Research on Auto-Classification Method of Remote Sensing Images in Mountainous Areas—An Application in Southwest of China

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Abstract  In mountainous areas, it is the undulant terrain, various types of geomorphic and land use that make the remote sensing images great metamorphism. Moreover, due to the elevation, there are many areas covered with shadow, clouds and snow that make the images more inaccurate. As a result, it would be very difficult to carry out auto-classification of RS images in these areas. The study took Southwest China as the case study area and the TM images, SPOT images as the basic information sources assisted by the auxiliary data of DEM, NDVI, topographical maps and soil maps to preprocess the images. After preprocessing by topographic correction and wiping off clouds, snow and shadows, all the image data were stacked together to form the images to be classified. Then, the research used segmentation technology and hierarchical method to extract the main types of land use in the area automatically. The results indicated that the qualitative accuracies of all types of land use extracted in Southwest China were above 90 percent, and the quantitative accuracies was above 86 percent. The goal of reducing workloads had been realized.

Keywords  segmentation; hierarchical method; auto-classification; mountainous areas; Southwest of China

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Introduction

In recent years, the technology of auto-classification of remote sensing images has achieved rapid development and widespread application. From spectrum statistical classification to the neural network classification of imitating human vision law, from the introduction of experts in a professional system to the building of an image analysis system using reasoning model, the accuracy of classification to a certain degree in different aspects had been improved. However, it is regretful that all the researches were based on small-scale experiments, and the applications of automatic extraction to obtain the main types of land use were very scarce in large scale. Particularly, in mountainous areas, the electromagnetic spectrum reflection differed greatly in different slope terrain and position, which caused the shadow region and the weak-signal area in corresponding remote sensing images. Moreover, the vertical variation of mountainous climate made the water and the heat...
disproportionate, which made the vegetation cover and the land utilization diversified. As a result, the color of ground objects on images was complex and diverse, so not only one kind of color spots represented several kinds of types, but also one kind of type had different color expression. Therefore, the application of auto-classification of remote sensing images in mountainous areas is facing many difficulties\(^5\). The study applied multi-hierarchy remote sensing (RS) auto-classification in the extraction of main ground objects of the research area - Southwest China, and achieved verified accuracy by taking many types of images besides Thematic Mapper (TM) images. The study also made certain exploration on the technical routes and methods of auto-classification in the aspect of obtaining information on land use.

1 Study area and data base

1.1 Study area

Southwest China includes the provinces of Yunnan, Guizhou, Sichuan, and Chongqing city. The region except Sichuan basin is mainly a mountainous area with middle and high mountains, and the elevation is mostly above 1 000 m in the east and between 2 000 m and 3 000 m in the West. The climate is subtropical moist monsoon, and the vertical variation is obvious. The region is a national minority area with backward economic condition, and its karst landform area is one of China’s poorest areas.

1.2 Data sources

The research took TM images in October 2005 (30m) as basic information, and images in the year 2000 and 1995 as references. The auxiliary materials included:

1) The images of digital elevation model (DEM) of the Southwest on the scale of 1:250 000, and the slope and aspect images that were derived from the DEM images;

2) The land use/cover maps of each county on the scale of 1:100 000, the forest cover maps of some county on the scale of 1:10 000 and the land-use planning maps of some counties on the scale of 1:50 000;

3) The county boundaries of Southwest China, the division maps of the physiognomy and topography on the scale of 1:4 000 000, and the division maps of vegetable on the scale of 1 000 000;

4) The 6 000 sheets of field investigation photos.

2 Data preprocessing

2.1 Image correction

Image correction included the geometry correction in the horizontal direction and the topographical correction in the perpendicular direction. The remote sensing images and auxiliary data were geometrically corrected through the control points (GCP) according to the DEM images with a scale of 1:250 000. In the process of selecting GCP, we also considered the changes of surface feature, the origin of the relief maps and the express methods of key elements on the relief maps. In the process of topographical correction, we removed the deformation caused by elevation by importing DEM images with a scale of 1:250 000 to make the ground objects of RS images on the same plane. In the process of topographical correction, we also took the sensor scanning way, sensor factors such as platform altitude, incident angle size, incident angle direction and earth surface curvature into account\(^6\).

2.2 Disposing shadow

In order to dispose the influence of the shadow, we increased the brightness value of surface features in the sloping overcast and the image, and weakened the brightness value of surface features located in the sun slope through the model as below\(^7\):

\[
NB_i = 255 \times \left( \frac{OB_i}{\sum OB_i} \right), \quad i = 1, \ldots, n
\]

where, \(NB_i\) was normalized luminance value of pixel; \(OB_i\) was the value luminance of pixel; \(i\) was the wave band.

2.3 Elimination of cloudy and snowy regions

The mending method was used to eliminate the cloudy and snowy regions, namely we used the remote sensing images of close time interval to replace some big snowy area. First, transformation models of look-up tables were established by the correlative analysis of source images and match images. Then,
the transformation models were used to transform the histograms of source images to match the histograms of objective (match) images. The spectrum match can produce certain information loss. It was especially important to select match images with similar histogram shape, average value and similar variance with the purpose of reducing information loss. It was better to select the images with average value in the middle as far as possible to prevent the luminance value of images from excessive compression and the inflation.[8]

2.4 Division of remote sensing images

The auto-classified images were divided according to the boundaries of the division maps of the physiognomy and topography, the boundary of each county and the division maps of vegetation to reduce the data quantity and the influence of the region difference. The images were redivided according to the scene if the image spanned two or several scenes.[6]

3 Method and process

The auto-classification took a sample-based fuzzy classified method based on the hierarchy of ground objects to extract the main types of land use in Southwest China. The main process was as follows: First, the images were segmented into spots and the average attribute value of each spot was calculated in each data layer. Second, the hierarchy of ground objects was established. Finally, the auto-classification used a function named member function on each needed data layer to extract ground objects based on certain hierarchy automatically by analyzing the spectrum characteristics of sample spots.

3.1 Segmentation

The auto-classified images were segmented into polygonal objects with similar attribute information in different scales in different layers, adopting one novel unique image multi-resolution segmentation rule[9]. Throughout the segmentation procedure, the whole image was segmented and the image objects are generated based on several adjustable criteria of heterogeneity in color and shape. Adjustment of the so-called scale parameter indirectly has great effect on the average object size: a larger value leads to bigger objects and vice versa. Additionally, the influence of shape as well as the image’s channels on the object’s homogeneity can be adjusted. During the segmentation process, all generated image objects were linked to each other automatically. In the research, the criteria of heterogeneity in color and shape were 0.7 and 0.3 respectively, and the density and smooth degree were assigned the proposition of 0.7 and 0.3.

3.2 Sampling

We extracted dry land, paddy field, construction land, forestland, meadow, bush, rivers and lake automatically. The field photos were located correctly on the segmented images, and the samples of each type of ground objects are selected. The expression forms of the above types were analyzed to form the sampling standard. In the sampling process, it was better to select the sample in mass in the main layers using extraction and deleted the ones with large deviation on these data layers. In order to reduce the influence of shadows, we selected samples in shady and sunny area respectively. Quantity of samples was moderate. Too little samples couldn’t give the trend of membership function, while too much made the mean attribute value distribution too wide to show the characteristic of differentiated function correctly. Choosing the samples could not be finished at one time. It was connected with differentiated function and automatic classification. If the deviation between the extraction result and the factual result was too much, some samples should be reselected and even deleted. The sampling process and classification was the course where humans and computers interacted many times.

3.3 Spectrum analysis

For each divided images by certain region, the average attribute value of each sample on all data layers was calculated, and the distribution range of average attribute of every kind of ground object sample was drawn out to form a distribution curve.

3.4 Establishment of membership functions

The segmentation process could produce additional
attribute information, which could be used in the subsequent classification as the main condition. The overall fuzzy value \((f)\), the subordinate degrees to certain type of ground objects, were calculated and changed into unified range function from zero to one.

The overall fuzzy value \((f)\) was computed based on the spectral heterogeneity and the shape heterogeneity as follows:

\[
 f = w_h + (1 - w)h_{shape} \\
 h_{color} = \sum c w_c (\sigma_{c,merge}^n - (n_{obj1} \sigma_{c}^{obj1} + n_{obj2} \sigma_{c}^{obj2})) \\
 h_{shape} = w_{shape} h_{compact} + (1 - w_{shape}) h_{smooth} \\
 h_{merge} = n_{merge} \left( l_{merge} \sqrt{n_{obj1}} - (n_{obj1} l_{obj1} + n_{obj2} l_{obj2}) \right) \\
 h_{smooth} = n_{merge} \left( l_{merge} h_{obj1} - (n_{obj1} l_{obj1} h_{obj1} + n_{obj2} l_{obj2} h_{obj2}) \right)
\]

Where \(f\) was the overall fuzzy value; \(c\) was the data layer; \(w\) was the user-defined weight for color (against shape) from 0 to 1; \(w_c\) was the weights of \(c\) layer; \(h_{smooth}\) was shape heterogeneity; \(h_{merge}\) was Compact heterogeneity; \(n_{merge}\) was the object size after merged, \(n_{obj1}\) and \(n_{obj2}\) are the \(n_{obj1}\) and \(n_{obj2}\) before merged; \(l\) was the object perimeter and \(b\) was the perimeter of the bounding box; \(l_{merge}\), \(l_{obj1}\) and \(l_{obj2}\) are the object perimeter after merged and before merged object — \(obj1\) and \(obj2\); \(b_{merge}\), \(b_{obj1}\) and \(b_{obj2}\) are the perimeter of bounding box after merged and before merged—the merged object \(obj1\) and \(obj2\).

At the same time, each layer’s mean value was calculated from the layer values of all \(n\) pixels that formed an image object using the following formula:

\[
 c_i = \frac{1}{n} \sum_{i=1}^{n} c_{li}
\]

Where \(c_i\) was the average value of each spot; \(c_{li}\) was feature value range, and for 8 bit data the value range was [0, 255].

On each datum layer, the average value of each spot \((c_i)\) and the fuzzy value \((f)\) have formed a functional relationship, which was the membership function and which could be revised according to the need. The membership function could be produced automatically and manually, so it was the window of human-computer interaction (Fig.1). It was the fuzzy value \((f)\) that interpreted the classification of spot waiting to be differentiated. The concrete principle was as follows: first, compare the fuzzy value in each layer of all samples and pick out the largest ones, then compare the selected value and choose the sample whose fuzzy value was still the largest one; finally, merge the spot into the type the sample represented. Then, the spot that had the same average value \((c_i)\) was merged into the same type.

3.5 Auto-classification

Hierarchical method (Fig.2) was used to divide ground objects step by step \cite{10-11}. First, the ground objects were divided into two types of vegetation and no-vegetation. Second, the subclasses were reclassified according to the relationships with water. Third, the final ground object types were extracted by the membership functions established or automatically created according to the value of each spot. The establishment of a membership function and the auto-classification needed many repetitions and tests.

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**Fig.1** The membership function

**Fig.2** Hierarchical directory structure of ground objects
Finally, the results of auto-classification were exported out in the form of vector (*.shp).

4 Problems and solutions

4.1 Spectral heterogeneity

Spectral heterogeneity included “Same spectral from different materials” and “Same material with different spectral”. “Same spectral from different materials” referred to the phenomenon that the same type of ground objects has different spectra \(^{[12]}\). According to the analysis, the phenomenon resulted from factors such as slope, crops seasonal expression, vegetation coverage degree and mixed vegetation etc. In order to be advantageous for operation, we first analyzed the pseudo-color map composited by TM4, TM3 and TM2. And then, the possible expressions of each type of ground objects on images were concluded and each expression was endowed with a subclass, which was classified by the routine auto-classification of sampling, establishing member function and auto-classification. Finally, the subclasses of the same type of ground objects were united into one type. The most common method used was the subclasses established in the sunny and shadow region respectively.

“Same material with different spectra” referred to the phenomenon that different types of ground objects have the same spectrum characteristics. Generally speaking, the geographical environment usually expressed certain regularities. For example, it is impossible for plowed land to exist in a region with very steep slope, and it is impossible for paddy land to exist in a region with very high elevation. As a result, we included other distribution characteristics. Also, the member functions were established on the data layers of slope, elevation, normalized vegetation index (NDVI), TM4/TM3. Those member functions were used in the process of auto- classification to correct the errors of classification.

4.2 Boundaries transition

Natural objects were usually interlaced in distribution, so the boundaries among different types were not so obvious. Such phenomenon was called boundaries transition. In the research, the auto-classification was fuzzy classification based on the member function, and the shape of member function determined the classification. As a result, the problem of boundaries transition could be solved by adjusting the shape of the member functions continually.

5 Verification

In this study, field samples and the spots from the photograph were adopted to verify the extraction result in the aspect of qualitative and quantitative accuracy respectively. The number of spots consistent with the corresponding verified spots were written down in the name of right spots and made their ratio as the qualitative accuracy. The ratio of the area of the right spots and the total area of verified spots was called quantitative accuracy. The verified results are in Table 1.

It can be found from the inspection results that: (1) the qualitative accuracy of water body, paddy field, dry land, construction land, forest land, bush forest, grassland were up to 90%. The qualitative accuracy for water was above 95%, and the qualitative accuracy

| Types          | Verified spot number (A) | Right spot number (B) | Qualitative accuracy \((B/A\times100\%)\) | Quantitative accuracy \((S_a/S_b\times100\%)\) | Mixed with          |
|----------------|--------------------------|-----------------------|-------------------------------------------|-------------------------------------------|---------------------|
| Dry land       | 272                      | 259                   | 95.22                                     | 87.74                                     | Grassland          |
| Paddy land     | 342                      | 318                   | 92.98                                     | 85.62                                     | Construction land   |
| Construction   | City 164                | 151                   | 92.07                                     | 84.21                                     | Paddy land         |
|               | Country 142             | 135                   | 95.07                                     | 84.12                                     | Paddy land         |
| Forestland     | 302                      | 272                   | 90.07                                     | 80.38                                     | Shrub land          |
| Shrub land     | 85                       | 78                    | 91.76                                     | 83.51                                     | Grassland          |
| Grassland      | 45                       | 41                    | 91.11                                     | 82.34                                     | Shrub land          |
| River          | 50                       | 49                    | 98                                        | 90.13                                     | Construction land   |
| Lake           | 30                       | 29                    | 93.33                                     | 92.21                                     | Paddy land          |
was above 92% for construction land, paddy field and dry land. (2) The quantitative accuracy was not very high in the whole but still exceeded 80%, and the quantitative accuracy for water was above 90%. The qualitative accuracy for forestland, bush, and meadow was relatively low but the obscurity degree among water body, paddy field and construction land was not very outstanding except the high obscurity in meadow and dry land. The accuracy of water extraction was so high in both aspects of quantitative and qualitative that it could be extracted and its dynamic changes could be analyzed conveniently. It was especially effective to use automatic extraction in the region with alternating large area of dry land and paddy field. Though the accuracy rate in the area with large coverage of vegetation was relatively lower, the purposes of reducing workload and improving the quality of artificial classification could still be achieved.

6 Conclusion

1) The auto-classification on the land use/cover in mountainous areas was feasible.

2) The automatic extraction course needed the intervention of the expertise, because the whole process was the repeat of human-computer interaction from choosing sample, forming the membership function to auto-classification. In the process of classification, it is useful to take some assistant imagery processing measures to allow certain ground objects to stand out and to improve the accuracy of auto-classification.

3) The participation of auxiliary data in the form of member function produced artificially could solve such phenomena to a certain degree as the same spectral from different materials, same material with different spectral, and border transitions, etc in the course of manual interpretation.

4) The computer auto-classification cannot be independent from manual interpretation. On the contrary, it serves the manual interpretation in the aspect of improving accuracy and reducing workload.

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