Dynamic monitor on urban expansion based on a object-oriented approach

Chunyang He; Jing Li; *JinShui Zhang;Yaozhong Pan; YunHao Chen
Key Laboratory of Environmental Change and Natural Disaster,
Ministry of Education of China, Beijing Normal University;
College of Resources Science & Technology,
Beijing Normal University, the People's Republic of China, 100875
* Corresponding author: zhangjsh@ires.cn

***Abstract*—In this paper, a new object-based change detection approach is developed. The approach consists of three steps: (1) producing multi-scale objects from multi-temporal remote sensing images by combining the spectrum, texture and context information; (2) extracting potential change object by the comparison of the attributes of shape, structure, texture, etc. of each object; (3) determining the changed object and detecting urban expansion area with the help of in-situ investigation. When the object-based approach was applied to the urban expansion detection in Haidian District, Beijing, China with the support of two Landsat Thematic Mapper (TM) data in 1997 and 2004, the satisfactory results were obtained. The overall accuracy is about 80.3%, Kappa about 0.607, which are more accurate than post-classification change detection. The newly developed object-based change detection approach possesses the advantage of its reduction to error accumulation of image classification of individual date and its independence to the radiometric correction to some extent.**

Keywords- change detection; object-orient; similarity; remote sensing; texture; land use/cover

I. INTRODUCTION

Timely and accurate change detection of earth's surface features is extremely important for understanding relationships and interactions between human and natural phenomena in order to promote better decision making [1]. Urban is the most sensitive in land use/cover change. To obtain the urban land use/cover change information is important for urban decision-making and sustainable development. The current change detection approach with remotely sensed data can be generally grouped as two types of spectral classification-based approach and pixel-by-pixel radiometric comparison approach. The former has the obvious limitation for its cumulative error in image classification of an individual date and the latter needs the strict radiometric correction, which is becoming the obstacle for their wide application in current urban expansion detection.

Objected-oriented change detection extracts the change information from the two temporal remotely sensed data based on object unit using the texture, structure and etc. There are some studies on the objected-oriented change detection. Ecological theory, in particular hierarchy theory, predicts that changes in landscape spatial pattern and temporal scales at which they are assessed [2]. Volker Walter segments the image using GIS database to obtain the change information [3]. Andreas S. Laliberte takes analysis for mapping shrub encroachment from 1937 to 2003 in southern New Mexico [4]. L. Bruzzone brought an adaptive parcel-based technique for unsupervised change detection. Ola Hall take a multiscale object-specific approach to digital change detection. All of above have made some success in change detection with objected-oriented change detection approach [5], whereas such application needs prior knowledge that leads to error accumulation, or average spectral information as object unit that destroy the spatial information.

Given the shortcoming of traditional land use/cover change detection and object-oriented approach, which are influenced by the sensor and weather. In this paper, making full use of the stability of spatial object texture between two temporal remotely sensed data, a new urban change detection approach that computes the object texture similarity between the two image at different is developed to extract the urban change information in order to obtain the urban/non-urban changed information accurately, which makes up for the shortcoming based on post-classification that produces the error accumulation and the present object-oriented approach that destroys the spatial information.

II. OBJECT-ORIENTED CHANGE DETECTION

Object, which is extracted from remotely sensed images, is the pixel collection that contains spectral, spatial properties. Let us consider two co-registered multispectral images, *X1* and *X2*, acquired in the same area at two different times, t1 and t2. Objects A and B are extracted from the *X1* and *X2*, respectively. Let *C* be defined the shared object of the two images, which satisfies the following conditions:

$$C = A \cap B \qquad (1)$$

$$S = R_C^{t1} \sim R_C^{t2} \qquad (3)$$

$R^{t1}_{A} = (f^{t1}_{i1}, f^{t1}_{i2}\ldots, f^{t1}_{iv}\ldots f^{t1}_{iR})$ is object A' the property collection, where f^{t1}_{iv} is the object A' v property, such as spectral, texture and etc. $R^{t2}_{B} = (f^{t2}_{i1}, f^{t2}_{i2}\ldots, f^{t2}_{iv}\ldots f^{t2}_{iR})$ is

The research is supported by National Hi-Tech Research and Development Program of China, (No. 2003AA131080)

object B' the property collection, where f^{t2}_{iv} is the object B' *v* property. *S* is the relationship of the entire object C' features which is shared by the two images. *S* will determine whether the object C will be changed or not at some rules.

III. FLOW OF OBJECT-ORIENTED URBAN CHANGE DETECTION

The approach of object-oriented urban change detection computes the two co-registered images' shared object similarity in order to determine whether the object has changed or not based on the multiscale object unit. Flow chart is illustrated in Fig. 1

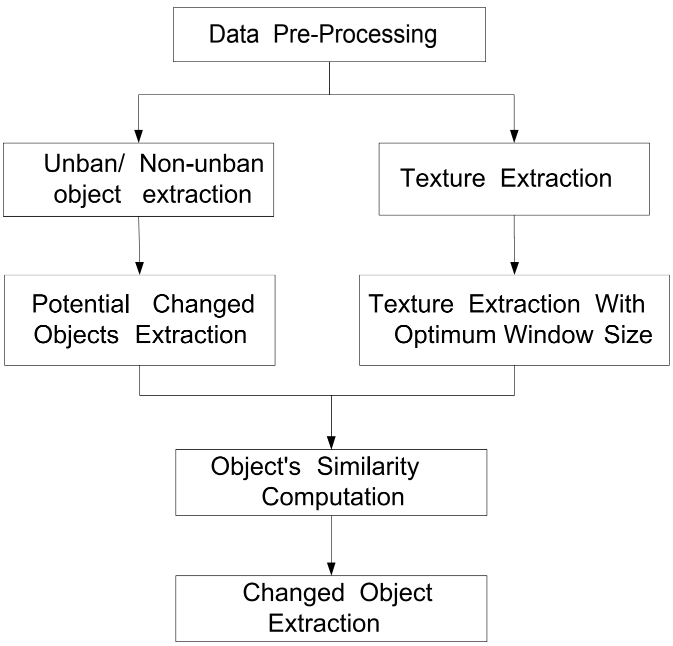

Figure 1. Flow Chat of Object-Oriented Change Detection

A. Extract the urban/non urban objects

Multiscale objects are extracted from the two images at different times according to the spectrum, texture, structure and context. In this study, we focus on urban and non-urban land type. Some land types such as water, vegetation are merged into non-urban, while others are merged into urban. The urban/non urban objects will be extracted from the two images by use of object-oriented supervised classification method.

B. Extract the potential change objects

There are two parts in urban change detection including urban changing into non-urban and non-urban changing into urban. From the first step, make the two result images from which the urban/non-urban objects are extracted by transfer image operation. There are four changed land type: urban to urban, non-urban to non-urban, urban to non-urban, non-urban to urban. The last two land change types are defined as the potential changed land type, while the former two change land types, which are classified accurately, are considered as unchanged land type. The potential changed objects are emphases during the urban object-oriented change detection.

C. Extract the texture information with the optimum window size

Texture property that is the pixel frequency of the images is the synthesis of the objects' shape, size, shadow and hue, and reflects the local pixels' gray value and hue rules. The texture property of the same land type possess stabilization without changing with times, which is usually to be adopted in change analysis about images at different times. The texture property is related to the pixel window size, and texture is extracted at different pixel window from different resolution images. So experiments are necessary to make certain the optimum window size in order to extract the texture information.

D. Compute potential change objects' similarity

After step (3) and (4), the objects' similarities are computed by use of the potential objects' properties including texture and structure. There are two kinds of modes to compute objects' similarity: Distance method and correlation coefficient.

(a) **Distance method** Similarity is computed by use of pixels' gray value, statistical value and property value. Generally. Distance is long, while the similarity is little. The method of absolute minus, average absolute minus and square minus are usually used during the distance computation.

(b) **Correlation method** Similarity is computed by use of two images vector's angles. The normalized multiplied correlation and correlation coefficient method are usually used. Let Xij belong to object A, while Yij belong to object B, then the similarity can depicted as follow.

$$S(A,B) = \frac{\sum_i \sum_j X_{ij} * Y_{ij}}{\sqrt{\sum_i \sum_j X_{ij}^2 * \sum_i \sum_j Y_{ij}^2}} \tag{3}$$

*X*ij and *Y*ij are the gray value of the two images, respectively, or some statistical value such as values of the mean, variance peak and etc, or the single pixel's change property value such as texture value, grades value and blur property value.

The objects' similarity is computed by use of spatial information, which are not same when the indices are different. Let us define the optimum spatial information indices that can separate the change/non-change object adequately.

The segregative degree of change/non-change objects, which are described as follow, is defined in order to separate the changed/unchanged objects.

$$f(c,uc) = \frac{|Mean_c - Mean_{uc}|}{Var_c + Var_{uc}} \tag{4}$$

$f(c,uc)$ is the segregative degree of changed/unchanged objects. $Mean_c$ and $Mean_{uc}$ is the mean value of change/non-change objects' similarity collection, respectively. Var_c and Varuc are variance values of the change/unchanged objects' similarities' variance. The higher of $f(c,uc)$ is, the more different between changed/unchanged object is, which can distinguish the changed object from non-changed object more effectively, otherwise the $f(c,uc)$ is lower, which can't distinguish them effectively.

E. set the threshold to extract the changed objects

The difference of texture between urban and non-urban is high, so the texture properties change a lot during the process of urban to non-urban or non-urban to urban. The changed objects that are extracted satisfy the follow:

$$O \begin{cases} 1 & (S > T) \\ 0 & (S < T) \end{cases}$$

S is the similarity degree. T is the threshold that is the boundary of changed and unchanged objects. If S is greater than T, objects have changed.

IV. CHANGE DETECTION EXPERIMENTS IN HAIDIAN DISTRICT

The study area is located westward and northwestward of Beijing, which is the center of scientific research of Beijing Capital and the important base of vegetable production. The urbanization in such place is mightiness. Obtaining urban change information is important for urban planning decision-making.

In this study, the cloud-free Landsat TM (123/32) images are used which are acquired on 1997-05-16 and 2004-5-19. The pixel size is 30m×30m. TM3, TM4 and TM5 contain the most abundant vegetation information. So such three bands are selected to extract urban change information. After image pre-processing, extracting urban/non-urban, determining the potential change objects, extracting texture information with optimum window size, computing the potential objects' similarity, setting threshold to extract the change objects, the results of urban/non-urban changed objects of Haidian District are obtained from 1997 to 2004, which compares with the post-classification.

A. Data Pre-processing

The data pre-processing includes the geometric correction and study area extraction. Firstly, the geometric correction that adopts two rank polynomial and double linear interpolation algorithm are applied at the 1997 image based on the 1999 image. Then 2004 image is corrected based on the 1997 image. After examination, RMS is less than one pixel. Finally, the study area is extracted from the corrected images.

B. Extract the urban and non-urban objects

In this study, eCognition3.0, which is the first object-oriented software, is adopted to extract the multiscale objects from the two images. The spectral parameter is set 0.8, while shape parameter is set 0.2, which includes smooth and density parameter, 0.9 and 0.1 respectively. The homogeneous object contains at least 20 pixels, which avoids producing minute size objects and satisfies the urban/non-urban change's basic unit. Because the transformation between urban and non-urban is the emphasis, urban, street and etc are grouped into urban, while forest, grass, rice field, garden are grouped into non-urban.

C. Extract the potential changed objects

Overlapping the maps by use of the map algebra produces four land types, including urban, urban to non-urban, non-urban to urban, non-urban. The non-urban to urban and urban to non-urban are looked upon as the potential changed objects.

D. Extract the texture information with optimum window size

In this study, the objects' similarities are computed using texture property. At present, the gray co-occurrence matrix brought forward by Haralick is used widely. The variance gray co-occurrence matrixes are extracted by Envi4.0. There are twenty typical changed and unchanged objects that are selected out to compute their similarities in order to obtain the optimum window size under which can distinguish changed objects form unchanged objects effectively.

The twenty changed and unchanged objects' values of mean and variance are computed according to the formula 3, and the segregative degrees about changed and unchanged objects with different window size are computed. The segregative degree under 3×3 window size is the highest, about 1.3360. We can draw a conclusion that the optimum window size that computes the objects' similarity from TM image is 3×3.

E. Combine the object to extract the changed information

During the object-oriented change detection, the object that shared by the two images are defined as the minimum unit. Illustrated in Fig2, the green parcels are the common part of the red polygons (1997) and the blue polygons (2004), which are the shared objects of the two images.

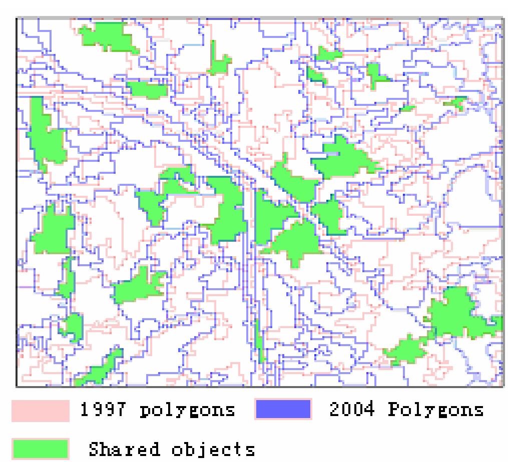

Figure 2. The Shared Objects of two images

The crossing point value of changed/unchanged curve is set the threshold, which is about 0.1157 [6]. The urban/non-urban objects' changed information is extracted. (Fig.3).

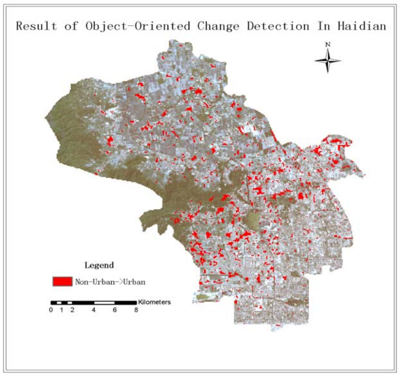

Figure 3. Result of the Objected-Oriented Change Detection

V. ACCURY ASSESSMENT

The 300 checked points are selected by use of the equalized random sample in order to illuminate the object-oriented urban change detection. The results are illustrated in Tab.2 and Tab.3. The accuracy of the object-oriented, overall accuracy about 78.7%, Kappa about 0.607, is higher than the post-classification's, which shows that the object-oriented change detection can obtain the change detection information effectively.

TABLE I. ACCURACY OF THE OBJECTED-ORIENTED CHANGE DETECTION

	Validated data				
	Changed	Unchanged	Total	Production accuracy	Loss error
Changed	135	15	150	90.0%	10.0%
Unchanged	44	106	150	70.7%	29.3%
Total	179	121	300		
Production accuracy	75.4%	87.6%			
Loss error	24.6%	12.4%			
Overall accuracy=80.3% Kappa=0.607					

TABLE II. ACCURACY OF THE POST-CLASSIFICATION CHANGE DETECTION

	Validated data				
	Changed	Unchanged	Total	Production accuracy	Loss error
Changed	128	22	150	85.3%	14.7%
Unchanged	56	94	150	60.0%	37.3
Total	184	116	300		
Production accuracy	69.6%	81.0%			
Loss error	30.4%	29.0%			
Overall accuracy =74.0% Kappa = 0.480					

VI. CONCLUSIONS

In this study, urban land use change information is extracted with the texture similarity by use the object-oriented approach. The results show that the change detection approach can extract the urban/non-urban change information effectively.

Firstly, the urban/non-urban change information are extracted by use of the texture similarity, which can avoid the strict radiometric correction. Because the texture property of the same land type will not change at different times, which have the strong stability, such property can be usually applied at the multitemporal images change analysis. Such method can also be able to be applied at the change information extraction from the images acquired by the different sensors.

Secondly, the accuracy of the object-oriented, which overall accuracy is about 80.3% and Kappa is about 0.607, is higher than the post-classification's, which overall accuracy is about 74.0% and Kappa is about 0.480. The object-oriented change detection approach integrates the multi-datasource including spectrum, texture and shape to extract the urban/non-urban objects, which possesses the more accuracy than post-classification that extracts the urban/non-urban information with the only spectral information. And the potential changed objects' similarity that can further identify that determine whether the changed objects will be changed or not can reduce error accumulation at some degree. While the error accumulation is the key factor that reduces the accuracy during the post-classification change detection.

Finally, the accuracy of the changed pixels extraction achieves 70.7%, which shows that the objects' similarity can separate changed/unchanged object effectively based on the object as the basic unit.

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