Detecting urban vegetation from IKONOS data using an object-oriented approach

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***Abstract*— Urban vegetation plays a very important role in urban planning, environmental protecting, and sustainable development policy making. High resolution remote sensing imageries like IKONOS can provide such information economically and timely. However, the traditional classifying method based on pixel results in poor accuracy for the increased resolution causes not only in inter-class spectral variability but also intra-class spectral variability. Thus, developing a new method to extract thematic information from high resolution remotely sensed data might become one of the most challenging tasks of remote sensing within the coming years.**

This research proposed an object-oriented method to obtain the distribution of grass and tree in urban environment. The whole process included two steps: first, the original IKONOS data and the derived data of NDVI and VI were segmented at scale 5 and then, the objects obtained from this finer segmentation process were classified into two categories (vegetation and non-vegetation) using the feature space composed of mean NDVI, ratio near-infra, mean VI, ratio green band, and mean red band; second, the data of IKONOS, NDVI and VI within the vegetation area were segmented at scale 100, and then the objects from this lager scale segmentation were classified by the feature of Stddev red-infra into grass and tree. The result of accuracy assessment showed that the proposed method had produced distributed vegetation with over 97% overall accuracy.

Keywords-Urban vegetation; object-oriented method; IKONOS

I. INTRODUCTION

Urban vegetation is very important for people's living because it not only provides visual joy for people, but also influences directly or indirectly urban environment through its physical characteristics. For example, it influences urban environmental conditions and energy fluxes by selective reflection and absorption of solar radiation and by modulation of evapotranspiration [1]; the presence and abundance of vegetation in urban areas may also influence air quality and human health [2]. Thus, a reliable measure to the distribution of urban vegetation is getting more significant.

Traditionally, field survey and visual interpretation from aerial photography are widely used to extract such information. However, these methods are both time-consuming and expensive; moreover, field survey or aerial photography is usually scheduled once in a few years or longer. Thus, they are difficult to maintain an up-to-date database. Satellite remote sensing imageries, especially with their high spatial resolution like IKONOS (1m for the pan data), have the advantage of frequent revisit, large-scale coverage, and low cost, which can provide multi-temporal data for urban land use mapping, change detecting, and environmental monitoring.

While remote sensing imagery is introduced into applied areas, many vegetation indexes such as NDVI (normalized difference vegetation index), VI (vegetation index), SVI (Soil vegetation index), which are representative of plant's photosynthetic efficiency, have been widely used for presenting vegetation cover from different data source [3]. However, because of the coarse resolution of the remote sensing imageries like TM, it is impossible to exactly extract vegetation information from such imageries.

High resolution imageries can provide more precise distribution of objects for mixed pixels are much reduced. However, at high resolution imageries, an area that is formerly spectral uniform will be composed of pixels with a higher degree of spectral variation. Therefore, the statistical classification procedures based on pixels which have successfully separated spectral classes from coarse or medium resolution imageries based on their spectral properties alone do not work well at classifying high resolution imagery. An alternative solution, object-oriented classification method, is to incorporate as much information on spatial neighborhood properties as possible into the classification process [4]. The object-oriented method does not only resolve the problems mentioned above, but also can separate some classes which can not be separated by pixel-based method. In our case study, it is hardly to separate trees and grasses only based the spectral properties for their spectral information is close; their difference is in their texture characteristics, which the new method can solve easily.

The research reported here is to detect two kinds of urban vegetation using object-based method which, in fact, involves two steps, segmentation and classification. There are three aims of this study: the first is how to select original source as the segmentation, the second is how to extract thematic information at different scale and how to determine scales, the third is how to decide the feature space to classify objects.

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II. TEST AREA AND DATE PREPARATION

A radiometric and geometrically corrected, pan-sharpened, multi-spectral IKONOS sub-scene of 1 m pixel resolution acquired during September, 2002 is employed in the present study. This imagery is produced by fusing 11-bit of 1 m resolution panchromatic (0.45-0.90 μm) and 4 m resolution multi-spectral - blue (045-0.53 μm), green (0.52-0.61 μm), red (0.64-0.72 μm) and near infra-red (0.77-0.88 μm) channels via principal component analysis. The image of the test area (Fig.1) is 900 pixels and 800 lines, covering a part of Nanjing city in the Jiangsu province of China.

Other kind of data, a subset of 0.6m pan-sharpened multi-spectral Qucikbird image acquired in October 2002 covering the same test area is used here to evaluate the classified results.

It should be noticed here that the relative geometrically correction is processed to the two imageries though the two kinds of data have the same projection type, for when closely to compare the two data, there is still several pixels mismatching between them.

Figure 1. The subset of the test area (R: near infrared band, G: red band, B: green band)

III. METHODOLOGY

As noted in the introduction part, the object-oriented method includes two steps of segmentation and classification. The former relates to the grouping of image elements according to homogeneity into “objects”; while the latter is to classify these objects into categories. In this study, the process of segmentation and classification are used at two scales. At the first cycle, imagery data and the derived data are segmented at finer scale and the vegetation and non-vegetation information are obtained through near neighbor classification method using the feature space; at the second cycle, the resource of data in the vegetation area are segmented at coarser scale and then, the sub-class of grass and tree are acquired by the feature space (Fig. 2). During these processes, three problems should be resolved: the choice of data source for segmentation, the determination of scale for different type thematic information extraction, and the composition of feature space for classification.

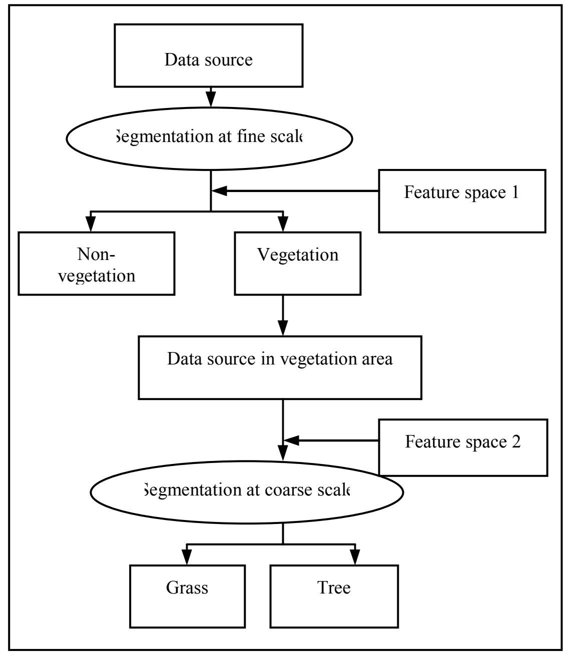

Figure 2. The flow chart of the process

A. Segmentation

The method, fractal net evolution approach is employed in this research. Using a parented segmentation algorithm, it allows homogeneous image object extraction in any desired resolution. This entails the simultaneous representation of image information on different scales.

Data source should be carefully considered for the results of the image segmentation strongly depend on the image data and the assessment of the segmentation results depends on the classification task. In this case study, we consider two items about extracting vegetation information and analyzing high resolution remote imageries in former researcher’s work: vegetation indexes are important for extracting vegetation information; the incorporation of spatial variation (image texture) in image classification procedures is an increasingly important aspect for high spatial resolution remotely sensed data analysis, and the overall improvement in classification accuracy indicates that the addition of image texture improves image classification [5].

Scale is important for segmentation because it determines the maximal allowed heterogeneity of the objects and thus indirectly influences the average object size. The final decision of scale parameters is often made by an interpreter based on his or her visual inspection of the image. But it is very consuming to conduct classification with all the possible scale parameters. Huang [6] proposed a method based on the max-area of objects to decide the optimum scale. She think that in the object-oriented classification system, the area of the object plays the same role as the pixel size in the image, and among area parameters, the maximum area of objects can present the changing characteristic with increasing of scale.

B. *Classification*

The classification process is based on fuzzy logic, to allow the integration of a broad spectrum of different object features such as spectral values, shape, or texture for classification. Utilizing not only image object attributes, but also the relationship between net worked image objects, results in sophisticated classification incorporating local context [7].

Here, the nearest neighbor classifier (NN) is used to classify the segmented objects. The method classifies image objects by a given feature space and with the help of given samples representing the concerned classes. After a representative set of sample objects has been declared for each class, the algorithm searches for the closest sample object in the feature space for each image object. If an image object's closest sample object belongs to class A, the object will be assigned to class A.

At this stage, there are two problems to be resolved. The first problem is sample choice for each category which is a prerequisite for better classification accuracy. This process is just like traditional method of supervised classification to choose sample area. The samples for each class should be representation all of the conditions of the category; otherwise, objects originally belonging to A will be classified to B or unclassified.

The second problem is to decide which features should be involved in the feature space to classify objects. Feature view can help to select features which have the possibility to separate classes; and the separation distance between different classes can be used to determine the optimum feature space through testing the samples of each category.

IV. RESULTS AND DISCUSSION

According to former researchers' work, the vegetation index of NDVI and VI, the texture characters of variance and mean coming from 7×7 window size [8 and 9] and the four bands of blue, green, red and near-infrared are chosen as the source of the segmentation for separate vegetation and non-vegetation.

During the process of scale increasing, not all of the areas of objects are increasing, but indicate complex. Fig. 3 shows the change trend of max-area of objects with the scale increasing. There are several phases and every phrase represents a range of optimum scales for a special category. In our test area, the scale 5 is used to extract vegetation information in case of the omission of some small trees or grasses; and the scale 100 is used to separate grass and trees from vegetation map.

At the segmented map by scale 5, the aim is to extract vegetation from the original data. Through feature view, Mean NDVI, ratio near-infra, mean VI, ratio green band, mean red band, Homogeneity by co-occurrence method are firstly chosen as the feature space. Fig. 4 shows the separation distance of feature spaces composed of different features. Based on the maximum distance 3.1, the optimum feature space can be determined by the following five features, Mean NDVI, ratio near-infra, mean VI, ratio green band, mean red band. The classified map is shown in Fig. 5.

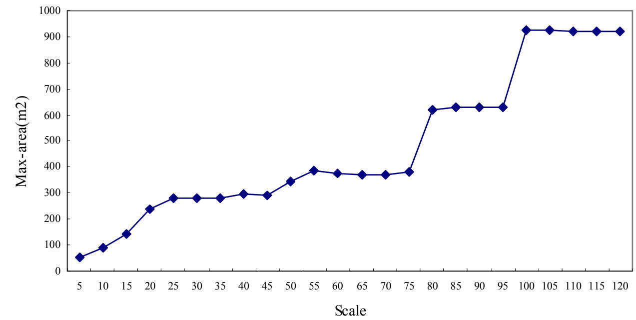

Figure 3. Change of objects max-area with segmentation scale

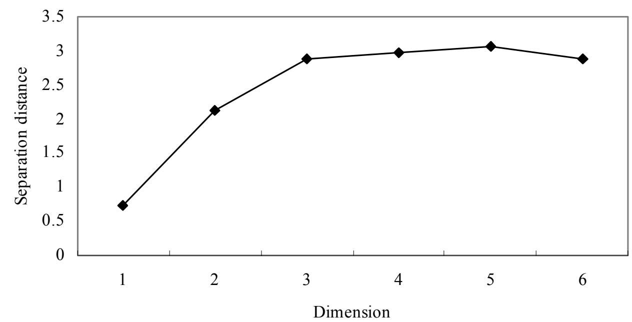

Figure 4. Optimum feature space for separate vegetation and non-vegation

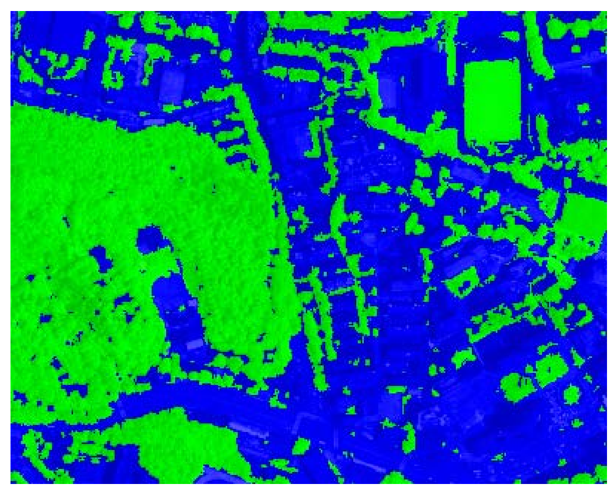

Figure 5. Spatial distribution of vegetation

Since the vegetation and non-vegetation information have been separated, the non-vegetated area can be considered as mask in order to avoid its neighbor influence to vegetation information. So the second segmentation is carried out within the vegetated area. At the segmented map by scale 100, the main goal is to separate tree and grass. Stddev red-infra, ratio red-infra, mean red-infra, contrast of red-infra, and homogeneity of red-infra are chosen firstly by view feature to constitute the feature space. Fig. 6 indicates the result of separation distance of different constituted feature space. Through comparing the separation distances, the feature space composed by Stddev red-infra feature is considered the optimum and the maximum distance is 2.78 (Fig. 6). The classified result is shown in Fig. 7.

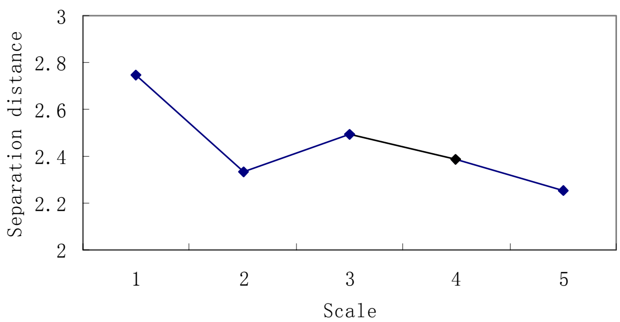

Figure 6. O ptimum feature space for separate vegetation and non-vegation

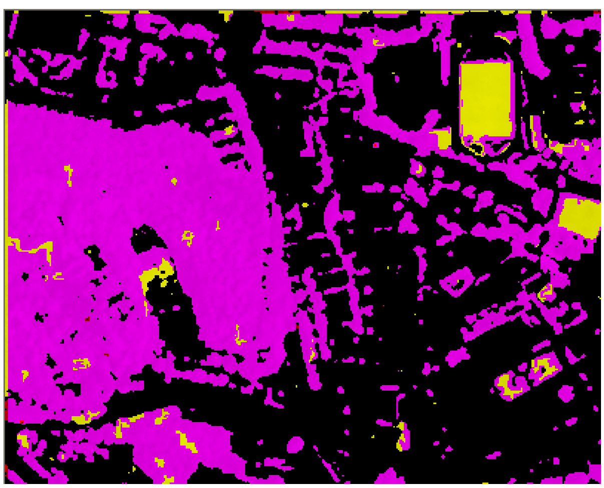

Figure 7. Spatial distribution of vegetation

The contingency table is acquired by the randomly distributed 200 points at both resulted and reference map. The reference value is got from the QuickBird data and combined field survey. Table 1 show that every category's producer's accuracy and user's accuracy are very high. The total accuracy (0.97) and the Kappa coefficient (94.35%) indicate that the method used in this study is reliable.

TABLE I. CONTINGENCY MATRIX FORM THE TEST AREA

Reference data	**Classified results**			
	Tree	***Grass***	***Non-veg***	***Producer's accuracy***
Tree	111	0	2	0.9823
Grass	0	10	1	0.9109
Non-veg	3	0	73	0.9605
User's accuracy	0.9737	1	0.9737	

a. Total accuracy: 0.9700

b. Kappa coefficient: 94.35%

V. CONCLUSION

This study proposed a method to detect grass and tree information in urban environment from high resolution remote sensing imageries. The accuracy result shows that the method is reliable to obtain the desired information. The desired information can refer to other thematic information, for example, water surface, impervious surface, and so on. But it should be noted here that when the aimed information is different, the scale and the feature space should be different and which are should determined by the characteristic of the aimed objects. From this study, the following conclusion can be made:

1) For special information extraction, the derived data are very useful. In our case study, NDVI, VI and texture characters are very helpful in the segmentation stage for they can enhance the vegetation information and enlarge the separation among different classes. Certainly, the derived data should be carefully tested before they are used to segment; otherwise, they will decrease the segmented results.

2) Segment special information and mask non-specified information can improve the classified results. Such disposal will remove the noise by neighboring influence from other types when to obtain sub-classes.

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