COMPOUNDED METHOD FOR LAND COVERING CLASSIFICATION BASED ON MULTI-RESOLUTION SATELLITE DATA

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Abstract: As to the synthetical estimation of land covering parameters or the compounded land covering classification for multi-resolution satellite data, former researches mainly adopted linear or nonlinear regression models to describe the regression relationship of land covering parameters caused by the degradation of spatial resolution, in order to improve the retrieval accuracy of global land covering parameters based on the lower resolution satellite data. However, these methods can't authentically represent the complementary characteristics of spatial resolutions among different satellite data at arithmetic level. To resolve the problem above, a new compounded land covering classification method at arithmetic level for multi-resolution satellite data is proposed in this paper. Firstly, on the basis of unsupervised clustering analysis of the higher resolution satellite data, the likelihood distribution scatterplot of each cover type is obtained according to multiple-to-single spatial correspondence between the higher and lower resolution satellite data in some local test regions, then Parzen window approach is adopted to derive the real likelihood functions from the scatterplots, and finally the likelihood functions are extended from the local test regions to the full covering area of the lower resolution satellite data and the global covering area of the lower resolution satellite is classified under the maximum likelihood rule. Some experimental results indicate that this proposed compounded method can improve the classification accuracy of large-scale lower resolution satellite data with the support of some local-area higher resolution satellite data.

Key words: Multi-spatial resolution, Land covering, Compounded classification, Parzen window.

1. INTRODUCTION

With the continuing improvements of earth observing technologies in multi-spatial resolution, multi-temporal resolution and multi-spectral resolution, compounded analytic technique based on multi-source satellite data has become one of the most important basic problems that need to be resolved urgently in this field. More actual information about the land covering circumstances could be obtained through the combination of multi-source satellite data, which could also decreases the mistiness of data analysis and data understanding, improves the efficiency of multi-source data utilization. Recent years has seen many developments in compounded classification methods, many researchers combined higher and lower resolution satellite data together with other data to analyze land cover mapping (Cihlar 2000).

Regression analysis technique has been widely used in compounded classification (Fazakas et al. 1996). In 2002, Tomppo et al. proposed a method to combine Landsat-TM data and IRS-1C WiFS data together with field data, and nonlinear regression analysis was used to derive models for volume and biomass parameters (Tomppo et al. 2002). However, regression model is a kind of indirect expansion of parameter scale, and couldn't authentically represent the complementary characteristics of spatial resolutions among different satellite data at arithmetic level. In other researches, higher resolution data and other data are used to instruct the supervised classification of lower resolutuon data. A global network of training sites using 156 Landsat scenes was derived to identify over 9000 pixels in the AVHRR data, and a global land cover classification product was provided in 1998 (DeFries et al. 1998). Both AVHRR data and geophysical datasets (e.g. climate, elevation) were combined for large-scale land-cover mapping in China, and land-cover dataset derived from TM data was used to assess the accuracy of the classification (Liu et al. 2003).

In the field of land covering classification of remote sensing data, the maximum likelihood approach is one of the most common methods. The precondition of maximum likelihood approach is the presupposition that statistical characters of cover types follow normal distribution. However, the presupposition would bring evident reduction of classification accuracy when real statistical distribution doesn't conform to normal distribution. Multi-spatial resolution data give us a new possibility to calculate the real likelihood function of each cover type (Qin et al. 2003).

This paper presents a compounded method for land covering classification of multi-resolution satellite data at arithmetic level. According to multiple-to-single spatial correspondence between the higher and lower resolution satellite data, likelihood functions of all cover types are obtained through the decomposition from a pixel in the lower resolution data to corresponding block of pixels in the higher resolution data, then the global covering area of the lower resolution data is classified using the likelihood functions. The compounded method attempts to acquire real likelihood functions of cover types in the lower resolution data with the assistance of the higher resolution data in some local regions, thereby realizes higher resolution accuracy classification over the large-scale lower resolution data.

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2. DESCRIPTION OF THE METHOD

The method presented in this paper aims to classify lower resolution data with the support of higher resolution data. Experiment data include lower resolution data, and higher resolution data that cover some local regions of the lower resolution data. The method only adopts single classification feature for the lower resolution data, but there's no such constraint for the higher resolution data.

The method adopts several pairs of test regions to derive likelihood distribution functions of all cover types. As to each pair of test regions, details of processes are as follows.

1) Choose a test region from the higher resolution data in which the characters of one or several cover types are distinct, then segment corresponding region from the lower resolution data. The lower resolution region is co-registered with the higher resolution region using ground control points. This pair of regions is analyzed in following processes in order to extract likelihood function of one or several cover types. Since the size of test region matters the extracting accuracy a lot, sizes of all pairs of test regions should not vary greatly. This problem would be discussed in the conclusion

2) Utilize ISODATA clustering algorithm to classify the higher resolution region.

3) Obtain classified result of the lower resolution region and calculate likelihood of each pixel belonging to its cover type according to multiple-to-single spatial correspondence between the higher and lower resolution satellite data (Zhukov et al. 1995). Then likelihood distribution scatterplot of each cover type is formed as shown in Figure 1, the x-axis of which is classification feature of the lower resolution data and the y-axis is likelihood value. It is questionable when the dominant land cover type covers much less than 50% of the pixel (Cihlar 2000), therefore pixels whose likelihood values are less then 1/3 are removed from the scatterplot.

4) Derive likelihood function from the scatterplot. Two-dimensional circularly symmetric normal Parzen window (Duda et al. 2001) is adopted to describe the scatterplot, as shown in Figure 2. The height of Parzen-window estimate shows the density at each point of scatterplot. As to each feature value on x-axis, peak value of Parzen-window estimates is considered as the likelihood that the feature value is classified as the cover type, as shown in Figure 3.

In the process of extracting likelihood function of a cover type, at least one test region from the higher resolution data should be chosen. Several likelihood functions of same cover type extracted from respective test regions are incorporated into one likelihood function based on the maximum likelihood principle. As the higher resolution regions are classified using unsupervised method and classification features of the higher and lower resolution data are not optimum, classification errors may exist in likelihood distribution scatterplots, therefore every likelihood function is examined and unsuitable ones are abandoned. Finally, with likelihood functions of all cover types, the global covering area of the lower resolution data is classified under the maximum likelihood rule.

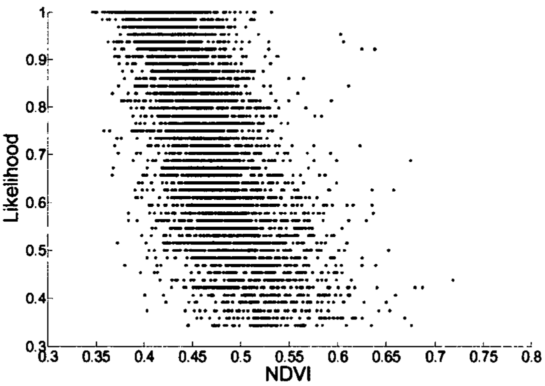

Figure 1. Distribution scatterplot of a cover type

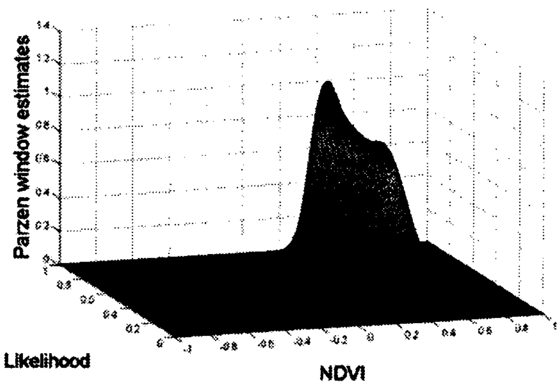

Figure 2. Parzen-window estimate of the scatterplot

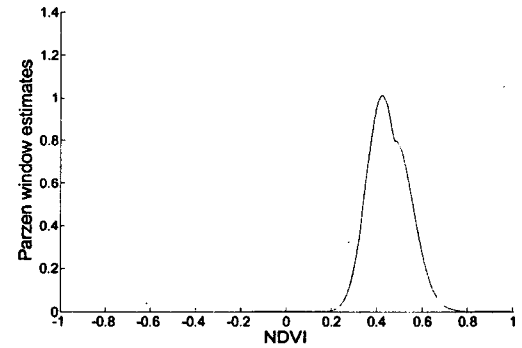

Figure 3. Likelihood function of the cover type

3. EXPERIMENTS AND RESULTS

3.1 First Experiment

The studied area is located in Beijing. Landsat TM data and MODIS data acquired on May 19, 2001 are used for the study. We choose NDVI of TM and MODIS as the classification features. MODIS Bands 1 and 2 which are sampled at 250m nadir spatial resolution generate 250 m MODIS NDVI product. TM data of 30m resolution are resampled to 31.25m resolution. Therefore, the resolution ratio between MODIS and TM data is 1:8, and each pixel of MODIS corresponds to a block of 8×8 pixels of TM.

Five cover types are considered in the studied area: Forest, Farmland, Barren land (including thin shrub), Residential area and Water body. We adopt six pairs of test regions (as the black rectangles shown in Figure 5,), which are respectively co-registered and registration errors are less than one pixel. ISODATA approach is employed to classify higher resolution test regions, and final likelihood functions of five cover types (Figure 4) are extracted from likelihood distribution scatterplots. As the window function in Parzen window approach is of the form of bivariate normal density, the shapes of the likelihood function curves are similar to normal density, but essentially likelihood function represents the density of points in likelihood distribution scatterplot. Furthermore, we could notice that the y-axis values of likelihood function curve might exceed 1, because the curve just represents the density of likelihood and hasn't been scaled.

Global covering area of MODIS is classified with the likelihood functions under the maximum likelihood rule, and the result is shown in Figure 5. Post processing includes eliminating isolated points from the classified result. The overall classification accuracy is 78.50%, and the corresponding confusion matrix is shown in Table 1.

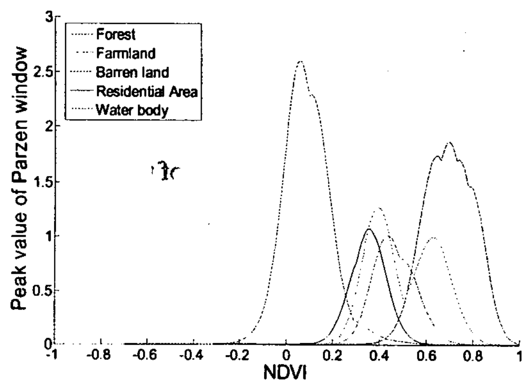

Figure 4. Likelihood functions of five cover types

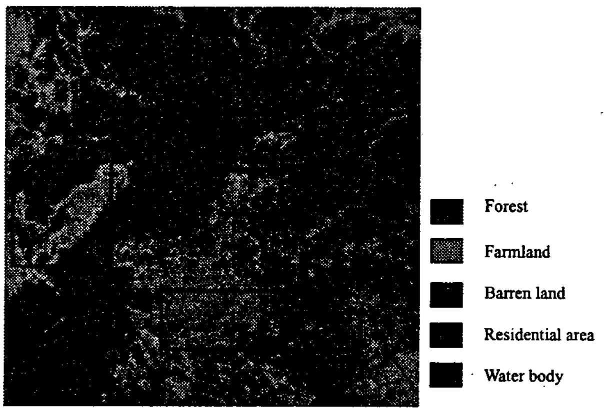

Figure 5. Classification result of MODIS data using the compounded method

The classification accuracies of Farmland and Residential Area are a little lower than that of other cover types. Because some farmland areas of growing crops have high NDVI values, they are classified into the cover type of forest, and on the other hand, some farmland areas are classified as barren land for there weren't crops growing in those areas at the time. The comparison between classification accuracy of the proposed compounded method and that of ISODATA approach is listed in Table 2. The global covering area of MODIS data is classified with ISODATA approach, and the classification feature is also NDVI of MODIS. The overall classification accuracy of ISODATA approach is 74.17%. We can see from the table that the result of compounded method is much better than that of the traditional unsupervised method.

3.2 Second Experiment

The second studied area is located in Miyun, Beijing. IKONOS MSI data of May 7, 2002 and TM data of June 15, 2002 are used in the experiment. The IKONOS data haven't a near-infrared band, therefore we use all three bands (blue, green and red) of IKONOS as classification features. As to TM data, we use the first principal component of following three bands as classification feature: band5 / (3×band7), band3 / band1, (band4×2) / band3. The spatial resolution of IKONOS MSI data is 4m, and the spatial resolution of TM data is 25m. The TM data are resampled to 24m resolution, then a pixel of TM corresponds to a block of 6×6 pixels of IKONOS. Nine pairs of test regions are segmented from original data to extract likelihood functions, and the resulting likelihood functions are shown in Figure 6. Global covering area of TM is classified using the functions, and accuracy of the classification result is assessed by IKONOS PAN and MSI bands.

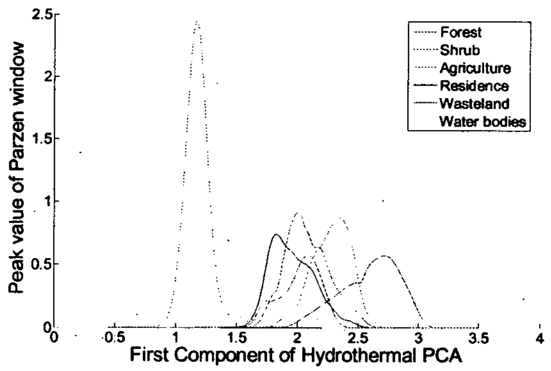

Figure 6. Likelihood functions in second experiment

The overall classification accuracy of the new proposed compounded method is 53.40%. To compare with unsupervised method, the global covering area of TM is classified with ISODATA approach, and overall classification accuracy is 51.40%. Both accuracies are low because there exists much cloud in TM data and inexistence of near-infrared band leads errors to the unsupervised classification over IKONOS test regions.

	Reference Classes					Users Accuracy
	Forest	Farmland	Barren land	Residential area	Water body	
Forest	146	20	2	0	0	86.90%
Farmland	0	73	34	14	1	59.84%
Barren land	2	10	102	11	1	80.95%
Residential area	3	12	15	60	4	63.83%
Water body	0	0	0	0	90	100.00%
Producers Accuracy	96.69%	63.48%	66.67%	70.59%	93.75%	

Table 1. Confusion matrix

	Forest	Farmland	Barren land	Residential Area	Water body	Overall accuracy
Compounded classification	86.90%	59.84%	80.95%	63.83%	100.00%	78.50%
Unsupervised classification	79.35%	57.72%	80.95%	58.10%	100.00%	74.17%

Table 2. Comparison of Accuracies between compounded method and unsupervised method

The likelihood function curve of Wasteland is overlaid by likelihood function curves of other cover types, which results in that no points in global covering area of TM data are classified as Wasteland, therefore the classification accuracy of Wasteland is zero and affects the overall accuracy. The main reason lies that the classification feature of the lower resolution data in this experiment could not separate wasteland from other cover types.

4. CONCLUSION

Both experiments demonstrate that the compounded method put forward in this paper improves classification accuracy compared with traditional unsupervised method. The compounded method means to utilize the complementary characteristics of spatial resolutions among different satellite data at arithmetic level, and extract likelihood distribution functions of cover types through unsupervised classification of higher resolution satellite data and multiple-to-single spatial correspondence between the higher and lower resolution satellite data. The compounded method realizes higher resolution accuracy classification over lower resolution data and achieves the purpose of obtaining better classification accuracy with less expenditure of purchasing data.

There're also some limitations in our experiments. Only single classification feature is adopted for the lower resolution data, whereas single feature might not result in high classification accuracy. Multiple classification features would be introduced into the compounded method in further research. On the other hand, the main limitation exists in the process of extracting likelihood function from likelihood distribution scatterplot. The process adopts Parzen window approach which could embody the distribution density of points in scatterplot, however, it might lead uncertainty because the number of points varies a lot in different scatterplots and influences the height of Parzen window estimation greatly. Therefore we require that sizes of all test regions not differ widely, and further research would attempt to reform scatterplot under the principle of retaining the original distribution implied in it.

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