Object-based Analysis for Extraction of Dominant Tree Species

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Abstract As forest is of great significance for our whole development and the sustainable plan is so focus on it. It is very urgent for us to have the whole distribution, stock volume and other related information about that. So the forest inventory program is on our schedule. Aiming at dealing with the problem in extraction of dominant tree species, we tested the highly hot method-object-based analysis. Based on the ALOS image data, we combined multi-resolution in eCognition software and fuzzy classification algorithm. Through analyzing the segmentation results, we basically extract the spruce, the pine, the birch and the oak of the study area. Both the spectral and spatial characteristics were derived from those objects, and with the help of GLCM, we got the differences of each species. We use confusion matrix to do the Classification accuracy assessment compared with the actual ground data and this method showed a comparatively good precision as 87% with the kappa coefficient 0.837.

Key words Tree species, Object-based analysis, High-resolution image, Fuzzy classification

1 Introduction

Remote sensing and image interpretation technology have been widely used in large-area forest management in recent years. Based on the interpretation of image data, we improve our efficiency and save a lot cost. But in previous program, we considered TM, MODIS *etc*. Mid or low-resolution images most for image interpretation process, form which we can only get the rough information of the forest like pure or not pure. We have no idea about detailed forest types which can be very important in forest inventory program. With the high-resolution image occurring, it is much easier for us to get more information from imagery data because we could see more clearly even a separate tree. In spite of this, automatically classification of forest types is still problematic due to the phenomenon that different types may have the same spectral reflection characteristics. As the traditional classification method could not satisfy the demand the accuracy we need and the sault-pepper phenomenon of the result seriously affects our judgment. So, how to extract useful information from the high-resolution image data, and how to effectively classify the different types of forest deserves discussion. Fortunately, researchers explored a new try in image processing field. That is the object-based analysis. Previous studies on high-resolution image proved there is much information contained in spatial relations of pixels. The contribution of textural and structural information is also very important in image analyzing process. With this method brought up, some researchers have been concentrated on taking advantage of the spatial information lied in the image. Chubey *et al.* (2006) got forest structure parameters using objected-based classification method. Herrera *et al.* (2004) identified the tree species in the non-forest area. Shiba and Itaya (2006) estimated the forest volume in middle Japan based on high resolution images and take into account of environmental change. Lackner and Conway (2008) automatically divided the land cover using IKONOS image and the accuracy is up to 88%. Mallinis *et al.* (2008) tested the multi-resolution image segmentation on an area located in Greece and got a nice result. Bunting and Lucas extract tree crown information from mingled forest based on CASI data and high-resolution data. Wang Changying *et al.* (2008) studied the land cover types of Yalutsangpo River district using SPOT-5 images combining NDVI and shape *et al.* texture parameter by object-based analysis. Generally, image object-based classification method includes four steps: image segmentation stage; object analysis stage; classification stage and the accuracy assessment stage. However, how to effectively use the object features and how to solve the mixture of classes of each object. We will try to combine the two steps in a system. This paper explores a way to extract dominant tree species using the object-oriented analysis in eCognition combined with fuzzy classification means and present the possibility of automatically identify trees from high resolution images.

2 Main content of experiment

Object-based classification generally consists of three steps: (i) creation of image objects using an image segmentation algorithm; (ii) extraction of object features; (iii) classification using the features. This study we will try to integrate these steps to improve dominant tree species identification taking advantage of the high-resolution image.

2.1 Image segmentation Multi-resolution segmentation is a region-merging algorithm which first proposed by Martin Baatz and Arno Schape. The whole process showed in Fig. 1 is described as follows: at the beginning, pixels are firstly merged into many small objects or regions and then these small objects are continued being merged into larger regions.

This image segmentation requires several parameters decided by users according to demand. They are: (i) weights of associat-

Received: April 21, 2015 Accepted: June 26, 2015
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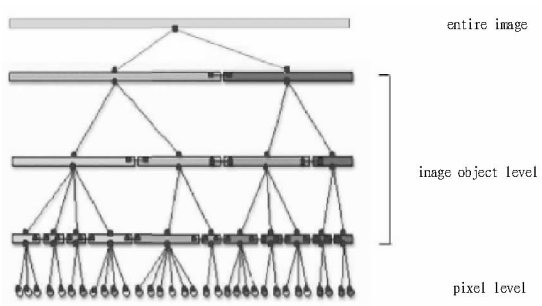

Fig. 1 The structure of muti-resolution segmentation of eCognition

ed layers; (ii) a color/shape ratio closely related to spectral/shape criterion of homogeneity; (iii) a compactness/smoothness ratio according to the object shape; (iv) a scale parameter which decides how large the objects are. Heterogeneity in eCognition considers primarily color and shape of objects. The heterogeneity f is controlled by these parameters we set.

$$f = w_{color} \cdot \Delta h_{color} + w_{shape} \cdot \Delta h_{shape}$$
$$w_{color} \in [0,1], w_{shape} \in [0,1], w_{color} + w_{shape} = 1 \quad (1)$$

where Δh_{color} and Δh_{shape} are the indexes of shape and color, respectively; Δw_{color} and Δw_{shape} are the weight of them.

In order to realize multi-bands segmentation, we need to add another w_c which defines the weight of all layers.

$$\Delta h_{color} = \sum_c w_c [n_{merge} \cdot \sigma_{c,merge} - (n_{obj\_1} \cdot \sigma_{c,obj\_1} + n_{obj\_2} \cdot \sigma_{c,obj\_2})] \quad (2)$$

where n_{merge} is the number of pixels within merged objects; n_{obj_2}, n_{obj_1}, are the number of pixels before being merged in object 1 and 2 respectively; σ_c is the standard deviation within objects of layer c.

Shape heterogeneity describes the shape from the opposite two sides-the smoothness and compactness.

$$\Delta h_{shape} = w_{copmt} \cdot \Delta h_{copmt} + w_{smooth} \cdot \Delta h_{smooth} \quad (3)$$

$$\Delta h_{smooth} = n_{merge} \cdot \frac{l_{merge}}{b_{merge}} - (n_{obj\_1} \cdot \frac{l_{obj\_1}}{b_{obj\_1}} + n_{obj\_2} \cdot \frac{l_{obj\_2}}{b_{obj\_2}}) \quad (4)$$

$$\Delta h_{copmt} = n_{merge} \cdot \frac{l_{merge}}{\sqrt{b_{merge}}} - (n_{obj\_1} \cdot \frac{l_{obj\_1}}{\sqrt{b_{obj\_1}}} + n_{obj\_2} \cdot \frac{l_{obj\_2}}{\sqrt{b_{obj\_2}}}) \quad (5)$$

where l is perimeter of object; b is perimeter of object's bounding box.

2.2 Object features The features we used in this study based on spectral and texture information calculated from the objects derived from segmentation. Besides spectral characteristics like mean value of each layer, vegetation index and stand deviation of each band, higher-order texture measurement such as GLCM (Grey Level Co-occurrence Matrix) was applied in our study. GLCM is a tabulation of how often different combinations of grey levels occur at a specified distance and orientation in an image object. The character values of this matrix are very useful in classification for presenting the DN change rule.

2.3 Fuzzy classification method Fuzzy classification is a classic soft classifier which takes some factors into account including uncertainty in sensor measurement, vague class descriptions and class mixtures due to limited resolution. Compared with crisp classification, this method change the "true or false" into the continuous range of [0, …., 1]. Avoiding arbitrary sharp thresholds, fuzzy logic imitates the complexity of real world much better than the simple boolean systems do. Fuzzy logic can model imprecise human thinking and can represent linguistic rules. Based on the fuzzy logic membership function, we select some features to representing the dominant tree species in the study area. We used some experimental function to describe the change potential of different selected characteristics. In the classification process, different objects were labeled different degrees and at last decide the class considering comprehensible factors.

2.4 Study area The study was undertaken in a mature forest ecosystem located in the Dailing distict of Yichun, China (Fig. 1). The study area is a part of Da Hinggan Ling. Forests in the study area consist mainly of coniferous species including Korea pine, larches and spruce occurring at the top of the mountain or hillside. Deciduous forests consisting mainly of oaks and birch occurring in pure stands and mixed with conifers are present at lower elevations.

2.5 Data preparation Digital image data was acquired over the study area by the AlOS satellite on 8 September 2010. This data set was consisted of single panchromatic band imagery with the spatial resolution of 2.5m and 4-band multi-spectral imagery with the spatial resolution of 4m divided into the following spectral bands: blue (420 – 500nm), green (520 – 600nm), red (610 – 690nm) and near-infrared (760 – 890nm).

2.6 Application of the proposed method We have two level segmentations. The first is to separate forest from other types of land cover. We use a much bigger scale. Considering it is related to NDVI index, we add the NDVI band in the segmentation process. In this level, we use NDVI value as a condition to extract all the forestland. We set the weights of every band as 1, the scale parameter is 50 and shape 0.2, compact of object 0.5. And then we use a smaller scale to segment the forest area again making sure it was divided into homogeneous objects. We set the weights of spectral bands as 0.5, NDVI layer 1 and panchromic layer 1, the scale parameter is 30 and shape 0.1, compact of object 0.7. The segmentation result is shown in Fig. 3.

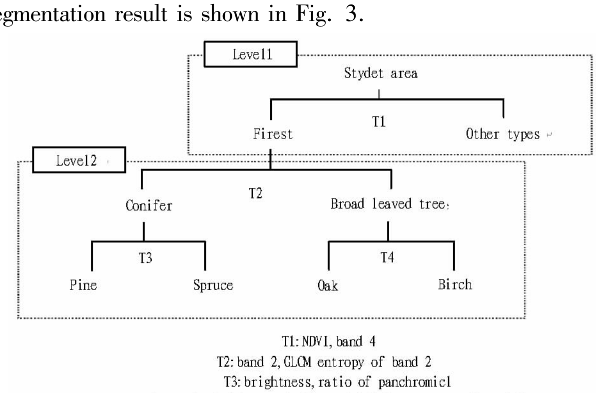

Fig. 2 Flow chart of classification

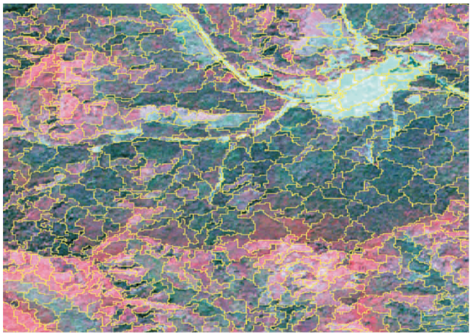

Fig. 3 Segmentation result

Having found that conifer and broad-leaved trees obviously different in reflecting near-infrared band, we separate them mostly under this condition. Comparing the sample data, pine and spruce have the detailed difference; we add the panchromic band information to separate these two kinds. As for oak and birch, we use the standard deviation of near-infrared band to identify them because they're so similar in spectral reflectance, so we have to find some texture difference as additional information in this process. The whole process is expressed Fig. 2 and segmentation result showed in Fig. 3. We can get the classification result showed in Fig. 4. We can see clearly in the image that non-forest area could be clearly seen in the red color though there are some shadow areas were wrong classified. The dominant tree species were extracted. And we can see most area covers the pine and this was the same with the truth. And there were still some broad-leaved tree species could not be identified.

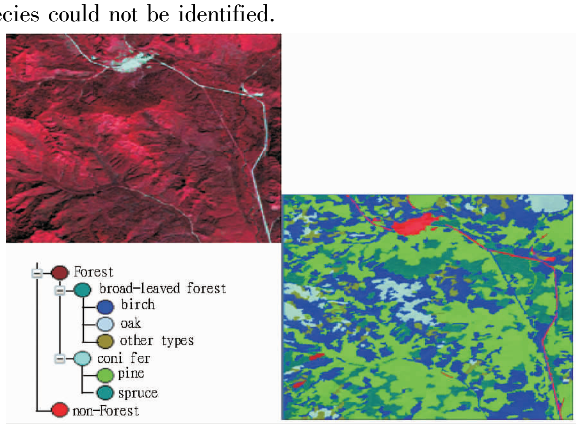

Fig. 4 Original image and classification result

In this paper, we evaluated the classification result by confusion matrix showed in Table 1. We got a high accuracy in classifying conifer forest while the oak and the birch were not that easily separated. Basically, we extracted the dominant tree species who occupied at least 65% space of sample area.

Table 1 Confusion matrix of result

overall accuracy = 0.87

Kappa coefficient = 0.83

Classes	Spruce	Pine	Birch	Oak	Total
Spruce	90	0	0	0	90
Pine	0	100	0	0	100
Birch	0	0	70	40	110
Oak	0	0	10	10	110
Total	90	100	80	50	

3 Conclusions

We can classify most of the dominant tree species in the study area. Derived from the true sample, we can conclude that due to the differences of the spectral and texture information between each kind, we can separate conifer forest and broad leaved forest, spruce and conifer , and even oak and birch. We can identify the tree category if it takes 70% space of a sample area. Choosing some object as validations, we can get all the accuracy assessment indexes clearly in the confusion matrix. The overall accuracy is about 87% and the kappa coefficient is 0.837. It reflects a high accuracy in this classification and it shows the potential to identify more detailed tree species using object-based analysis. Conclusion and Future Work: From an object we can not only get the spectral information but also texture that will help a lot in the classification. It provides us so many characteristics to express each class and make it easy to find some effective clues to extract what we need. However, our study also has some problems. (i) We can only identify the dominant tree species which occupied 65% of whole area. As to a more complicated situation, we still cannot solve. (ii) The accuracy assessment process is not that rigorous because we only have the point samples, for a further study we should use polygon samples. (iii) These thresholds used in the experiment were settled based on the data we use, as for other situations, they may not fit. (iv) We have not made any quantitative assessment of the segmentation result. Next, we can try to find a good way to assess it.

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[12] NIU JQ, XU F. Study on optimization of land use structure based on RS and ecological green equivalent[J]. Journal of Xinyang Teachers College (Natural Science Edition), 2009, 22(3): 410 – 413. (in Chinese).

[13] MAO WY. Overview of eco-environment impact assessment[M]. Beijing: China Environmental Science Press, 1998. (in Chinese).

[14] LIU NF, MING DP, YANG JY. Optimization of land use structure based on ecological green equivalent[J]. Geomatics and Information Science of Wuhan University, 2002, 27(5): 493 – 500. (in Chinese).

[15] ZHANG J, GONG JB, CHEN LW. A quantitative discussion on forest coverage of the optimum forest protective effect[J]. Scientia Silvae Sinicae, 1996, 32(4): 317 – 324. (in Chinese).

[16] GONG YB, ZHANG J, CHEN LW. Study on forest coverage of the optimum forest protective effect of a country[J]. Journal of Sichuan Agricultural University, 1996, 14(2): 231 – 236. (in Chinese).

[17] HU HK, ZHENG CY. Environmental impact assessment of land use change based on ecological green equivalent——A case study of Meizhou[J]. Research of Agricultural Modernization, 2008, 29(6): 743 – 746. (in Chinese).

[18] ZHAO D, LI F, WANG RS. Optimization of urban land structure based on ecological green equivalent: a case study in Ningguo City, China[J]. Acta Ecologica Sinica, 2011, 31(20): 6242 – 6250. (in Chinese).

[19] FENG XP. Analysis on countermeasures of water and soil conservation and eco – environment construction in China[J]. Agricultural Science & Technology, 2015, 16(2): 373 – 379.