A Spectral and Textural Knowledge-Based Approach for Automated Extraction of Topographical Factors from Remotely Sensed Images

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ABSTRACT: A prototype expert system is developed to demonstrate the feasibility of classifying multispectral remotely sensed data on the basis of spectral and textural knowledge. In this paper, the spectral and textural properties of settlement place, vegetation, water area, soil, etc. are discussed and a production algorithm of texture image is studied. According to the relationships of band-to-band and category-to-texture, a knowledge base represented by rules and weights is established. The method presented in this paper is of fast computation speed and high classification accuracy.
KEY WORDS: Artificial Intelligence, Classification,Knowledge Base, Image Processing

Parametric pattern recognition techniques are widely used to classify land-cover categories in multispectral remotely sensed data (Landgrebe, 1981). Parametric classifiers are based on the statistical distribution of the feature vectors. The limitations of statistical methods are that they cannot directly utilize nonparametric knowledge, and have a low classification accuracy. Therefore, they cannot fulfil the productive task of the automated extraction of topographical map factors. In order to improve the classification accuracy, some knowledge-based classification methods were presented in (Wharton,1987, Mehldau et al, 1990, Ferrante, 1984). A knowledge-based classification system for high spatial and spectral resolution images was pressented in (Wharton, 1987), and a C-extension for rule-based image classification system was presented in (Mehldau, 1990). Because the two classification systems were developed in ideal conditions, there are some limitations when they are used for remotely sensed images. The multispectral image analysis system (MSIAS) presented in (Ferrante, 1984) is a knowledge-based spectral classification system developed by Ferrante et al. The system was designed to use a hierarchical decision tree structure with two classification levels for TM data. Because the approach does not provide a method of recovering from decision errors, the final classification is highly sensitive to errors at any decision levels. The classification results were considered unreliable.

In this paper, the spectral and textural features of map factors in remotely sensed images such as settlement place, water, vegetation and soil and the establishment of knowledge base are discussed. A classification method integrating parametric pattern recognition technique with knowledge base is presented here. The method above can extract validly topographical factors such as settlement place, water, forest, soil and road. Experimental results demonstrate that the method is of fast conputation speed and high classification accuracy.

RESEARCH SCHEME

The reflectance-spectral and textural properties of map factors such as settlement place, water, vegetation and soil are different from each other. They give important evidence for visual interpretation. However, for various reasons, the different objects of the same category (e.g. buildings of different materials) have distinct spectral reflectances, and therefore different tones or colors in image. In the process of visual interpretation, the regions of same tone or color are distinguished, then the categories of the regions are determined.

The research scheme in this paper bears analogy to visual interpretation process. The first step is to segment the preprocessed image with unsupervised classification algorithms based on spectral and textural features, and compute the averages of every band data and textural energy image for each segmentation region. The second step is to determine the category of each segmentation

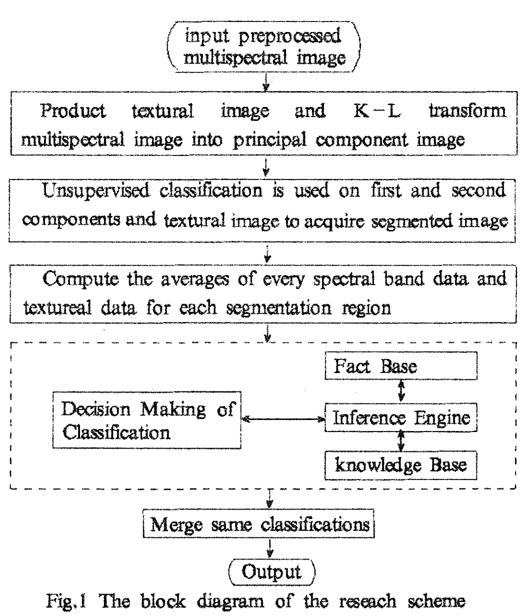


Fig.1 The block diagram of the reseach scheme

region, using knowledge base. These categories are the sub-classes of topographical map factors to be extracted. For example, settlement places are divided into asphalt and concrete roof settlement places. The third step is to merge the sub-classes of same map factors into one. The reseach scheme is shown in Fig. 1.

The following sections are devoted to the production of texture energy image, the establishment of knowledge base and the decision making of classification. Principal component transformation and unsupervised classification algorithms are presented in relevant documents in detail. They will not be discussed here.

PRODUCTION OF TEXTURAL IMAGE

The Production of texture image is to enhance the image data of a band selected from multispectral images using rule-based localized enhance technique(Zhang et al, 1991), and based on this to generate textural image using a texture energy technique.

The texture energy technique was presented by Laws (Wechsler,1980). The idea of this technique is similar to that of Fourier transformation, but it is implemented in space domain. Two steps are required for the implementation of this technique.

The first step is to compute the convolution of the given image $f(i,j)$ with mini-mask $h(s,p)$ (e.g., Laplacian and gradiant operator, generally 3×3 or 5×5) to detect the pixels on edges:

$$g(i,j)=\sum_{s=0}^{N-1}\sum_{p=0}^{N-1} f(i-s,j-p)\cdot h(s,p) \qquad (1)$$

where N is the size of the mini-mask.

The second step is to abstract texture energy in a larger size window, which is defined as the square sum of grey levels within the window. The sum of absolute value is used to substitute for the square sum for the convenience of computation, then

$$G(i,j)=\frac{1}{M^2}\sum_{k=0}^{M-1}\sum_{l=0}^{M-1} |g(i-k,j-l)| \qquad (2)$$

where M is the size of the window. Generally $M=9$, 15 or 21.

In essence, the texture energy algorithm is to find out the pixels on edges and to regard the statistical signal energy as the apparent feature of textural signal.

ESTABLISHMENT OF KNOWLEDGE BASE

In order to use knowledge for automated extraction of map factors, a knowledge base must be established. Two things must be done: one is to research the spectral and textural properties of objects, the other is to represent the inherent and interrelative features of objects.

Each category of objects has its inherent spectral and textural properties. The properties can be acquired with visual interpretation experiences and the spectral reflectance curves of objects that have been known. In the following paragraph, the spectral properties of 4 ground objects(i.e.,vegetation, soil, water and buildings) are discussed simply.

Green vegetation has a low reflectance in the 0.35-to-0.7 μm region with a slight rise at 0.55μm, and a higher reflectance in the near-infrared($0.75-1.35\mu$m), but low reflectances at 1.4, 1.9 and 2.7μm. The reflectance curve of soil is less complex than that of vegetation. The reflectance of soil generally increases with the increasing of wavelength, especially in the 0.35-to-1.4μm region. Because soil is a complex mixture, and has various types, the spectral reflectance features of which are different. Water has a low reflectance in the visible band and a tendency of decreasing in the near-infrared. Asphalt and concrete roofs of buildings have the reflectance profile typical of man-made materials, i.e., a generally increasing reflectance with increasing wavelength. The reflectance varies with the age of the building. Roofs of natural materials have the same reflectance as the natural materials. All above can be found in relevant documents.

Besides spectral properties for object interpretation in images, the textural properties are very important. For example, soil and buildings have the similar spectral properties, i. e., a generally increasing reflectance with increasing wavelength, but their textural properties are quite different.

In the knowledge base we have established, there are two kinds of knowledge, i.e., band-to-band (BB) and category-to-texture (CT),which are expressed in terms of rules and weights. A rule is a comparision between band and band or texture and threshold. A weight is a supporting or opposing evidence weight when the rule is right or false. A knowledge sub-base for a certain category is composed of a set of rules and weights. For example, the knowledge sub-base for the forest interpretation in TM image is composed of

rule 101: band(4)>sum (1,2,3) [50, 0]
rule 103: band(2)>band (1) [10, 10]
rule 106: min(4,5,6)<sum (1,2,3) [0, 50]
rule 114: band(0)(texture image)< 20 [20, 10]

where band(i) stands for the value of band i, sum( ) denotes the sum of the bands in parentheses, min( ) denotes the minimum of the bands in parentheses, the first and second number in brackets[ ] indicate the supporting and opposing evidence weight, respectively. The minimum weight is 0, and maximum weight is 100. A rule is a constraint in essence. According to the roles they play in category interpretation, constraints are divided into mandatory constraints, optional constraints and contradictory constraints. Mandatory constraints are represented by having the supporting and opposing weights greater than zero so that evidence is added for valid constraints and subtracted otherwise. Optional constraints are represented by having only the supporting weight greater than zero so that evidence is added if the constraint is valid, otherwise do nothing because the failure of an optional constraint does not necessarily refuse a category. Contradictory constraints are represented by having only the opposing weight greater than zero so that evidence is subtracted if the constraints is invalid, otherwise do nothing because the success of a contradictory constraint does not neccessarily support a category.

We have established the knowledge sub-bases for 8 categories:forest, grass, new/old buildings, clear/turbid water, soil and cropland in SPOT/TM image, as well as a programme for increasing, deleting and modifying the knowledge base interactively.

CONTROL STRATEGY AND DECISION MAKING

In knowledge base, each category has its independent sub-base represented by a set of rules and weights. If only one constraint in a sub-base is valid for a segmentation region, we cannot conclude the region is the category corresponding to the sub-base, because the knowledge sub-base of that category consists of several rules and weights, and they are a whole. Neither is the idea is not preferable that only when all the constraints in a sub-base are valid for a segmentation region can we conclude the region is that category. Because the base has been established in ideal conditions, there are always some differences between ideal conditions and realities. For the above reasons, we present control strategies as follows:

1. Compute the supporting and opposing evidence amounts of candidate category using all sub-base for each segmentation region.

2. Compute category scores with a function of the relative proportion of supporting and opposing evidence.

3. Make decisions based on the scores achieved.

Equation (3) and (4) are used to compute category scores. Equation (3) is used if the supporting evidence is greater than the opposing evidence, otherwise (4) is used.

$$score = 100(1 - Eopp/Esup) \quad (3)$$

$$score = 100(1 - Esup/Eopp) \quad (4)$$

where Esup is the amount of supporting evidence and Eopp is the amount of opposing evidence.

As a result, a category score of a region is computed for each sub-base. All the category scores of a region are ordered based on their values. If the maximum score is smaller than a certain threshold(e.g.,20), and if the region doesn't belong in a corresponding category, then it is represented by category 0 (i. e., to refuse recognition). If the maximum score is bigger than the threshold and the difference between the first and second maximum is smaller than a certain threshold(e.g., 5), the region is considered unidentifiable. Then, man interference is necessary. Otherwise, the segmentation region is considered as the category corresponding to the maximum score.

EXPERIMENTAL RESULTS AND CONCLUSIONS

The method presented in this paper has been evaluated by testing its classification accuracy for the 512-by-512 pixel SPOT image. The main topographical factors in the image are settlement place, water, soil and forest. Firstly, the image is divided into 21 classifications as segmented image by K-means algorithm. Secondly, seven categories such as new/old settlement places, forest, clear/turbid water and cropland are extracted based on spectral and textural knowledge. Finally, new/old settlement place and clear/turbid water are merged into settlement place and water respectively. A part of experimental results is shown in Fig.2. The classification accuracies of the presented method and the K-means lgorith are shown in table 1.

accuracy (%) / algorithm / classification	K－means	knowledge-based technique
forest	confusion with crops	94
new settlement	64	86
old settlement	73	88
clear water	83	90
turbid water	81	87
cropland(crops)	confusion with forest	84
other	71	82

Table 1. Accuracy comparison between knowlege-based technique presented in this paper and k-means

Table 1 shows that K-means algorithm has a low classification accuracy. The one reason is that the sand content of water changes greatly in the region covered by the image. Of the 7 categories in the image water even occupies 3, the rest 4 categories are found confused so heavily that they are unidentifiable. The solution of the problem is to increase the amount of classifications. But the amount of work is too great for man to interpret and merge the classifications, For this reason, such a large number(e.g.,21) of classifications are segmented by knowledge-based classification method in advance. After that, with a little man interference, the knowlege base is used to discriminate the above classifications (e. g. , segmentation regions) automatically. Because water and forest have typical reflectance curves, and the textural properties of settlement place are very different from those of the others, they can be discriminated with a high accuracy by a knowledge-based technique.

Our programmes were designed in C language, and ran on MC-6700. It took 12 minutes to segment the 512-by-512 pixel image into 21 classifications using K-means algorithm. Based on that, it took 6 minutes to merge 21 classifications into 7 categories using the spectral and textural knowledge base.

The results above support the following conclusions:

1. It is feasible to segment an image first using an unsupervised classification algorithm, then to discriminate the category of every segmentation region using a knowledge base. It is of fast computation speed and high classification accuracy.

2. The method presented in this paper not only can segment an image into regions of same properties, but also can discriminate the categories of the regions automatically.

REFERENCES

Ferrante, R.D.,M.J. Carlutto, J. Pomaraede, and P.W. Bain, 1984. Multispectral image analysis system. In Proc. 1st. Conf. Artificial Intelligence Applications (Denver, Co), pp. 357-363.

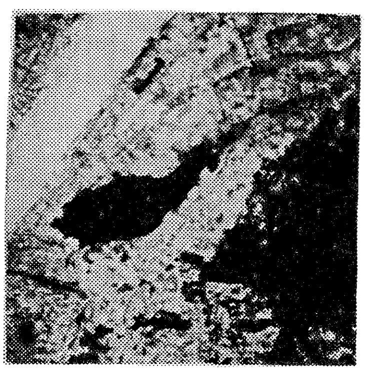
Landgrebe, D.A.,1981. Analysis technology for land remote sensing. Proc. IEEE, Vol. 69, No. 5, pp.628-642.

Mehldau, G., and R. A. Schowengerdt, 1990. A C-extension for rule-based image classification systems. Photogrammetric Engineering and Remote Sensing, Vol. 56, No. 6, pp.887-892.

Wechsler, H., and T. Citron, 1980. Feature extraction for texture classification. Pattern Recognition, IZ, pp. 301-311.

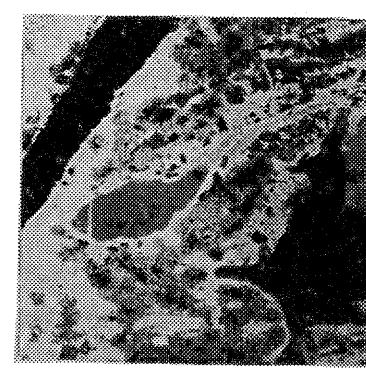
Wharton, S.W., 1987. A spectral-knowledge-based approach for urban land-cover discrimination. In proc. IEEE, Vol. GE-25, No. 3, pp.272-282.

Zhang Xiangqian, Li Xiaofeng and Yu Xuchu, 1991. A rule-based method for contrast enhancement. Proc. of The Chinese Joint Conference on Pattern Recognition and Artificial Intelligence, Harbin, China, pp.69-72.



(a) Part of a SPOT image, band 2

(b) Textural energy image.



(c) The image classified into 21 classifications by k-means.

(d) 7 classifications such as forest, new/old settlement place, clear/turbid water, cropland extracted by the knowledge-based technique.

(e) The image classified into 7 classifications by k-means.

(f) Merging the 7 classifitions of Fig. 2 (d) into 4 categories such as drttlement place, forest, water area and cropland.

Fig.2 A Part of experimental results.