ESPRIT-BASED SCATTERING POWER DECOMPOSITION BY USING MODIFIED VOLUME SCATTERING MODEL

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1. INTRODUCTION

Land surface classification is one of the important applications of POLSAR (Polarimetric SAR) image analysis. Since the POLSAR images have multi-polarization images of HH, HV, VH, and HH polarization, the scattering nature of terrain can be effectively discriminated. There are many classification/discrimination techniques such as simple HV basis imaging, the Pauli basis imaging, H-Alpha-Anisotropy imaging[1],[2], power decomposition imaging[3],[4], [5]. The most frequently used method is the H-Alpha-Anisotropy based on the eigenvalues of coherency matrix. The second one is the scattering power decomposition based on physical scattering models, which was first developed by A. Freeman and S. Durden[3]. The extended methods were proposed by Y.Yamguchi, et. al., with additional components, the helix component and several types of volume scattering components[4].

As for the scattering power decomposition techniques the covariance matrix or coherency matrix obtained by POLSAR images is used for the decomposition. In these types of techniques, we have many unknowns to be determined such as power of each component and some of the elements in each component-covariance matrices. The number of unknowns exceeds to the number of independent observables in POLSAR images. Therefore some assumptions are adopted to obtain unique solution. For example. in the Freeman decomposition, they adopted two assumptions. The first assumption is that the volume scattering components is known, which can be modeled by return from cloud of randomly oriented dipoles. The second is that (1,1)-element in the covariance matrix for double-bounce component is -1 when surface scatter is dominant otherwise (1,1)-element of that for double-bounce component is 1. In the Yamaguchi's decomposition, they added several additional volume scattering matrices. In this technique, we should select suitable one among the candidates of volume scattering covariance matrices that can be estimated by the co-polarization power ratio[4]. Accuracy of decomposition in these techniques depends on the validity of the assumptions. When some of the assumptions cannot holds good, negative power components often appear.

One of the best solutions to overcome this negative component-power problem is to get additional independent observables. As the authors discussed in [6], [7], when we apply the concept of the power decomposition to POL-INSAR data sets, we can obtain additional independent observables. Clearly, we also have additional unknowns corresponding to complex coherence of each component. However, applying the ESPRIT analysis to the POLSAR data set, we can estimate the suitable volume scattering matrix among potential candidates by using complex eigenvalue distribution in the ESPRIT analysis. In [7], we adopted Yamaguchi's volume scattering model to make the candidates. However, there still remain errors in some data sets. Development of Suitable volume scattering model to make the candidates of volume scattering matrices was the future problem to be solved.

Recently, Dr. Arii, et. al., proposed modified volume scattering model for the power decomposition[8]. They used the model for POLSAR data set and an adaptive technique is employed to overcome the negative-power problem. Their modified volume scattering model can be also applied to our POL-INSAR analysis directly. By using their model, we can express randomness of the forest as well as the orientation of the branches and trunks. One of the important feature of this model can be seen in the $(1,2), (2,1), (2,3), (3,2)$-th elements in the volume component covariance matrices. In the Yamaguchi's model, they belong to the helix component, however they can be also modeled in the volume component in their model. In this abstract, basic concept of the Pol-InSAR image decomposition technique is summarized. In the final paper, quantitative analysis of the ESPRIT-based POL-INSAR with modified volume scattering model is presented.

2. SCATERING COMPONENT DECOMPOSITION FOR POLSAR IMAGES

The conventional scattering component decomposition techniques employ covariance matrices derived by the POLSAR image pixels. The Freeman decomposition technique decomposes the matrix into three scattering models corresponding to surface (single bounce), diplane (double bounce) and volume (random) scattering component[3]. Yamaguchi *et. al.,* extend the method into 4-componnent decomposition with the additional helix scattering component[4]. It can be shown by

$$\boldsymbol{C} = f_s\boldsymbol{C}_s + f_d\boldsymbol{C}_d + f_v\boldsymbol{C}_v + f_h\boldsymbol{C}_h \tag{1}$$

where the subscripts s, d, v, and h denotes single-bounce, double-bounce, volume and helix component, respectively. The matrices $\boldsymbol{C}_i$ and f_i ($i = s, d, v$ or h) denote covariance matrix and power coefficient of each component, respectively. The (1,2)-th and (2,1)-th elements in C is assumed to be equal in the technique, then we have 5 independent observables. This means that we can estimate only one unknown in addition to f_i $(i = s, d, v, h)$. To solve (1) uniquely, the $\boldsymbol{C}_v$ and $\boldsymbol{C}_h$ are assumed to be known. The one additional unknown is assigned to one of the elements in $\boldsymbol{C}_s$ or $\boldsymbol{C}_d$ corresponding to their contributions. As described here, several assumptions are required due to limitation of the number of observables. These assumptions sometimes cause physically unacceptable decomposition results such as negative power components.

3. SCATTERING COMPONENT DECOMPOSITION FOR POL-INSAR IMAGES

For realizing a robust decomposition technique, it would be the key to increase the number of independent observables. The authors have focused on the interferometric observations. Since the incident angles in interferometric pair observations are almost the same, therefore decomposed results in each data set will be also assumed the same. They can be written by

$$\begin{aligned}
\boldsymbol{C}_{MM} &= f_s\boldsymbol{C}_s + f_d\boldsymbol{C}_d + f_v\boldsymbol{C}_v + f_h\boldsymbol{C}_h, && \text{(2a)}\\
\boldsymbol{C}_{MS} &= f_s\boldsymbol{C}_s e^{j\theta_s} + f_d\boldsymbol{C}_d e^{j\theta_d} + f_v\boldsymbol{C}_v e^{j\theta_v} + f_h\boldsymbol{C}_h e^{j\theta_h}, && \text{(2b)}
\end{aligned}$$

where $\boldsymbol{C}_M M$ and $\boldsymbol{C}_{MS}$ are the auto-covariance matrices of master data and covariance matrix between master and slave data, respectively. The additional observables in $\boldsymbol{C}_{MS}$ bring us 5 new independent observables. The number of new unknowns, which correspond to interferometric phase of each component is 4. Therefore we can determine one more unknown without assumptions. This means that we can estimate α and β in [3] without assumptions if we know $\boldsymbol{C}_v$. The remaining problem is the estimation of $\boldsymbol{C}_v$. As shown in (2b), single- and double-bounce components correlate well and we will have $e^{j\theta_s}$ and $e^{j\theta_d}$ for their complex coherence in good POL-INSAR data set. We can estimate single- and double-bounce components easily by using the ESPRIT method when there exist no volume and helix components in (2a) and (2b). This means that the magnitude of the complex coherence for single- and double-bounce components becomes 1 when we remove other component (volume and helix) correctly. By using property, we can select the suitable type of the volume scattering matrix among the potential candidates. In the previous technique [6], we adopted Yamaguchi's model. However, power of volume scattering component sometimes overestimated especially weak volume scattering region. This will be caused by the inadequate set of volume scatterings. In this report, we adopt Dr. Arii and Dr. van Zyl's modified model. Randomness of the forest as well as tree trunks orientation can be effectively modeled the model, then more suitable model can be selected by the ESPRIT method. As pointed out previously, the covariance matrices derived by the modified volume scattering model often have non-zero entry in the first off-diagonal elements that will be effective to correct estimation of volume scattering power as well as to remove modeling error(s) of helicity.

4. CONCLUSION

In this abstract, we describe just the concept of scattering component decomposition technique for Pol-InSAR data set. Decorrelation effect, especially for the temporal decorrelation in repeat-pass observation, will severely affect the method. Quantitative analysis with E-SAR, SIR-C/X-SAR and ALOS/PALSAR data will be provided in the final paper. Also application results for classification of terrain and so forth will be shown.

5. REFERENCES

[1] J. S. Lee and E. Pottier, *Polarimetric radar imaging from basics to applications*, CRC Press, 2009.

[2] S. R. Cloude and E. Pottier, "A review of target decomposition theorems in radar polarimetry," *IEEE Trans. Geoscience and Remote Sens.*, vol. 34, no. 2, pp. 498–518, Mar. 1996.

[3] A. Freeman and S. Durden, "A three-component scatering model for polarimetric sar data," *IEEE Trans. Geoscience and Remote Sens.*, vol. 36, no. 3, pp. 963–973, May 1998.

[4] Y. Yamaguchi, T. Moriyama, M. Ishido, and H. Yamada, "Four-component scattering model for polarimetric sar image decomposition," *IEEE Trans. Geoscience and Remote Sens.*, vol. 43, no. 8, pp. 1699–1706, Aug. 2005.

[5] Y. Yajima, Y. Yamaguchi, R. Sato, H. Yamada, and W. -M. Boerner, "Polsar image analysis of wetlands using a modified four-component scattering power decomposition," *IEEE Trans. Geoscience and Remote Sens.*, vol. 46, no. 6, pp. 1667–1773, June 2008.

[6] H. Yamada and Y. Yamaguchi andR. Sato, "Polarimetric scattering model decomposition for pol-insar data," in *Proc. of IGARSS 2008*, July 2008.

[7] H. Yamada and Y. Yamaguchi andR. Sato, "Scattering component decomposition for pol-insar data and its application," in *Proc. of IGARSS 2009*, July 2009.

[8] M. Arii and J. van Zyl andY. Kim, "Adaptive decomposition of polarimetirc sar covariance matrices," in *Electronic Proc. of IGARSS 2008*, July 2009.