A novel deorientation method for PolSAR data processing postprint

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Abstract

In PolSAR data processing, deorientation operation is often necessary. The existing deorientation method uniformly deorients all the sub-scatterers of a resolution cell with one orientation angle. For high entropy situation, the sub-scatterers have diverse OAs, and the effect of the existing method is unsatisfactory. A novel deorientation method is proposed to well treat the high entropy situation. Cloude' s eigen-decomposition to the coherency matrix is first carried out. The three eigenvectors are then separately deoriented with their own orientation angles. Experiments demonstrate that the proposed method is suitable for extraction of urban regions, especially for extraction of oriented urban regions. VDE VERLAG GMBH Berlin Offenbach.

Full Text

Preamble

A Novel Deorientation Method for PolSAR Data Processing

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Abstract

In polarimetric synthetic aperture radar (PolSAR) data processing, deorientation operations are frequently required. Conventional deorientation methods uniformly apply a single orientation angle to deorient all sub-scatterers within a resolution cell. However, in high-entropy scenarios, sub-scatterers exhibit diverse orientation angles (OAs), rendering the existing approach ineffective. To address this limitation, we propose a novel deorientation method specifically designed for high-entropy situations. The method first performs Cloude' s eigen-decomposition on the coherency matrix, then separately deorients the three eigenvectors using their respective orientation angles. Experimental results demonstrate that the proposed method is particularly effective for urban area extraction, especially in oriented urban regions.

1 Introduction

Deorientation operations constitute a critical component in fully polarimetric synthetic aperture radar (PolSAR) data processing. The conventional deorientation method, proposed in [?, ?] and widely adopted in practice, rotates the coherency matrix by a certain angle about the radar line of sight (LOS), utilizing only a single "mixed" orientation angle (OA). However, a typical resolution cell contains numerous scatterers that may possess different orientation angles. For instance, in urban regions not aligned with the flight track direction, a single cell may contain roofs with azimuth slopes, oriented walls, and oriented dihedral structures [?], each exhibiting distinct OAs. A single OA cannot adequately represent such complex scattering scenarios. Therefore, we propose a novel deorientation method that incorporates orientation angle variations (three distinct OAs) to better accommodate scatterers with different OAs within a single resolution cell.

2.1 Existing Method

The widely adopted conventional deorientation method [?, ?] can be expressed as follows, where T and T_c denote the original coherency matrix and the deoriented coherency matrix obtained using the existing method, respectively, and $R(\theta)$ represents the orientation angle rotation matrix. The orientation angle θ can be derived using either of the two approaches proposed in [?, ?]. In [?], the OA is obtained from the phase difference between co-polarization terms based on the circular polarization covariance matrix, while in [?] it is equivalently derived by minimizing the cross-polarization power. The derived OA is given by:

$$1c100()(),()0cos2sin20sin2cos2TRTRR$$

where Re(·) denotes the real part of a complex number.

Method

Here, we reconsider and reinterpret the existing method from a different perspective. Through Cloude' s eigen-decomposition [?], the coherency matrix can be decomposed as:

$$3311HiiiiiiTkkT$$

where λ_i, k_i, and T_i represent the eigenvalue, eigenvector, and single target, respectively, and the ordering 123 is assumed. This decomposition provides a statistical interpretation of the target, specifically adopting a three-symbol Bernoulli process [?]. Consequently, the existing method from equation (1) can be rewritten as:

$$3311c11()()()()iiiiTRTRRTR$$

In this formulation, the three single targets T_1, T_2, and T_3 are deoriented about the radar LOS using a single common OA. However, as previously noted, sub-scatterers within a single resolution cell likely possess different OAs, implying that T_1, T_2, and T_3 each have their own distinct orientation angles. Motivated by this observation, we propose a novel deorientation method in which T_1, T_2, and T_3 are separately deoriented using their respective OAs.

3.1 Proposed Method

The proposed method reconstructs the sub-scatterers of a resolution cell by projecting them onto three orthogonal single targets through Cloude-Pottier eigen-decomposition of the coherency matrix. The three single targets are then deoriented separately as follows:

$$31p1()()iiiiTRTR$$

The range of θ_i is $[-45^\circ, 45^\circ]$. The derived OA θ_i in equation (10) is equivalent to that derived in [?].

3.2 Physical Interpretation

where T_p is the deoriented coherency matrix obtained using the proposed deorientation method, T_i is the single target derived from equation (2), and θ_i represents the OA of each single target. A notable feature of the proposed method is that the real part of the T_{p13} element becomes zero, which aligns with Huynen' s deorientation theory stating that the Huynen parameter H (the real part of the T_{p13} element) vanishes after deorientation [?]. In contrast, this is not true for the existing method, where the real part of the T_{c23} element becomes zero.

The eigenvector k_i is modeled here using Kennaugh-Huynen's co-diagonalization of the scattering matrix [?, ?], from which its OA θ_i can subsequently be derived. The corresponding scattering matrix S_i of eigenvector k_i can thus be modeled as:

$$SSdSSiiiiiiSRRSRR$$

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

$$Scossin()sincosiiiiiR$$

$$Scossin().sincosiiiiijRj$$

The eigenvector k_i can be obtained by expanding and rewriting the scattering matrix from equation (6) in the Pauli basis as:

$$1212121212cos22cos2sin2sin222sin2sin2cos222(1)(2)(3).iiiiiiiiiiiiiiiiiTiiixxxxxxkjxxxxjkkk$$

The orientation angle θ_i can be derived from equation (9) as:

$$3Re11atan.22Re1iiiiikkkk$$

The fundamental concept of the proposed method is to rotate the three single targets about the LOS separately using different OAs, rather than rotating them together with a single OA. While numerous decomposition approaches exist for representing a distributed target as three single targets, Cloude’ s eigen-decomposition is selected here. As an analytical tool, Cloude’ s eigen-decomposition provides a concise and unique decomposition of the coherency matrix, enabling interpretation of the target in a higher-dimensional space. Through eigen-decomposition, the coherency matrix is decomposed into three statistical single targets (three eigenvectors), and the mean OAs of these three single targets are all compensated. This makes the proposed method particularly suitable for urban region extraction, especially for characterizing oriented urban regions.

In oriented urban regions, a single resolution cell may contain roofs with azimuth slopes, oriented walls, oriented dihedrals, and other structures. These sub-scatterers are distributed among the three single targets T_i, and the proposed method separately rotates each of the three single targets using their own orientation angles.

4.1 Mathematical Comparison

From a mathematical perspective, the sole distinction between equations (4) and (5) is that the existing method uniformly rotates the three eigenvectors (the three targets) with a single OA θ about the LOS, whereas the proposed method separately and adaptively rotates each eigenvector with its own OA (θ_1, θ_2, and θ_3) about the LOS. Consequently, the proposed method can be viewed as a natural extension of the existing approach. The three deoriented eigenvectors produced by the existing method remain orthogonal, which is not the case for the proposed method. However, both deoriented coherency matrices, T_c and T_p, are positive semi-definite and physically meaningful.

The OA θ_i can be derived from equation (9) as shown above.

4.2 Experimental Results

We conducted several experiments to demonstrate the different performance characteristics of the two methods using RADARSAT-2 PolSAR data from the San Francisco area [**?**]. The data are in single-look complex (SLC) format. To reduce speckle and obtain coherency matrix format data, a 7$×$7 refined Lee filter was applied. Only a portion of the scene was utilized for analysis.

4.2.1 Comparisons Between the OAs

We compared the OA θ from equation (2) used in the existing method with the OA θ_1 from equation (10) of the dominant eigenvector used in the proposed method, as shown in Figure 1 [Figure 1: see original paper]. Four typical 100$×$100 patches were selected for detailed comparison. As illustrated in the Google Earth optical image in Figure 2 [Figure 2: see original paper], patches 1 through 4 correspond to ocean, urban, oriented urban, and park regions, respectively.

The statistical distributions of OA θ from the existing method and OA θ_1 from the proposed method for these four patches are presented in Figure 3 [Figure 3: see original paper]. Overall, θ and θ_1 show general consistency, though θ_1 of the dominant eigenvector exhibits higher noise levels, as noted in [**?**]. Figure 1 demonstrates that the OAs exhibit large negative values in oriented urban regions, such as patch 3, which is physically reasonable.

4.2.2 Impacts of the Two Methods on Model-based Decomposition

The two deorientation methods produce different effects on polarimetric model-based decomposition, as demonstrated below. For emphasis, we selected the Freeman-Durden three-component decomposition (FDD) without modifications [**?**], applied to both deoriented matrices T_c and T_p.

First, we examined the negative power problem. The negative power phenomenon in FDD violates physical reality. With original FDD, 14.86% of pixels exhibit negative power. This decreases to 8.74% for FDD with the existing deorientation method and further reduces to 7.77% for FDD with the proposed method, demonstrating that the proposed method more effectively mitigates this physically unrealistic phenomenon.

Second, we analyzed the impacts on the proportional power distribution among the three scattering mechanisms. Color-coded decomposition results for original FDD, FDD with the existing method, and FDD with the proposed method are shown in Figure 4 [Figure 4: see original paper], where blue represents surface scattering, red represents double-bounce scattering, and green represents volume scattering.

The average power proportions for the four patches are summarized in Tables 1-4 -.

Table 1: Average power proportions of patch 1 (ocean region)

Method	Surface	Double-bounce	Volume
FDD	92.29%	2.58%	5.14%
FDD with the current method	92.46%	2.72%	4.82%
FDD with the proposed method	94.17%	4.43%	1.40%

Table 2: Average power proportions of patch 2 (urban region)

Method	Surface	Double-bounce	Volume
FDD	29.32%	51.12%	19.56%
FDD with the current method	31.16%	52.78%	16.06%
FDD with the proposed method	33.78%	54.95%	11.27%

Table 3: Average power proportions of patch 3 (oriented urban region)

Method	Surface	Double-bounce	Volume
FDD	3.47%	68.74%	27.79%
FDD with the current method	-7.78%	104.3%	3.47%
FDD with the proposed method	16.11%	38.96%	44.93%

Table 4: Average power proportions of patch 4 (park region)

Method	Surface	Double-bounce	Volume
FDD	19.49%	8.07%	72.44%
FDD with the current method	21.05%	16.39%	62.56%
FDD with the proposed method	34.72%	26.70%	38.58%

In Figure 4, the red colors in urban regions are strengthened by the proposed deorientation method, particularly in oriented urban regions such as patch 3. With the existing method, patch 3 (oriented urban region) is not identified as double-bounce scattering dominant but rather as volume scattering dominant. The proposed method improves this classification, with green colors in patch 3 partially transitioning to red or yellow. The power proportions in Tables 2-3 support these visual changes. From a target classification perspective, the proposed method is more suitable for urban region extraction, especially for oriented urban regions. In park regions such as patch 4, green colors are weakened by the proposed method, but the region remains correctly classified as volume scattering dominant. Table 4 confirms that the proposed method yields lower average volume scattering power than the current method.

5 Discussion

The proposed deorientation method is specifically designed to better handle high-entropy regions, which typically include oriented urban areas and forested regions. For oriented urban regions, the proposed method demonstrates more reasonable and superior performance compared to the existing method, as previously shown. For forest regions, the proposed method yields lower average volume scattering power than the existing method.

Although forest regions can still be correctly identified as volume scattering dominant using the proposed method (e.g., patch 4), one might question whether the method underestimates volume scattering power in such areas. First, volume scattering is modeled as backscattering from a cloud of dipoles whose OAs follow a probability distribution. The commonly used uniform and half-cosine distributions are centered at zero, consistent with the OA distribution of patch 4 shown in Figure 3. Second, the eigenvector corresponding to the dipole scattering mechanism represents the volume scattering component. The proposed method compensates for the mean OA (or center OA) of the OA distribution for each eigenvector. Since OAs in forest regions are generally centered at zero, the deorientation effect on the volume scattering eigenvector is minimal. Therefore, the proposed method does not underestimate volume scattering power for this typical case. For the few targets with mean OAs not centered at zero, the mean OAs of the dipole scattering eigenvectors will be rotated, potentially leading to underestimation of canopy volume scattering power—a foreseeable limitation of the proposed method. However, it is unrealistic to expect a single method to be optimal for all target types.

6 Conclusion

Building upon the existing deorientation methods proposed by Lee et al. and An et al., which utilize a single average OA to uniformly rotate the coherency matrix, we have proposed a novel deorientation method designed to accommodate scatterers with different OAs within a single resolution cell. The method separately rotates the three single targets using their own OAs obtained through eigen-decomposition of the coherency matrix. A key feature of the proposed method is its consistency with Huynen' s deorientation theory: the real part of T_{13} becomes zero after deorientation, which is not the case for the existing method. Experimental results demonstrate that the proposed method is suitable for urban region extraction, particularly for oriented urban regions.

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

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