A novel interpretation of the PolSAR coherency matrix data: Postprint

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Abstract

Cloude-Pottier incoherent target decomposition (ICTD) and Touzi ICTD has been widely applied as a popular approach to interpret the scattering characteristics of a target in polarimetric synthetic aperture radar (PolSAR) data processing. However, they have a common drawback, i.e. proliferation of parameters (PoP) is unavoidable. Paladini et al. solved this problem by developing an orientation-invariant ICTD based on the coherency matrix under circular polarization basis. As an alternative to Paladini decomposition, we proposed a novel ICTD based on the frequently used coherency matrix under linear polarization basis. The proposed method can also avoid the problem of PoP, and avoid the ambiguity of alpha angle of Paladini decomposition as well. Real PolSAR data is processed to validate the proposed decomposition.

Full Text

Preamble

A Novel Interpretation of the PolSAR Coherency Matrix Data

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ABSTRACT

Cloude-Pottier incoherent target decomposition (ICTD) and Touzi ICTD have been widely applied to interpret the scattering characteristics of targets in polarimetric synthetic aperture radar (PolSAR) data processing. However, these methods share a common drawback: the proliferation of parameters (PoP) is unavoidable. Paladini et al. addressed this issue by developing an orientation-invariant ICTD based on the coherency matrix in the circular polarization basis. As an alternative to the Paladini decomposition, we propose a novel ICTD based on the commonly used coherency matrix in the linear polarization basis. The proposed method not only avoids the PoP problem but also eliminates the alpha angle ambiguity inherent in the Paladini decomposition. Real PolSAR data are processed to validate the proposed decomposition.

Index Terms–Coherency matrix, ICTD, PolSAR, target decomposition

1. INTRODUCTION

Target decomposition is a popular approach for understanding scattering mechanisms in polarimetric synthetic aperture radar (PolSAR) data processing. Target decomposition methods can be categorized into coherent target decomposition (CTD) based on the scattering matrix and incoherent target decomposition (ICTD) based on second-order statistical coherency or covariance matrices. Since incoherent scattering is predominant in real-world scenarios, ICTD has attracted significant attention.

Huynen pioneered target decomposition theory [1], but his method has not been widely adopted due to its preference for symmetric and regular targets [2]. Currently, the main research focuses in ICTD are eigen-decomposition [3-5] and model-based decomposition [6-13].

Eigen-decomposition was pioneered by Cloude and Pottier [3], though Huynen criticized this approach for generating a serious proliferation of parameters (PoP) [14]. Touzi also developed a successful ICTD based on his target scattering vector model (TSVM) [4], but the PoP issue remained. Paladini et al. proposed a novel ICTD using the coherency matrix in the circular polarization basis, successfully solving the PoP problem [5]. However, a potential limitation of the Paladini decomposition is that its alpha angle is identical to the Cloude-Pottier alpha angle, which physically mixes the alpha and helix angles.

For model-based decomposition, three-component or four-component decompositions offer clear physical interpretation and are easy to implement [6-9], but they suffer from information loss. Chen et al. proposed a novel model-based decomposition with separate orientation angles for odd- and double-bounce models [10]; however, we contend that the helix component should be modeled as the asymmetry of odd- and even-bounce scatterers rather than as an independent scattering component. Van Zyl et al., Cui et al., and Wang et al. proposed non-negative eigenvalue decomposition [11-13], but their interpretation of scattering mechanisms is partially based on eigen-decomposition rather than scattering models.

As an alternative to the Paladini decomposition, our proposed ICTD, which is based on the commonly used coherency matrix in the linear polarization basis, also avoids the PoP problem while additionally eliminating the alpha angle ambiguity present in the Paladini ICTD.

2. MATRIX DEFINITIONS

For coherent scattering, the complete polarimetric information is contained in the scattering matrix, where the subscript HV denotes vertical polarization transmission and horizontal polarization reception.

Two frequently used scattering vectors are the Pauli basis scattering vector kP and the circular polarization basis scattering vector kC, where the superscript t denotes matrix transposition and the subscripts L and L denote left circular polarization and its orthogonal counterpart, respectively.

For incoherent scattering, the complete polarimetric information is contained in the second-order statistical coherency matrix T in the linear polarization basis or the coherency matrix G in the circular polarization basis. The coherency matrices are obtained through averaging, where <•> denotes temporal or spatial averaging and the superscript † denotes complex conjugation and transposition. Both T and G have nine degrees of freedom (DoFs). The Cloude-Pottier, Touzi, and proposed ICTDs are based on the coherency matrix T, whereas the Paladini ICTD is based on the coherency matrix G.

3. THE PROPOSED ICTD

The proposed ICTD is based on the eigen-decomposition of the coherency matrix T, where Λ is the diagonal matrix containing the eigenvalues 1, 2, and 3 (with 1 2 3 assumed), and U consists of three eigenvector columns k1, k2, and k3.

The matrix U is modeled as the product of six unitary transformation matrices, each with one degree of freedom. In the following subsections, we detail the models of matrices Λ and U. Since matrix Λ has three DoFs, matrix U has six DoFs.

3.1. Information Extraction from the Matrix Λ

The matrix Λ takes the form Λ=diag(1, 2, 3) and possesses three independent parameters. For more convenient physical interpretation, we propose replacing the three eigenvalues with three physically meaningful parameters: the total power SPAN, the scattering entropy H, and the anisotropy A.

The SPAN represents the total backscattered power from the target and was introduced by Cao et al. for classification applications [15]. The entropy H serves as an indicator of scattering randomness. The anisotropy A also carries physical significance.

3.2. Model of the Matrix U

3.2.1. Model of the Dominant Eigenvector k1

For a three-dimensional complex vector k1, there are six DoFs. Two DoFs are lost due to (1) absolute phase indeterminacy and (2) unitary constraints [5], leaving four independent parameters for modeling k1.

We model k1 using Touzi’ s TSVM as

$$k_1 = \begin{bmatrix} \cos\alpha_s \cos\tau_m \\ \sin\alpha_s \cos\tau_m e^{j\Phi_{\alpha_s}} \\ \sin\tau_m e^{j\psi} \end{bmatrix}$$

The parameter represents the orientation angle of k1. The parameter m is the helix angle of k1, which measures the asymmetry of the target represented by k1. The parameter s is the scattering type magnitude, an important parameter for discriminating odd- and even-bounce scattering. The parameter Φ s is the scattering type phase, which can distinguish dipoles from quarter-wave targets and has been applied to ship recognition and other tasks [4].

The alpha angle in Paladini ICTD is identical to the Cloude-Pottier alpha angle, which physically mixes the alpha and helix angles [4]. The parameter s from TSVM and our ICTD avoids this ambiguity. These four parameters have clear physical meanings and eliminate some ambiguities of the Cloude-Pottier alpha-beta model [4].

In low-entropy scattering scenarios, the dominant eigenvector described by these four parameters accounts for the dominant or global scattering characteristics, while the subdominant eigenvectors described by the remaining two parameters capture the local scattering characteristics. In high-entropy scenarios, the scattering power of the subdominant eigenvectors becomes comparable to that of the dominant eigenvector, and the last two parameters contain more information than in low-entropy cases.

Through the proposed ICTD, nine independent parameters are extracted from the coherency matrix: SPAN, H, A, , m, s, Φ s, Ψ, and Γ. Thus, the proposed ICTD avoids the PoP problem, and all decomposed parameters have explicit physical meanings.

3.2.2. Model of the Subdominant Eigenvectors

As matrix U has six DoFs and the dominant eigenvector occupies four, only two DoFs remain for the subdominant eigenvectors k2 and k3. After applying appropriate transformations [5], the subdominant eigenvectors are modeled by two unitary transformation matrices as

$$U = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\Psi & -\sin\Psi \\ 0 & \sin\Psi & \cos\Psi \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & e^{j\Gamma} & 0 \\ 0 & 0 & e^{-j\Gamma} \end{bmatrix}$$

The parameter Ψ measures the relative magnitude of the second and third eigenvector elements and is interpreted as the local orientation angle of the target. The parameter Γ introduces a phase difference that contains information about the local helix characteristic of the target. The physical basis of these two parameters requires further validation. In [16], these last two parameters are interpreted as "relative orientation" and "relative helicity," both of which are depolarization parameters.

4. EXPERIMENTAL RESULTS

In this section, RADARSAT-2 C-band PolSAR data from the San Francisco Bay area are processed to demonstrate the nine decomposed parameters. The data are in single-look complex format. A refined Lee filter is applied to suppress speckle and obtain coherency matrix data. Only a portion of the scene is used.

The total power SPAN is shown in Fig. 1(a), where dihedral targets with specular scattering exhibit higher backscattered power. The scattering entropy H is displayed in Fig. 1(b), revealing that park areas and oriented urban areas with greater scattering randomness have higher entropy values. The anisotropy A is presented in Fig. 1(c); for ocean and urban areas, the minimum eigenvalue is very small, resulting in large A values.

The orientation of the dominant eigenvector is shown in Fig. 1(d), where blue-colored areas correspond well to oriented urban regions. The helix angle m of the dominant eigenvector is displayed in Fig. 1(e), showing small values across the entire scene. The scattering type magnitude s is shown in Fig. 1(f), being close to /2 for urban areas and near zero for ocean areas. The scattering type phase Φ s is presented in Fig. 1(g), which contains physical information as previously discussed.

The local orientation Ψ is shown in Fig. 1(h), exhibiting large values for oriented urban and park areas because the sub-scatterers within each resolution cell have diverse orientations. The local helix angle Γ is displayed in Fig. 1(i) and appears generally noisy.

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5. DISCUSSION

The similarities and differences between the Paladini ICTD and the proposed ICTD are discussed.

First, the similarities are: (1) both avoid the PoP problem; (2) both are serial (multiplicative) decompositions, whereas other common decompositions are parallel (additive); and (3) both ICTDs have ambiguities in their helix angles. For the proposed ICTD, the helix angle cannot describe asymmetry when s equals /2, while for the Paladini ICTD, the helix angle cannot describe asymmetry when the alpha angle equals zero.

Second, the differences are: (1) the proposed ICTD is based on the commonly used coherency matrix T, whereas the Paladini ICTD is based on coherency matrix G; and (2) the dominant eigenvector model in our ICTD is based on TSVM, which eliminates the alpha angle ambiguity present in the Paladini ICTD.

6. CONCLUSION

A novel serial (multiplicative) ICTD of the coherency matrix is proposed, yielding nine independent parameters with explicit physical meanings. The proposed decomposition successfully avoids the PoP problem. Real PolSAR data were processed to demonstrate the effectiveness of the approach. A classification method based on these nine parameters is currently under investigation.

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Figure. 1. Results of the parameters (a) SPAN, (b) H, (c) A, (d) , (e) m, (f) s, (g) Φ s, (h) Ψ, and (i) Γ.

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

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