Expert Classification Method Based on Patch-Based Neighborhood Searching Algorithm

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Abstract  The expert knowledge has been widely used to improve the remotely sensed classification accuracy. Generally, the expert classification system mainly depends on DEM and some thematic maps. The spatial relationship information in pixel level was commonly introduced into the expert classification. Because the geographic objects were found spatially dependent relationship to a certain degree, the commonly used basic unit of spatial relationship information in pixel greatly limited the efficiency of spatial information. A patch-based neighborhood searching algorithm was proposed to implement the expert classification. The homogeneous spectral unit, patch, was used as the basic unit in the spatial object granularity, and different types of patches’ relationship information were obtained through a spatial neighborhood searching algorithm. And then the neighborhood information and DEM data were added into the expert classification system and used to modify the primitive classification errors. In this case, the classification accuracies of wetland, grassland and cropland were obviously improved. In this work, water was used as base object, and different types of water extraction methods were tested to get a result in a high accuracy.

Keywords  classified patches; spatial relationship; expert knowledge

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Introduction

The information of earth surface collected from the aircraft or spacecraft remote sensing has been applied to land resource monitoring, agriculture production assessment, disaster mitigation, urban planning, surveying, mapping and other related fields\cite{1}. The classical remote sensing classification was to classify the remotely sensed image depending upon the visual interpretation, which is time-consuming and the results were usually different because of interpreters’ experience. With the development of the computer technique, computer-aided classification gradually replaced the visual interpretation. Computer-aided classification could be divided into two types: supervised and unsupervised classification. Areas of interest (AOI) with definite class types need to be selected before implementing image classification if the supervised method is employed. Through comparing...
the spectral attribute similarity of any other areas in the image with the AOI, the classes in the image will be decided. In a broad sense, the artificial intelligent methods such as artificial neural networks (ANN) and genetic algorithm (GA) should belong to the supervised method. While in the unsupervised classification, it is not necessary for the remote sensed image interpreter to have to collect AOI before implementing classification and the classified result depends on clustering pixels according to their spectral distances. In this approach, some independent spatial patches with no class attributes can be gotten, which class types must be defined by the interpreter. As it is difficult to achieve a required accuracy using ordinary classification, some expert knowledge is usually integrated into the classification to improve the classification accuracy.

The remotely sensed image classification was generally reported in three levels. Firstly, only spectral characteristics in pixel were used in the image classification, in which individual or multi-bands spectral data might be used. Secondly, above spectral information is integrated with spatial distribution patterns of spectrum such as texture[2] or some simple spatial relationships in pixel level[3] in the image classification. Thirdly, except for the mentioned spectral information, DEM and other GIS thematic data could be used in the image classification, in which the earth object distribution were used as criteria to improve the classification accuracy[4,5]. In this paper, a hybrid method was proposed to implement image classification, in which the DEM data and the GIS spatial relationship were introduced as auxiliary information. The object-level spatial relationships were firstly extracted from the initially supervised classified patches that were used as basic analytical units, and then they were used as a part of expert knowledge in the object-level spatial inference to implement an expert classification. The result showed an obvious improvement for the classification accuracy.

1 Expert classification

The classification result was often not satisfactory by using only spectral features, thus, some auxiliary information such as topography, soil type and historical classified type were introduced to improve the classification result. The auxiliary data are all related to the distribution pattern of the earth objects and effective to improve the classification result. According to the earth science theory, every geographical phenomenon could be described as the distribution of regional variables. Remotely sensed image is the representation of the geographical phenomenon, therefore, there must contain the regional variables in the images[6]. Based on this concept, new classification method of adding the spatial relationship information was developed[3]. According to the classification granularity theory proposed by Li Deren and Di Kainen there are two basic granularities, the pixel level and the object level in the classification[7]. Most of the classification methods mentioned above are focused on the pixel level. However, the spatial relationships among features are usually object-based, the object level granularity will be more proper to be considered in the RS image classifications.

The information used in the early stages of object-level granularity classification such as the angular second moment, correlation and entropy is the texture information in the RS images[8]. Some new classification methods based on object level granularity were recently proposed, which is heavily based on the segmented patches. However, the segmented patches were affected by segmentation methods and parameters, and there may yield quite different patches using different methods[9]. And no general standards were reported to assess the segmented patches, which hindered the application of this method.

The classified patches, which were the result of the spectral information clumping, could be regarded as the object for the spatial relationship inference. This paper attempted to introduce the inference knowledge of the spatial object to enhance the classification accuracy. This method was considered effective only given some conditions satisfied, firstly, the reference class that was used to inference other class should be extracted with a high accuracy, and secondly, the relationship between reference class and inferred class should be able to depict as the computer algorithm. In this study, the extracted water body, with high classification accuracy, was used as the reference class to
inference the wetland class because the distribution of wetland is closely related to water body. The classification errors in wetland were then corrected by using DEM data and the obtained spatial relationship in patches.

2 Experiment and procedures

The study area is located in the eastern Hubei Province of China, and its extent is from 112°55'E to 115°14'E, from 29°35'N to 31°25'N. Wuhan City is the economic, cultural and political center of both the study area and the province. The remotely sensed data includes two temporal TM/ETM+ images acquired in Oct. 1988 and Nov. 2002, respectively. The general classification methods could not match the accuracy demand. In order to improve the classification results, we proposed a spatial relationship method. Water body was first extracted which had a high accuracy in the primitively classification results. The non-water area was then identified and was then classified as forest, farmland, wetland, urban, and bare land with supervised classification. In conjunction with the DEM data and patch spatial relationship, the expert knowledge was used in the expert system to correct the regular errors and the final result was achieved in a higher accuracy. The processing flow is as follows (Fig. 1).

![Flowchart of expert classification](image)

Fig.1 Flowchart of expert classification

2.1 Reference object extraction

In this paper, water body was used as the reference object, so it’s of critical importance to exact the water in a high accuracy. Although various methods of extracting water body could get high accuracy, it still needs to be processed to minimize the extract error when the water body was taken as the reference object in the inference process. A best extraction method must be identified before implement the inference. The simplest method to extract the water body was to determine a threshold using one-channel information. Analysis showed that the spectral characteristics of water body had obviously difference with other terrain targets in the band 5 of Landsat TM image. A threshold of 25 was found to be most reasonable in differentiating water from non-water area in our study. The extraction approach yields a good result except for a mountain shade’s confusion. In Fig. 2, the shadow strip of Mount Guishan along the Yangtze River within Wuhan City was mistakenly classified as water body. A better result could reach when multi-bands of spectral information were used. In multi-spectral remotely sensed image classification, the ratio or difference of spectral bands was usually used to enhance the contrast between the water body and other terrain targets over the image. In this paper, the ratio of band 5 and band 2 of Landsat TM image was used to extract water body. Although this band combination could reduce the shade effect to some extent, it can not eliminate that effect if the slope of the mountain is too large. Another method is band difference. It was found that the spectral sum of bands 2 and 3 of Landsat TM image is far greater than that of bands 4 and 5 for water body. Therefore, the four bands were chosen to extract water body with a threshold and could eliminate the shade effect[10]. There are some haze areas in the images of our
study area acquired in 2002, which bring difficulty in water extraction. The tasseled cap transformation (TCT) is usually used to reduce the effect of haze. To improve the TCT result, the at-satellite reflectance was used as the basis of the transformation so that to eliminate the effect of atmospheric impact for the use of across-scene and multi-temporal images[11]. The TCT transformation of Landsat 7 is depicted as follows.

$$\text{Brightness}=B_1 \times 0.356\ 1 + B_2 \times 0.397\ 2 + B_3 \times 0.390\ 4 + B_4 \times 0.696\ 6 + B_5 \times 0.228\ 6 + B_7 \times 0.159\ 6$$

$$\text{Greenness}=B_1 \times (-0.334\ 4) + B_2 \times (-0.354\ 4) + B_3 \times (-0.455\ 6) + B_4 \times 0.696\ 6 + B_5 \times (-0.024\ 2) + B_7 \times (-0.263\ 0)$$

$$\text{Wetness}=B_1 \times 0.262\ 6 + B_2 \times 0.214\ 1 + B_3 \times 0.092\ 6 + B_4 \times 0.065\ 6 + B_5 \times (-0.762\ 9) + B_7 \times (-0.538\ 8)$$

The information of water body could be well extracted from the wetness layer when a threshold was set according the wetness value. By this way, the haze areas could be isolated from images more easily than other methods. In addition, the ratio method was also found to be effective in removing the haze effect.

### 2.2 Patch-based neighborhood searching algorithm

In this study a raster thematic neighborhood searching algorithm based on spatial patches was proposed, and the algorithm and the spatially patch shape parameters calculation were implemented by the spatial modeling language (SML) in IMAGINE ERDAS8.6. The principle of the searching method was obtained by searching all objects within the threshold distance of a reference object, and after the clump (obtaining the patches’ ID, area, position and the class attribution) procedure, a map was received to record the IDs of searched patches and all the neighborhood patches within a defined distance of the reference object.

### 2.3 Expert classification based on spatial relationship of patches

The supervised classification was implemented for the non-water images, and the original classification results were gotten. And then the extracted water layer, DEM and the water neighborhood object information was added into the expert classification system to improve the original classification results. The expert system was composed of global database, knowledge base, inference engine and user interface. In this study, the knowledge classifier of IMAGINE ERDAS8.6 was selected as a platform, and the inference engine, user interface and global database were constructed on it. The kernel issue of the expert system was how to transform the expert knowledge into the knowledge base understood by a computer. In this paper, as the remotely sensed image was acquired between October to November, some rice paddies have been harvested, were similar to the wetland, which were mistakenly classified as wetland in the original classification results. Some grassland are confused with the wetland. According to previous study, the wetland in the study area belongs to middle and lower reaches shallow plant sub-region of Yangtze River, where the wetland is mainly distributed along the water body[12]. So the water body was used as the reference object to search neighborhood patches and we could consider the wetland should be within a spatial distance of rivers and lakes. When the wetland patch was within the threshold distance, the original class kept unchanged and when the patch was out of the threshold distance, the original class would
be modified as its correct type. In Fig.3, (a) and (c) are magnified final classification results, (b) and (d) are magnified Landsat TM false color composition images (RGB bands 4, 3, 2).

Fig. 3 showed a result of expert classification. Some errors of supervised classification were corrected, which were highlighted to show the difference between the two classified methods. The results showed that the farmland in Fig.3(a) and grassland in Fig.3(c) were mistakenly classified as wetland by the supervised classification method, and corrected by the expert classification proposed in this paper. In this study, using the patches relationship of wetland and water, and integrating the elevation and slope information from the DEM, some regularly mis-classified areas were corrected to the right classes.

2.4 Accuracy assessment of supervised and expert classification

In this study 500 check points (the point number of each class must be more than 10) were randomly selected to compare the classification accuracies of both supervised and expert classification. The results of the accuracy assessment were summarized as follows (Tables 1-5).

Above accuracy assessment results showed that the expert classification method based on spatial relationship of patches can obviously improve the classification results. Accuracies of wetland and grassland

| Point number | Training data (known cover types) | Total |
|--------------|----------------------------------|-------|
|              | Water   | Urban | Wetland | Grassland | Forest | Bare land | Farmland |       |
| Water        | 57      | 0     | 0       | 0         | 0      | 1         | 0        | 58    |
| Urban        | 0       | 24    | 0       | 0         | 0      | 3         | 4        | 31    |
| Wetland      | 0       | 0     | 39      | 25        | 0      | 0         | 37       | 101   |
| Grassland    | 0       | 0     | 0       | 36        | 3      | 0         | 13       | 52    |
| Forest       | 0       | 0     | 0       | 5         | 40     | 0         | 2        | 47    |
| Bare land    | 0       | 0     | 0       | 0         | 0      | 34        | 0        | 34    |
| Farmland     | 1       | 3     | 3       | 4         | 0      | 4         | 162      | 177   |
| Total        | 58      | 27    | 42      | 70        | 43     | 42        | 218      | 500   |
were increased. Because the aim of the classification in this study was for a further study of soil erosion, the classification standard of bare land was more strictly confined to the unused land without any vegetation, which lead to less area of bare land in the final classification results. As the spectral property of urban area is very complicated, which is easily confused with other land use types especially bare land. As for the farmland mainly consisting of rice paddy and upland field, its area was relatively large and the spectral characteristics were complicated depending on distinct types of crops, which made the farmland was almost confused with most of land use/cover types. According to the accuracy assessment, the overall accuracy of supervised classification was 78.40%, while that of expert classification reached 90.60%. And the Kappa coefficients were 0.724 and 0.874, respectively.

### 3 Results and conclusions

The phenomena of “same objects with different spectrum and different objects with similar spectrum” were very common in the nature. So the accuracy of spectral classification methods sometimes can not match the accuracy demand. The spatial relationship classification method, which could take the spatial distribution regularity into account, was introduced in the classification to improve the classification accuracy in this paper. According to our study, the homo-

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**Table 2** Confusion matrix of results by expert classification

| Point number | Water | Urban | Wetland | Grassland | Forest | Bare land | Farmland | Total |
|--------------|-------|-------|---------|-----------|--------|-----------|----------|-------|
| Water        | 57    | 0     | 0       | 0         | 0      | 1         | 0        | 58    |
| Urban        | 0     | 24    | 0       | 0         | 0      | 3         | 4        | 31    |
| Classification result | Water | 0     | 0       | 31        | 1      | 0         | 0        | 35    |
| Grassland    | 0     | 0     | 3       | 61        | 3      | 0         | 3        | 70    |
| Forest       | 0     | 0     | 0       | 5         | 40     | 0         | 2        | 47    |
| Bare land    | 0     | 0     | 0       | 0         | 0      | 34        | 0        | 34    |
| Farmland     | 1     | 3     | 8       | 3         | 0      | 4         | 206      | 225   |
| Total        | 58    | 27    | 42      | 70        | 43     | 42        | 218      | 500   |

**Table 3** Accuracy of classification results of supervised classification

| Point number | Training data | Classification result | Correct | Producer accuracy | User accuracy |
|--------------|---------------|-----------------------|---------|-------------------|---------------|
| Water        | 58            | 58                    | 57      | 98.28%            | 98.28%        |
| Urban        | 27            | 31                    | 24      | 88.89%            | 77.42%        |
| Wetland      | 42            | 101                   | 39      | 92.86%            | 38.61%        |
| Grassland    | 70            | 52                    | 36      | 51.43%            | 69.23%        |
| Forest       | 43            | 47                    | 40      | 93.02%            | 85.11%        |
| Bare land    | 42            | 34                    | 34      | 80.95%            | 100.00%       |
| Farmland     | 218           | 177                   | 162     | 74.31%            | 91.53%        |

**Table 4** Accuracy of classification results of experts classification

| Point number | Training data | Classification result | Correct | Producer accuracy | User accuracy |
|--------------|---------------|-----------------------|---------|-------------------|---------------|
| Water        | 58            | 58                    | 57      | 98.28%            | 98.28%        |
| Urban        | 27            | 31                    | 24      | 88.89%            | 77.42%        |
| Wetland      | 42            | 35                    | 31      | 73.81%            | 88.57%        |
| Grassland    | 70            | 70                    | 61      | 87.14%            | 87.14%        |
| Forest       | 43            | 47                    | 40      | 93.02%            | 85.11%        |
| Bare land    | 42            | 34                    | 34      | 80.95%            | 100.00%       |
| Farmland     | 218           | 225                   | 206     | 94.50%            | 91.56%        |

**Table 5** Kappa statistics comparison of both classifications

| Class      | Supervised classification Kappa | Expert classification Kappa |
|------------|--------------------------------|------------------------------|
| Water      | 0.980 5                        | 0.980 5                      |
| Urban      | 0.761 3                        | 0.761 3                      |
| Wetland    | 0.329 8                        | 0.875 2                      |
| Grassland  | 0.642 2                        | 0.850 5                      |
| Forest     | 0.837 1                        | 0.837 1                      |
| Bare land  | 1                               | 1                            |
| Farmland   | 0.849 7                        | 0.850 3                      |
geneous units that generated from supervised classification could be used as spatial objects, and their spatial relationship could be used to improve the classification accuracy. The ordinary classification methods usually consider the spatial relationship among the pixels and mainly focus on the pixel-level texture. The object-level spatial information has been ignored in the ordinary classification, which is more meaningful for the expression of the spatial regularity. In this study, the spatial relationship was extracted from the object-level to correct the regular error so as to improve the final results, and the spatially dependent relationship of different terrain objects was used for a better exploration of information hided in images, which brought more effective utilization in the image analysis. In our experiment, the results of supervised classification and feature extraction were taken as initial information to mine the terrain spatial patterns. Based on the geospatial knowledge, the regular error of initial classification was corrected using the expert classification system in the software of IMAGINE ERDAS8.6. In this study, different extraction methods of reference object, water, from Landsat TM image were discussed. The results suggested that four bands combination method ((band2+ band3)-(band4+band5)) could extract the water body very well without haze in the images. If there are hazes in the images, the TCT transformation method based on the at-satellite reflectance could get better results than the four band combination one. And the ratio method (band2/band5) could also get good results.

The method proposed in this paper still needs more attempts to verify its efficiency, and many problems are also in need to be studied. Firstly, the common spatial relationship of geographical objects is too difficult to generalize, especially identified by a computer algorithm. Secondly, the reference object like water with high extraction accuracy is not easy to be found, which would limit its application. Finally, the texture information in object level would be more meaningful. Obviously, when the multi-source information can be integrated, the extraction accuracy for single type of objects would be improved greatly, which will encourage the application of the proposed method.

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