CLUSTERING POLARIMETRIC SAR IMAGE UNDER DEORIENTATION THEORY

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ABSTRACT

In natural complex terrain surfaces, scattering targets with random orientations produce random fluctuating echoes which lead to confused classifications by directly using target decomposition on polarimetric SAR (PolSAR) image. In order to reduce the influence, the target vector is transformed into the state with minimization of cross-polarization. Then a set of new parameters *u*/*v*/*w* are used to characterize scattering mechanisms under the deorientation theory, and the fuzzy membership is adopted instead of "hard" division of parameter plan. Characterizing the sample coherency matrices as complex Wishart distribution, the PolSAR image is clustered based on Bayes Maximum Likelihood (ML) criteria. Experiment is carried out on an L-band NASA/JPL SIR-C PolSAR image over Danshui town, Guangdong, China. Comparison results with the popular used methods show that the proposed method provides a significant improvement in classification and the associated scattering mechanism of class is more accurate and beneficial for automatic terrain recognition.

Index Terms—Deorientation, pattern classification, fuzzy clustering, radar polarimetry, SAR

1. INTRODUCTION

The polarimetric information in SAR becomes more and more useful in target detection, urban area detection, terrain classification, and etc. Among these, the classification of complex terrain surface using polarimetric SAR (PolSAR) imagery is one of the most important SAR applications, in both quantity and quality ways. Unsupervised classification methods of SAR image can be broadly divided into two categories: the methods based on traditional image processing and the methods based on the physical mechanism of wave propagation. It is shown that methods in the second category have more advantages in this field, especially the unsupervised classification methods [1]-[7]. Van Zyl [1] first proposed an unsupervised method, and then Freeman and Durden [2] introduced a three-component method. The widely used target decomposition (TD) theory is presented by Cloude and Pottier [3], [4], and they also proposed an unsupervised classification scheme based on it. Clustering is another type of classification technique. Lee and *etc* [5]-[7] proposed several unsupervised clustering methods based on TD and distribution of the PolSAR observation. All these methods use the $H/\bar{\alpha}$ or $H/\bar{\alpha}/A$ classification results to initialize cluster centers.

One of the most widely used clustering methods is fuzzy *c*-mean (FCM) [8]. The FCM is nonlinear in nature; it is sensitive to the initialization of the clustering center. However, in natural complex terrain surface, scatter targets with random orientations always product randomly fluctuating echoes. It means that different scatters with different orientations could make similar scattering and the same scatters with random orientations could make different scattering which can lead to confused classifications. In addition, it is shown from the quantitative study of Lopez-Martinez [9], [10] and Lee [11] that the entropy H is always underestimated while the anisotropic A is always over estimated and $\bar{\alpha}$ also presents a bias with respect to its true value. So, it is difficult to cluster randomly oriented and randomly distributed scatter targets correctly using $H/\bar{\alpha}/A$. More recently, the of deorientation theory [12] is introduced to reduce the fluctuating influence of randomly distributed orientation by turning the target vector to the state of minimization of cross-polarization (min-x-pol), and a set of new parameters, e.g. u, v, are proposed. They contain all the information that α has, and can present more characteristic information of scattering mechanisms. These parameters are more effective in describing target characteristics and can make better classification.

An unsupervised classification method is proposed in this paper. The method is achieved by combining the target deorientation and adapted FCM to clustering the PolSAR image represented by coherency matrix. After deorientation, the fuzzy membership is adopted instead of "hard" division of parameter plan. The PolSAR image is classified based on adapted FCM using revised Wishart distance measure.

2. POLARIZATION DEORIENTATION

A new polarization base (h', v') can be obtained by rotating the linear polarization base (h, v) by an angle ψ along with the sight line. Then, the electrical vector $\boldsymbol{E}$ under original base is transformed to $\boldsymbol{E}'$ under new base. Moreover, the relationship between the target vector $\boldsymbol{k}_P'$ and $\boldsymbol{k}_P$ is

$$\boldsymbol{k}_P' = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos 2\psi & \sin 2\psi \\ 0 & -\sin 2\psi & \cos 2\psi \end{bmatrix} \cdot \frac{1}{\sqrt{2}} \boldsymbol{k}_P \tag{1}$$

Because the rotation of the polarization base along the sight line is equivalent to the inverse rotation of the target, equation (1) also describes the target rotation.

In order to reduce the influence of the target orientation, a certain rotation angle ψ_m need to be obtained. By rotating the target through ψ_m angle along with the sight line, the target orientation is transformed into the state of min-x-pol. Thus makes the scattering information of the target be concentrated on the col-pol and reduces the fluctuation caused by random orientation of the identical targets.

Minimizing the cross-polarization of the target vector $\boldsymbol{k}_P'$ and assuming $\psi_m \in [0, \pi/2)$, we can obtain [12]

$$\psi_m = \Big[sign\{\cos(\phi_2 - \phi_3)\} \times \frac{2\beta - 2[\beta]_\pi + \left[\tan^{-1}\{\tan 2\beta \cdot |\cos(\phi_2 - \phi_3)|\}\right]_\pi}{4} \Big]_{\pi/2} \tag{2}$$

where $[x]_y$ is the remainder of x divide y and $sign(\cdot)$ is the sign function. It can be seen that $\phi_3 - \phi_2$ describes the degree of the asymmetry of the target. If the target is reflection symmetric, i.e. $\phi_3 - \phi_2 = 0, \pi$, then ψ_m exactly equals to $-\beta/2$ where β is the orientation angle. This result is identity with the results obtained by Cameron [13] and Cloude [14].

Although α is roll-invariant and suitable for analysis free from the orientation, but the parameter $\bar{\alpha}$ represents the probabilistically averaged col-pol characteristics of the target scattering mechanism and contains mixed information. So, parameter $\bar{\alpha}$ introduces fuzziness into the terrain surface classification using $H/\bar{\alpha}/A$. To solve this problem, a parameterized eigenvector $\boldsymbol{k}_L$ is defined as

$$\boldsymbol{k}_L = e^{i\phi_0} \left[\sin c \cos a \quad \cos c e^{i(\phi_x - \phi_0)} \quad \sin c \sin a \cdot e^{i2b} \right]^T \tag{3}$$

where

$$a = \tan^{-1}\left(\left| \frac{S_{vv}}{S_{hh}} \right| \right), \quad b = \frac{1}{2}\arg\left(\frac{S_{vv}}{S_{hh}} \right), \quad c = \cos^{-1}\left(\frac{|S_{hv}|}{\|\boldsymbol{k}_L\|} \right) \tag{4}$$

For revealing the common feature of the targets of a certain terrain class, without influence of random orientation, a set of new parameter, u, v, and w, is defined according to parameterized eigenvector $\boldsymbol{k}_L$

$$u = \sin c \cos 2a, \quad v = \sin c \sin 2a \cos 2b, \quad w = \cos c. \tag{5}$$

where w indicates the amplitude ratio of co-pol and x-pol scatterings, u indicates the amplitude ratio of co-pol scatterings in case of little x-pol scattering , and v denotes the phase difference of co-pol scatterings when both co-pols have comparable amplitudes [12]. It can be seen that this new set of parameters makes it easy to describe the feature of the object and is helpful to classification.

Deorientation operation makes two identical scatter objects with different orientations yield the same scattering and thus makes them as the same class, and makes different classes for those different scatter targets which might produce similar scattering before deorientation.

For unsupervised classification of terrain surface, the parameter plan of *u*-*v*-*H* is divided into 8 zones in [12] by considering the different scattering mechanism and different terrain class. However, the method uses “hard” thresholds and those thresholds are arbitrary to some extent and need to be tuned in practical application.

3. UNSUPERVISED CLASSIFICATION USING WISHART DISTANCE MEASURE

Obviously, the arbitrariness of boundary values of the parameter plan is caused by the non-crisp relationship between the observations and the classes, which can be seen as fuzziness. Therefore, the simple hard-threshold dividing method is not suitable enough in nature.

Clustering the patterns means partition a pattern space into c clusters. And fuzzy clustering gives each example a multi-class arrangement, i.e. each example is related to all clusters but has different grade of the relationship (called membership). From this point of view, membership gives a fuzzy partition which can be seen as an unsupervised classification of data.

In practice, the PolSAR image is always multilook. The covariance matrix $\boldsymbol{C}$ of multilook PolSAR image obeys the complex Wishart distribution [15]. Moreover, coherency matrix $\boldsymbol{T}$ and covariance matrix $\boldsymbol{C}$ conserve unitary similarity transform. Hence, the pdf of coherency matrix $\boldsymbol{T}$ is also complex Wishart which can be written as

$$P(\boldsymbol{T} \mid \boldsymbol{T}_i) = \frac{L^{Lp} |\boldsymbol{T}|^{L-p} \exp\left(-L \cdot tr\left(\boldsymbol{T}_i^{-1}\boldsymbol{T}\right)\right)}{\pi^{\frac{p(p-1)}{2}} \Gamma(L) \ldots \Gamma(L-p+1) |\boldsymbol{T}_i|^L} \tag{6}$$

where L is the equivalent look, $tr(\cdot)$ is the trace of the matrix, p is the dimension of the target and $\boldsymbol{T}_i$ denotes the feature coherency matrix of the ith class.

The revised Wishart distance

$$d_{ik} = \ln(\boldsymbol{T}_i) - \ln(\boldsymbol{T}_k) + tr\left(\boldsymbol{T}_i^{-1}\boldsymbol{T}_k\right) - p \tag{7}$$

is used as the measure of similarity of the example and the cluster center. Calculating the partial differential of object function of FCM with respect for $\boldsymbol{T}_i$ and let it equal to zero. We can derive that

$$\boldsymbol{T}_i = \sum_{k=1}^{n} \mu_{ik}^{m_c} \boldsymbol{T}_k \Big/ \sum_{k=1}^{n} \mu_{ik}^{m_c} \tag{8}$$

where m_c is a tuning parameter which controls the degree of fuzziness, and μ_{ik} is the membership of kth example to the ith class.

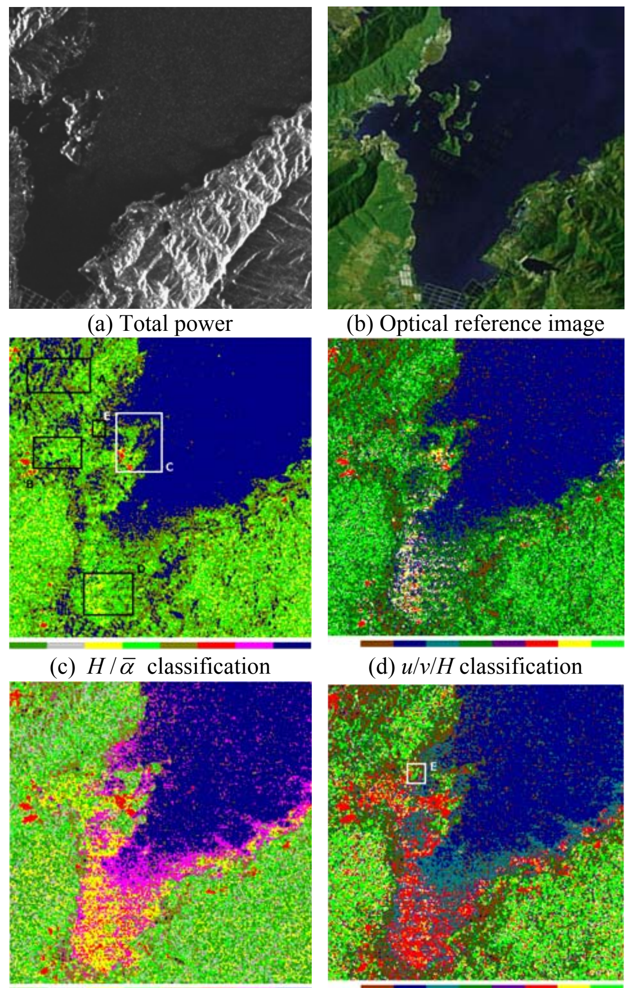
In practical implementation, the solution of $\boldsymbol{T}_i$ and μ_{ik} can be achieved through an iterative method. The most popular algorithm is an iterative scheme called alternating optimization (AO). In summarize, the algorithm flow is described as bellow:

1. Perform eigen-analysis (target decomposition) [3] to the PolSAR date, calculate the entropy H and construct the parameterized object vector $\boldsymbol{k}_p$.
2. Transform the target orientation into a state with min-x-pol.
3. Calculate parameters u and v, and use partitions in [12] of $u/v/H$ feature space as initial classes.
4. Obtain the initial cluster centers by averaging coherency matrices in the same class.
5. Calculate the distance measure d_{ik} using Equ. (7) for each example to every cluster centers, and then label the example as the class which minimizes the object function J_e.
6. Updating cluster centers by calculate (8) using newly labelled averaged coherency matrices.
7. Stop the iteration if one of the following three situations achieves: it meets the user defined iteration times, the absolute difference between object functions of the two contiguous iterations is less than a pre-defined small positive value, or the migration ratio of classes is more than a user defined threshold. Otherwise, loop back to the step 5.

4. EXPERIMENT RESULT

The PolSAR data of NASA/JPL SIR-C over Danshui town, Guangdong, China is used for classification. Fig. 1(a) and 1(b) are the total power of the SIR-C data at L-band and an optical reference image, separately. Based on the scattering mechanisms, the u-v-H feature space is divided into 8 zones [12]. Although the high-order scatterings are not significant in SIR-C frequency, an additional classes corresponding to it is still set because this type of scatterings are found in the test data. Five regions are chosen for comparing different classification performance and marked in Fig. 1(c) and 1(f). Region A at top left is selected from mountain area, region B in the middle left and region D in the middle at bottom are two portions in the bay near coast, region C includes several islands in the sea, and in region E there is a small peninsula. In order to compare with another widely used unsupervised classification method, the number of iteration is fixed to ten.

Firstly, because parameter $\bar{\alpha}$ represents the average scattering mechanism, it causes confusion in classifications. As shown in Fig. 1(c), serious classification errors are found in region A, region B and region D, labelling many data belonging to flat ground as "sea" and labelling a lot of data of sea surface as "heavy canopy" or "forest". The mistakes are more observable by comparing Fig. 1(c) with the optical reference image 1(b). Obviously, these results are not reasonable. By using the set of new parameters, e.g. u, v and H, the classifications in region A are improved as shown in Fig. 1(d), and high-order scatterings, demonstrating the complex reflection and refraction phenomena near the coast, are recognized with advantage. Unfortunately, there still have misclassifications in region D and almost all the data in region B are misclassified to "forests". Consequently, directly applying hard-threshold division on feature plain always products many misclassifications no matter using $H/\bar{\alpha}$ or $u/v/H$.



(a) Total power (b) Optical reference image

(c) $H/\bar{\alpha}$ classification (d) $u/v/H$ classification

(e) Method proposed by Lee (f) Proposed method

Fig. 1. Comparison of the classification results.

Secondly, it can be seen that the classification performance is significantly improved by comparing the results using proposed method in Fig. 1(f) with 1(c) and 1(d). The data in region B and region D are classified to the high-order scatterings class and double scatterings class. At the same time, besides maintaining the islands' terrain type as "forest" and "canopy", the contour of islands and coast are more clearly, the shape and position of the boundaries are correct comparing with Fig. 1(a) and 1(b)

Furthermore, comparison is also performed with another popular clustering method [5] proposed by Lee and etc. Although the algorithm yields correct result in region D, there are still many misclassifications in region B due to the usage of parameter $\bar{\alpha}$ to some extent. Another problem of that method resides in the terrain type assignment (pink color section in Fig. 1(e)). That method classifies these data to low entropy volume scattering mechanism, while the method that we proposed in this paper labels them as low entropy surface scattering (single scattering) in the state of the amplitude ratio of co-pol scattering is big. Obviously, the classification result is more reasonably agree with the reality in our method.

At last, the proposed method has advantages in labelling detail terrain feature. The small peninsula in region E in Fig. 1(f) is classified and labelled correctly, but it can not be distinguished in results using other three methods.

5. CONCLUSION

Due to the existence of orientation angles, identical scattering targets with different orientations may bring out different scattering mechanisms that belong to two different classes, whereas two different scattering targets may produce similar echoes that could be classified to the same class. It is so much confused to represent and understand the terrain surface. It is proved that parameter α in TD theory is roll-invariant, i.e. α is independent to orientation. But the $\bar{\alpha}$ is a metric of probabilistic average of co-pol scatterings, which mixes information of all the scatterings. Especially in the case of complex random targets within multiple scattering, each α angle contains its own information of random targets, which might be missed by the average operation. Thus makes the confused classification by using $\bar{\alpha}$.

The advantage of deorientation theory is that it can enhance the characteristics of scattering targets, extract information of different scatterings more independently, and improve the classification performance. Using the set of parameters u, v and H can make the description of scattering targets more intuitively and benefit to classification, i.e. it can provide better initialization of cluster centers for the non-linear clustering algorithm.

No matter in the $H/\bar{\alpha}$ or $u/v/H$ feature plan, there has no crisp linear boundaries between different scattering types. It is reasonable to describe the relationships between examples and scattering classes using fuzzy memberships. Combining with the probability distribution of the coherency matrix, the proposed clustering method is more applicable than methods by dividing feature space or the clustering method initialized using $H/\bar{\alpha}$ classifications. And the classification results are benefit to terrain representation and PolSAR imagery understanding.

Acknowledgements: *The research work is sponsored by the National Key Fundamental Research & Development Programs of China, No. 001CB309403 and the National Natural Science Foundation of China, No. 60574033.*

6. REFERENCES

[1] J. J. van Zyl, “Unsupervised classification of scattering behavior using radar polarimetry data,” *IEEE Trans. Geosci. Remote Sensing*, vol. 27, no. 1, pp. 36-45, 1989.

[2] A. Freeman, S. L. Durden, “A three-component scattering model for polarimetric SAR data,” *IEEE Trans. Geosci. Remote Sensing*, vol. 36, no. 3, pp. 963-973, 1998.

[3] S. R. Cloude, E. Pottier, “A review of target decomposition theorems in radar polarimetry,” *IEEE Trans. Geosci. Remote Sensing*, vol. 34, no. 2, pp. 498-518, 1995.

[4] S. R. Cloude, E. Pottier, “An entropy based classification scheme for land application of polarimetric SAR,” *IEEE Trans. Geosci. Remote Sensing*, vol. 35, no. 1, pp. 68-78, 1997.

[5] J. S. Lee, M. R. Grunes, T. L. Ainsworth, L. J. Du, D. L. Schuler, S. R. Cloude, “Unsupervised classification using polarimetric decomposition and the complex Wishart classifier,” *IEEE Trans. Geosci. Remote Sensing*, vol. 37, no. 5, pp. 249-2258, 1999.

[6] L. Ferro-Famil, E. Pottier, J. S. Lee, “Unsupervised classification of multifrequency and fully polarimetric SAR images based on the H/A/Alpha-Wishart classifier,” *IEEE Trans. Geosci. Remote Sensing*, vol. 39, no. 1, pp. 2332-2342, 2001.

[7] J. S. Lee, M. R. Grunes, E. Pottier, L. Ferro-Famil, “Unsupervised terrain classification preserving polarimetric scattering characteristics,” *IEEE Trans. Geosci. Remote Sensing*, vol. 42, no. 4, pp. 722-731, 2004.

[8] B. Tso and P. M. Mather, *Classification Methods for Remotely Sensed Data*, Taylor & Francis, London, 2001.

[9] C. Lopez-Martinez, E. Pottier, S. R. Cloude. Statistical assessment of eigenvector-based target decomposition theorems in radar polarimetry. *IEEE Trans. Geosci. Remote Sensing*, vol. 43, no. 9, pp. 2058-2074, 2005.

[10] C. Lopez-Martinez, E. Pottier, I. Hanjnsek, J. S. Lee, X. Fabregas, “Polarimetric speckle noise effects in quantitative physical parameters retrieval,” *EUSAR*, Ulm. Germany, pp. 223-227, 2004.

[11] J. S. Lee, D. L. Schuler, and T. L. Ainsworth, “Scattering model based speckle filtering of polarimetric SAR data,” *EUSAR*, Ulm. Germany, pp. 203-207, 2004.

[12] Feng Xu and Ya-Qiu Jin, “Deorientation theory of polarimetric scattering targets and application to terrain surface Classification,” *IEEE Trans. Geosci. Remote Sensing*, vol. 43, no. 10, pp. 2351-2364, 2005.

[13] W. L .Cameron, L. K. Leung, “Feature motivated polarization scattering matrix decomposition,” in *IEEE 1990 Int. Radar Conf.*, pp. 549-557, May 7-10, 1990.

[14] S. R. Cloude, K. P. Papathanassiou, E. Pottier, “Radar polarimetry and polarimetric interferometry,” *IEICE Trans. Electron.*, vol. E84-C, no. 12, pp. 1814-1822, 2001.

[15] Henri Maître and et al, *Traitement des Images de Radar à Sysnthèse d’Ouverture*. Publishing House of Electronics Industry, Beijing, 2005.