

New Classification Algorithm Using Spatial Information for High Resolution Image Data

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Abstract

In the last several years, it has been clarified that conventional land-use/cover classification method can not achieve expected classification accuracies for high ground resolution image data such as SPOT HRV and Landsat TM data. In this paper, a new landcover/use classification algorithm in order to solve the above problem for high resolution images is presented.

This algorithm is based on a two stage recognition model of landcover/use. In this model, a landcover category of each pixel is identified by the component ratio of landcover elements surrounding the corresponding pixel. The classification procedure can be divided into 3 steps, i.e. the first step is the recognition of landcover elements using a pixel-by-pixel classification method; second step is the calculation of the component ratio on local image region; third step is the final decision for landcover categories using minimum distance classifier.

The results of experiments showed that this algorithm achieved 6-18% improvements of classification accuracies.

1. Introduction

Various point wise (pixel-by-pixel) classification algorithms have been applied to Landsat MSS data (80m resolution) or other remotely sensed data with similar ground resolutions to generate thematic maps, according to an assumption that the landcover classes such as urban, forest, agriculture, etc. can be recognized by spectral informations of each pixel. However this assumption may not hold for Landsat TM data with an improved resolution of 30m. The land-cover ground unit may be resolved into multiple spectrally different land cover components by the high resolving power of TM sensor. Although TM data has supplied much more spatial and spectral informations than MSS, it has actually lowered the accuracy of land-cover classification [1], especially in areas such as urban which show a considerable spatial and spectral varieties. In other words, it became impossible to recognize land-cover classes directly on the basis of point wise analyses. In order to make full use of TM data, a spatial information based approach to the problem of identifying land-cover classes in TM data is proposed in this paper. The algorithm developed for this approach uses a classified result by a conventional point wise classification as an input. This result can be considered to be a kind of a map made by depicting the spectrally dissimilar cover component types in the image. The classified result is then re-classified into

land-cover classes by an analysis of spatial information contained in this result, namely the local frequency distribution of cover component types in the neighborhood of each pixel.

2. Principle

Many experiments have showed that TM data can distinguish only spectrally dissimilar cover component types. In order to identify land-cover classes, it can be assumed that a land-cover class is composed of two or more spectrally different cover component types and is characterized by a different proportion of cover components. For example, if we want to identify high density and low density urban areas, a point wise spectral classification can only recognize cover component types such as house roofs, concrete buildings, asphalt pavements, lawns ,etc. However these components are common to both the high density and low density urban areas, making it difficult to recognize them on the basis of point wise classifications. The major difference between the high density and low density urban areas lies in the proportions of their components. According to this model of land-cover classes, it may become possible to identify land-cover classes using a characteristic frequency distribution of cover component types around each pixel.

Thus, this method divide the whole land-cover classification process into two steps, i.e. a point wise classification into spectrally distinct cover components and a final classification into land-cover classes using the classification result as its input.

2.1 spectral classification (the first step)

In the first step, most of the existing supervised or unsupervised point wise classification procedures will be qualified enough to make a classification map depicting the spatial distribution of cover components.

If a supervised classification method is used, care must be taken to keep the training data as spectrally pure (narrowly peaked) as possible when choosing the training areas of each cover component type. Then spectrally dissimilar cover components can be recognized by their radiance values which are separable in the spectral feature space.

2.2 spatial information based classification (the second step)

In the second step of classification for land-cover class recognition, the frequency distribution of cover components within the neighborhood of each pixel is extracted. This distribution is used as the classification feature for the second step processing.

To do this, the number of occurrences of each cover component within a window surrounding the pixel is counted to com-

pute the frequency distribution. Then, each pixel located at the center of the window can be associated with a component-frequency vector (which in fact expresses a kind of histogram with regard to cover components). For example, if there are 7 possible spectral cover components, the window in Fig. 1 will result in (7,2,4,3,5,0,4) which will be used as the classification feature in the second step.

To implement the final land-cover classification, training data corresponding to land-cover classes should be taken again on the classification result of the first step, and supervised extraction of training data is recommended to obtain meaningful land-cover classes. Intuitively, training areas of the second step can be larger in area and be taken more roughly than that of the first step.

Because the dimension of the feature vector is equal to the number of possible cover components involved in spectral classification (i.e. the classification in the first step), the classification procedures such as maximum likelihood method will be difficult to adopt and take too much computing time to be practical.

In this research, a minimum city-block distance classification procedure was used to carry out efficient classification. First, the mean component frequency vector of training data were calculated. Then, the cover component frequency vector derived from the window was compared with each mean vector corresponding to its land-cover class by calculating city-block distances between them using the following expression.

$$D = \sum_{j=1}^N |f_{ij} - f_j| \quad (1)$$

- where, D : city-block distance
- N : number of possible spectral components
- f_{ij} : jth spectral component of the mean vector of ith land-cover class
- f_j : jth spectral component of the vector derived from a window

Then, the land-cover class with the minimum city-block distance is assigned to the center pixel of the window.

3. Experiment

The test data was a 6-band TM image resampled at 25m pixel (Fig. 2) covering Hiratsuka City, taken on Nov. 4th, 1984. In the first step, the spectral data were classified into 78 spectral cover component classes using supervised maximum likelihood classification method [2]. The component classes are listed in Table 1, and the classified result is shown in Fig. 3, where 78 component classes were merged into 14 categories according to Table 1 for an easy visual examination.

In the second step, 14 land-cover classes were chosen and

typical areas of each land-cover class were selected again for generating training data. Then, using the extracted feature, re-classification was implemented for window sizes from 2x2 to 9x9. Fig. 4 shows the classification result of this step at window size of 5x5.

4. Results

From the visual evaluation of classified result in the first step (Fig. 3), it is clear that in Hiratsuka City and its suburban areas, various spectral classes made it difficult to recognize the homogeneous urban area. On the contrary, the result of the second step showed blocks of homogeneous urban areas, which is similar to those made by human interpretation.

In order to quantitatively evaluate the classification accuracy in those two steps, accuracy assessments were performed, using a digital land use test site data made by Tokai University Research and Information Center. In this research, five categories of forest, agriculture, urban, water and others were used, which were merged from 14 land-cover classes as shown in Table 1.

The classification accuracies in percentage for the five categories are summarized in a confusion table (Table 2) together with overall classification accuracies.

From the confusion table, the accuracy of the classification proposed in this paper is better by about 6% at window size 5x5 compared with that of the spectral classification. The accuracy increases proportionally with the window size, but it saturates at window size of 5x5. This result gives us a hint about how to select the window size in the case of TM data. Too small windows will be subject to more statistical unstableness and are unable to resolve differences between similar land-cover classes, while too large window sizes will take more computing time and arise a kind of averaging effect on the result. By this effect, linear features such as narrow rivers, pavements and railways will disappear. So the window size of 5 pixels by 5 pixels (i.e. 25 pixels) may be the best size for TM data, corresponding to 125m by 125m on the ground.

From the confusion table, one can recognize another fact that the spatial information based re-classification procedure presented here is especially effective to urban areas. In urban areas the accuracy has increased to 81% (by 15%). The class "other" shows a very low accuracy. This phenomenon was perhaps originated from the bad spectral classification results. As "water" and "forest" are spectrally homogeneous classes, their accuracies remains unchanged.

5. Conclusions

Results from applying the spatial information based procedure have showed that this procedure increased the classification accuracy by about 6% in identifying land-cover classes compared

to a point wise classification using the spectral data only. The procedure also make it possible for analysts to choose more natural and macroscopically meaningful land-cover categories. This procedure also resulted in a kind of classification similar to a land-use classification. It provided a means for identifying meaningful land-cover classes which are composed of spectrally distinct cover components recognized by a point wise classification method.

A disadvantage of this procedure is that it takes about 3 times of computing time compared to a conventional spectral point wise classifiers.

6. References

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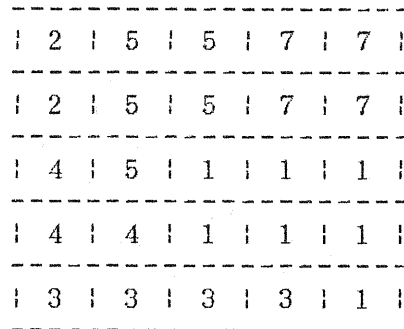


Fig. 1 a window with 5 pixels on each side

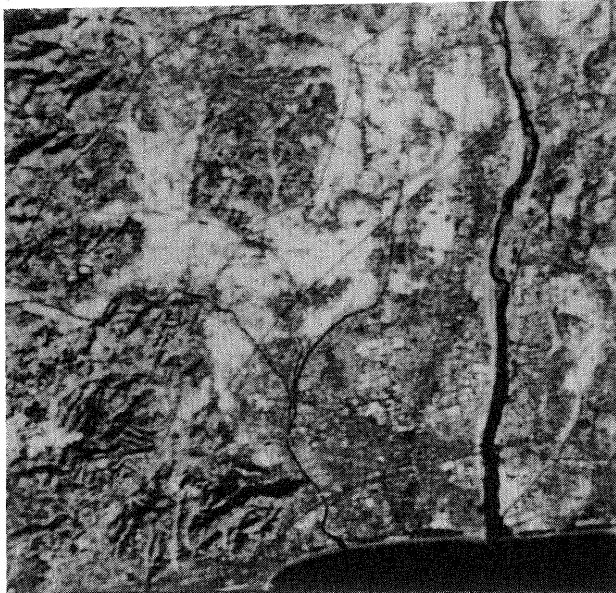


Fig. 2 original image of
TM data

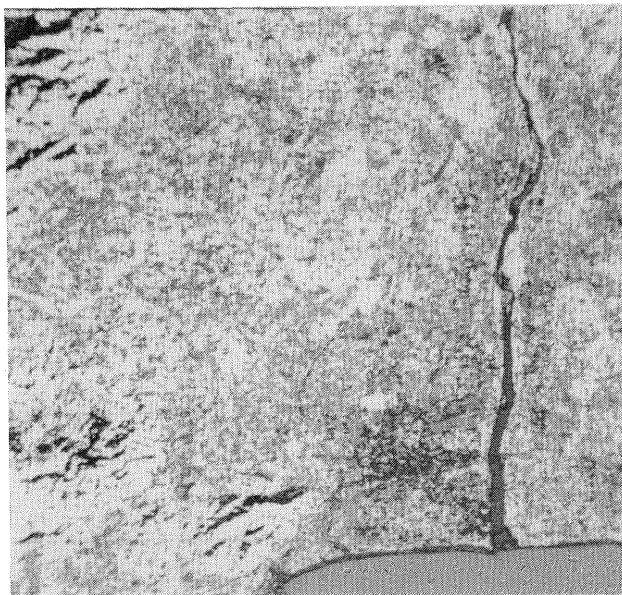


Fig. 3 classification result of
the 1st step

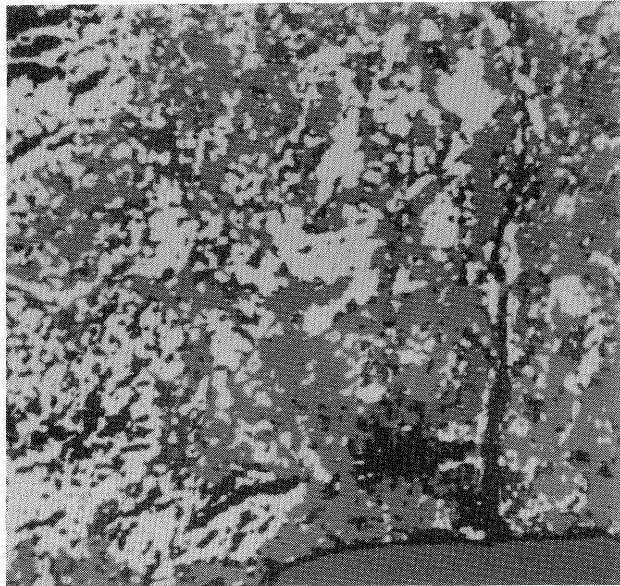


Fig. 4 classification result of
the 2nd step (window size 5)

Table 1 class list for each step
and accuracy assessment

No.	land-cover classes	number of spectral components	classes merged for accuracy
1	coniferous forest	7	
2	broad leaf forest, mixed forest	12	forest
3	shadow of mountains	4	
4	farm	2	agriculture
5	paddy	5	
6	factory	5	
7	high density urban	3	urban
8	low density urban	5	
9	sea	4	water
10	river, lake, pool	9	
11	grass	5	
12	golf links	2	
13	sand	11	other
14	cloud	1	
	total	78	

Table 2 classification accuracy (%)

spectral classification		spatial information based classification							
		window size							
		2x2	3x3	4x4	5x5	6x6	7x7	8x8	9x9
forest	59	54	60	59	62	59	60	59	58
agriculture	41	40	49	46	48	45	46	44	44
urban	66	72	77	78	81	82	83	83	84
water	70	70	70	71	70	71	70	71	70
other	37	32	31	28	27	24	22	20	19
overall	55.8	56.7	60.1	59.8	61.1	60.5	60.5	59.7	59.6