ON OPTIMAL POLARIMETRIC CHARACTERISTIC PARAMETERS FOR LAND-COVER CLASSIFICATION

Hiroyoshi YAMADA†, Souhei KAKIZAKI†, and Yoshio YAMAGUCHI†
Department of Information Engineering, Niigata University
Ikarashi 2-8050, Niigata-shi, 950-2181, Japan
E-mail : {yamada, yamaguch}@ie.niigata-u.ac.jp

1 Introduction

Land-cover classification is one of the important research applications in SAR (Synthetic Aperture Radar) remote sensing. Many classification algorithms have been proposed. Selection of effective feature parameters for classification affects performance of the algorithm. For polarimetric SAR (POL-SAR) data, so many feature parameters have been proposed. Needless to say, we can select pixel value in each image ($S_{\mathrm{HH}}, S_{\mathrm{HV}}, S_{\mathrm{VV}}$) as the feature parameter. In addition, Polarimetric entropy and alpha angle (H, α)[1], three component scattering model (P_s, P_d, P_v)[2], SDH decomposition (K_s, K_d, K_h)[3], and so forth, are the promising parameters. One may think that classification performance will be improved as the number of feature parameters are increased, however, that is not always true in general. We often obtain better results with selecting optimal combination of several feature parameters.

We can find a few reports on optimum parameter selection[4]. However, suitable parameter combination has not reported. Since the suitable combination of feature parameters may depends on scene in general, parameter selection algorithm have been desired. In this report, we evaluate effectiveness of the aforementioned feature parameters for land-cover classification with POL-SAR images by using principal component analysis. This is the fundamental research to develop optimal parameter selection scheme. Evaluation results of AIR-SAR data (San Francisco images) are provided. These results show that we can obtain better classification results with the optimal (or suitable) selection of several effective feature parameters.

2 POL–SAR Image Classification

A supervised maximum likelihood (ML) classifier is employed in this report. This classifier seeks a best-match category using a supervised training data set. The maximum likelihood determines the category based on the criterion,

$$G_i - \log|\boldsymbol{V}_i| - (\boldsymbol{x} - \bar{\boldsymbol{x}}_i)^H \boldsymbol{V}_i^{-1} (\boldsymbol{x} - \bar{\boldsymbol{x}}_i), \tag{1}$$

where i denotes the number of categories to be classified, and superscript H denotes complex conjugate transpose. $\boldsymbol{V}_i$ and $\bar{\boldsymbol{x}}_i$ are the covariance matrix and mean feature vector of the category i, respectively. A feature vector pertaining to a pixel is defined as

$$\boldsymbol{x} = [x_1, x_2, \cdots, x_N]^T, \tag{2}$$

where T denotes transpose. The component of the vector, x_k, can be any feature parameter concerning the pixel. The dimension of the vector N is determined by the number of the used parameters.

Generally, the performance ML estimation will be improved with increasing N. However, since ranges of value in each POL-SAR feature parameter are diverse, suitable weighting (or

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scaling) of each parameter should be required. This may be highly scene dependent, therefore, very difficult to be estimate. Therefore, we focus on optimal selection, or combination of parameters for POL-SAR land-cover classification in this report.

3 Feature Parameters in POL–SAR Image

In this section, we briefly describe the property of each feature parameter employed here.

Each Polarization Component: $S_{\mathrm{HH}}, S_{\mathrm{HV}}, S_{\mathrm{VV}}$

POL-SAR images are provided as 4 (or 3) images with combinations of transmitting and receiving polarizations. S_{ij} denotes the scattering parameters for i-polarization transmitting and j-polarization receiving. The scattering property changes as the target shape and/or distribution.

SDH Decomposition: (K_s, K_d, K_h)[3]

This is one of the famous scattering matrix decomposition schemes. Any scattering matrix can be decomposed into sphere(K_s), diplane (or dihedral, K_d), and helix(K_h) components, where sphere components means scattering components which equal to the scattering matrix for conductive sphere, and so on.

Three component scattering model: (P_s, P_d, P_v)[2] This is the model based decomposition scheme. In this decomposition, physical scattering property of natural targets are assumed (*e.g.* average of $S_{\mathrm{HH}}S_{\mathrm{HV}}^* = 0$ for surface scatterer, where $*$ denotes complex conjugate). The parameter P_s, P_d, and P_v denotes contribution by surface, double bounce, and volume scatterer, respectively.

Polarimetric entropy and alpha angle: (H, α)[1]

Polarimetric entropy (H) is the parameter to describe complexity of the scattering property. This value becomes maximum $(H = 1)$ for the complex (random) polarimetric scatterings, and minimum $(H = 0)$ for simple (rank 1) scatterings. α denotes polarization dependency of the scatter, where $\alpha = 0°, 45°, 90°$ denotes plate, wire, and corner reflector type scattering, respectively.

4 Principal Components Analysis

Since we adopt the supervised ML classifier, it is clear that the feature parameters having different values in each training data set (class) are feasible. Ideally, the parameters that yield $\sum_{i,j,i\neq j} \bar{\boldsymbol{x}}_i^H \bar{\boldsymbol{x}}_j \to \min$ are the best parameters in view of class discrimination. However, this approach becomes difficult for large number of classes and parameters. This equation also means that independency among each feature vector is improved when we choose optimal parameters. Principal components analysis is the suitable technique for the evaluation.

In this analysis, we define overall training data sets as

$$\bar{\boldsymbol{X}} = [\bar{\boldsymbol{x}}_1, \bar{\boldsymbol{x}}_2, \cdots, \bar{\boldsymbol{x}}_P] \tag{3}$$

where P denotes number of the selected classes. We normalize the matrix and derive principal components and their contributions. Cumulative contribution of from # 1 to #j components can be defined as

$$\frac{\lambda_1 + \lambda_2 + \cdots + \lambda_j}{\lambda_1 + \lambda_2 + \cdots + \lambda_P} \tag{4}$$

where λ_i denotes variance of the #i principal component. In view of class discrimination, it can be preferable that the number of dominant principal components is equals to P. To evaluate contribution of each feature parameter to the components, we also derive factor loadings, which explain how the feature parameter relates to the components. We should select feature parameters having strong contribution to the dominant principal components.

5 Experimental Results

Classified results of San Francisco image obtained by AIR-SAR are shown in Fig.1. In this classification, 4 categories ($P = 4$: residential, vegetation, seashore, and sea) are selected, and extract almost 6,000 pixels from each area as the training data sets. Figure 1(a) shows the classified image by using all 11 parameters ($N = 11$) denoted previous section. Contribution of each principal components evaluated by the feature vector of training area is listed in Table 1. Although there are 11 parameters, there is only one dominant component and remaining contributions are small. This can be considered that several feature parameters contain almost the same feature. Since there exists 4 categories to be classified, it is desirable that the number of dominant components becomes 4. Of course, it is not required necessarily, however, you may easily understand that good classification performance can be achieved when feature vectors span high-rank linear space.

Corresponding factor loadings for 3 dominant components are listed in Table 2. To enhance the second and third principal components, we should select the parameter(s) having strong contribution to the component. According to the table, P_d and H–α have the largest contribution to #2 and #3 component, respectively. As the results, we can understand that three component scattering model (P_s, P_d, P_v) and polarimetric entropy and alpha angle (H, α) are the optimal choice. Other parameters will not be needed because of enough contribution of P_s, P_v to #1 component. The classified results by these two sets of feature parameters (P_s, P_d, P_v and H, α, then $N = 5$) are shown in Fig.1(b). Contribution of each component is listed in Table 1(b). Clearly, contribution of #2∼#4 is enhanced. Classification accuracy is also shown in each figure. We can obtain classification performance improvements (80.3%→ 86.7%). In addition, this results show that feature vector rank reduction ($N = 11 \rightarrow 5$) can be realized with performance improvements, that reduces computational burden. Figure 1(c) and Table 1(c) shows the classification results and corresponding principal components contribution with polarization components and SDH decomposition. In this case, classification performance is degraded since exist only one dominant component.

6 Conclusions

In this report, we apply the principal components analysis to the feature vectors in POL-SAR land-cover classification, and show that the analysis is useful for discriminating contribution of individual feature parameters. Experimental results show that classification by optimally selected parameter realizes classification accuracy improvement as well as computational burden reduction. Here, we only show the results of AIR-SAR data set. We have verified availability of the analysis for PI-SAR data set. They will be presented in the symposium.

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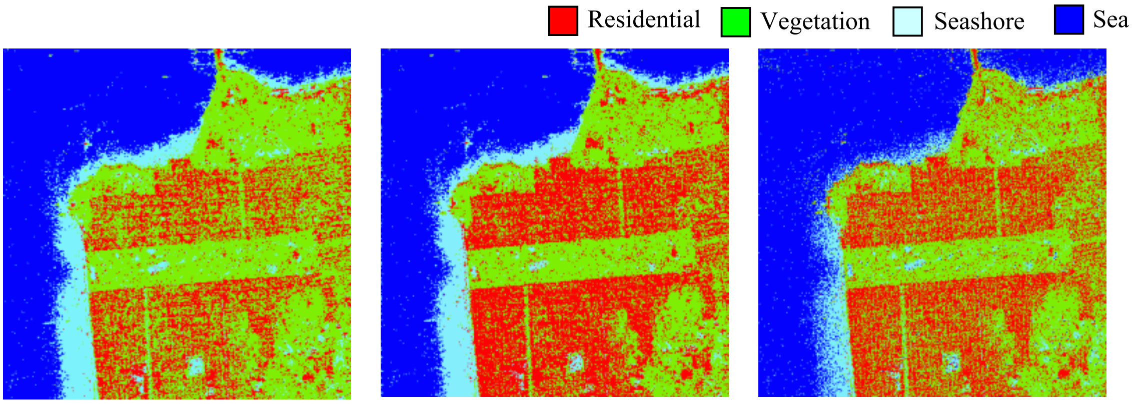

classification accuracy 80.3 %

(a) Classified by 11 parameters
($|S_{HH}|, |S_{HV}|, |S_{VV}|, K_s, K_d, K_h,$
P_s, P_d, P_v, H, α)

classification accuracy 86.7 %

(b) Classified by 5 parameters
(P_s, P_d, P_v, H, α)

classification accuracy 73.2 %

(c) Classified by 6 parameters
($|S_{HH}|, |S_{HV}|, |S_{VV}|, K_s, K_d, K_h$)

Fig.1 Classified results of San Francisco image obtained by AIR-SAR.

Table 1(a) Contribution of each principal components in Fig. 1(a)

No.	contribution	cumulative contribution
1	88.3 %	88.3 %
2	7.5 %	95.8 %
3	2.7 %	98.5 %
4	1.0 %	99.5 %
…	…	…
11	0.00 %	100.0 %

Table 1(b) Contribution of each principal components in Fig. 1(b)

No.	contribution	cumulative contribution
1	79.7 %	79.7 %
2	15.1 %	94.8 %
3	3.5 %	98.3 %
4	1.7 %	100.0 %
5	0.0 %	100.0%

Table 1(c) Contribution of each principal components in Fig. 1(c)

No.	contribution	cumulative contribution
1	96.3 %	96.3 %
2	2.7 %	99.0 %
3	0.8 %	99.8 %
4	0.2 %	100.0 %
5	0.0 %	100.0 %
6	0.0 %	100.0 %

Table 2 Factor loadings of all 11 parameters for dominant top 3 principal components

	#1 Comp.	#2 Comp	#3 Comp
S_{HH}	0.540	0.583	0.531
S_{HV}	0.812	0.350	0.132
S_{VV}	0.689	0.593	0.324
Ps	0.735	0.505	0.380
P_d	0.389	0.913	0.104
P_v	0.803	0.459	0.364
K_s	0.730	0.430	0.511
K_d	0.569	0.633	0.384
K_h	0.746	0.477	0.441
H	0.329	0.089	0.969
α	0.453	0.424	0.678