Adaptive polarimetric decomposition using incoherent ground scattering models without reflection symmetry assumption

Xiaoguang CHENG\textsuperscript{a,b,*}, Wenli HUANG\textsuperscript{c} and Jianya GONG\textsuperscript{b}

\textsuperscript{a}Nanjing Research Institute of Electronics Engineering, 99 Houbiaoying Road, Nanjing 210007, China; \textsuperscript{b}State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University, 129 Luoyu Road, Wuhan 430079, China; \textsuperscript{c}Department of Geographical Sciences, University of Maryland, College Park, MD 20742, USA

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Most of the current incoherent polarimetric decompositions employ coherent models to describe ground scattering; however, this cannot truly reflect the fact especially in natural ground surfaces. This paper proposes a highly adaptive decomposition with incoherent ground scattering models (ADIGSM). In ADIGSM, Neumann's adaptive model is employed to describe volume scattering, and to explain cross-polarized power in remainder matrix, so that we can obtain orientation angle randomness for both volume scattering and the dominant ground scattering. The computation of volume scattering parameters is strictly constrained for non-negative eigenvalues, while the volume scattering parameters that explain the most cross-polarized power are selected. When applying ADIGSM to NASA's UAVSAR data, the negative component powers were obtained in quite a few forest pixels. Compared with several newest decompositions, the volume scattering power is obviously lowered, especially in areas dominated by surface scattering or double bounce scattering. The orientation angle randomness of each component is reasonable as well. ADIGSM has potential to be applied in the fields such as PolSAR image classification, land cover mapping, speckle filtering, soil moisture and roughness estimation, etc.

Keywords: polarimetric synthetic aperture radar (PolSAR); polarimetric decomposition; non-negative eigenvalue decomposition (NNED); scattering model

1. Introduction

Polarimetry has expanded significantly with the increasing volume of polarimetric synthetic aperture radar (PolSAR) data and theoretical approaches (1). More than twenty model-based decompositions have been published over the last 16 years. The representative methods include Freeman–Durden decomposition (2), Yamaguchi decomposition (3), van Zyl hybird decomposition (4), and so on. Readers may refer to Refs. (5, 6) for detailed reviews. In recent years, multiple adaptive scattering models (7, 8, 10, 11) and non-negative eigenvalues decomposition (NNED) (4, 12–14) were proposed. Model-based decomposition was expanded by incorporating PolSAR interferometry (PolInSAR) in Ref. (15). The effect of deorientation over built-up areas was tested in Refs. (16, 17). Model-based decomposition was applied to the study of snow-covered area (18), man-made targets (19), soil moisture estimation (20), speckle filter (21), and landslides (22). The original Freeman–Durden decomposition was further improved in Refs. (11, 23–25). Cui et al. (11) and Singh et al. (26) performed unitary transformation twice to coherency matrix to implement reflection symmetric or reflection asymmetric decomposition. A novel decomposition on the basis of the nonlinear least square fitting was proposed by Chen et al. in 2014 (27).

However, coherent models, which assume the orientation angles of all elemental scatterers in a component are the same, are employed by most of the incoherent decompositions to describe two kinds of ground scattering, i.e. double bounce and surface scattering. With reflection symmetry assumption and elemental scatterers whose cross-polarized complex scattering coefficients ($S_{\text{cold}}$) are zero, the derived coherent ground scattering models cannot describe depolarizing effects. Thus, cross-polarized power is only attributed to volume scattering and helix scattering, possibly making the results violate non-negative eigenvalues constraint (NNEC) (11). In the newest NNED (4, 28–30), sometimes, a significant proportion of cross-polarized power cannot be explained by volume scattering and helix scattering (4), especially when volume scattering is computed without reflection symmetry assumption. To solve this problem, ground scattering is coherently modeled based on the scatterers with non-zero $S_{\text{HV}}$ (14, 29, 30). However, such scatterers do not belong to the widely recognized canonical scattering except helix scattering.

Obviously, coherent scattering assumption does not always hold for man-made targets, let alone for natural distributed targets. For example, rugged ground should produce surface scattering with a broad range of orientation angles. As shown in Refs. (7, 8), incoherent models are likely to predict positive cross-polarized power as long as the orientation angles in one component are diverse. Hong and Wdowinski (31) proved that double

*Corresponding author. Email: cheng-xg@outlook.com

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bounce scattering mechanism also produces cross-polarized power based on SAR phase measurements. Therefore, incoherent modeling of ground scattering is preferred. Although recently, Lee et al. (5) proposed decomposition with incoherent ground scattering models, their methods are with reflection symmetry assumption, hence some polarimetric information may be discarded. In addition, uniform distribution of orientation angles was assumed for volume scattering, which may not be coincident with the truth.

When importing NNEC to decomposition, the maximum volume scattering power in theory is adopted usually, so the overestimation of volume scattering power is nearly inevitable (32). When applying adaptive volume scattering models, the overestimation is more serious. Based on the above considerations, this paper proposes a highly adaptive decomposition with incoherent ground scattering models (ADIGSM), in which NNEC without reflection symmetry assumption is applied in the computation of helix scattering and volume scattering parameters. The volume scattering parameters that explain the most cross-polarized power are selected. Volume scattering and the dominant ground scattering are all described by Neumann’s adaptive incoherent model (9). Furthermore, the validity of ADIGSM was evaluated using the data from uninhabited aerial vehicle SAR (UAVSAR). Testing results show that the pixels with negative ground scattering power were rare and mainly located in forest. Compared with the three latest NNED (29, 30), ADIGSM lowered the estimation of volume scattering power in nearly every pixel. The orientation angle randomness of each component was reasonable as well.

2. Scattering models

All the used scattering models in ADIGSM are briefly introduced in this section. In this paper, $T_{mn}$ stands for the element in the $m$th row and $n$th column of matrix $[T]$.

2.1. Helix scattering model

The helix scattering model $[T_{fl}]$ could be found in Ref. (3), so the authors would not give it here.

2.2. Volume scattering model

An adaptive reflection symmetric scattering model $[T_{Neum}]$ was raised by Neumann in Ref. (9), on the basis of unimodal circular normal von Mises distribution and elemental scatterer with $S_{fl} = 0$. Its obvious advantages over X-Bragg model and improved Yamaguchi’s volume scattering model were pointed out in Ref. (5). Arii’s model (8) is also quite adaptive with solid physical background, but its orientation angle randomness range is [0, 0.91].

$$[T_{Neum}] = \frac{1}{L+N} \begin{bmatrix} L & g_e(\tau)M^* & 0 \\ g_e(\tau)M & \frac{1}{2} + g(\tau)/2 & 0 \\ 0 & 0 & \frac{1}{2} - g(\tau)/2 \end{bmatrix}$$

with

$$L = |S_{HH} + S_{VV}|^2, M = (S_{HH} + S_{VV})(S_{HH} - S_{VV})^*, N = |S_{HH} - S_{VV}|^2$$

$$\tau = I_0(k)e^{g\cdot\tau}, \quad g_e(\tau) = I_1(k)/I_0(k),$$

$$g(\tau) = I_2(k)/I_0(k)$$

where $S_{HH}$ and $S_{VV}$ are complex scattering coefficients, HH stands for horizontal transmitting and horizontal receiving, VV stands for vertical transmitting and vertical receiving; * is the complex conjugate operator; $\tau$ is the randomness of orientation angles with a range of $[0, 1]; k$ is the concentration degree of orientation angles; $I_n(k)$ is the modified Bessel function of order $n$ and parameter $k$. When a horizontal dipole is used as an elemental scatterer, the volume scattering model is

$$[T_{Vol_{hh}}] = \frac{1}{2} \begin{bmatrix} 1 & g_e(\tau_V) \\ g_e(\tau_V) & \frac{1}{2} + g(\tau_V)/2 \\ 0 & 0 \end{bmatrix}$$

When a vertical dipole is used as an elemental scatterer, the volume scattering model is

$$[T_{Vol_{vv}}] = \frac{1}{2} \begin{bmatrix} 1 & -g_e(\tau_V) \\ -g_e(\tau_V) & \frac{1}{2} + g(\tau_V)/2 \\ 0 & 0 \end{bmatrix}$$

where $\tau_V$ is the $\tau$ of volume scattering.

2.3. Ground scattering model

As a generic incoherent model, $[T_{Neum}]$ is also capable of modeling surface scattering and double bounce scattering (33). Since $[T_{Neum}]$ is trace-normalized, we may assume $S_{HH} = 1$ and $S_{VV} = b_1 + b_2$ as in Refs. (2, 34). If we model both double bounce and surface scattering with $[T_{Neum}]$, and take the power and orientation angle randomness into account, then there will be $(2 + 1 + 1) \times 2 = 8$ parameters. However, with reflection symmetric models, at most 5 non-zero elements in the measured coherency matrix $[\langle T \rangle]$ can be explained, where $\langle \rangle$ stands for ensemble averaging. In this sense, we could only model one kind of ground scattering with $[T_{Neum}]$ and the other with a fixed model. When surface scattering is modeled by $[T_{Neum}]$, double bounce scattering is modeled by $[T_{Dan}]$ (see Equation (6), $S_{VV} = -1$ is assumed); when double bounce scattering is modeled by $[T_{Neum}]$, surface scattering
is modeled by $[T_{\text{Surf}}]$ (see Equation (7), $S_{VV} = 1$ is assumed). $[T_{\text{Dbl}}]$ and $[T_{\text{Surf}}]$ were also used in Refs. (2, 3, 5, 35).

$$
[T_{\text{Dbl}}] = \begin{bmatrix}
0 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 0
\end{bmatrix}
$$  

(6)

$$
[T_{\text{Surf}}] = \begin{bmatrix}
1 & 0 & 0 \\
0 & 0 & 0 \\
0 & 0 & 0
\end{bmatrix}
$$  

(7)

3. Proposed method: ADIGSM

This section describes the decomposition procedure. Figure 1 shows the flow chart of ADIGSM.

3.1. Deorientation

In order to make $\langle |T| \rangle$ be closer to reflection symmetry assumption, so it is more reasonable to utilize $[T_{\text{Neum}}]$, we perform deorientation to $\langle |T| \rangle$ and obtain the deoriented result $[T_{\text{AC}}]$. The details of deorientation could be found in Ref. (15).

3.2. Helix scattering power computation

Helix scattering power $P_C$ is first calculated as (see Ref. (3) for details):

$$
P_C = 2|\text{Im}(\langle T_{23} \rangle)|
$$  

(8)

In this paper, $\text{Re}(x)$ and $\text{Im}(x)$ denote the real and imaginary part of complex number $x$, respectively. Subtracting helix scattering from $[T_{\text{AC}}]$, we have

$$
[T_{\text{AC-noh}}] = [T_{\text{AC}}] - P_C[T_H]
$$  

(9)

Once $[T_{\text{AC-noh}}]$ computed with Equation (8) violates NNEC, $P_C$ is reselected as the maximum value that makes $[T_{\text{AC-noh}}]$ satisfy NNEC.

3.3. Volume scattering parameter computation

The formulas of computing volume scattering power $P_V$ with reflection symmetry assumption and NNEC were given in Ref. (4). They were extended without reflection symmetry assumption in Refs. (29, 30). Subtracting volume scattering from $[T_{\text{AC-noh}}]$, the remainder matrix $[T_{\text{Remainder}}]$ is

$$
[T_{\text{Remainder}}] = [T_{\text{AC-noh}}] - P_V[T_V]
$$  

(10)

where $[T_V]$ is the volume scattering model. In Refs. (4, 28–30), the maximum $P_V$ (denoted as $P_{V_{\text{max}}}$) that makes $[T_{\text{Remainder}}]$ positive semidefinite is selected, so $[T_{\text{Remainder}}]$ is strictly semidefinite. We have:

$$
||[T_{\text{Remainder}}]|| = ||[T_{\text{AC-noh}}] - P_{V_{\text{max}}}[T_V]|| = 0
$$  

(11)

$||[T]||$ is the determinant of matrix $[T]$. From Equation (11), we can know if $[T_V]$ is positive definite (most available $[T_V]$ satisfy this requirement), then $P_{V_{\text{max}}}$ is the smallest eigenvalue of $[T_V]^{-1}[T_{\text{AC-noh}}]$. For adaptive volume scattering models, the parameters that give the maximum $P_{V_{\text{max}}}$ (denoted as $P_{V_{\text{max}}_{\text{max}}} \text{ max}_{P_{V}}$) are selected. Above criterion is named as “maximum $P_V$ criterion.” It could be easily proved that, if $\text{Re}(T_{12})$ in $[T_{\text{AC-noh}}]$ is
positive, then \( P_{V_{\text{max}}} \) given by \([T_{\text{Vol}}(\tau_V)]\) is larger than that by \([T_{\text{Vol}}(\tau_V)]\), and we should select \([T_{\text{Vol}}]\); otherwise, we should select \([T_{\text{Vol}}(\tau_V)]\). Here, we denote the selected model as \([T_{\text{Vol}}]\).

Evidently, maximum \( P_V \) criterion tends to overestimate real \( P_V \) because the maximum \( P_V \) in theory is selected. Therefore, it is necessary to put forward a new criterion. It is widely recognized that cross-polarized power mainly or even entirely comes from volume scattering [2, 3, 11, 25, 34, 35]. Viewed from this angle, we could let volume scattering explain as much cross-polarized power as possible. The cross-polarized power that cannot be explained by volume scattering and helix scattering, namely, \( P_X \) is expressed as:

\[
P_X = P_{33} = A_{33} - P_V B_{33} \tag{12}
\]

where \( A_{33} \), \( B_{33} \), and \( P_{33} \) stand for \( T_{33} \) of \([T_{\text{Vol}}(\tau_V)]\), \([T_{\text{Vol}}]\), and \([T_{\text{Vol}}(\tau_V)]\), respectively. We could infer from Equation (12) that, \( P_X \) decreases with \( P_V \) when \( B_{33} \) is fixed. In other words, when we use a fixed \([T_{\text{Vol}}]\), the maximum \( P_V \) constrained by NNEC will allow volume scattering to explain the most cross-polarized power, so \( P_X \) will be minimal. However, for adaptive models such as \([T_{\text{Vol}}]\), the maximum \( P_V \) does not always yield the minimum \( P_X \) because \( B_{33} \) varies. Here, we select the combination of volume scattering parameters that produces the minimum \( P_X \) (denoted as \( P_{X_{\text{true}}} \)). This new criterion is named as "minimum \( P_X \) criterion."

\( \tau_V \) is the only parameter of \([T_{\text{Vol}}(\tau_V)]\) and empirically confined in [0.50, 1.00] (9). For each \( \tau_V \) we compute \([T_{\text{Vol}}(\tau_V)]\) and corresponding \( P_{V_{\text{max}}} \). Among all results, we choose the \( \tau_V \) and \( P_{V_{\text{max}}} \) that give \( P_{X_{\text{min}}} \), and refer to the chosen \( \tau_V \) as \( \tau_V_{\text{min}} \) and \( P_{V_{\text{max}}} \) as \( P_{V_{\text{max min}}} \). Since \( P_{V_{\text{max min}}} \) is the maximal one of all \( P_{V_{\text{max}}} \), we have \( P_{V_{\text{min x min}}} \leq P_{V_{\text{max min}}} \). Thus, the minimum \( P_X \) criterion tends to lower the estimation of \( P_V \). Combining this conclusion with Equation (12), we conclude that the minimum \( P_X \) criterion gives larger \( B_{33} \) and \( \tau_V \). Finally, \([T_{\text{Remainder}}]\) is expressed as:

\[
[T_{\text{Remainder}}] = [T_{\text{MaxC}}] - P_{V_{\text{min x min}}} [T_{\text{Vol}}(\tau_V_{\text{min x min}})]
\begin{bmatrix}
F_{11} & F_{12} & F_{13} \\
F_{12} & F_{22} & F_{23} \\
F_{13} & F_{23} & F_{33}
\end{bmatrix}
\tag{13}
\]

If volume scattering cannot explain \( T_{13} \) in \([T_{\text{MaxC}}]\) and make \( F_{13} = 0 \), then \( F_{33} > 0 \). \( F_{33} = 0 \) requires \( F_{13} = 0 \). Since \([T_{\text{Vol}}]\) is reflection symmetric and \([T_{\text{MaxC}}]\) generally does not have \( T_{13} = 0 \), we can expect in most cases, \( F_{13} \neq 0 \) and \( F_{33} > 0 \).

### 3.4. Ground scattering solution

The next step is determining which kind of ground scattering should be modeled by \([T_{\text{Neum}}]\). Usually, in surface scattering models, \( T_{11} > T_{22} + T_{33} \), whereas in double bounce scattering models, \( T_{11} < T_{22} + T_{33} \) (33). As a result, the authors give the following criterion: if \( F_{11} > F_{22} + F_{33} \), then surface scattering is the dominant ground scattering, and \([T_{\text{Remainder}}]\) is decomposed into Equation (14); if \( F_{11} < F_{22} + F_{33} \), then double bounce scattering is the dominant ground scattering, and \([T_{\text{Remainder}}]\) is decomposed into Equation (15). \( P_S \) and \( P_D \) are the power of surface scattering and double bounce scattering, respectively, while \( \tau_S \) and \( \tau_D \) are corresponding \( \tau \).

\[
[T_{\text{Remainder}}] = P_S[T_{\text{Neum}}(\tau_S)] + P_D[T_{\text{Dbl}}] \tag{14}
\]

\[
[T_{\text{Remainder}}] = P_D[T_{\text{Neum}}(\tau_D)] + P_S[T_{\text{Surf}}] \tag{15}
\]

when solving Equations (14) and (15), we assume that \( S_{11} = 1 \) and \( S_{V} = b_1 + b_2 \alpha \) as given in Refs. (2, 34). With above assumption, if \( \text{Im}(F_{12}) \neq 0 \), we could get the following equations from Equation (14):

\[
\frac{g^2(\tau_S)}{1 - g(\tau_S)} = \frac{|F_{12}|^2}{2F_{11}F_{33}} \tag{16}
\]

\[
L = \frac{(1 + b_1)^2 + b_2^2}{(1 - b_1)^2 + b_2^2} = \frac{(1 - g(\tau_S))F_{11}}{2F_{33}} = k_1 \tag{17}
\]

\[
\frac{\text{Re}(M)}{\text{Im}(M)} = \frac{1 - b_1^2 - b_2^2}{2b_2} = \frac{\text{Re}(F_{12})}{\text{Im}(F_{12})} = k_2 \tag{18}
\]

\( \tau_S \) could be solved from Equation (16). We could get the following equations from Equation (15):

\[
g(\tau_D) = \frac{F_{22} - F_{33}}{F_{22} + F_{33}} \tag{19}
\]

\[
L = \frac{(1 + b_1)^2 + b_2^2}{(1 - b_1)^2 + b_2^2} = \left( \frac{|F_{12}|(1 - g(\tau_D))}{2F_{33}g(\tau_D)} \right)^2 = k_1 \tag{20}
\]

\[
\frac{\text{Re}(M)}{\text{Im}(M)} = \frac{1 - b_1^2 - b_2^2}{2b_2} = \frac{\text{Re}(F_{12})}{\text{Im}(F_{12})} = k_2 \tag{21}
\]

\( \tau_D \) could be solved from Equation (19). In Equations (14) and (15), the solutions of \( S_{V} \) are

\[
b_1 = \frac{(k_1 - 1)(1 + k_2^2)(1 + k_1) - k_2\sigma)}{D - 2k_1} \tag{22}
\]

and

\[
b_2 = \frac{\sigma - k_1(4k_2 + \sigma)}{D}
\]
\[
b_1 = \frac{(k_1 - 1)((1 + k_2^2)(1 + k_1) + k_2\sigma)}{D - 2k_1} \quad (23)
\]

\[
b_2 = -\frac{\sigma + k_1(4k_2^2 + \sigma)}{D}
\]

with

\[
\sigma = 2\sqrt{k_1(k_2^2 + 1)} \quad (24)
\]

\[
D = (k_1^2 + 1)(k_2^2 + 1) - 2k_1(k_2^2 - 1)
\]

For the two solutions in Equations (22) and (23), the one whose \(b_2\) sign is the same as \(\text{Im}(F_{12})\) should be chosen.

If \(\text{Im}(F_{12}) = 0\), then \(b_2 = 0\), \(b_1\) is:

\[
b_1 = \frac{\sqrt{k_1} - 1}{\sqrt{k_1} + 1} \quad (25)
\]

or

\[
b_1 = \frac{\sqrt{k_1} + 1}{\sqrt{k_1} - 1} \quad (26)
\]

The two \(b_1\) solutions in Equations (25) and (26) are the inverse of each other. Which one is better may be determined with the assistance of physical models, like Bragg model (7). For example, for surface scattering, Bragg model predicts \(|S_{PV}| < 1\), so the smaller one of Equations (25) and (26) should be chosen.

Given \(S_{TV}\), we could obtain \(L\) and \(N\) from Equation (2). In Equation (14), \(P_S\) and \(P_D\) are calculated as:

\[
P_S = \frac{L + N}{L} F_{11}
\]

\[
P_D = F_{11} + F_{22} + F_{33} - P_S
\]

If \(P_D < 0\), then \(P_D = 0\), \(P_S = F_{11} + F_{22} + F_{33}\). In Equation (15), \(P_S\) and \(P_D\) are calculated as:

\[
P_D = \frac{L + N}{N} (F_{22} + F_{33})
\]

\[
P_S = F_{11} + F_{22} + F_{33} - P_D
\]

If \(P_S < 0\), then \(P_S = 0\), \(P_D = F_{11} + F_{22} + F_{33}\).

4. Experiment results and discussion

We tested ADIGSM on NASA’s airborne L-band UAVSAR (36) data collected near Howland forest, Maine, USA on 5 August 2009 under a clear weather. This study site contains forests, bare lands, rivers, wetlands, roads, buildings, and so on. The data were downloaded from Alaska Satellite Facility website (37). The look angle range is approximately [25°, 65°], while the local incidence angles vary within [0°, 90°]. Basic scattering area correction, antenna pattern correction, and range dependent radiometric correction have been performed. The resolution of ground range image was 5 m. Lee sigma filtering (38) was implemented in a 9 × 9 window. Figure 2 shows an inset of the study site (the geographic coordinate of image center is 68.656°W, 44.943°N), where \(P_{\text{span}}\) is the span of \(|\langle[T]\rangle|\).

4.1. Results

Negative \(P_S\) appear in 2.52% of pixels and are mainly located in dense forests; negative \(P_D\) appear in 0.08% of pixels and are mainly distributed in sparse forests. Dense natural forests are colored with bright green in (c), indicating \(P_V\) is large. Manual check shows that \(P_D\) is often much larger than \(P_S\). \(P_V\) concentrates in [0.60, 0.90] (the mean value is 0.758 and the standard deviation is 0.092), which is consistent with the observations in (9). \(P_D\) primarily locates in [0.10, 0.35] (the mean value is 0.188 and the standard deviation is 0.090). In the upper right corner of the image, there is a sparse forest. In comparison to dense forests, this area has higher proportion of \(P_S\). Since the local tree cover is much lower than dense forests, it is reasonable to have more surface scattering from ground. Its \(P_V\) range is approximately the same as that of dense forests, while \(P_S\) range is [0.00, 0.35]. Most of the areas that are dominated by surface scattering, such as river surfaces, airport, and grasslands, are colored with blue, showing that \(P_S\) is high. River surfaces typically exhibit low \(P_S\) and \(P_V\). But in places where river makes a turn or river branches meet, \(P_V\) or \(P_S\) is significantly higher. Near the river dam, \(P_V\) and \(P_S\) are higher than those of ordinary river surfaces, which are probably due to the waves caused by the dam and tiny river islands. In urban areas where the main buildings are oriented parallel to SAR azimuth direction, roads and buildings are generally characterized by fairly low \(P_S\), \(P_D\), and \(P_V\); which is within expectations for man-made targets.

The results of ADIGSM were compared against the decompositions by Freeman and Durden (2) (short for FDD), Singh et al. (26) (short for Singh_1), Singh et al. (25) (short for Singh_2), Cui et al. (29), and Wang et al. (30). Two decompositions were raised in Ref. (29), one was based on Eigen-decomposition, namely, Cui_1, and the other on model fitting, namely, Cui_2. \([T_{\text{vol}}]\) and maximum \(P_V\) criterion were applied to Wang, Cui_1, and Cui_2 decomposition. In the results by FDD,
Singh_1, and Singh_2, the proportions of $|T_{\text{Remainder}}|$ violating NNEC are 75.44, 44.75, and 48.11%, respectively. Their results were thus excluded from further analysis. Cui_1, Cui_2, and Wang decompositions belong to NNED and compute volume scattering parameter without reflection symmetry assumption, so currently they are most suitable for comparing with ADIGSM. Wang and Cui_2 decompositions provided quite similar results. Therefore, Figure 3 offers the profiles of component powers given by Cui_1, Wang decompositions, and ADIGSM along the three 500-m-transects in Figure 2(b) covering forests (red transect), urban areas (blue transect), and airport (green transect). These three transects were selected because they were representative enough of the study site. Please note that the profiles by Cui_1 and Wang overlap in many locations.

Compared with Wang, Cui_1, and Cui_2 decomposition, ADIGSM successfully lowers the estimation of $P_i$, especially in airports and some urban areas. For example, in location 63–68 of Figure 3(d), $P_V/P_{\text{span}}$ is reduced by over 0.10. Consequently, in Figure 3(f) and (i), $P_S/P_{\text{span}}$ given by ADIGSM is mostly higher or at least equal to that by other decompositions. In airport, ADIGSM offers larger $P_D$ than Cui_1 and Wang. That could be understood in the following way: first, $P_i$ given by ADIGSM is lower than the results by Cui_1 and Wang decomposition, making the increasing of $(P_D + P_S)$ quite natural; second, the increasing of $P_D$ is nearly negligible in Figure 3(h). Although in forests, ADIGSM does not obviously lower $P_I$ its $P_D/P_{\text{span}}$ profile is more stable than that of Cui_1. Wang decomposition gives $P_S = 0$ in nearly every location. On the contrary, ADIGSM gives positive $P_S$ in most locations with only a few exceptions, although the values are relatively low. Finally, $(P_S + P_D)/P_V$ is in $[0.13, 0.35]$, agreeing quite well with the report in Ref. (9).

$	au_V$ of forests are a bit higher than that of airports, while a large proportion of $	au_V$ in urban areas are 0.50. Compared with urban areas, $	au_D$ of forests are much higher, which is anticipated for natural targets. By converting Neumann’s forest observations (9) of ground scattering under Pauli-basis to $\tau_D$, the obtained $\tau_D$ fits well with our results. We also notice that the mean value of $\tau_S$ in airports is higher than urban areas. Considering
that the grasslands surround the runway of airport, we believe that this phenomenon makes sense.

4.2. Discussion

According to the experiment results, ADIGSM has fairly good applicability. It at least works fairly well for areas dominated by surface scattering or double bounce scattering. For forest where volume scattering dominates, the results are still relatively good. Experiment also shows ADIGSM lowers the estimation of volume scattering power when comparing with the three latest NNED. Its estimated ground scattering power as well as \( \tau \) of different components are reasonable to a large degree. Minimum \( P_x \) criterion successfully lowers the estimation of volume scattering power. The authors also found that ADIGSM often works well in the differentiation of oriented buildings and forests.

Figure 3. The profile of different computed parameters along three transects. In all sub-figures, the horizontal axis is the pixel’s relative position along transects. (a–c, j) are along the red transect in Figure 2(b); (d–f, k) are along the blue transect in Figure 2(b); (g–i, l) are along the green transect in Figure 2(b). In (a–i), red lines are the results of Cui_1 decomposition, green lines are the results of Wang, and black lines are the results of ADIGSM.
As three representative latest model-based decompositions, the methods by Lee et al. (5), Cui et al. (29), and Wang et al. (30) improve the traditional decompositions in different aspects. For example, Cui and Wang decompositions utilize the whole polarimetric information, which is seldom realized in previous methods and they are not on the basis of reflection symmetry assumption. Lee’s method can give the shape factor for volume scattering or orientation angle randomness for dominant ground scattering. However, as pointed out in former sections, they both have their deficiencies.

In ADIGSM, the cross-polarized power in $[T_{\text{Remainder}}]$ is attributed to the dominant ground scattering with Neumann’s incoherent model, so that it could obtain the orientation angle randomness for volume scattering and the dominant ground scattering, which is not achieved in the methods proposed by Lee et al. (5), Wang et al. (30), and Cui et al. (29). It is worth to note that Neumann (9) obtained orientation angle randomness for different components with the assistance of PolInSAR data, while ADIGSM gives such information with only PolSAR data. Volume scattering parameters are computed without reflection symmetry assumption, so more information could be utilized in comparison to Lee’s method (5). Minimum $P_X$ criterion is proved to be superior to maximum $P_Y$ criterion. In addition, assuming orientation angles not to be uniformly distributed is more reasonable than Lee’s method (5). As an innovative decomposition, ADIGSM can be easily simplified to Freeman–Durden decomposition or other decompositions by adding or excluding some components or setting specific orientation angle randomness values.

5. Conclusions

The unique abilities of ADIGSM in explaining cross-polarized power, obtaining orientation angle randomness for the dominant ground scattering, avoiding negative power, and lowering the overestimation of volume scattering power have been well proved in previous sections. Although in a few forest pixels negative powers were obtained, we may assume that only one ground scattering exist and perform two-component fitting to $[T_{\text{OIC-model}}]$, and examine whether negative power could be avoided or not. In the future, different incoherent scattering models, such as X-Bragg model (7) and Arii’s model (8), may be applied to ADIGSM to test their performances. In addition, we may try to utilize the decomposed parameters for applications such as PolSAR image classification (33, 39, 40), speckle filtering preserving the dominant scattering mechanism (41), soil moisture and roughness estimation (7), SAR radiometric calibration (42), radar signal simulation (43), land cover mapping (44, 45), forest inventory and understory mapping (46, 47).

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Notes on contributors

Xiaoguang Cheng is an engineer in Nanjing Research Institute of Electronics Engineering. He received a doctor degree in engineering from State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing (LIESMARS), Wuhan University in 2014. His main research interests include polarimetric SAR, LiDAR, and GIS spatial analysis.

Wenli Huang is currently a PhD candidate in University of Maryland at College Park. Her main research directions are the applications of full-waveform LiDAR and PolSAR in remote sensing of environment.

Jianya Gong is an academician of Chinese Academy of Science and director of the LIESMARS, Wuhan University, China. His research interests include geospatial data structure and data model, geographical information system software, geospatial data sharing and interoperability, photogrammetry, GIS, and remote sensing applications.

References

(1) Ouchi, K. Recent Trend and Advance of Synthetic Aperature Radar with Selected Topics. Remote Sens. 2013, 5 (2), 716–807.
(2) Freeman, A.; Durden, S.L. A Three-component Scattering Model for Polarimetric SAR Data. IEEE Trans. Geosci. Remote Sens. 1998, 36 (3), 963–973.
(3) Yamaguchi, Y.; Moriyama, T.; Ishido, M.; Yamada, H. Four-component Scattering Model for Polarimetric SAR Image Decomposition. IEEE Trans. Geosci. Remote Sens. 2005, 43 (8), 1699–1706.
(4) van Zyl, J.J.; Arii, M.; Kim, Y. Model-based Decomposition of Polarimetric SAR Covariance Matrices Constrained for Nonnegative Eigenvalues. IEEE Trans. Geosci. Remote Sens. 2011, 49 (9), 3452–3459.
(5) Lee, J.-S.; Ainsworth, T.L.; Wang, Y. Generalized Polarimetric Model-based Decompositions Using Incoherent Scattering Models. IEEE Trans. Geosci. Remote Sens. 2014, 52 (5), 2474–2491.
(6) Chen, S.-W.; Li, Y.-Z.; Wang, X.-s.; Xiao, S.-p.; Sato, M. Modeling and Interpretation of Scattering Mechanisms in Polarimetric Synthetic Aperture Radar: Advances and Perspectives. IEEE Signal Process. Mag. 2014, 31 (4), 79–89.
(7) Hajnsek, I.; Jagdhuber, T.; Schon, H.; Papathanassiou, K.P. Potential of Estimating Soil Moisture under Vegetation Cover by Means of PoISAR. IEEE Trans. Geosci. Remote Sens. 2009, 47 (2), 442–454.
(8) Arii, M.; van Zyl, J.J.; Kim, Y. A General Characterization for Polarimetric Scattering from Vegetation Canopies. IEEE Trans. Geosci. Remote Sens. 2010, 48 (9), 3339–3357.
(9) Neumann, M. Remote Sensing of Vegetation Using Multi-Baseline Polarimetric SAR Interferometry: Theoretical Modeling and Physical Parameter Retrieval. Ph.D., Université de Rennes 1, Rennes, 2009.
(10) Antropov, O.; Rauste, Y.; Hame, T. Volume Scattering Modeling in PolSAR Decompositions: Study of ALOS PALSAR Data over Boreal Forest. *IEEE Trans. Geosci. Remote Sens.* 2004, 49 (10), 3838–3848.

(11) Cui, Y.; Yamaguchi, Y.; Yang, J.; Park, S.-E.; Kobayashi, H.; Singh, G. Three-component Power Decomposition for PolSAR Coherency Matrix Data Based on Adaptive Volume Scatter Modeling. *Remote Sens.* 2012, 4 (6), 1559–1572.

(12) Kusano, S.; Takahashi, K.; Sato, M. Volume Scattering Power Constraint Based on the Principal Minors of the Coherence Matrix. *IEEE Geosci. Remote Sens. Lett.* 2014, 11 (1), 361–365.

(13) Liu, G.; Li, M.; Wang, Y.; Zhang, P.; Wu, Y.; Liu, H. Four-component Scattering Power Decomposition of Remainder Coherence Matrices Constrained for Nonnegative Eigenvalues. *IEEE Geosci. Remote Sens. Lett.* 2014, 11 (2), 494–498.

(14) An, W.; Xie, C. An Improvement on the Complete Model-based Decomposition of PolynSAR Data. *IEEE Geosci. Remote Sens. Lett.* 2014, 11 (11), 1926–1930.

(15) Chen, S.-W.; Wang, X.-S.; Li, Y.-Z.; Sato, M. Adaptive Model-based PolynSAR Coherence. *IEEE Trans. Geosci. Remote Sens.* 2014, 52 (3), 1705–1718.

(16) Lee, J.-S.; Ainsworth, T.L. The Effect of Orientation Angle Compensation on Coherence Matrix and PolynSAR Target Decompositions. *IEEE Trans. Geosci. Remote Sens.* 2011, 49 (1), 53–64.

(17) Chen, S.-W.; Ohki, M.; Shimada, M.; Sato, M. Deorientation Effect Investigation for Model-based Decomposition over Oriented Built-up Areas. *IEEE Geosci. Remote Sens. Lett.* 2013, 10 (2), 273–277.

(18) Park, S.-E.; Yamaguchi, Y.; Singh, G.; Yamaguchi, S.; Whitaker, A.C. PolynSAR Signal Response of Snow-Covered Area Observed by Multi-temporal ALOS PALSAR Fully PolynSAR Mode. *IEEE Trans. Geosci. Remote Sens.* 2014, 52 (1), 329–340.

(19) Duan, J.; Zhang, L.; Xing, M.; Wu, Y.; Wu, M. PolynSAR Target Decomposition Based on Attenuated Scattering Center Model for Synthetic Aperture Radar Targets. *IEEE Geosci. Remote Sens. Lett.* 2014, 11 (12), 2095–2100.

(20) Jagdhuber, T.; Hajnsek, I.; Bronstert, A.; Pathapanassioti, K.P. Soil Moisture Estimation under Low Vegetation Cover Using a Multi-angular PolynSAR Decomposition. *IEEE Trans. Geosci. Remote Sens.* 2013, 51 (4), 2201–2215.

(21) Ding, Z.; Zeng, T.; Dong, F.; Liu, L.; Yang, W.; Long, T. An Improved PolynSAR Image Speckle Reduction Algorithm Based on Structural Judgement and Hybrid Four-Component PolynSAR Decomposition. *IEEE Trans. Geosci. Remote Sens.* 2013, 51 (8), 4438–4449.

(22) Li, N.; Wang, R.; Deng, Y.; Liu, Y.; Wang, C.; Balz, T.; Li, B. PolynSAR Response of Landslides at B-X-Band following the Wenchuan Earthquake. *IEEE Geosci. Remote Sens. Lett.* 2014, 11 (10), 1722–1726.

(23) Jiao, Z.; Yang, J.; Yeh, C.; Song, J. Modified Three-component Decomposition Method for PolynSAR Data. *IEEE Geosci. Remote Sens. Lett.* 2014, 11 (1), 200–204.

(24) Wang, Y.; Liu, H.; Jiu, B. PolynSAR Coherency Matrix Decomposition Based on Constrained Sparse Representation. *IEEE Trans. Geosci. Remote Sens.* 2014, 52 (9), 5906–5922.

(25) Singh, G.; Yamaguchi, Y.; Park, S.E.; Cui, Y.; Kobayashi, H. Hybrid Freeman/Eigenvalue Decomposition Method with Extended Volume Scattering Model. *IEEE Geosci. Remote Sens. Lett.* 2013, 10 (1), 81–85.

(26) Singh, G.; Yamaguchi, Y.; Park, S.E. General Four-Component Scattering Power Decomposition with Unitary Transformation of Coherence Matrix. *IEEE Trans. Geosci. Remote Sens.* 2013, 51 (5), 3014–3022.

(27) Chen, S.-W.; Wang, X.-S.; Xiao, S.-P.; Sato, M. General Polarimetric Model-based Decomposition for Coherence Matrix. *IEEE Trans. Geosci. Remote Sens.* 2014, 52 (3), 1843–1855.

(28) Arii, M.; van Zyl, J.J.; Kim, Y. Adaptive Model-based Decomposition of PolynSAR Covariance Matrices. *IEEE Trans. Geosci. Remote Sens.* 2011, 49 (3), 1104–1113.

(29) Cui, Y.; Yamaguchi, Y.; Yang, J.; Kobayashi, H.; Park, S.E.; Singh, G. On Complete Model-based Decomposition of PolynSAR Coherence Matrix Data. *IEEE Trans. Geosci. Remote Sens.* 2014, 52 (4), 1991–2001.

(30) Wang, C.; Yu, W.; Wang, R.; Deng, Y.; Zhao, F. Comparison of Nonnegative Eigenvalue Decompositions with and without Reflection Symmetry Assumptions. *IEEE Trans. Geosci. Remote Sens.* 2014, 52 (4), 2278–2287.

(31) Hong, S.-H.; Wdowski, S. Double-bounce Component in Cross-polarimetric SAR from a New Scattering Target Decomposition. *IEEE Trans. Geosci. Remote Sens.* 2014, 52 (6), 3039–3051.

(32) Cheng, X.; Huang, W.; Gong, J. Improved van Zyl Polarimetric Decomposition Lessening the Overestimation of Volume Scattering Power. *Remote Sens.* 2014, 6 (7), 6365–6385.

(33) Freeman, A. Fitting a Two-component Scattering Model to PolynSAR Data from Forests. *IEEE Trans. Geosci. Remote Sens.* 2007, 45 (8), 2583–2592.

(34) An, W.; Cui, Y.; Yang, J. Three-component Model-based Decomposition for Polarimetric SAR Data. *IEEE Trans. Geosci. Remote Sens.* 2010, 48 (6), 2732–2739.

(35) Rosen, P.A.; Hensley, S.; Miller, T.; Shaffer, S.; Suellerschoen, R.; Jones, C.; Zehter, H.; Madsen, S. UAVSAR: A New NASA Airborne SAR System for Science and Technology Research. 2006 IEEE Conference on Radar, IEEE: Verona, NY, 2006; pp 22–29.

(37) Vertex: ASF’s Data Portal. https://vertex.daac.asf.alaska.edu/ (accessed May 1, 2012).

(38) Lee, J.-S.; Chen, A.J. Improved Sigma Filter for Speckle Filtering of SAR Imagery. *IEEE Trans. Geosci. Remote Sens.* 2009, 47 (1), 202–213.

(39) Cheng, X.; Huang, W.; Gong, J. A Decomposition-free Scattering Mechanism Classification Method for PolSAR Images with Neumann’s Model. *Remote Sens. Lett.* 2013, 4 (12), 1176–1184.

(40) Zhang, G.; Wang, H.; Zhu, X.; Xu, X.; Yu, Y. ESM and Radar Intelligence Fusion Recognition Based on Multiple Classifiers. *Command Inf. Syst. Technol.* 2013, 4 (6), 54–58.

(41) Lee, J.-S.; Grunes, M.R.; Schuler, D.L.; Pottier, E.; Ferro-Famil, L. Scattering-model-based Speckle Filtering of PolynSAR Data. *IEEE Trans. Geosci. Remote Sens.* 2006, 44 (4), 176–187.
(42) Cheng, X.; Pinto, N.; Gong, J. Terrain Radiometric Calibration of Airborne UAVSAR for Forested Area. Geo-Spatial Inf. Sci. 2012, 15 (4), 229–240.
(43) Ma, H.; Lin, X.; Cheng, W. Radar Echo Signal Simulation for Radar Operation Training Command. Command Inf. Syst. Technol. 2011, 2 (3), 66–71.
(44) da Silva, A.Q.; Paradella, W.; Freitas, C.; Oliveira, C. Evaluation of Digital Classification of Polarimetric SAR Data for Iron-mineralized Laterites Mapping in the Amazon Region. Remote Sens. 2013, 5 (6), 3101–3122.
(45) Whitcomb, J.; Moghaddam, M.; McDonald, K.; Podest, E.; Chapman, B. Progress on SAR-based Mapping and Change Detection for Boreal Wetlands of North America. IEEE International Geoscience and Remote Sensing Symposium (IGARSS); IGARSS: Munich, 2012.
(46) Dickinson, C.; Siqueira, P.; Clewley, D.; Lucas, R. Classification of Forest Composition Using Polarimetric Decomposition in Multiple Landscapes. Remote Sens. Environ. 2013, 131 (15), 206–214.
(47) Gallant, A.L.; Kaya, S.G.; White, L.; Brisco, B.; Roth, M.F.; Sadinski, W.; Rover, J. Detecting Emergence, Growth, and Senescence of Wetland Vegetation with Polarimetric Synthetic Aperture Radar (SAR) Data. Water 2014, 6 (3), 694–722.