CLASSIFICATION OF CASI-3 HYPERSPECTRAL IMAGE BY SUBSPACE METHOD

Buho Hoshino[1], Hasi Bagan[2], Akihiro Nakazawa[3], Masami Kaneko[1], Masaki Kawai[4], and Tetuo Yabuki[1]

[1] *Department of Biosphere and Environmental Sciences, Rakuno Gakuen University, Bunkyoudai Midorimachi 582, Ebetsu city, Hokkaido, 069-8501, Japan.*
aosier@rakuno.ac.jp; kaneko@rakuno.ac.jp; Yabuki@rakuno.ac.jp

[2] *Center for Global Environmental Research, National Institute for Environmental Studies, 16-2 Onogawa, Tsukuba-city, Ibaraki, 305-8506, Japan.*
hasi.bagan@nies.go.jp

[3] *Asia Air Survey Co. Ltd., Kanagawa Prefecture 215-0004, Japan.*
aki.nakazawa@ajiko.co.jp

[4] *Earth Remote Sensing Data Analysis Center, Tokyo, 104-0054, Japan.*
kawai@ersdac.or.jp

Abstract—This study presents a supervised subspace learning classification method which can be applied directly to the original set of spectral bands of hyperspectral data for land cover classification purpose. The CLAss-Featuring Information Compression (CLAFIC) method is used to generate the appropriate feature subspace for each class on the training data set by Karhunen-Loève transform (also known as the principal component analysis). Then, using the iterative learning technology of averaged learning subspace methods (ALSM) to rotate the subspaces slowly for optimizes the subspaces to get better classification accuracy. We carried out experiments with 68 spectral bands Compact Airborne Spectrographic Imager-3 (CASI-3) data set. Experimental results show that Subspace method is a valid and effective alternative to other pattern recognition approaches for the mapping grass species and monitoring grass health using hyperspectral remote sensing data. Moreover, it is worth noting that the ALSMs are easily applied (i.e. they only request to set two parameters and can be directly applied to hyperspectral data) and they can entirely identify the training samples in a finite number of steps.

Keywords — hyperspectral data, subspace methods, CASI-3

I. INTRODUCTION

Hyperspectral data provides detailed spectral information about ground cover classes than traditional multispectral sensors. However, in the supervised classification, the curse of dimensionality (also known as “Hughes effect”) can be observed that occurs when the dimensionality of the data is quite high while at the same time there is a limited numbers of training samples available [1]. The recent developed subspace methods have been used to solve remote sensing image classification problems and have shown potential for efficient classification of high dimensional remote sensing data classification [2]. Subspace methods reduce data dimensionality by incorporating feature extraction into the classification process. The subspace methods using the transformation algorithms, which project the high-dimensional data onto lower dimension feature subspace that preserves most of the information that allows for the separation of classes, to overcoming the curse of dimensionality. In this study, we adopt the subspace classification method on the Compact Airborne Spectrographic Imager-3 (CASI-3)

Hyperspectral data to identify different grass species and monitoring grass health.

II. SUBSPACE METHODS

The subspace method is supervised classification method. In this method, each pixel is represented in terms of *n* features or measurements and is viewed as a point in an *n*-dimensional space. In the subspace methods, the primary model for a class is a subspace. Each class is represented by a subspace spanned by a group of basis vectors, and the classification criterion for input pattern is its distance from the class subspace. We assume that a hyperspectral data of a given site is available, containing *n* bands, that implicit pixels were *n*-dimensional vector. And assume the user defined classes of $\omega^{(1)}, \omega^{(2)}, \cdots, \omega^{(c)}$ appears. A set of labeled pixels for all such classes should also be available, divided into a training data set and a test data set. The objective is to establish subspaces in the feature space which separate samples belonging to different classes. The effectiveness of the subspace space is determined by how well samples from different classes can be separated.

The basic Subspace method is called class-featuring information compression (CLAFIC) [3], the procedure of which is as follows.

Let n be the number of input feature dimension, which is equal to the number of bands; let $\varphi_{k,i}$ ($1 \le i \le r$, $1 \le k \le c$) be the basis vectors of the subspace of class $\omega^{(k)}$ which are computed from class training samples by *QR* eigenvalue and eigenvector solve algorithms; here r denote the subspace dimension and c denote the number of classes. The dimensionalities of class subspaces are decided in the CLAFIC stage and then are kept constant during the learning process. The calculation of projection length of pixel x in subspace of class $\omega^{(k)}$ is given by

$$P_k = \sum_{i=1}^{r} (x, \varphi_{k,i})^2 / \|x\|^2 \qquad (1)$$

After compute the projection length between the pixel x and each subspace, then label pixel x into the classes that have the largest projection length.

The misclassifications occur in CLAFIC is mainly due to overlap of class subspaces. To separate subspace from each other, averaged learning subspace methods (ALSM) have been proposed [3] [4]. In ASLM, the class subspaces are slowly rotated to reduce the overlap between subspaces. The ALSM is described as follows:

At the iteration t, the conditional correlation matrix is computed by

$$P_t^{(i,j)} = \sum_x \left\{ xx^T \,\middle|\, x \in \omega^{(i)}, x \mapsto \omega^{(j)} \right\} \qquad (2)$$

symbol $\mapsto$ denotes the training sample x belongs to class $\omega^{(i)}$ that has been misclassified into class $\omega^{(j)}$.

Once the conditional correlation matrix was generated, the correlation matrix for class $\omega^{(i)}$ are updated as follows:

$$P_t^{(i)} = P_{t-1}^{(i)} + \alpha \sum_{j=1, j\ne i}^{c} P_t^{(i,j)} - \beta \sum_{j=1, j\ne i}^{c} P_t^{(j,i)} \qquad (3)$$

where α and β are learning parameters both usually have small positive constant values. Then, calculate the eigenvalues and eigenvectors of $P_t^{(i)}$ to generate new subspace of class $\omega^{(i)}$ [5]. The iterations will end when either the entire training data are fully recognized or the maximum number of iterations has been reached. Selecting both the subspace dimension and learning parameters is important in the subspace training phase. Usually, when choose the subspace dimensions for each class as the same value and set the two learning parameters equal to each other in ALSM, the recognition accuracy can reach higher [2].

III. EXPERIMENTAL RESULTS

A. Study Area and Data Set

The CASI-3 Hyperspectral data acquired on July 30, 2008 during 10:36~10:39 a.m. Tokyo standard time for a study site at Field Production Science Center (University Campus Farm), Rakuno Gakuen

University, Japan (Fig. 1). Table 1 presents the training and test data set used for classification.

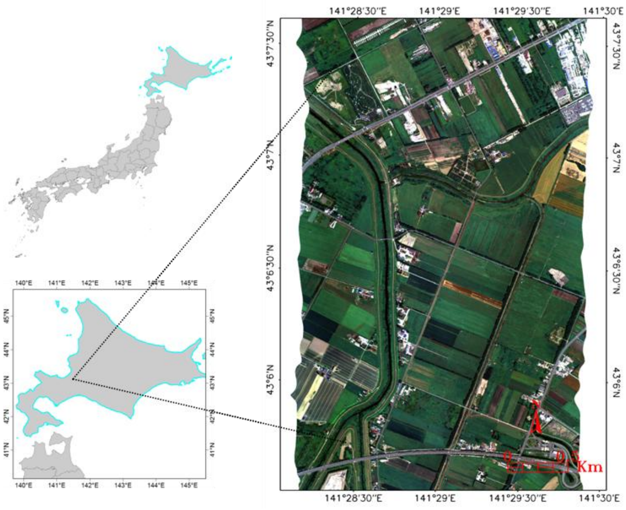

Fig. 1 Location of the study area. The right side image shows the full scene CASI-3 data set (RGB =central wavelength: 636.73, 549.81 and 433.12 nm).

TABLE I

DESCRIPTION OF LAND-COVER CLASSES AND NUMBER OF TRAINING AND TEST SAMPLES IN THE EXPERIMENTS

Class	Training samples	Test samples
C1. Water	563	336
C2. Woods	881	560
C3. Roofs	629	*390*
C4. Grass01	566	404
C5. Grass02	458	295
C6. Grass03	741	302
C7.Grass04	493	388
C8. Grass05	439	333
C9. Grass06	568	380
C10.Grass07	469	287
C11. Grass08	365	274
C12. Bare	1026	706
C13. Road	704	466
C14. Grass09	1216	707
C15. Grass10	338	162
Total	*9456*	*5990*

The CASI-3 was operated in hyperspectral mode, with a ground spatial resolution of 1.5 m. The spectral configuration of the sensor was set to consist of 68 spectral channels each about 10 nm in width spanning the spectrum from 403 to 1058 nm.

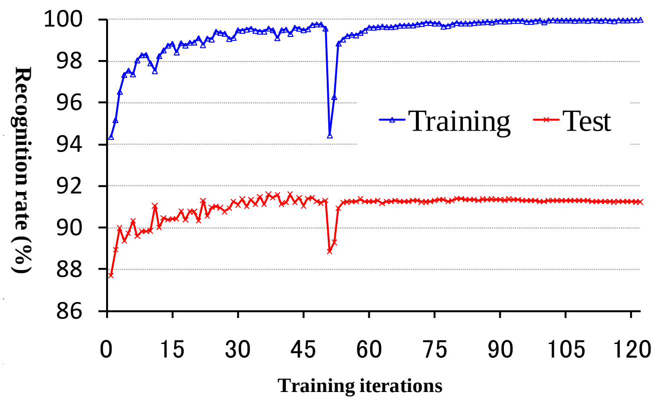

Fig. 2 Plots of the accuracy rate vs. the number of iterations for the training and test samples.

Fig. 3 Classification map obtained with the fixed subspace method. The subspace dimension was 7 and both learning parameters were 0.25.

The test samples were not joined to the training process, but were used only to assess the classification accuracy. Here we used the fixed dimension of 7 with both learning parameters set to 0.25. The classification accuracy on test dataset was 91.2% when training was over (at 122), however the best test data accuracy of 91.6% was reached at traitraining iteration was 37. As shown in Fig. 2, the accuracy of the training and testing data set increases steadily with the learning iteration. When the training data is convergent of 100% accuracy, the classification accuracy of test set almost increases or very close to the best accuracy. Table 2 presents the corresponding confusion matrix [6].

TABLE Ⅱ

CONFUSION MATRIX FOR THE CLASSIFICATIONS PERFORMED BY SUBSPACE METHOD WITH THE TEST DATA SET.

Class	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**User (%)**
1	327	1	0	0	0	0	0	0	0	0	0	2	0	0	0	99.1
2	5	508	0	0	0	0	0	0	0	0	0	0	0	13	0	96.6
3	1	0	284	0	0	0	0	0	0	0	0	23	43	0	0	80.9
4	0	0	0	404	0	0	0	0	0	0	0	0	0	0	0	100
5	0	3	0	0	292	2	0	0	0	0	0	0	0	0	6	96.4
6	0	0	0	0	2	295	0	0	0	0	0	0	0	0	1	99.0
7	0	3	0	0	1	4	387	0	0	0	0	1	0	0	0	97.7
8	0	0	0	0	0	0	0	323	0	0	0	0	0	0	2	99.4
9	3	0	0	0	0	0	1	0	319	3	0	0	0	0	0	97.9
10	0	2	0	0	0	0	0	0	0	284	0	1	0	0	0	99.0
11	0	0	0	0	0	0	0	0	0	0	274	31	0	0	0	89.8
12	0	0	61	0	0	0	0	10	0	0	0	600	92	0	0	78.6
13	0	0	45	0	0	0	0	0	0	0	0	26	331	0	0	82.3
14	0	38	0	0	0	1	0	0	61	0	0	22	0	694	10	84.
15	0	5	0	0	0	0	0	0	0	0	0	0	0	0	143	96.6
Prod. (%)	97.3	90.7	72.8	100	98.98	97.68	99.74	97	83.95	99.0	100	85.0	71.0	98.2	88.3	

Overall Accuracy: (5465/5990) 91.2354%; Kappa Coefficient = 0.9050

IV. CONCLUSION

We have investigated a subspace methods based on a combination of a normalization techniques and QR method on CASI-3 data with 68 bands. The CASI-3 hyperspectral imaging was shown to be a considerable technique to identify individual grass species and monitoring grass health, provide new indicators of spectral properties at leaf and canopy scales and estimate aboveground grass productivity. Our experiments performed by the subspace method also indicate that subspace method is a simple method to apply; it possesses high-speed convergence and can completely identify the training samples. In future studies, more analysis needs to be done to identify different grass species and monitoring grass health, and the potential of other types hyperspectral data and the suitability of the method described here will be investigated.

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