AN EFFICIENT SUPERVISED CLASSIFICATION METHOD OF REMOTELY SENSED MULTISPECTRAL IMAGES

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ABSTRACT

A method is proposed for supervised classification of remotely sensed multispectral images with high accuracy and high efficiency. The method Modified Linear Discriminant Function (MLDF) produces a binary division tree by dividing training data until all the terminal nodes of the tree have only one kind of category. After production of the tree, whole image data are classified. Numerical simulation indicates the method has as high accuracy as Maximum Likelihood method does and as high efficiency as a Binary Division Tree classifier does.

INTRODUCTION

Supervised classification is one of the basic processes in the application of remote sensing technology to various fields. It is indispensable analysis of remotely sensed multispectral images, for example, in environmental monitoring. For monitoring earth environment using satellite, it is important that a classifier must have high efficiency as well as high accuracy. Among the methods proposed so far, maximum likelihood classifier (MLH) is well-known and most accurate on the assumption that the generality of training data is satisfied (Fujimura, 1978), but it requires much time to classify the image. On the other hand, Binary Decision Tree (BDT) classifier (Inamura, 1979) is one of the most efficient methods, but it has lower accuracy than MLH does on the assumption above. A method having high efficiency as well as high accuracy has been required.

Here, we propose a new method having both high accuracy and high efficiency. We call the method as Modified Linear Discriminant Function (MLDF). The method MLDF is expanded from BDT. We introduce linear discriminant function into boundary selection in BDT. The division boundary of MLDF is determined using binary division technique in a clustering method BDC-LDF (Hanaizumi, 1995a, b). The boundary is selected among valleys in density histogram obtained from image data projected onto a single dimensional subspace. As we do not use the statistics (such as mean and variance) of training data, we can regard MLDF as a nonparametric classifier.

In this paper, we describe the principle and the procedures of MLDF. The validity of MLDF is confirmed by numerical simulation and classification of real remote sensing images.

PRINCIPLE

In the feature space, MLH produces hyper-quadratic boundaries which theoretically achieve the highest accuracy with much time for the classification. BDT achieves high speed with some loss of accuracy by limiting number of boundaries for binary division of data. It is known that the accuracy of linear discriminant function (LDF) algorithm is identical to that of MLH when all training data sets have the same variance-covariance matrix. By using LDF algorithm hierarchically, we achieve highly accurate (as well as MLH) and highly efficient (as well as BDT) .

The basic ideas of the proposed method MLDF are to label pixels in training area with category identification, to merge all the pixel data in all training areas into one group and to apply binary division process to the group so that all data in a terminal node have the same identification. After production of decision tree, all image data are classified as flowing down the tree.

DATA COMPRESSION

At first, we select training data for the classification by assigning training areas. As these training data contain noise, we reduce the noise by compression of training data. We compress them by averaging pixel densities of neighboring 4 pixels. This averaging process achieves both reduction of processing time and stabilization of boundary for data division. After averaging, we assign category number to all training data as an identifier, and merge them into a group.

PROJECTING DATA ONTO 1D SUBFEATURE SPACE

In boundary search for binary division of training data, the increase of the number of spectral bands reduces efficiency. In order to reduce the quantity of data with the minimum loss of information, we apply principal component analysis (PCA) to the merged training data and obtain the first two principal components. We suppose that image data have p spectral bands. Using variance covariance matrix Σ_T, the PCA process is written by

$$B\Sigma_T B' = \begin{bmatrix} \lambda_1 & & & \\ & \lambda_2 & & 0 \\ & & \vdots & \\ 0 & & & \lambda_p \end{bmatrix}, \tag{1}$$

$$B = [\boldsymbol{b}_1, \boldsymbol{b}_2, ..., \boldsymbol{b}_p], \tag{2}$$

where, λ_i {i = 1, 2, ..., p} are eigen values and $\lambda_1 \geq \lambda_2 \geq ... \geq \lambda_p$, and $\boldsymbol{b}_i$ {i = 1, 2, ..., p} eigen vectors. The first two principal components P_1 and P_2 are obtained from inner products between spectral density vector assigned to a pixel and eigen vectors $\boldsymbol{b}_i$ {i = 1, 2}, respectively. For abbreviation, we define PCA vector $\boldsymbol{P}$ as

$$\boldsymbol{P} = P_1 + jP_2. \tag{3}$$

After compressing the training data into 2D PCA vectors, we produce 8 histograms from inner product among PCA vector $\boldsymbol{P}$ and projection vectors

$$W_k = \cos(k\pi/8) + j\sin(k\pi/8) \quad (k = 0, ..., 7). \tag{4}$$

Now, the merged training data are compressed onto 1D subfeature space with the minimum loss of information about data distribution, and we obtain 8 histograms.

SELECTION OF DIVISION BOUNDARY

We firstly select a candidate for the optimum boundary for the binary division in each of 8 histograms, then determine the optimum boundary among the candidates. Generally speaking, the optimum boundary in clustering minimizes the ratio of within-group-sum-of-squares to intragroup-sum-of-squares. We adopt a clustering criterion for the selection of the optimum boundary.

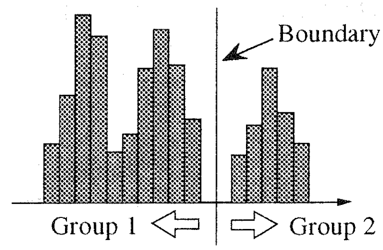


Fig. 1 Valleys and boundary selected in a histogram.

We suppose that number of training data is l and a histogram has total-sum-of-squares S_T, and assume that histogram is divided into two groups which have l_1 and l_2 data and within-group-sum-of-squares S_1 and S_2, respectively, as shown in Fig.1. The total-sum-of-squares S_T is written as

$$S_T = S_1 + S_2 + S_A, \tag{5}$$

where, S_A is intra-group-sum-of-squares. We select the candidate among valleys in the histogram minimizing an index

$$R = S_1 + S_2. \tag{6}$$

As histograms have own dispersion in abscissa, we use normalized index R / S_T for the selection of the optimal boundary among the candidates. The boundary in an one dimensional subfeature space corresponds to a hyperplane in the full feature space. These division procedures are applied recursively until all groups at terminal nodes have identical category number. The coefficient vector projecting spectral density vector onto the histogram on which the optimal boundary is selected and threshold (position of the boundary) are stored at the node of the binary division tree.

CLASSIFICATION OF WHOLE IMAGE

After production of binary division tree from training data, we classify whole image data by flowing pixel data down the tree. At a non-terminal node, we obtain inner product between pixel data and coefficient vector assigned the node, compare it with the threshold assigned, and determine the division path accordingly to the result of the comparison.

PROCEDURES

The following is procedures of MLDF.
1)Select training areas for categories to be classified.
2)Apply data compression process to pixel data in all training areas.
3)Label all compressed data. We use category number as the identifier.
4)Merge all compressed data into a group.
5)Apply PCA process and obtain the first two components.
6)Produce 8 histograms from the components.
7)Select the optimal boundary for binary division and divide data group into two subgroups.

8)If all data in a subgroup have the same identifier, stop the further division of the subgroup, else repeat procedures 5) - 7) until only one identifier is observed in the subgroup.
9)Classify whole image by flowing pixel data down the tree.

Figure 2 indicates the procedures.

SIMULATION

We evaluate the performance of MLDF in terms of accuracy and efficiency by comparison with that of MLH and that of

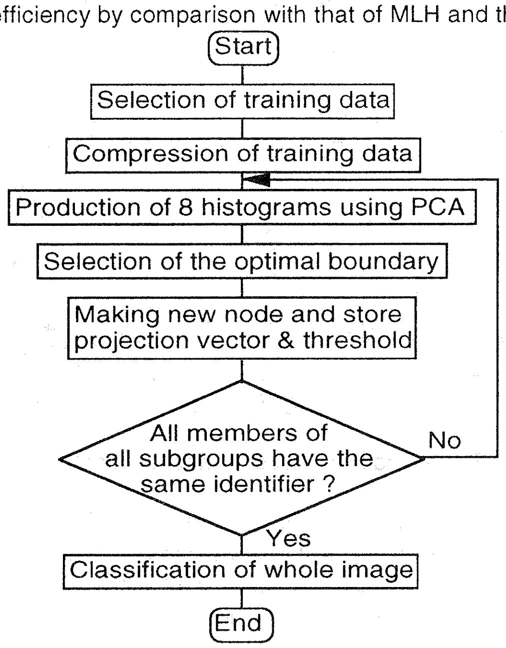


Fig. 2 Processing flow of MLDF.

BDT. These three methods were applied to an artificial image (256 columns x 256 lines x 3 bands) having 16 uniform areas with multidimensional normal noise component whose variance covariance matrix is

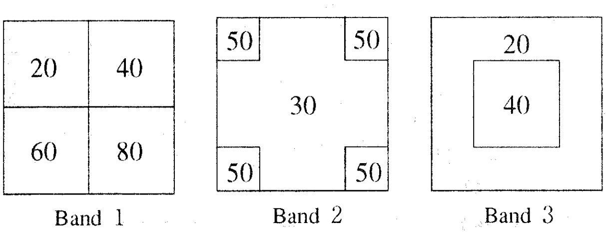


Fig. 3 Spectral densities of the artificial image.

$$\Sigma = \begin{bmatrix} 10.965 & 0.996 & -0.833 \\ 0.996 & 15.718 & -1.830 \\ -0.833 & -1.830 & 4.239 \end{bmatrix}. \qquad (7)$$

Figure 3 shows spectral densities of the image. The image has 12 categories. We selected upper-left 10 x 10 pixels square as training area for every category. We applied MLH, BDT and MLDF to the image with changing the

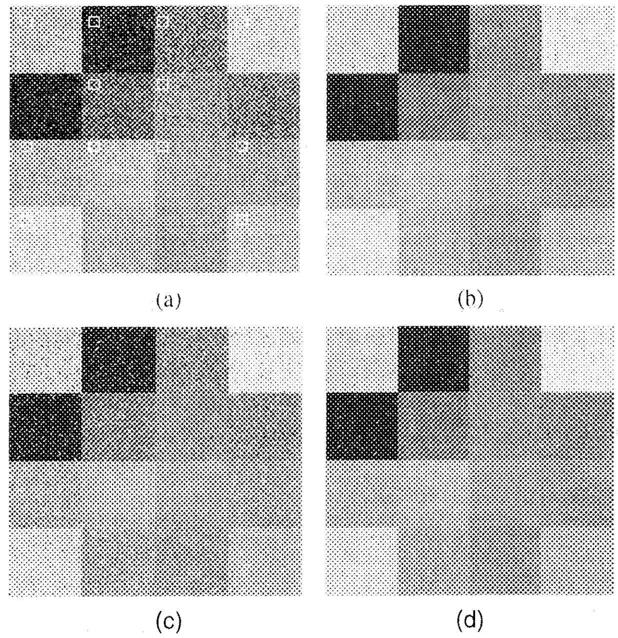


Fig. 4 An example of data set (a = 1) : (a) original image, (b) result processed by MLH, (c) one by BDT and (d) by MLDF.

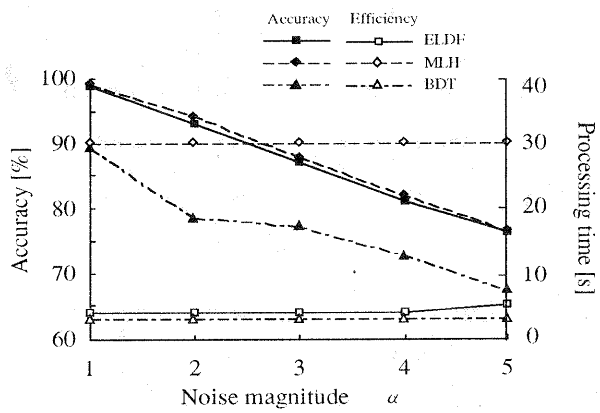


Fig. 5 Accuracy and efficiency of MLH, BDT and MLDF.

magnitude of noise components by $\alpha\Sigma$ (α = 1 ~ 5). In these processes, we consider that generality of training data is perfectly satisfied. Figure 4 shows the original image (a), result processed by MLH (b), one by BDT (c) and by MLDF (d), where α = 1. The result of numerical evaluation is indicated in Fig. 4, where we plot mean correct classification rate and processing time for several magnitudes of noise component. From these result, we see that accuracies for all methods decrease with increase of noise, but accuracy of MLDF is always as same as that of MLH. On the other hand, MLDF is highly efficient as well as BDT.

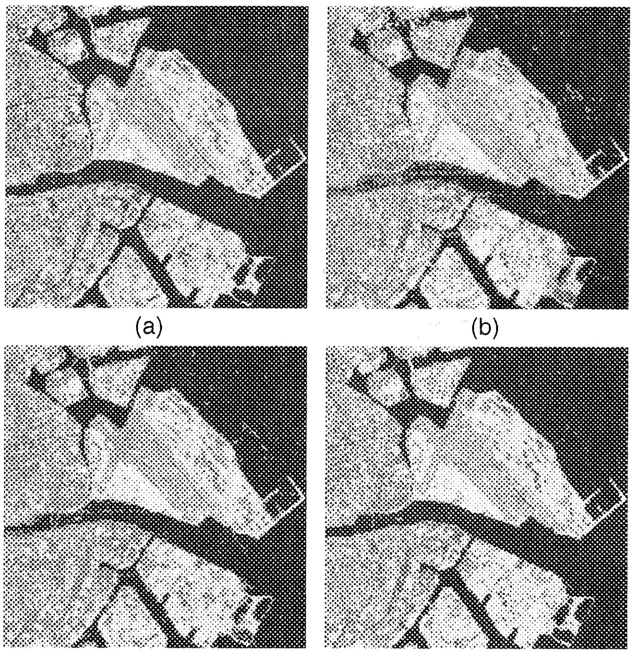
ACTUAL IMAGE PROCESSING AND DISCUSSION

We evaluate the performance of MLDF by using two types of actual remote sensing images.

COASTAL REGION IMAGE

Some coastal region images include urban and sea areas in their scenes. Data in the former area have very large variance in spectral density but those in the latter very small one. It is known that larger variance category often appears on smaller variance category areas in results processed by MLH. In order to evaluate the performance of MLDF for such images, we apply the three methods to a coastal region LANDSAT/TM image having 256 columns, 256 lines and 3 spectral bands, and compare their results. Figure 6 shows original image (a), result processed by MLH (b), one by BDT (c) and by MLDF (d). In these processes, we use 9 categories; urban area, sea, vegetation, river, and others. Processing times are 23 seconds by MLH, 3 seconds by BDT and 5 seconds by MLDF. Several pixels in river are miss-classified into urban area in the results processed by MLH and by BDT, but MLDF does not yield such error.

AGRICULTURAL REGION



(a) (b)

(c) (d)

Fig. 6 Original Kawasaki image (a), result processed by MLH (b), one by BDT (c) and by MLDF (d).

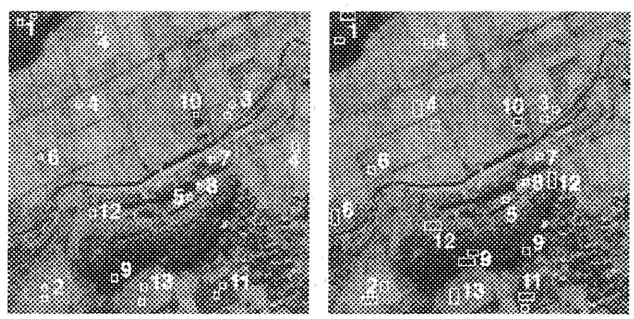
We have had a data set acquired on Dec. 1977 at Fukue, Aichi prefecture in Japan. The data set consists of airborne MSS images and ground truth. We applied the three methods to the data set. We use 512 x 512 pixel image with 5 spectral bands whose wavelength regions are shown in Table 1. Table 2 indicates 13 categories we used, and Fig. 7 indicates training areas (a) and test areas (b) for

Table 1 Observation band of multispectral image.

Band No.	Wavelength [μm]
1	0.35 - 0.40
2	0.47 - 0.49
3	0.54 - 0.56
4	0.66 - 0.68
5	0.80 - 0.90

Table 2 Categories used in the processing.

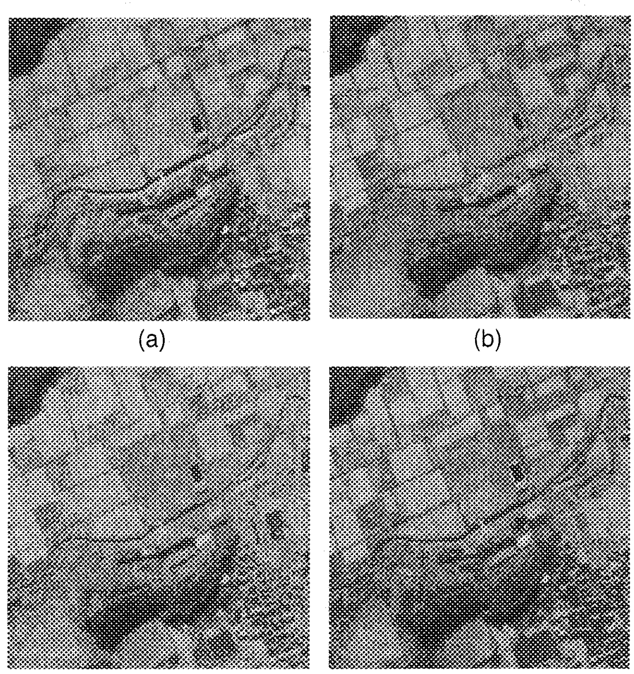
No.	Category	No.	Category
1	Pine (medium)	8	Zinc roof (pink)
2	Bare soil (light)	9	Pine (dark)
3	Field (radish)	10	Swimming pool
4	Rice field	11	Zinc roof (green)
5	Concrete	12	Pine (light)
6	Field (cabege)	13	Bare soil (dark)
7	Slate		



(a) (b)

Fig. 7 Training areas (a) and test areas (b).

numerical evaluation. Figure 8 shows original image (a), result processed by MLH (b), one by BDT (c) and by MLDF (d). Result of numerical evaluation of accuracy is shown in Table 3, where upper, middle and lower lines indicate correct classification rates in MLH, BDT and MLDF, respectively. Mean correct classification rate (MCCR) and processing time are also listed in Table 4 with results for three spectral band image for the same region. We chose spectral bands 3, 4



(a) (b)

(c) (d)

Fig. 8 Original Fukue image (a), result processed by MLH (b), one by BDT (c) and by MLDF (d).

Table 3 Confusion matrix for MLH, BDT and MLDF.

Area	Category 1	2	3	4	5	6	7	8	9	10	11	12	13
	88.00								12.00				
1	81.25								18.50			0.25	
	87.25								11.50			1.25	
		99.36			0.43		1.91						0.64
2		86.54			7.48								5.98
		95.73											4.27
			100.00										
3			93.83	4.94		1.23							
			100.00										
			0.17	98.81								1.02	
4				98.81		4.44						1.19	
				97.95		0.17						1.88	
					100.00								
5					100.00								
					66.67		33.33						
			2.22			97.78							
6			6.22	0.89		91.11					0.89	0.89	
	0.89		1.33			74.67					9.33	0.04	
					1.67		98.33						
7					6.67		93.33						
					3.33		96.67						
								100.00					
8								100.00					
							2.08	97.92					
	5.36								94.64				
9	3.73								96.27				
	4.90								95.10				
					1.23					98.77			
10										100.00			
										98.77	1.23		
					0.61						99.08		0.31
11		18.04	1.22							0.31	51.38		29.05
											100.00		
	3.42			1.24								95.34	
12	0.62			0.62		0.93						97.83	
	11.18			4.66								84.16	
													100.00
13			0.62										99.38
													100.00

Table 4 Mean correct classification rate for MLH, BDT and MLDF.

	5 band		3 band	
Method	Accuracy	Time	Accuracy	Time
MLH	96.79 [%]	303 [s]	95.48 [%]	133 [s]
BDT	89.03	18	90.88	11
MLDF	94.06	20	92.73	19

and 5, and evaluate the change of accuracy and efficiency using the identical training and test areas. Table 4 tells us that MCCRs slightly decrease or almost the same accordingly to reduction of number of spectral bands five to three, and that processing time in both MLH and BDT depends on the number of spectral bands. In MLDF, processing time fully depends on size of binary division tree, therefore, much information brought by larger number of spectral bands may gives more suitable division boundary which efficiently reduces size of the tree. This is the reason why processing time of MLDF in classification of 5 spectral band image is almost as same as that of 3 band image. There is possibility that MLDF is more efficient than BDT.

CONCLUSIONS

We proposed a highly accurate and efficient method MLDF for supervised classification of remotely sensed multispectral images. The method MLDF is expanded from BDT which is very efficient. Image data are projected onto eight 1D subfeature spaces to produce histograms with compression of data. The division boundary is selected among all valleys in histograms using a clustering criterion that the optimal boundary minimizes the ratio of sum of within-group-sum-of-squares to intragroup-sum-of-squares. MLDF produces binary division tree by applying the division process recursively. Each node of the tree has coefficient vector for data projection and threshold for data division.

As division boundary in histogram corresponds to hyperplane in full feature space, MLDF is regarded as a kind of linear discriminant function method. On the other hand, as no statistics for training data is used in selection of division boundary, MLDF is also regarded as a nonparametric supervised classification method. From evaluation of performance using artificial image and actual remotely sensed multispectral images, it is confirmed that MLDF has as high accuracy as MLH does and as high efficiency as BDT does. Improvement of MLDF in term of efficiency and analysis of classification with less generality training data are subjects for a future study.

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