Polarimetric Decomposition Based on Particle Swarm Optimization and Its Data Analysis

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Abstract—This paper deals with a polarimetric decomposition considering azimuth rotation based on evolutionary algorithm. Polarimetric data in urban and mountain areas are affected by azimuth rotation. Thus, the decomposition results derived by the same target with different azimuth rotation angle are changed. Some researchers examined to compensate this rotation by mathematical inverse rotation. In this report, the differences of covariance matrix before and after the compensation are used to estimate the contributions of three decomposition components. An evolutional algorithm to determine the contributions is a particle swarm optimization (PSO) which is one of the evolutional algorithms. We apply the proposed method to ALOS/PALSAR data and compare the results between four component decomposition method and proposed method.

Keywords-component; POLSAR; Decomposition; Covariance matrix; Particle swarm optimization

I. INTRODUCTION

Polarimetric decomposition technique is very useful to analyze the polarimetric synthetic aperture radar (POLSAR) data [1],[2]. There are some algorithms for polarimetric decomposition. Freeman and Durden proposed a fundamental decomposition algorithm dealing with three scattering components [1] and Yamaguch extended their algorithm to four scattering components [2]. Recently, some researchers examine the polarimetric decomposition to compensate a covariance matrix for azimuth orientation angle [3]. In this paper, a polarimetric decomposition technique considering azimuth rotation based on evolulational algorithm is proposed. I derive the differences of covariance matrix before and after compensating an azimuth rotation angle and these differences are used as an optimization problem. The evolulational algorithm to solve optimization problem is particle swarm optimization (PSO) [4]. I apply the proposed method to ALOS/PALSAR data and compare the results of four component decomposition method [2] and proposed method. In section II, a polarimetric decomposition based on particle swarm optimization is introduced. The experimental results are shown in section III and conclusions are presented in section IV.

II. POLARIMETRIC DECOMPOSITION BASED ON PARTICLE SWARM OPTIMIZATION

A. Three-component decomposition

The scattering matrix and covariance matrix are defined as follows:

$$ S(HV) = \begin{bmatrix} S_{HH} & S_{HV} \\ S_{HV} & S_{VV} \end{bmatrix} $$ (1)

$$ C(HV) = \begin{bmatrix} \langle S_{HH}S_{HH} \rangle & \sqrt{2}\langle S_{HH}S_{HV} \rangle & \sqrt{2}\langle S_{HH}S_{VV} \rangle \\ \sqrt{2}\langle S_{HV}S_{HH} \rangle & 2\langle S_{HV}S_{HV} \rangle & \sqrt{2}\langle S_{HV}S_{VV} \rangle \\ \sqrt{2}\langle S_{VV}S_{HH} \rangle & \sqrt{2}\langle S_{VV}S_{HV} \rangle & \langle S_{VV}S_{VV} \rangle \end{bmatrix} $$ (2)

where $\langle \rangle$ denotes an ensemble average and * is a complex conjugate. Due to the backscattering, it is assumed that $S_{HH}$ is equal to $S_{VV}$. Freeman and Durden proposed three-component scattering model for POLSAR image decomposition based on a covariance matrix [1]. In case of their decomposition, the measured covariance matrix is decomposed as

$$ \langle C(HV) \rangle = f_s\langle C_{\text{surface}} \rangle + f_d\langle C_{\text{double}} \rangle + f_v\langle C_{\text{volume}} \rangle $$ (3)

where $f_s$, $f_d$ and $f_v$ are the expansion coefficients for surface, double and volume scattering components, respectively. It is assumed that $\langle C_{\text{surface}} \rangle$, $\langle C_{\text{double}} \rangle$ and $\langle C_{\text{volume}} \rangle$ do not have (1,2), (2,1), (2,3) and (3,2) components by the reflection symmetry property ($\langle S_{HH}S_{HV} \rangle = \langle S_{HV}S_{VV} \rangle \equiv 0$).

$$ C_{\text{surface}} = \begin{bmatrix} \beta^2 & 0 & \beta \\ 0 & 0 & 0 \\ \beta & 0 & 1 \end{bmatrix}, \quad C_{\text{double}} = \begin{bmatrix} 1 & 0 & \alpha^* \\ 0 & 0 & 0 \\ \alpha & 0 & \beta \end{bmatrix}, \quad C_{\text{volume}} = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 2 & 0 \\ 0 & 1 & 3 \end{bmatrix} $$ (4a,b,c)

where $\alpha$ and $\beta$ are the polarization ratios between $HH$ and $VV$ of double and surface scatterings. The decomposition results which are a power of each component are obtained as

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radar line of sight (LOS) is considered to a covariance matrix, $B$. 

### b) Surface scattering case

If the azimuth rotation which means a rotation around the direction of radar platform’s orbit, a ground-wall structure or wall is regarded to be rotated in the projection plane as shown in Fig. 1(b). Thus, three-component scattering component proposed by Freeman and Durden can not be applied to these areas where the reflection symmetry is not satisfied. Azimuth rotation angle $\theta$ in the projection plane, that is perpendicular to range direction, can be estimated as follows. The scattering matrix rotated by $\theta$ is expressed as

$$
\begin{bmatrix}
S(HV(\theta))
\end{bmatrix} =
\begin{bmatrix}
\tilde{S}_{HH} & \tilde{S}_{HV} \\
\tilde{S}_{HV} & \tilde{S}_{VV}
\end{bmatrix}
$$

(9)

The elements of scattering matrix in circular polarization basis (LR) are derived by the following transformation.

$$
S_{LL} = \frac{1}{2}(\tilde{S}_{HH} - \tilde{S}_{VV} + j2\tilde{S}_{HV}),
S_{RR} = \frac{1}{2}(\tilde{S}_{HH} - \tilde{S}_{VV} + j2\tilde{S}_{HV})
$$

(10a,b)

If $\tilde{S}_{HV}$ in eq. (10) is assumed to be zero, $\text{Arg}(-S_{LL}S_{RR}^*)$ provides the rotation angle $\theta_{LL-RR}$.

$$
\text{Arg}(-S_{LL}S_{RR}^*)_{\theta_{LL-RR}} \approx -4\theta
$$

(11)

Thus, an approximated rotation angle $\theta$ in pixel of image can be estimated from the measured POLSAR data and inverse rotation (-$\theta$) can be done by eq. (6). The measured data which has an azimuth rotation angle $\theta$ is expressed as $<[C(HV(\theta))]>$. The data after turning $<[C(HV(\theta))]$ to -$\theta$ is denoted as $<[C(HV(0))]$. Then a difference between $<[C(HV(\theta))]>$ and $<[C(HV(0))]>$ is calculated. In the case where the double-bounce scattering component is mainly rotated, the difference is derived as follows.

Case A (double bounce is mainly affected by the rotation):

$$
\{<[C(HV(\theta))]> - <[C(HV(0))]>\}_{\text{double-bounce}}
$$

$$
\begin{align*}
\Delta C_{H_1} &= f_{C_1} \left[\cos^2 \theta - 1\right] + 2Re(\alpha) \sin^2 \theta + \alpha' \cos^2 \theta - \alpha \sin^2 \theta \\
\Delta C_{H_2} &= 2f_{C_2} \left[1 + \left|\alpha\right|^2 - 2Re(\alpha)\right] \sin^2 \theta \cos^2 \theta
\end{align*}
$$

(12a)
In eq. (12a), the volume component disappears, because volume scattering assumed by Freeman and Durden is generated by a cloud of uniformly distributed thin wire and (4c) is not affected by $\theta$. Similarly, I can derive the difference in the case where the surface scattering component is mainly rotated.

Case B (surface scattering is mainly affected by the rotation):

$$\Delta C_n = f_s \left[ \left\{ \beta \right\} \text{cos} \theta + \left\{ \alpha \right\} \text{sin} \theta \right] - f_s \left[ \left\{ \beta \right\} \text{cos} \theta - \left\{ \alpha \right\} \text{sin} \theta \right]$$

$$\Delta C_n = f_s \left[ \left\{ \beta \right\} \text{sin} \theta + \left\{ \alpha \right\} \text{cos} \theta \right] - f_s \left[ \left\{ \beta \right\} \text{sin} \theta - \left\{ \alpha \right\} \text{cos} \theta \right]$$

$$\Delta C_n = 2f_s \left[ \left\{ \beta \right\} \text{cos} \theta \right] - 2f_s \left[ \left\{ \beta \right\} \text{sin} \theta \right]$$

$$\Delta C_n = f_s \left[ \left\{ \beta \right\} \text{sin} \theta + \left\{ \alpha \right\} \text{cos} \theta \right] - f_s \left[ \left\{ \beta \right\} \text{sin} \theta - \left\{ \alpha \right\} \text{cos} \theta \right]$$

$$\Delta C_n = -\sum f_s \left[ \left\{ \beta \right\} \text{sin} \theta \right] - f_s \left[ \left\{ \beta \right\} \text{cos} \theta \right] + f_s \left[ \left\{ \beta \right\} \text{sin} \theta \right] - f_s \left[ \left\{ \beta \right\} \text{cos} \theta \right]$$

$$\Delta C_n = -\sum f_s \left[ \left\{ \beta \right\} \text{cos} \theta \right] - f_s \left[ \left\{ \beta \right\} \text{sin} \theta \right] - f_s \left[ \left\{ \beta \right\} \text{cos} \theta \right] - f_s \left[ \left\{ \beta \right\} \text{sin} \theta \right]$$

The unknown parameters in eq.(13) are $\alpha$, $\beta$, $f_s$, and $f_d$. If these parameters are estimated, the power contributions of surface, double-bounce, and volume scatterings are derived as

$$P_s = f_s \left[ \left\{ \beta \right\} \text{cos} \theta \right] + f_s \left[ \left\{ \beta \right\} \text{sin} \theta \right]$$

$$P_d = \text{Total Power} - P_s - P_v$$

$$\text{Total Power} = \left\{ \left( \left\{ \beta \right\} \text{cos} \theta \right) \right\} + 2 \left\{ \left\{ \beta \right\} \text{sin} \theta \right\} + \left\{ \left\{ \beta \right\} \text{cos} \theta \right\}$$

In order to estimate the unknown parameters, I use a particle swarm optimization (PSO) [4].

C. Particle Swarm Optimization

Particle swarm optimization technique can be used to find an approximated global optimal solution to an optimization problem [4] and has been shown to be useful for optimization about a multidimensional problem in various applications. A swarm is modeled by particles in multidimensional search space. These particles have a position and a velocity and move in the search space due to two essential reasoning capabilities which are related to their own best position and the best position in the swarm. Particles can communicate best positions to each other and adjust their own position and velocity based on these good positions. The velocity $v$ and position $x$ of $nth$ particle are defined as

$$v_{x,n+1} = \omega v_{x,n} + C_1 r_1 \left( p_{x,n} - x_{n,n} \right) + C_2 r_2 \left( g_{x,n} - x_{n,n} \right)$$

$$x_{x,n+1} = x_{x,n} + v_{x,n+1}$$

where $\omega$ is an inertial weight, $C_1$ and $C_2$ are an acceleration coefficient, $r_1$ and $r_2$ are a random variable. $p$ is the best position in each particle and $g$ is the best position in the swarm. $k$ is an iteration index. In the optimization, the position and velocity of each particle is adjusted to minimize or maximize a fitness of objective function. A procedure of PSO is as follows. At first, this technique prepares a set (swarm) of candidate solutions (particles). Next, the fitness of each particle is evaluated. If a fitness level is reached to a termination condition, it is considered that an approximated solution is found. If the fitness level is not reached to the condition, the velocity and position updates are carried out.

In the case of polarimetric decomposition, the particles are related to $\alpha$, $\beta$, $f_s$, and $f_d$. An objective function to estimate unknowns parameters in eq.(13) is explained. The difference before and after compensating the measured coherency matrix can be derived as $\{ -(C(\alpha)) \} - \{ C(\beta) \}$. According to (13), a mathematical difference $\{ -(C(\alpha)) \} - \{ C(\beta) \}$ which are calculated by the expected parameters $f_s$, $f_d$, $\alpha$, and $\beta$ of PSO are provided. The following optimization can be examined by PSO.

$$\{ -(C(\alpha)) \} - \{ C(\beta) \}$$

III. EXPERIMENTAL RESULTS

PALSAR data is used to confirm that proposed decomposition works. The HH image which consists of 400 by 400 pixels is shown in Figure 2. There is a dockyard, residential and mountain areas in this image. Figure 3 shows an image of azimuth orientation angle of Fig.2. Figure 4 shows the decomposition results estimated by proposed method. In Fig 4, each calculation is treated to be ratio as:

$$\text{Ratio} = P_i / \text{Total power}$$

Moreover, the decomposition results estimated by original four component decomposition [3] are shown in Fig.5. Two urban areas are compared. The difference between two urban areas is an azimuth rotation angle estimated by eq (11). Urban area 1 is about 2.4 degrees. Urban area 2 is about -24.6 degrees. Four component scattering decomposition method and proposed method provide same result with respect to urban area 1. Since the azimuth rotation angle in this area is small, the differences of eq. (13) are almost zero. In urban area 2, two methods
provide the different results. Four component scattering decomposition method estimates that a volume scattering is dominant. The proposed method shows that a double bounce scattering is dominant.

IV. CONCLUSION

In this paper, a polarimetric decomposition technique considering azimuth rotation based on evolutional algorithm was proposed. We derived the differences of covariance matrix before and after compensating an azimuth rotation angle. These differences are used as an optimization problem. The evolutional algorithm to solve optimization problem is particle swarm optimization. We applied the proposed method to ALOS/PALSAR data and compared the results of four component scattering decomposition method and proposed method. In urban area, the difference between two methods was confirmed.

REFERENCES