Three-Component Decomposition of Polarimetric SAR Data Integrating Eigen-Decomposition Results

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Abstract. This paper presents a novel three-component scattering power decomposition of polarimetric SAR data. There are two problems in three-component decomposition method: volume scattering component overestimation in urban areas and artificially set parameter to be a fixed value. Though volume scattering component overestimation can be partly solved by deorientation process, volume scattering still dominates some oriented urban areas. The speckle-like decomposition results introduced by artificially setting value are not conducive to further image interpretation. This paper integrates the results of eigen-decomposition to solve the aforementioned problems. Two principal eigenvectors are used to substitute the surface scattering model and the double bounce scattering model. The decomposed scattering powers are obtained using a constrained linear least-squares method. The proposed method has been verified using an ESAR PolSAR image, and the results show that the proposed method has better performance in urban area.

1. Introduction
Polarimetric synthetic aperture radar (PolSAR) is sensitive to the geometric structure, orientation and physical characteristics of scattering targets. Polarimetric target decomposition (PTD) is a useful tool to identify and separate scattering mechanisms [1]-[4]. One of the most used PTD methods, Freeman and Durden's three-component decomposition method, decomposes PolSAR data into three power categories: surface, double-bounce, and volume scattering power. When decomposing surface scattering power and double-bounce power, some artificial settings were applied in the three-component decomposition due to the number of unknowns is larger than it of the observation. This approach is best when either double bounce contribution or surface contribution is close to zero. In real case, especially in double-bounce and surface contribution mixed place, speckle-like decomposition results will be introduced due to artificial settings. Another problem of three-component decomposition method is that the volume scattering power is usually overestimated in oriented urban areas. Though it can be partly solved by deorientation process [5], it still exists in some highly oriented urban areas [6]. This paper integrates the results of eigen-decomposition to solve these two problems. As discussed in [7], it is needless to artificially set parameters to be fix values, and the eigen-decomposition results can directly provide parameters. Based on this, the surface and double bounce scattering models can be calculated by eigen-decomposition results. Finally, the decomposed scattering powers are obtained using a constrained linear least-square method.

A brief description of the decomposition algorithm is presented in Section 2. Section 3 provides the three-component scattering decomposition algorithm integrating eigen-decomposition. In Section 4 the algorithm is illustrated using ESAR PolSAR data. Finally, conclusion is given in Section 5.
2. Decomposition algorithms

2.1. Three-Component Decomposition method

Fully polarimetric SAR system measures the $2 \times 2$ complex scattering matrix $[S]$ of each cell in image. The Pauli vector can be defined as

$$k_p = \frac{1}{\sqrt{2}} [S_{hh}, S_{hv}, S_{vh}, 2S_{vv}]^T$$

(1)

Where $S_{hh}, S_{hv}$ and $S_{vh}$ are elements of $[S]$. 

The coherence matrix is defined as

$$[T] = \left[ \begin{array}{ccc} T_{11} & T_{12} & T_{13} \\ T_{21} & T_{22} & T_{23} \\ T_{31} & T_{32} & T_{33} \end{array} \right]$$

(2)

The rotated coherency matrix with rotation angle $\theta$ can be obtained as

$$[T(\theta)] = \left[ \begin{array}{ccc} T_{11}(\theta) & T_{12}(\theta) & T_{13}(\theta) \\ T_{21}(\theta) & T_{22}(\theta) & T_{23}(\theta) \\ T_{31}(\theta) & T_{32}(\theta) & T_{33}(\theta) \end{array} \right] = [R_p(\theta)][T][R_p(\theta)]^H$$

(3)

Where $[R_p(\theta)] = \left[ \begin{array}{ccc} 1 & 0 & 0 \\ 0 & \cos 2\theta & \sin 2\theta \\ 0 & -\sin 2\theta & \cos 2\theta \end{array} \right]$ 

The angle $\theta$ can be obtained as [5]

$$\theta = \frac{1}{4} \tan^{-1} \left( \frac{2 \text{Re}(T_{23})}{T_{22} - T_{33}} \pm n\pi \right) \quad n = 0,1$$

(4)

Therefore, the rotated coherency matrix can be expressed as the sum of three matrices including surface, double-bounce, and volume scattering matrices.

$$[T(\theta)] = f_s[T]_s + f_d[T]_d + f_v[T]_v$$

(5)

Where $f_s$, $f_d$ and $f_v$ are the coefficients corresponding to the surface scattering coherency matrix $[T]_s$, the double-bounce scattering coherency matrix $[T]_d$, and the volume scattering coherency matrix $[T]_v$, respectively. $[T]_s$ or $[T]_d$ will be set to be a fixed value depending on which scattering is dominant.

2.2. Eigen-decomposition

Eigen-decomposition of the coherency matrix can be expressed as

$$[T] = \sum_{i=1}^{3} \lambda_i \bar{e}_i \bar{e}_i^H$$

(6)

Where $\lambda_1, \lambda_2$ and $\lambda_3$ are the eigenvalues, $\bar{e}_i$ represents the normalized eigenvector corresponded with $\lambda_i$, $e_m$ is the $m-th$ element of the $\bar{e}_i$ ($m=1,2,3 \ i=1,2,3$).

The two principle eigenvectors $\bar{e}_1$ and $\bar{e}_2$ can be viewed as the same as the surface and double-bounce scattering mechanism[7]. This means that the eigen-decomposition results can be directly used as prior information to fix unknown values in three-component decomposition method.

3. Modified three-component scattering decomposition
The three-component scattering decomposition suffers from scattering mechanism ambiguity in some oriented urban areas. Chen et al.[8] proposed a general model-based decomposition, which by separating double and odd bounce orientation angles, to solve the volume contribution overestimation problem. However, this approach used a nonlinear least squares optimization technique that will introduce heavy computation burden.

In this paper, the eigen-decomposition method are integrated with model-based decomposition. The $[T]_s$ and $[T]_d$ can be determined directly by $e_s$ and $e_d$, 

$$[T]_s = e_s e_s^H, [T]_d = e_d e_d^H$$  

(7)

Where

$$\begin{align*}
e_s = e_1, e_d = e_2 \\
e_s = e_2, e_d = e_1 \\
\text{Re}\{e_{11}/e_{12}\} < \text{Re}\{e_{21}/e_{22}\}, \\
\text{Re}\{e_{11}/e_{12}\} \geq \text{Re}\{e_{21}/e_{22}\}
\end{align*}$$  

(8)

The proposed decomposition can be written as

$$[T] = f_s [T]_s + f_d [T]_d + f_v [T]_v + [T]_{\text{residual}}$$  

(9)

The residual matrix $[T]_{\text{residual}}$ is used to measure the performance of the decomposition results. The criterion is to minimize $\| [T]_{\text{residual}} \|_2$ (L2-norm of $[T]_{\text{residual}}$).

$$\begin{align*}
\text{minimize} & \quad \| [T]_{\text{residual}} \|_2 \\
\text{subject to} & \quad [T]_{\text{residual}} = [T] - f_s [T]_s - f_d [T]_d - f_v [T]_v
\end{align*}$$  

(10)

Note that $[T]_s$, $[T]_d$ and $[T]_v$ are all known, $f_s$, $f_d$ and $f_v$ should be no less than zero. The decomposition turns to be a linearly constrained least-squares problem[9],

$$\begin{align*}
\min \frac{1}{2} \|egin{bmatrix}
T_{s11} & T_{s12} & T_{s13} \\
\text{Re}\{T_{s12}\} & \text{Re}\{T_{s12}\} & \text{Re}\{T_{s12}\} \\
\text{Im}\{T_{s12}\} & \text{Im}\{T_{s12}\} & \text{Im}\{T_{s12}\} \\
\text{Re}\{T_{s13}\} & \text{Re}\{T_{s13}\} & \text{Re}\{T_{s13}\} \\
\text{Im}\{T_{s13}\} & \text{Im}\{T_{s13}\} & \text{Im}\{T_{s13}\} \\
T_{d11} & T_{d12} & T_{d13} \\
\text{Re}\{T_{d12}\} & \text{Re}\{T_{d12}\} & \text{Re}\{T_{d12}\} \\
\text{Im}\{T_{d12}\} & \text{Im}\{T_{d12}\} & \text{Im}\{T_{d12}\} \\
\text{Re}\{T_{d13}\} & \text{Re}\{T_{d13}\} & \text{Re}\{T_{d13}\} \\
\text{Im}\{T_{d13}\} & \text{Im}\{T_{d13}\} & \text{Im}\{T_{d13}\} \\
T_{v11} & T_{v12} & T_{v13} \\
\text{Re}\{T_{v12}\} & \text{Re}\{T_{v12}\} & \text{Re}\{T_{v12}\} \\
\text{Im}\{T_{v12}\} & \text{Im}\{T_{v12}\} & \text{Im}\{T_{v12}\} \\
\text{Re}\{T_{v13}\} & \text{Re}\{T_{v13}\} & \text{Re}\{T_{v13}\} \\
\text{Im}\{T_{v13}\} & \text{Im}\{T_{v13}\} & \text{Im}\{T_{v13}\} \\
\end{bmatrix}\begin{bmatrix}
x \\
y \\
z
\end{bmatrix}
\end{align*}$$  

such that $0 \leq x_1$, $0 \leq x_2$, $0 \leq x_3$

(11)

Where $\bar{x} = [x_1, x_2, x_3]^T = [f_s, f_d, f_v]^T$.

Since the trace of $[T]_s$, $[T]_d$ and $[T]_v$ are all equal to one, $f_s$, $f_d$ and $f_v$ can be regarded the contribution $P_s$, $P_d$ and $P_v$ of each scattering mechanism to the span.

4. Experimental results and discussion

The ESAR L-band fully polarized images were used to validate the modified three-component scattering power decomposition model.

The results of applying the original Freeman decomposition (F30)[2], three decomposition with deorientation (F3R)[5] and the proposed method (E3) to the three patches (forest, oriented urban and orthogonal urban) of ESAR image are shown in Figure 1. The RGB represents double-bounce, volume and surface scattering components respectively.
As can be seen in Figure 1, in forest area, all of the three methods have the similar decomposition results. In oriented urban area, volume scattering is the dominant scattering in the result of F3O. This is because oriented area will induce significant cross-polarization power. Though in F3R, orientation angle compensation can reduce cross-polarization power and the urban area appears to be not that green as F3O results, the dominant scattering is still volume scattering. This is because the orientation angle of oriented urban is very high. The proposed method, however, can reduce volume scattering contribution significantly. In orthogonal urban area, which is the orthogonal urban area, the dominant scattering powers are all double bounce contribution. The results of this area are also similar. However, speckle-like decomposition results are shown in F3O and F3R results, this is because of the artificial settings. In E3 result, the decomposition results are smooth, which would be helpful for further image interpretation.

In order to examine results quantitatively, the decomposed power contributions of the three methods are shown in Table 1.

| Patch Name          | Method | $P_v$ | $P_d$ | $P_s$ |
|---------------------|--------|-------|-------|-------|
| Forest              | F3O    | 17.45 | 20.19 | 62.36 |
|                     | F3R    | 23.50 | 28.78 | 47.72 |
|                     | E3     | 41.68 | 25.86 | 32.46 |

The contribution of volume scattering in oriented urban area is suppressed to 32.46% by proposed method. Both the double bounce and surface scattering contributions are enhanced accounting to 41.68% and 25.86% respectively. Therefore, the proposed method improves the decomposition results and can be more consistent with the real situation of oriented urban areas.

5. Conclusion
This paper integrates the results of eigen-decomposition to solve the volume scattering overestimation in some oriented urban areas and artificial parameter setting problems. Two principal eigenvectors are used to substitute the surface scattering and double bounce scattering models. The decomposed scattering powers are obtained using a constrained linear least-squares method. The proposed method has been verified using an ESAR PolSAR image, and the results show that the proposed method has better performance in oriented urban area.

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