{bmatrix} \cos\tau_i & j\sin\tau_i \\ j\sin\tau_i & \cos\tau_i \end{bmatrix}$$

The model of eigenvector k_i can be obtained by expanding and rewriting (9) in the Pauli basis:

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

The OA θ_i of k_i or T_i can be calculated by:

$$\theta_i = \frac{1}{2}\tan^{-1}\left(\frac{2\Re\{k_{i2}k_{i3}^*\}}{|k_{i2}|^2 - |k_{i3}|^2}\right)$$

where k_{ij} denotes the j-th element of eigenvector k_i. The obtained θ_i matches the result of Bombrun et al. (2010).

Once OA θ_i is derived, the de-oriented coherency matrix T_p can be obtained using (8). The (1, 3) element of T_p is calculated as:

$$T_p(1,3) = \sum_{i=1}^{3} \frac{j\sin 4\tau_i}{8}(|x_{i1}|^2 - |x_{i2}|^2)$$

It can be seen from (13) that $T_p(1,3)$ is purely imaginary, which is consistent with Huynen’ s desying operation requiring that the real part of the (1, 3) element of the de-oriented coherency matrix be zero [?]. However, this is not the case for Lee’ s or An’ s existing methods, where the real part of the (2, 3) element of the de-oriented coherency matrix T_c becomes zero instead.

3.2 Physical Interpretation

Our objective is to better handle the deorientation of mixed targets in high-entropy cases. Unlike the existing method that uniformly rotates the three eigenvectors (targets) by a common OA, the proposed method rotates each of the three single targets about the LOS separately using their own OAs. This makes the proposed method suitable for characterizing high-entropy regions, particularly oriented urban areas, because the scattering mechanisms in these regions are complex and the main sub-scatterers within a cell likely have diverse OAs.

Consider oriented urban regions as an example. A single cell may contain roofs with azimuth slopes, oriented walls, oriented dihedrals, and other features. These underlying sub-scatterers form a mixed distributed target that is projected onto three single targets T_i (i=1,2,3). The proposed method rotates these three single targets by their respective OAs, thereby achieving fine deorientation. Through separate and fine deorientation rather than uniform deorientation, we can expect to obtain better results than those from the existing method.

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4. Comparisons Between the Existing Method and the Proposed Method

4.1 Mathematical Comparison

From a mathematical perspective, the only difference between (7) and (8) is that the existing method uniformly rotates the three eigenvectors (targets) by a common OA θ about the LOS, while the proposed method separately rotates them by their own OAs θ_1, θ_2, and θ_3. The proposed method can be viewed as a natural extension of the existing method. The three de-oriented eigenvectors from the existing method remain orthogonal, but this is not true for the proposed method. However, both de-oriented coherency matrices—T_c and T_p—are positive semi-definite and physically meaningful.

4.2 Comparison of Experimental Results

Several experiments were conducted to demonstrate the different performances of the two methods, validate the effectiveness of the proposed method, and show its superiority in characterizing oriented urban regions.

4.2.1 The PolSAR Data C-band RADARSAT-2 PolSAR data of the San Francisco Bay area were used for validation. The data are in single-look complex (SLC) format, and a 7×7 refined Lee filter was applied to each pixel to suppress speckle and estimate the coherency matrix. Only a portion of the scene was used. Figure 1 [Figure 1: see original paper] shows the Google Earth optical image of this area. The azimuth direction of the PolSAR data is oriented up-down. Four typical 100×100 patches were selected for subsequent processing: patch 1 (ocean region), patch 2 (urban region), patch 3 (oriented urban region), and patch 4 (park region).

4.2.2 OA Comparison Two OAs were compared: the OA θ from (5) of the existing method and the OA θ_1 from (12) of the dominant eigenvector from the proposed method. Figure 2 [Figure 2: see original paper] shows the results. For further comparison, the statistical distributions of the two OAs in the four selected patches are displayed in Figure 3 [Figure 3: see original paper]. Figures 2 and 3 reveal that the OA from the existing method and the dominant OA from the proposed method are generally consistent. The dominant OA from the proposed method appears noisier because the OA from the existing method represents an averaged or mixed version. For patches 1, 2, and 4, the OAs are generally distributed symmetrically around zero. For patch 3 (oriented urban region), the OAs appropriately show large negative values.

4.2.3 Impacts on Model-Based Decomposition The different impacts of the two methods on PolSAR model-based polarimetric decomposition were evaluated. Since we focus only on deorientation methods, the original Freeman-Durden three-component decomposition (FDD) without modifications was selected [**?**]. FDD was performed on the de-oriented T_c and T_p, decomposing total backscattering into surface scattering, double-bounce scattering, and volume scattering components.

First, the negative power problem was investigated. It is well known that the surface or double-bounce scattering power may become negative in FDD, violating physical reality. Based on original FDD, 14.86% of pixels had negative surface or double-bounce scattering power. With the existing deorientation method, this decreased to 8.74%, and with the proposed method, it further decreased to 7.77%. Thus, the proposed method achieves greater reduction of this physical violation phenomenon and is more effective than the existing method.

Second, the impacts on decomposed scattering mechanisms and power proportions were compared. Color-coded decomposition results for FDD, FDD with the existing method, and FDD with the proposed method are shown in Figure 4 [Figure 4: see original paper], where blue, red, and green denote surface, double-bounce, and volume scattering, respectively. The average power proportions for the four patches are listed in Table 1 .

As shown in Figure 4, both methods perform similarly in low-entropy ocean regions (patch 1), with Table 1 supporting this finding. Thus, using a single OA in the existing method effectively handles low-entropy situations. In urban regions, red colors are strengthened by the proposed method, particularly in oriented urban regions like patch 3. With the existing method, patch 3 (oriented urban region) is misclassified as volume scattering dominant rather than double-bounce scattering dominant. However, using the proposed method, green colors in patch 3 partially turn to red or yellow as expected, demonstrating improvement. The power proportions for patch 3 in Table 1 confirm this color change. From a target classification perspective, the proposed method is more suitable for extracting urban regions, especially oriented urban regions. In park regions like patch 4, green colors are lightened by the proposed method, but the region can still be generally discriminated as volume scattering dominant. Table 1 supports the observation that the proposed method yields lower average volume scattering power than the existing method, though volume scattering remains dominant.

The effectiveness and improvement of the proposed method were also verified using other speckle reduction window sizes and L-band E-SAR PolSAR data from the Oberpfaffenhofen area, yielding similar results not presented here due to space constraints.

5. Discussions

This section addresses several important issues.

First, oriented surface and double-bounce sub-scatterers within a resolution cell produce additional cross-polarization backscattering and typically have diverse OAs in high-entropy cases. Ideally, we would individually de-orient each oriented surface and double-bounce sub-scatterer. However, according to state-of-the-art PolSAR target decomposition, such detailed decomposition and deorientation is not feasible. Therefore, we reconstruct sub-scatterers using Cloude-Pottier' s eigen-decomposition to obtain three single targets representing all sub-scatterers, then de-orient them separately by their own OAs to achieve fine deorientation. While numerous decomposition methods exist for distributed targets, Cloude' s eigen-decomposition provides a concise decomposition of the coherency matrix by reconstructing underlying single targets based on scattering orthogonality.

Second, the proposed deorientation method is designed to better handle high-entropy regions like oriented urban areas and forest regions. For oriented urban regions, the proposed method demonstrates more reasonable and superior performance than the existing method. For forest regions, the proposed method yields lower average volume scattering power. Although forest regions can still be correctly discriminated as volume scattering dominant (e.g., patch 3), one might question whether the proposed method underestimates volume scattering power in these areas. Volume scattering is modeled as backscattering from a cloud of dipoles whose OAs follow probability distributions—commonly uniform or half-cosine distributions centered at zero [?, ?]. This centering at zero is consistent with the OA distributions in patch 4 shown in Figure 3. The eigenvector corresponding to the dipole scattering mechanism represents the volume scattering component. The proposed method compensates the mean OA (center OA) of the OA distribution for each eigenvector. Since OAs in forest regions generally center at zero, the deorientation effect on the volume scattering eigenvector is minimal. Thus, the proposed method does not underestimate volume scattering power for this typical case. For the few targets whose mean OAs are not centered at zero, the mean OAs of dipole scattering eigenvectors will be rotated, potentially underestimating canopy volume scattering power—a foreseeable limitation. However, it is unrealistic to expect one method to fit all target types.

Third, although three eigenvectors are utilized, their scattering mechanisms need not be explicitly interpreted. The three eigenvectors are simply obtained and de-oriented.

Finally, all deorientation methods aim to produce results consistent with ground truth, but theoretical evaluation of which result is closer to ground truth remains difficult. Both T_c and T_p are approximations of the ideal de-oriented coherency matrix. Experimental results merely demonstrate the different performances of the two methods and validate the effectiveness and improvement of the proposed approach.

6. Conclusion

As an alternative to existing deorientation methods that use a single mixed OA to uniformly rotate the coherency matrix, we propose a novel deorientation method designed to accommodate sub-scatterers with different OAs within a resolution cell. The proposed method separately rotates the three single targets representing all sub-scatterers. A key feature is its consistency with Huynen' s desying operation: the real part of the (1, 3) element of the coherency matrix becomes zero after deorientation. Experimental results demonstrate the advantage of the proposed method, particularly its suitability for extracting urban regions, especially oriented urban regions.

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Table 1. Average power proportions of the three scattering mechanisms for patches 1-4 with FDD, FDD with the existing method, and FDD with the proposed method. PS, PD, and PV denote power proportions of surface, double-bounce, and volume scattering components, respectively.

Method	Patch 1 PS	Patch 1 PD	Patch 1 PV	Patch 3 PS	Patch 3 PD	Patch 3 PV
FDD with proposed method	16.11%	38.96%	44.93%	34.72%	26.70%	38.58%

Figure 1. Google Earth optical image of the data.

Figure 2(a). OA of the existing method.
Figure 2(b). OA of the dominant eigenvector of the proposed method.

Figure 3. Two OAs' distributions in the four selected patches.

Figure 4(a). Decomposition results of FDD.
Figure 4(b). Decomposition results of FDD with the existing method.
Figure 4(c). Decomposition results of FDD with the proposed method.

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