Statistical Analysis of SPOT HRV/PA Data

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Abstract

Statistical characteristics of SPOT HRV panchromatic data (HRV/PA) are studied in detail. Although the spatial resolution of PA data is superior to the previous ones, because of the mono-spectral structure of them, generally it is difficult to classify an image of PA data by previous methods such as a most-likely method, a cluster analysis and so on. A trial classification method of PA data is proposed, which needs two variable parameters at least. One of them is a conventional gray-level count. The mean power spectrum and the variance of the small matrix in an image are examined as the second parameter. The classification results of PA data by using of the mean power spectrum are given, and also compared with the ground-truth data.

I Introduction

The objective of this investigation is to examine statistical methods to classify SPOT (Systeme Probatoire d'Observation de la Terre) HRV/PA (Haute Resolution Visible/Panchromatic) images, similarly to multidimensional images. The spatial resolution (10m) of SPOT HRV/PA data is so superior to the previous ones acquired by civilian remote sensing satellites, which approaches the level provided by aerial photography. Furthermore, another feature of the SPOT satellite system is the extended function of viewing up to 27° off-nadir, which gives a stereoscopic image from two different orbits. So far many trial researches to use this PA data have been made, based on various statistical methods[1]. Especially, in order to obtain land cover maps by use of PA data, it is necessary to develop a new method. Because of the mono-spectral structure of PA data, it is difficult to classify an image of them by previous multidimensional analyses. To generate multidimensional image data, we examine the mean power spectrum and the variance of the small matrix in an image as the second variable parameter in addition to original gray level counts. We obtain the trial classification results of PA data by using of the mean power spectrum, which are compared with the ground truth data.
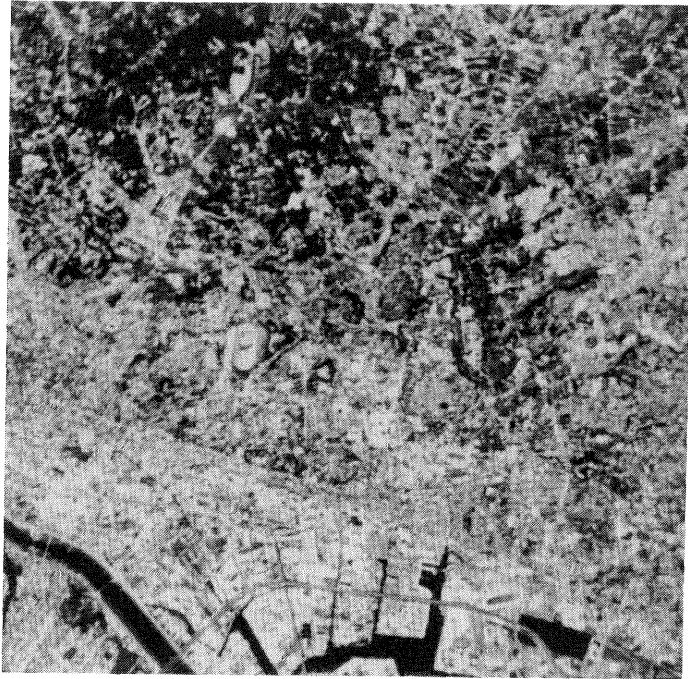
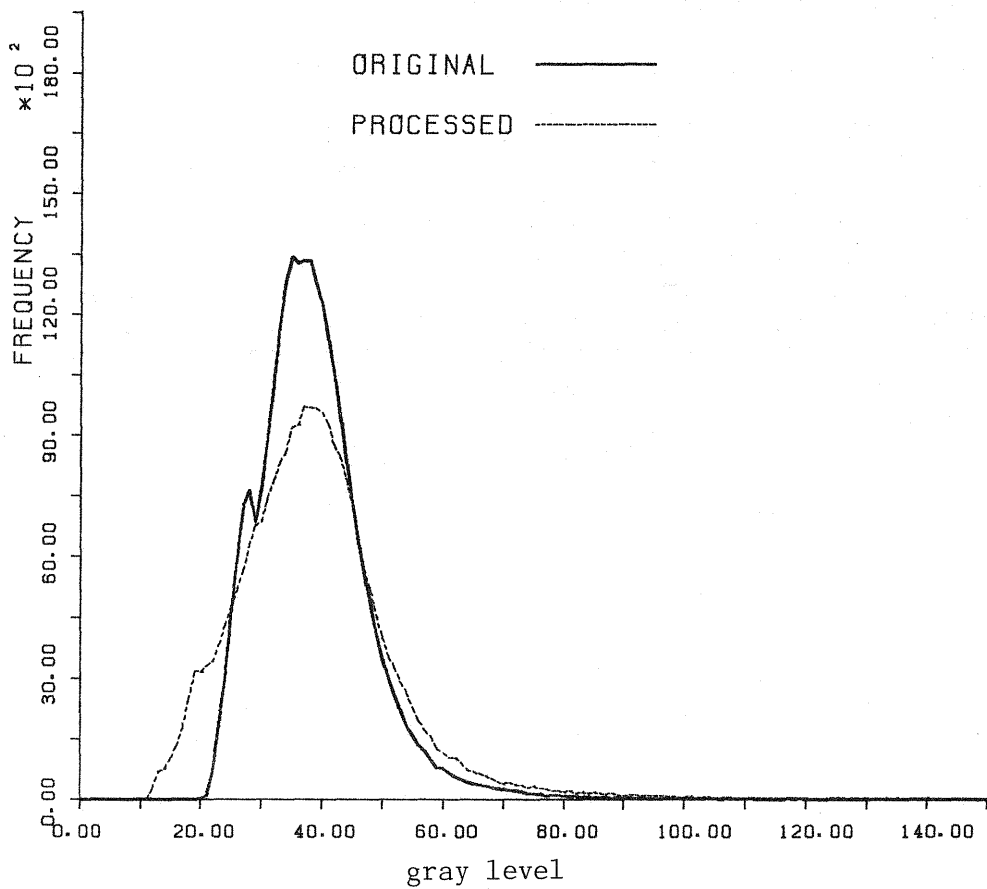Figure 1. Present study area of SPOT HRV/PA data
(1024 by 1024 pixels).

Figure 2. One-dimensional histograms of original PA data (a full line)
and processed one (a broken line) shown in Fig.1.

II Statistical evaluation

We show a present study area of 1024×1024 pixels used in this report in Fig.1, which scene of Tokyo (level 1B) was acquired on October 17, 1986. This study area contains several typical features: forest (upper left), river (lower left), sea (lower middle), pond (lower right), residential, industrial, urban area, etc. First we calculate an one-dimensional histogram of the study area, which is shown in Fig.2. In this plot, a full line means the histogram of the original data, and a broken line means the histogram of the processed data from the original one by means of the method described in Sec.III. As compared with Landsat Thematic Mapper data (TM), it seems that the effective dynamic-range is rather narrow. We can easily separate water area from land area in the case of the infrared imagery such as Landsat TM/Band 7. However, it is difficult to separate this study area into two by the one-dimensional histogram only. Furthermore, we generally need two or more dimensions of image data in order to classify images by multidimensional analysis. Fily and Rothrode[2] proposed the algorithm to extract the second parameter from the one-dimensional SAR image in order to classify pixels as ice or water. They calculated the variance of each small matrix in the image as the second parameter. So we tried the same algorithm in the study area. The results, however, were not enough to use for classification. Then, we examined another candidate for the second parameter.

III Two-dimensional analysis of SPOT PA data

We use gray level counts of image data as the first parameter, which represents the radiometric feature of each pixel. So we examined textural characteristics of small set of pixels as the second parameter. Finally, we selected the mean power spectrum (MPS) of small matrix as another variable parameter. It seems that MPS represents undulation of local area in an image. For instance, MPS of flat area such as sea is expected to be lower. On the other hand, MPS of artificial area such as urban or residential area seems to be higher. Thus, MPS has different characteristics as compared with gray level counts.

We define a 4×4 matrix of pixels to calculate MPS of local area, and also calculate the power spectrum $P(\omega_1, \omega_2)$ of each 4×4 matrix on base 2 by the standard method, where ω_i is a spatial frequency in i-axis. Here, we define MPS as follows:

$$\text{MPS} = \frac{1}{N^2-1} \sum_{\substack{(\omega_1,\omega_2) \neq 0}}^{N-1} P(\omega_1, \omega_2) \ , \tag{1}$$

where N=4 in the present analysis. $P(0,0)$ is excluded in summing up of Eq.(1). As $P(0,0)$ represents long wave length contribution, it is not necessary to estimate the undulation of short range contribution.

We calculate MPS of each 4×4 matrix of the area as shown in Fig.1 by using of Eq.(1), and show the result of the one-dimensional histogram of the processed data (the broken line in Fig.2). We estimate the two-dimensional histogram of this study area by use of these two parameters: the conventional gray level count and MPS by Eq.(1). The result is shown in Fig.3. Actually, the value of MPS is normalized so as to be comparable to one of the gray level count. We can detect some isolated
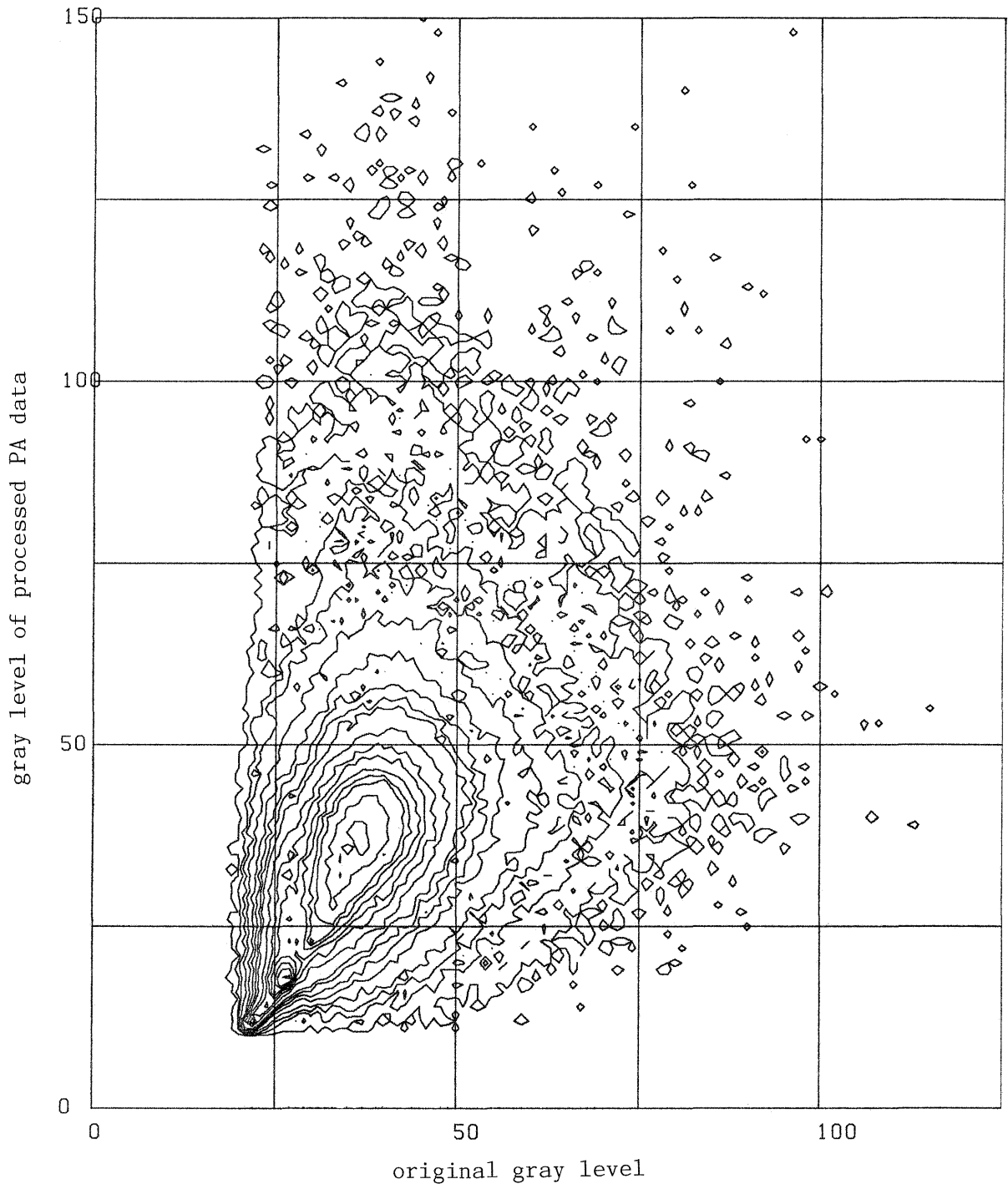
Figure 3. Two-dimensional histogram of original gray level
and MPS by Eq.(1) derived from the data in Fig.1

clusters in this histogram. If the cross-correlation between
two parameters is strong, these isolated clusters would not
appear, and also we obtain trivial results from this plot. Each
isolated cluster in Fig.3 represents one or more classes of land
cover.

Next, it is necessary to determine kinds of classes of
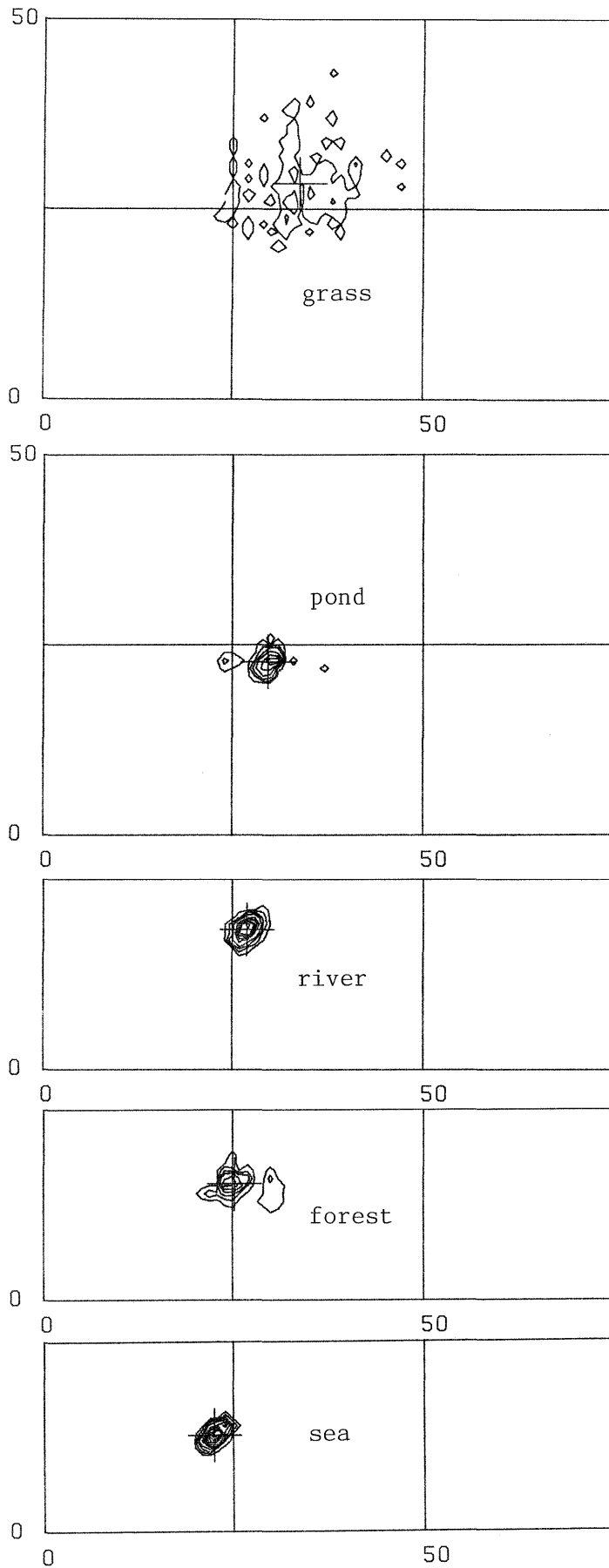clusters. So several typical training fields are selected from

Figure 4. Two-dimensional histograms of typical training fields in the same configuration in Fig.3.
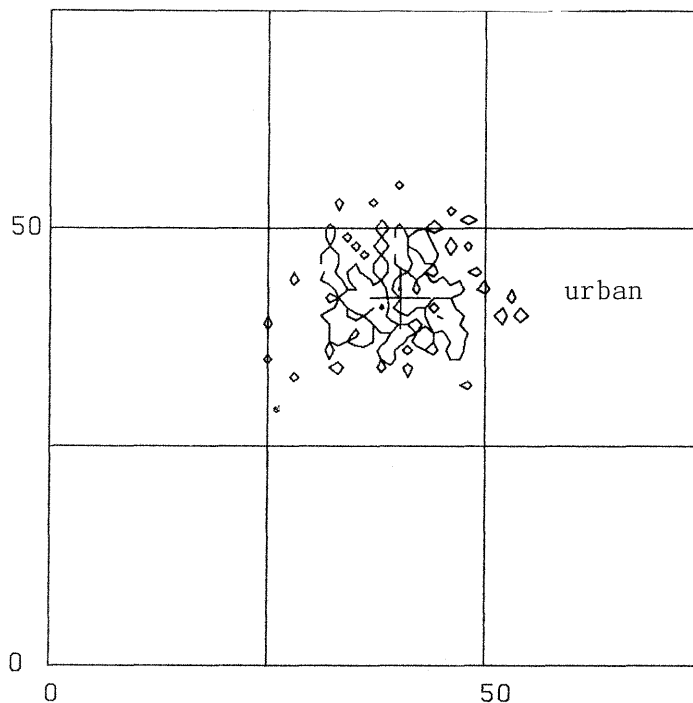
Figure 4. (continued).

the study area. Three samples are selected for water area: sea (lower middle), river (lower left), and pond (lower right). For plants, forest (upper left) and grass fields are selected. Urban area containing residential is also selected. The two-dimensional histograms of these training fields are shown in Fig.4 in the same configuration as Fig.3. The mark + in Fig.4 means the center of two-dimensional histogram of each training fields. If distributions of two classes are isolated in the histogram each other, we can classify them correctly. For example, as seen from Fig.3, one-dimensional histograms of gray level of sea, river, and pond are almost overlapped. So it is difficult to distinguish among these three classes by using of the one-dimensional data only. One of previous trial methods to overcome this difficulty is to compose new multidimensional image data of PA and HRV multichannel data[3]. These two data, however, were not acquired at the same time, that is, taken on different conditions. Namely, a correct recognition concerning objective study area may not be obtained by this method.

On the other hand, the two-dimensional histograms of three classes are separated as shown in Fig.4. Although we can classify these three classes correctly, the distributions of histograms of forest and river are almost overlapped, so we can not distinguish between two classes.

IV Classification method and result

After the two-dimensional histogram of the training field of each class is obtained by the method mentioned above, we classify the study area. Standard classification methods by using of Euclid distance such as a most-likely method or cluster analysis do not seem to be reasonable because of discrepancy
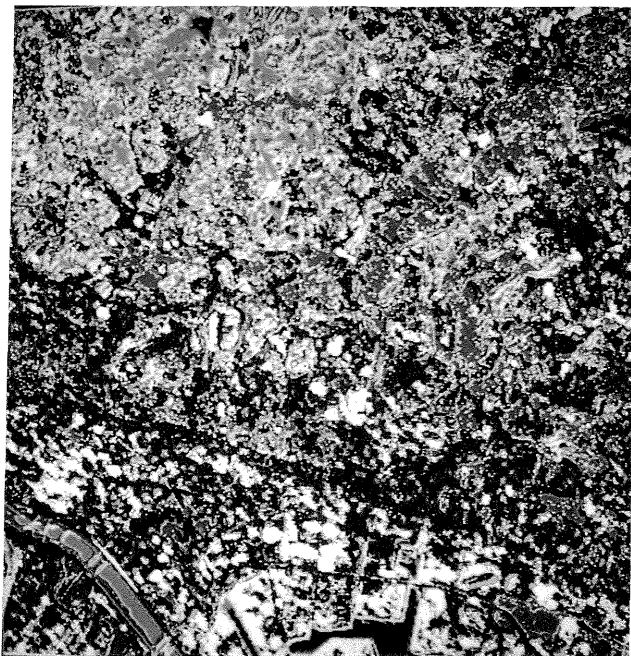
sea: blue

river: light blue

pond: pink

grass: green

bare soil: yellow

urban: red

mixed: black

unclassifiable: white

Figure 5. Classification result of Fig.1.

between an ellipsoid and contour lines of two-dimensional histogram of each training field. We adopted a manually controllable method, which is as essentially same as the multi-level slicing one. In the multi-level slicing method the boundary between an inner region and an outer one in the multidimensional space is generally defined to be rectangular. In the present method, we define this boundary line between them for one class manually according to a two-dimensional histogram produced from its class. Actually, the boundary line is drawn on a tablet by a stylus-pen, following displayed histogram data on CRT such as Fig.4.

One boundary data set is corresponding to one class. In this way all the boundary data sets are stored in memory of computer. Each pixel of an image is assigned to a proper class, judging from the boundary data sets. Pixels belonging to no class are assigned to unclassifiable area. If a classification result is not sufficient as compared with ground truth data, a corresponding boundary is improved repeatedly until a final result comes to be sufficient.

Figure 5 shows the trial classification result of Fig.1 based on the two-dimensional histograms of several training fields as shown in Fig.4. Especially, the result in water area is almost consistent with the ground truth data: river (light blue), sea (blue), and pond (pink). In the one-dimensional histogram, the regions of these water areas are almost overlapped as seen in Fig.4. So it is difficult to distinguish among them based on the gray level counts as mentioned above. Forest (upper left) is classified to river or sea. This misclassification is due to overlapping of two-dimensional histograms between forest and water area. Urban area containing residential (red) is spread over this study area. The

two-dimensional histogram of urban area is widely distributed as shown in Fig.4, because the contents of it contain many elements: commercial area, highways, railroads, bridges, and residential area. Grass fields (green), bare soil (yellow), and mixed area (black) are also shown in Fig.5. Unclassifiable area (white) mainly contains industrial one.

V Conclusions

We analyzed SPOT HRV/PA data by statistical methods. In order to classify a PA image, we examined the second variable parameter for multidimensional analysis. The mean power spectrum of a small matrix in an image was adopted as the another parameter in addition to gray level counts. We proposed the trial classification method manually controllable based on two-dimensional histograms of training field data. The present classification result was roughly consistent with the ground truth data. A misclassification result, however, occurs if two-dimensional histograms of training field data are overlapped. For this case, an another proper parameter is necessary for better recognition of land cover.

References

[1] Proceedings of the 1984 SPOT Symposium (American Society of Photogrammetry, 1984).
[2] M.Fily and D.A.Rothrock: Extracting Sea Ice Data from Satellite Imagery, Digest of the 1985 International Geoscience and Remote Sensing Symposium, p.432(1985).
[3] G.Cliche, F.Bonn, and P.Teillet: Integration of the SPOT Panchromatic Channel into Its Multispectral Mode for Image, Photogrammetric Engineering and Remote Sensing, Vol.51, No.3, p.311(1985).