A novel polarimetric interferometric SAR coherence parameter and its application in buildings detection (Postprint)

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Date: 2017-03-10T00:00:00+00:00

Abstract

Detection of man-made buildings is important in land use monitoring and land management applications. Generally, polarimetric synthetic aperture radar (PolSAR) data are processed for building detection. However, buildings that are not aligned with the radar flight track are often misclassified as forest, because oriented buildings generate additional cross-polarization components. Polarimetric interferometric SAR (PolINSAR) acquires two measurements with either a spatial baseline or a temporal baseline. For PolInSAR with a temporal baseline, i.e., repeat pass PolInSAR, the two polarimetric measurements are sensitive to temporal variations of targets. Buildings, regardless of their orientation, exhibit high coherence, whereas certain natural targets exhibit low coherence. This paper proposes a novel parameter that represents the mean PolINSAR coherence and can be utilized to discriminate between buildings and certain natural targets. The parameter is derived from the coherence optimization theory of Cloude and Papathanassiou, and represents the mean of the three optimal coherences weighted by three pseudo-probabilities. Based on this new parameter and SPAN, a building detection method is further proposed. The excellent performance of the proposed method for building extraction is demonstrated through processing of L-band E-SAR repeat pass PolINSAR data from the Oberpfaffenhofen area, acquired by the German Aerospace Center (DLR).

Full Text

Preamble

A Novel Polarimetric Interferometric SAR Coherence Parameter and Its Application in Buildings Detection

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Abstract—Man-made building detection is crucial for land use supervision and land control applications. While polarimetric synthetic aperture radar (PolSAR) data are generally effective for building detection, structures not aligned with the radar flight path are often misclassified as forest. This occurs because oriented buildings generate additional cross-polarization while reducing the corresponding double-bounce scattering signature. Polarimetric interferometric SAR (PolINSAR) acquires two measurements with either a spatial or temporal baseline. For repeat-pass PolINSAR, which utilizes a temporal baseline, the two polarimetric measurements are sensitive to target temporal variations. Buildings exhibit high coherence regardless of orientation, whereas many natural targets display low coherence. This paper proposes a novel parameter representing the mean PolINSAR coherence that can distinguish buildings from certain natural targets.

The parameter builds upon the coherence optimization theory of Cloude and Papathanassiou and is computed as the weighted average of three optimal coherences using three pseudo-probabilities. Based on this new parameter and the SPAN (total power), we further propose a building detection method. The excellent performance of our approach for building extraction is demonstrated through processing of L-band E-SAR repeat-pass PolINSAR data from the German Aerospace Center (DLR) over the Oberpfaffenhofen area.

1. Introduction

Building detection is essential for land use supervision and land control applications. Polarimetric target decomposition (PTD) is commonly applied to PolSAR data to interpret target scattering mechanisms [1]–[8]. The PTD concept was originally proposed by Huynen [1], though Huynen decomposition has not been widely adopted due to its preference for symmetric and regular targets [2]. Modern PTD has evolved into two main categories: eigenvalue/eigenvector-based decomposition and model-based decomposition. Eigenvalue/eigenvector approaches extract physically meaningful parameters from the eigenvalues and eigenvectors of the coherency or covariance matrix [3], [4], while model-based methods fit canonical scattering models to these matrices [5]–[8].

Buildings typically induce double-bounce scattering through specular reflections from ground-wall interactions. Both categories of PTD successfully characterize this double-bounce mechanism. However, when buildings are not aligned with the radar track, additional cross-polarization is introduced while the corresponding double-bounce scattering is reduced. Consequently, such buildings may be misclassified as forest, where cross-polarization dominates. Deorientation processing is often implemented prior to model-based PTD to mitigate this issue [6], [9]–[11], and it works well to some extent. Nevertheless, even with deorientation, buildings that are significantly oriented relative to the radar track may still be misclassified as forest [11].

Polarimetric SAR interferometry (PolINSAR) is a powerful technique primarily used for digital elevation model (DEM) generation and physical parameter estimation [12], [13]. PolINSAR collects data using either a spatial or temporal baseline. For repeat-pass PolINSAR, which employs a temporal baseline, the two measurements are sensitive to target temporal variations. Man-made buildings maintain high coherence between acquisitions regardless of orientation, while many natural targets, such as forests, exhibit relatively low coherence. Therefore, repeat-pass PolINSAR coherence can be exploited for building detection. This paper proposes a mean PolINSAR coherence parameter that measures target coherence as the average of three optimal coherences derived from coherence optimization theory [12], [13]. By combining this new parameter with SPAN, we develop a robust building detection method.

2. Mean PolINSAR Coherence Parameter

The proposed mean PolINSAR coherence parameter quantifies the polarimetric scattering coherence of targets between two repeat-pass PolINSAR acquisitions. It is based on the coherence optimization theory developed by Cloude and Papathanassiou [12], [13].

Repeat-pass PolINSAR acquires two polarimetric scattering matrices, $\mathbf{S}_1$ and $\mathbf{S}_2$. From these scattering matrices, the corresponding scattering vectors $\mathbf{k}_1$ and $\mathbf{k}_2$ in the Pauli basis can be derived. The 6×6 PolINSAR coherency matrix $\mathbf{T}_6$ is represented by

$$\mathbf{T}_6 = \begin{bmatrix} \langle \mathbf{k}_1 \mathbf{k}_1^{*T} \rangle & \langle \mathbf{k}_1 \mathbf{k}_2^{*T} \rangle \\ \langle \mathbf{k}_2 \mathbf{k}_1^{*T} \rangle & \langle \mathbf{k}_2 \mathbf{k}_2^{*T} \rangle \end{bmatrix} = \begin{bmatrix} \mathbf{T}_{11} & {}_{12} \\ {}^{*T}_{12} & \mathbf{T}_{22} \end{bmatrix}$$

where the superscript $*$ denotes complex conjugate and $\langle \cdot \rangle$ denotes ensemble averaging. The three 3×3 matrices $\mathbf{T}_{11}$, ${}_{12}$, and $\mathbf{T}_{22}$ are respectively

$$\mathbf{T}_{11} = \langle \mathbf{k}_1 \mathbf{k}_1^{*T} \rangle, \quad {}_{12} = \langle \mathbf{k}_1 \mathbf{k}_2^{*T} \rangle, \quad \mathbf{T}_{22} = \langle \mathbf{k}_2 \mathbf{k}_2^{*T} \rangle.$$

Two unitary complex projection vectors ω_1 and ω_2 are defined, and the coherence can be generally expressed as [13], [14]

$$\gamma = \frac{\omega_1^{*T} \; {}_{12} \omega_2}{\sqrt{(\omega_1^{*T} \mathbf{T}_{11} \omega_1)(\omega_2^{*T} \mathbf{T}_{22} \omega_2)}}.$$

To determine which combination of ω_1 and ω_2 yields maximum coherence, Cloude and Papathanassiou proposed a coherence optimization method. Detailed information about coherence definition and optimization can be found in [12] and [13]. The coherence optimization problem is transformed into two eigenvalue/eigenvector problems as follows:

$$\mathbf{T}_{22}^{-1}\ {}_{12}^{*T}\mathbf{T}_{11}^{-1}\ {}_{12}\omega_2 = \nu_2\omega_2,$$

$$\mathbf{T}_{11}^{-1}\ {}_{12}\mathbf{T}_{22}^{-1}\ {}_{12}^{*T}\omega_1 = \nu_1\omega_1.$$

By solving the first eigenvalue/eigenvector problem, three eigenvectors $\omega_{21}, \omega_{22}, \omega_{23}$ and three eigenvalues $\nu_{21}, \nu_{22}, \nu_{23}$ are obtained. Solving the second problem yields another three eigenvectors $\omega_{11}, \omega_{12}, \omega_{13}$ and eigenvalues $\nu_{11}, \nu_{12}, \nu_{13}$. The three optimal coherences can be obtained as

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Similar to the average alpha angle in Cloude-Pottier decomposition [3], the mean PolINSAR coherence parameter is defined as

$$\bar{\gamma} = p_1\gamma_1 + p_2\gamma_2 + p_3\gamma_3,$$

where p_1, p_2, and p_3 are the corresponding pseudo-probabilities with $p_i = \nu_{1i}/(\nu_{11} + \nu_{12} + \nu_{13})$. The physical basis is that γ_1, γ_2, and γ_3 occur with pseudo-probabilities p_1, p_2, and p_3, respectively. Thus, the mean PolINSAR coherence parameter provides a best estimate of γ_1, γ_2, and γ_3 [3].

The proposed mean PolINSAR coherence parameter can be generally used to measure target coherence for repeat-pass PolINSAR applications.

3. Buildings Detection Method

The proposed mean PolINSAR coherence parameter and SPAN (total power) are jointly utilized to detect buildings from repeat-pass PolINSAR data. SPAN represents the total power of the two measurements and is defined as

$$\text{SPAN} = \text{trace}(\mathbf{T}_{11}) + \text{trace}(\mathbf{T}_{22}).$$

The building detection algorithm is illustrated in Figure 1 [Figure 1: see original paper]. The procedure involves: (1) computing the SPAN from the repeat-pass PolINSAR data; (2) computing the mean PolINSAR coherence parameter; and (3) applying a dual-threshold criterion where a pixel is classified as building only if its SPAN exceeds Threshold 1 and its mean PolINSAR coherence exceeds Threshold 2.

As shown in Figure 1, the SPAN and mean PolINSAR coherence parameter are first calculated for each pixel. The SPAN is compared against Threshold 1. If a pixel' s SPAN surpasses this threshold, it undergoes further investigation using the mean PolINSAR parameter. Subsequently, if the mean PolINSAR parameter also exceeds Threshold 2, the pixel is recognized as a building.

4. Experimental Validation

This section validates the building detection algorithm using real repeat-pass PolINSAR data acquired by the German Aerospace Center’ s L-band E-SAR system over the Oberpfaffenhofen area. The temporal baseline was within one day.

Figure 2(a) [Figure 2: see original paper] shows a Google Earth optical image serving as reference. Figure 2(b) displays the SPAN image, where white indicates high SPAN values. Both forest and buildings generally produce high SPAN. Forests yield high SPAN partly due to random scattering from the canopy and partly from ground-trunk double-bounce scattering. Buildings generate high SPAN through ground-wall double-bounce scattering. Figure 2(c) presents the SPAN-based detection result, where pixels are coded white or black depending on whether SPAN is greater or smaller than Threshold 1. Both forest and buildings are detected simultaneously, demonstrating that SPAN alone cannot successfully extract buildings.

Figure 2(d) shows the mean PolINSAR coherence image, where white denotes high coherence. Buildings exhibit high mean coherence regardless of orientation, while forest displays low mean coherence due to temporal decorrelation. Figure 2(e) presents histograms of the mean PolINSAR coherence for two selected patches: forest and an oriented airport building, marked as Patch 1 and Patch 2 in Figure 2(a). The histograms demonstrate that the mean PolINSAR coherence effectively separates forest from buildings. Figure 2(f) shows the mean PolINSAR coherence-based detection result, where pixels are coded white or black based on whether their coherence exceeds Threshold 2. Buildings are successfully detected, including oriented isolated structures at the airport. However, large areas of Bragg surface scattering also exhibit high coherence—these correspond to farmlands with sparse short grass or no crops. Thus, using mean PolINSAR coherence alone cannot successfully extract buildings.

Figure 2(g) presents the detection result from the proposed method combining both parameters. Buildings are generally detected, including the oriented isolated airport structures. Compared to Figure 2(c), the proposed method eliminates forest areas with high SPAN because forest exhibits low mean coherence. Compared to Figure 2(f), the method removes Bragg scattering areas because, despite their high coherence, they have low SPAN values.

It is worth noting that two linear features within the red circles in Figure 2(g) are incorrectly detected as buildings, representing a potential limitation of the proposed method. These features are actually fences along roads that induce both high SPAN and high mean coherence. Although no building reference data were available, comparison with the Google Earth optical image demonstrates the effectiveness of the proposed method.

5. Conclusion

The mean PolINSAR coherence parameter is proposed as a general metric for measuring target coherence in repeat-pass PolINSAR. Buildings exhibit high coherence between measurements, and a detection method combining the mean PolINSAR coherence with SPAN is presented. Processing of repeat-pass PolINSAR data validates the building detection approach, and potential limitations are addressed.

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Figure 2. (a) Google Earth optical image; (b) SPAN image; (c) SPAN-based detection result. (d) Mean PolINSAR coherence parameter; (e) Histograms of mean PolINSAR coherence for selected forest and building patches. (f) Mean PolINSAR coherence-based detection result. (g) Building detection result using the proposed method.

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