Reprinted from

Eleventh International Symposium

Machine Processing of

Remotely Sensed Data

with special emphasis on

Quantifying Global Process: Models, Sensor Systems, and Analytical Methods

June 25 - 27, 1985

Proceedings

Purdue University
The Laboratory for Applications of Remote Sensing
West Lafayette, Indiana 47907 USA

HIGH ACCURACY CLUSTERING USING RESIDUAL IMAGE

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ABSTRACT

A new high accuracy clustering algorithm named a minimum residual clustering is presented in this paper. This algorithm can eliminate the disadvatages of a conventional maximum likelihood method assuming normal distributions and a clustering using a conbinational method while keeping advantages of these method. Thus the minimum residual clustering achieves an automatic classification with a high classification accuracy.

Simulation experiments of the algorithm and case studies using this algorithm were conducted. In case studies, a landcover classification and a forest type classification were examined using Landsat MSS data. As the results, the expected characteristics of the minimum residual clustering were confirmed. Further, processing times were about 1/5 compared to a conventional maximum likelihood method.

I. INTRODUCTION

A classification is a principal and time consuming processing phase in image processings for remote sensing. Two kinds of classification methods are usually used. The first one is a supervised method; typicaly a maximum likelihood method assuming a normal distribution of the samples are used and it has the advantage on the classification accuracy. The other is a unsupervised method; typicaly a clustering method using combinational algorithm is used and it has the advantage in an automatic processing.

These methods, however, have following disadvantages. Classification accuracy of clustering method is not sufficient in most applications, while the classification speed of a maximum likelihood method is slow and a very carful training data selection is necessary in order to maintain a high theoretical accuray.

We developed a table look-up maximum likelihood method(1), which can decrease classification time four to seven times to solve the time consuming ploblem of the maximum likelihood method. However the total procedure from training data seletions to classifications consumes much more time, because of the second problem of training data selections.

The objective of this study is to solve the above second problem of the maximum likelihood method. The new classification algorithm (called Minimum Residual Clustering) presented in this paper can reduce the disadvantages of a maximum likelihood classification method and clustering method while keeping advantages of those method. As a result, it can achieve an automatic classification with a high classification accuracy and high speed classification processes.

II. PRINCIPLE OF THE MINIMUM RESIDUAL CLUSTERING

Due to the inappropriate selections of training data, the maximum likelihood method can not achieve its high theoretical classification accuracy in practice. Following basic ideas of the minimum residual clustering were developed in order to reduce the inappropriateness of training data.

1) to use "residual images"(2) as a measure for inappropriateness of training data. Residual images supply a permissible value for inappropriateness of training data.
2) to extract classification classes

automatically using conventional clustering method until inappropriateness of training data decreases less than a permissible value.

3) to use a maximum likelihood classification method for a classification algorithm from the viewpoint of classification accuracy.

The meaning of inappropriateness of training data, the concept of training data and the classification procedure of the minimum residual clustering are discribed in the following sections.

A. INAPPROPRIATENESS OF TRAINING DATA

There are three kinds of inappropriatenesses. The first and second one are generated by the facts that the numbers of training classes and training data are too few,respectively. The third one is generated by the influences by sub-classes in a training class.

1. Ploblems for The Number of Training Classes.

From ten to twenty classification classes are used in most applications; e.g., in the case of a land cover classification. However, the number of classes is not sufficient in almost practical cases because of spectral varieties of objects in images. Thus spectral signatures of the training classes in these cases do not completly cover the total feafure space of the object image. Pixels far from the mean of the training classes in a feature space are forced to be assigned to a nearest class in a conventional maximum likelihood method.

2. Ploblems for The Number of Training Data

The number of training data included in each classes are usually from 40 to 400 in almost practical cases. The number is too few from a statistical viewpoint. Further, the total numbers of training data are also too small in general compared to the amount of the object image data. Thus it is estimated that statistical parameters of each training classes do not coincide with the true values of populations of the object image.

3. Ploblems for Subclasses

The sub-classes included in a training classes have two kinds of effects. The first one is a variance increase of the class(Figure 2.1-a). The second one is a mean sifting(Figure 2.1-b). These two effects generally happen simultaneously.

B. CONCEPT OF RESIDUAL IMAGES

A residual image is defined as a subtracted image between an original image and a "Mean Image" which is produced from a original image and classified image.

$$R(x,y)=\left\{f^2(x,y)-M^2(x,y)\right\}^{1/2} \qquad \ldots.(2.1)$$

R(x,y) : residual image
f(x,y) : original image
M(x,y) : mean image

where the mean image M(x,y) is defined as follows;

$$M(x,y)=m(Ci \mid Ci=g(x,y)) \qquad \ldots.(2.2)$$

$$m(Ci)=\Sigma f(x,y\in Ci) \;/\; Ni \qquad \ldots.(2.3)$$

$$(i=1,2,3,\;\ldots.,n)$$

g(x,y) : classified image g(x,y)= 1,2,3,...,Cn
n : number of classification classes
m(Ci) : mean of original values(f(x,y)) of pixels classified to a class-Ci
Ni : number of pixels classified to a class-Ci

Mean vector m(c) is calculated by using full image data (f(x,y)) for each classes. Thus the value of m(c) do not equal to a mean value of each training classs in generally. Values of a residual image R(x,y) is proportional to distances between the pixel(x,y) and the mean of the classified class in the feature space.

C. PROCEDURE OF THE MINIMUM RESIDUAL CLUSTERING

Figure 2.2 showes the classification procedure of the minimum residual clustering. Initial training data do not directly influence to the final classification result. These data are used in order to suggest the classification categories to which each final class would be assigned.

Iterations are finished when one or more of the following condltions are satisfied; 1) An iteration number reached the pre-set value, 2) The mean of a residual image decreased to a pre-set value, 3) The number of classes increased to the pre-set value, 4) A new class was not generated as a result of clusterings. New classes are not generated in the clustering procedure when 1) the class (cluster) is constructed with the fewer number of pixels than a pre-set value, 2) the minimum distance between the new class and the other already existing classes is less than a pre-set value.

III. SIMULATION

Expected main characteristics of the minimum residual clustering are 1) if the number of classes is not sufficient, these classes will be generated automatically, and 2) if a class is constructed with some sub-classes, these sub-classes will be splitted automatically. Simulation tests were done in order to confirm these charateristics.

A. OBJECT IMAGE OF THE SIMULATION

The object image has two channels with eight bits (256 density level). Nine classes are arranged in a rectangular lattice shape with the same separation in the feature space (Figure 3.1). Eight sub-classes surrounds each classes (Figure 3.1). Each pixel data constructing each sub-classes are generated by using random function N(m,1) (m:mean of each sub-classes). The total pixel number of each sub-classes is 192 (16x12). Figure 3.2 shows the disposition of these data patch (16x12 pixels) on the image. Thus, the image size is 128 pixels x 108 lines (Figure 3.3), and the minimum Euclidean distances within classes and sub-classes are about 32 and 8 in the feature space, respectively. Figure 3.4 shows the mean of each sub-classes (variance=1).

B. SIMULATION #1 (separability test of sub-classes)

Initial training data for all nine classes are extracted by sampling the data from all 72 (9x8) sub-class patches. In this case, there are training data for all nine classes which is constructed by eight sub-classes, but statistical parameters of the training data have distortions because of the sampling.

Figure 3.5 and 3.6 show residual images and classified images at each iteration, respctively. The number of extracted sub-classes is 58 at iteration #4. Mean values of residual images are shown in Figure 3.7. Total processing time is 1.5 hours by using a HP 1000 minicomputer system.

C. SIMULATION #2 (ability test for automatical extraction of classes and/or sub-classes)

Initial training data for all nine classes is extracted by sampling the data from only sub-class number four and five. Thus training data of each classes do not have data of six sub-classes (number 1,2,3,6,7 and 8).

Figure 3.8 and 3.9 show residual images and classified images at each iteration, respectively. The number of extracted sub-classes is 58 at iteration #4. Mean values of residual images are shown in Figure 3.10. Total processing time is 1.5 hours.

IV. CASE STUDY

It is expected in actual applications that the minimum residual clustering has the ability to extract sufficient number of classes for the case in which detailed training data selections are difficult. For example in the land-cover classification, extractions of appropiate training data are very difficult, becase many objects are mixed together especialy in urban areas. It is also very difficult in the forest type classification, because the spectral signatures of each classes are very similar.

Two case studies have been executed in this study in order to examine the ability of the minimum residual clustering. One case is the land cover classification of Osaka district and the other is the forest type classification of Mt.Fuji area using Landsat MSS data.

A. LANDCOVER CLASSIFICATION

The image size of the object image is 256 pixels x 256 lines (Figure 4.1). At first, the training data of four classes were extracted manually as the initial training data. Figure 4.2 and 4.3 show residual image at each iteration and the final classification result, respectively. Eighty classes were generated at the fourth iteration (Figure 4.4). The relation between iteration number and the mean of residual images is shown in Figure 4.5. The processing time is shown in Table 4.1.

In order to evaluate the classification accuracy of the result, the classified result using conventional method in which a skilled operator has managed the classification processes was used. It has been shown that the accuracy of the result using this method was better than that of the result using a conventional method.

B. FOREST TYPE CLASSIFICATION

The image size of the object image is 256 pixels x 256 lines (Figure 4.6). The number of initial training classes is seven. Figure 4.7 and 4.8 show residual images at each iteration and the final classifications result, respectively. Eighty classes were generated at the fifth interation (Figure 4.9). The variation of mean of residual images and processing time are shown in Figure 4.10 and Table 4.1, respectively.

In this result, conifer forests were classified into 5 forest groups, i.e. cryptomeria (Japanese ceder), Japanese cyress, pine tree, fir, larch, and Japanese spruce. Wide leaved forests were classified into two categories, high trees and low trees. Using conventional method, forest area of Landsat MSS images could be classified into only three groups, conifer forests, wide leaved forests and mixed forests. Thus a much finer classification was realized using this proposed algorithm.

V. CONCLUSIONS

Two simulations and two case studies showed following characteristics and ability of the minimum residual clustering.

1) If initial training data are constructed with some sub-classes, the sub-classes will be splitted automatically.
2) If the number of initial training classes are not sufficient, they will be generated automatically.
3) All image data are used as training data.
4) The maximum likelihood classification algorithm is used in the classification phase of each iteration.
5) The minimum residual clustering has higher classification accuracy than conventional clustering methods. It has a similar classification accuracy of classifications with a supervired method by a skilled operator with an intensive ground truth.
6) Processing duration are very shorter than that of a conventional clustering method using all object image data and a conventional maximum likelihood method.

VI. REFERENCE

1. K.Fukue,H.Shimoda and T.Sakata, "Table Look-up Maximum Likelihood Method", Journal of the Japan Society of Photogrammetry and Remote Sensing, Vol.20, No.2 (1981)
2. D.L.B.Jupp and K.K.Mayo, "The Use of Residual Image in Landsat Image Analysis", Photogrammetric Engineering and Remote Sensing, pp.595-640, Vol.48, No.4 (1982)

AUTHOR BIOGRAPHICAL DATA

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Toshibumi Sakata received B.S. degree of Chemical Engineering from Chiba University. He took Ph.D in Chemical Physics at the University of Tokyo and then joined to the institute of Industrial Science there, as a research assoiciate. He was a research scientist of Munich University during 1964 to 1966. In 1966 he moved to the Tokai University and he had a chair of professor in 1971. Presently he is the director of Tokai Research and information center, the Tokai University.

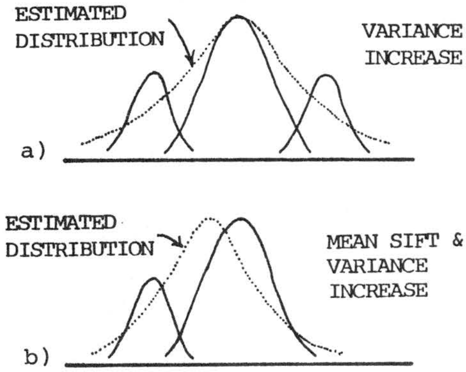

Fig. 2.1 Influences of sub-classes.
a) an effect of variance increase
b) an effect of mean sifting

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              PROCEDURE (the minimum residual clustering)

                TRD^0    : initial training data
                f(x,y)   : a original image
                g^i(x,y) : a classified image at iteration #i
                R^i(x,y) : a residual image at iteration #i
                M^i(x,y) : a mean image at iteration #i

   input      START PROCEDURE                                              output
                input of TRD
                i <-- 1        (i:iteration#)
                DO UNTIL (stop conditions will be satisfied)
TRD^(i-1)  ]
f(x,y)     ]---> 1.maximum likelihood classification ---------------->  g^i(x,y)
g^i(x,y)   ]
f(x,y)     ]---> 2.calculation of a mean image ---------------------->  M^i(x,y)
M^i(x,y)   ]
f(x,y)     ]---> 3.calculation of a residual image ------------------>  R^i(x,y)
R^i(x,y)   ]---> 4.extraction of pixels haveing a high -------------->  object pixels
f(x,y)     ]       residual value(R (x,y)) from f(x,y)                  of clustering
                 5.clustering by a combinational method ------------->  new training
                                                                        data TRD1
g^i(x,y)   ]
TRD^(i-1)  ]---> 6.modification old training data ------------------->  TRD2
f(x,y)     ]
TRD1       ]
TRD2       ]---> 7.renewal training data (TRD1 + TRD2) -------------->  TRD^i
                   i <-- i+1     (count up iteration#)
                END UNTIL
TRD^(i-1)  ]
f(x,y)     ]---> maximum likelihood classification ------------------>  g^i(x,y)
              END PROCEDURE
```

Fig. 2.2 The classification procedure of the minimum residual clustering.

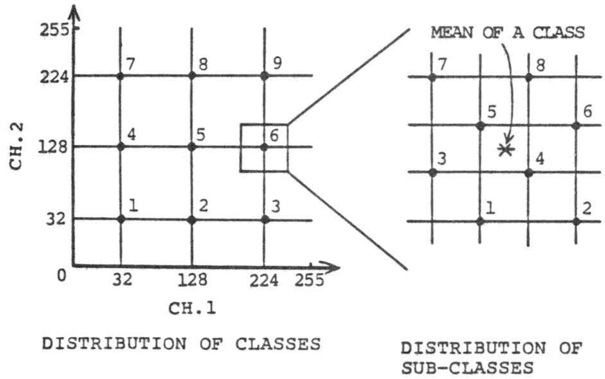

Fig. 3.1 The object image data in a feature space.
channel value = N(m,1)
m : mean of each sub-classes

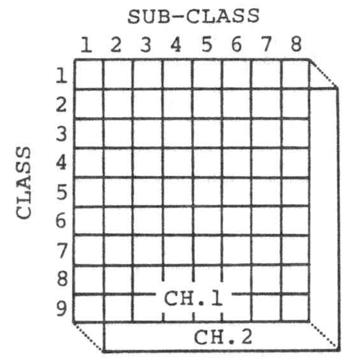

Fig. 3.2 The disposition of classes and sub-classes on the object image for simulations.

128 PIXELS

16 PIXELS

12 LINES

108 LINES

24 8	56 8	8 24	40 24	24 40	56 40	8 56	40 56
119 8	151 8	103 24	135 24	119 40	151 40	103 56	135 56
215 8	247 8	199 24	231 24	215 40	247 40	199 56	231 56
24 103	56 103	8 119	40 119	24 135	56 135	8 151	40 151
119 103	151 103	103 119	135 119	119 135	151 135	103 151	135 151
215 103	247 103	199 119	231 119	215 135	247 135	199 151	231 151
24 199	56 199	8 215	40 215	24 231	56 231	8 247	40 247
119 199	151 199	103 215	135 215	119 231	151 231	103 247	135 247
215 199	247 199	199 215	231 215	215 231	247 231	199 247	231 247

Fig. 3.4 Mean values of sub-classes in the object image for simulations.

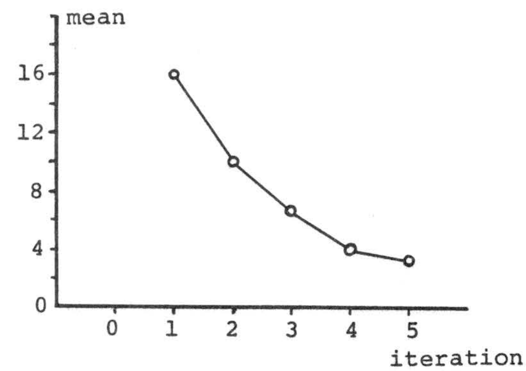

Fig. 3.7 Mean values of residual images in the simulation #1.

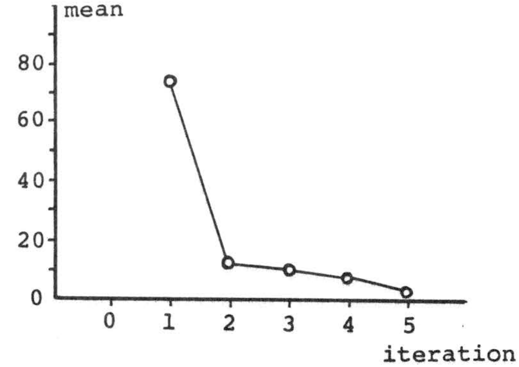

Fig. 3.10 Mean values of residual images in the simulation #2.

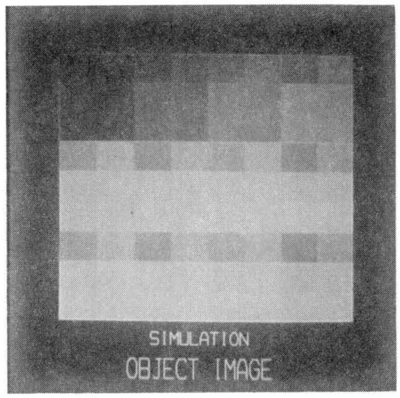

Fig. 3.3 The object image for simulations.

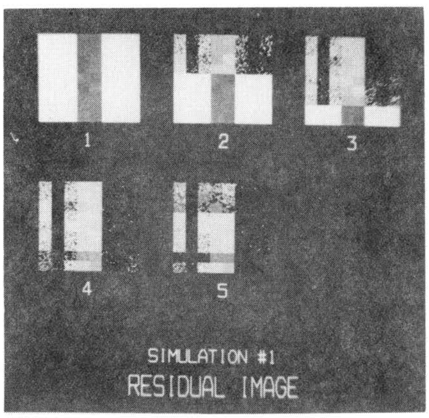

Fig. 3.5 Residual images in the simulation #1.

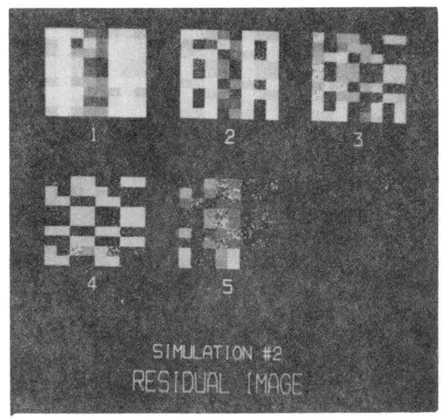

Fig. 3.8 Residual images in the simulation #2.

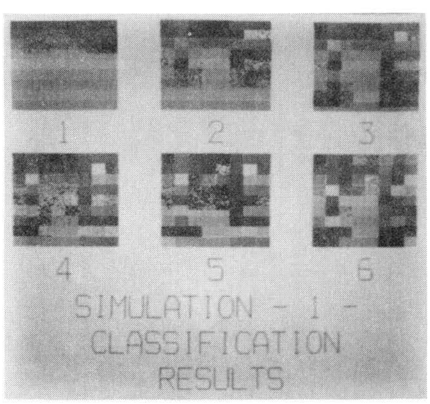

Fig. 3.6 Classified images in the simulation #1.

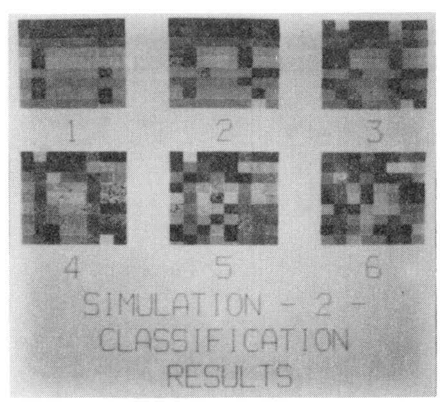

Fig. 3.9 Classified images in the simulation #2.

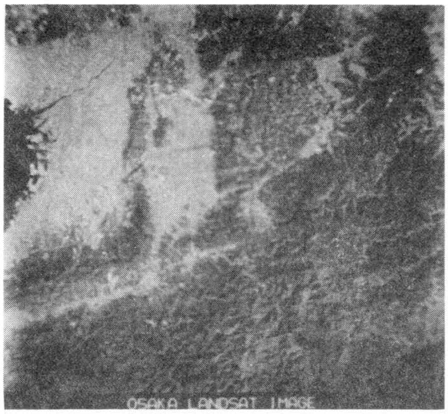

Fig. 4.1 The Landsat MSS image for the landcover classification.

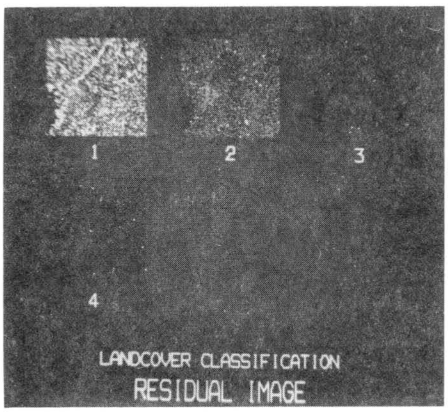

Fig. 4.2 Residual images in the case of the landcover classification.

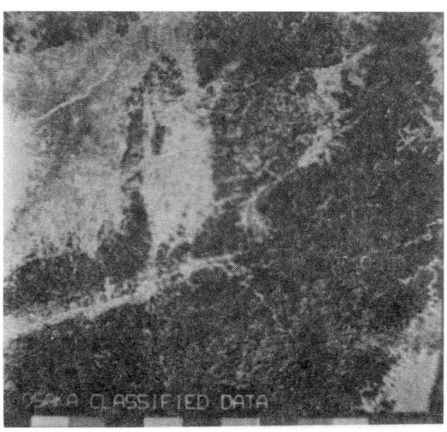

Fig. 4.3 The final classification result in the case of the landcover classification.

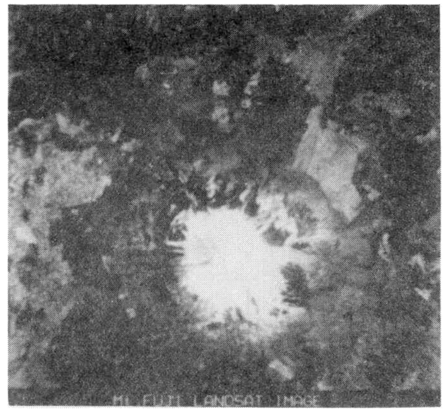

Fig. 4.6 The Landsat MSS image for the forest type classification.

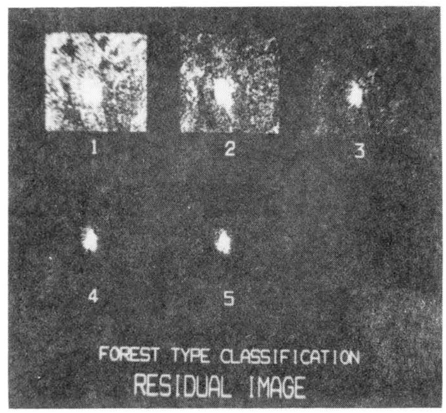

Fig. 4.7 Residual images in the case of the forest type classification.

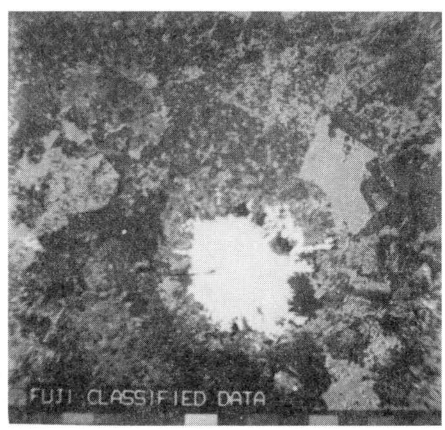

Fig. 4.8 The final classification result in the case of the forest type classification.

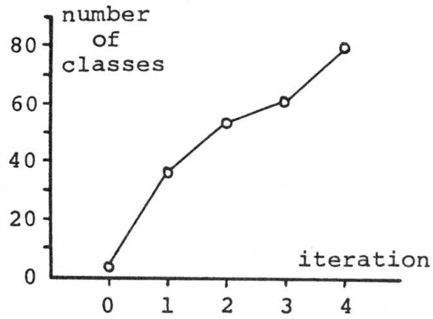

Fig. 4.4 The numbers of classes at each iterations in the case of the landcover classification.

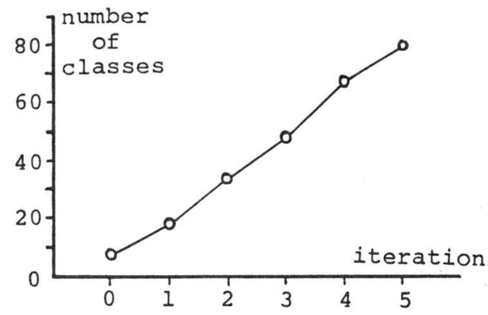

Fig. 4.9 The numbers of classes at each iterations in the case of the forest type classification.

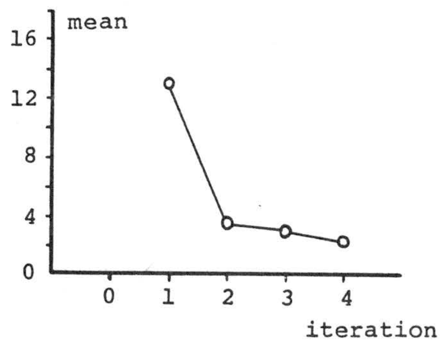

Fig. 4.5 The means of residual images in the case of the landcover classification.

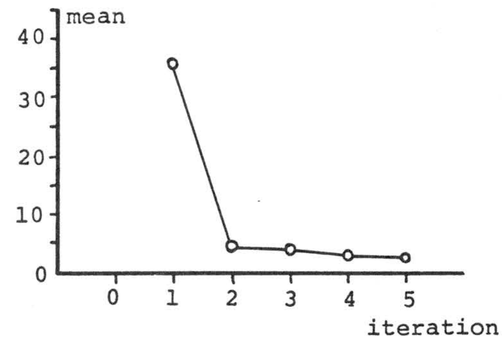

Fig. 4.10 The mean of residual images in the case of the forest type classification.

Table 4.1 The processing times per iterations.

	Land-cover Classification (256x256px,4ch)	Forest Type Classification (256x256px,4ch)
Maximum Likelihood Classification	2min. 49sec	4min. 24sec
Calculation of a Residual Image	1min. 49sec	1min. 55sec
Renewal of Training Data (using all image data)	1min. 50sec	2min. 0sec
Clustering	16min. 48sec	16min. 48sec
Calculation of New Training Data (for clustering result)	7sec	6sec