OBJECT-ORIENTED CHANGE DETECTION
FROM MULTI-TEMPORAL REMOTELY SENSED IMAGES

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ABSTRACT:

An object-oriented change detection algorithm was proposed and experimented to multi-temporal ALOS remotely sensed images. In contrast with conventional pixel-based algorithms, this approach processed homogenous blocks generated by object-oriented image segmentation for change detection. Similar pixels were merged into homogeneous objects by image segmentation at first, and each object (polygon) was described using spectral, texture, shape and other features, which were then exported as the .shp files of ArcGIS. Two segmented polygon layers from two-date remote sensed images were overlapped to create a new polygon layer, and attribute operations to each polygon in the overlapped layer were conducted to determine the thresholds and find those changed polygons. This object-oriented change detection approach was used to land cover change detection over the urban area and mining area of Xuzhou city, and the experimental results indicate that the proposed method is effective to change detection from multi-temporal ALOS satellite images.

1. INTRODUCTION

Land use/land cover information of urban areas is essential for urban planning and other purposes (Ridd and Liu, 1998). With the rapid economic and social development, the ground surface changed more quickly than ever before over urban areas. Among all available techniques, remote sensing constitutes the most feasible and efficient way for land cover change detection (Nemmour and Chibani, 2006). The traditional scheme for image processing has been pixel-based analysis, evidenced by both academic research and commercial remote sensing image analysis systems (Hurd et al, 1992; Wilkinson, 2005). The most conventional change detection method is based on multi-temporal image classification, in which either pairs of single-date classification maps are compared according to the transfer matrix (Hurd et al, 1992). Although this method is easy to implement, its efficiency is highly dependent upon prior classifications accuracy (Cardille and Foley, 2003). Other change detection algorithms include image differencing (Jensen and Toll, 1982; Singh, 1989), image overlaying (Howarth and Boasson, 1983), multi-temporal change vector (Lambin and Strahler, 1994), image regression (Ingram et al, 1981; Fraser, 2005), principal component analysis (Fung and LeDrew, 1987), neural networks (Woodcock, 2001) and support vector machines (Nemmour and Chibani, 2006). Despite the methodological strengths of all these methods, they are still based on pixel level processing, which is different from the structure of ground surface and human recognition to natural objects. Comparing with pixel-based methods listed above, some researchers have focused on the object-based image processing and change detection methods (IM et al, 2008; Blaschke, 2005; Walter, 2004). The objective of this paper is to develop an object-based change detection approach and then

use multi-temporal ALOS remotely sensed images to experiment its performance.

2. STUDY AREA AND DATA USED

2.1 Study Area

The study area is Xuzhou City, the northwest of Jiangsu Province of China, located at 33°43′~34°58′ N and 116°22′~118°40′ E. Xuzhou City is in the southeastern part of the North China Plain, and most of the study area is plain except some small number of hills. The city is crisscrossed by a network of rivers, and its whole forest coverage rate is 22.5%. In this paper, two case study areas were selected. Case area A is a square area around the Nanhu Campus of China University of Mining and Technology with size of 500×500 pixels, and case area B is Pangzhuang mining area located in the northwest of Xuzhou city with size of 375×375 pixels. Figure 1 shows the location of two case areas and their false composite images.

2.2 Data

ALOS stands for Advanced Land Observing Satellite, which was launched by Japan Aerospace Exploration Agency (JAXA) in January 2006. It has been developed to contribute to such fields as mapping, precise regional land coverage observation, disaster monitoring, and resource surveying. ALOS is equipped with three sensors: Panchromatic Remote-sensing Instrument for Stereo Mapping (PRISM) comprised of three sets of optical systems to measure precise land elevation, Advanced Visible and Near Infrared Radiometer type 2 (AVNIR-2) observing land covers and ground surfaces, and Phased Array type L-band Synthetic Aperture Radar (PALSAR) enabling day-and-night

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and all-weather land observation. AVNIR-2 multi-spectral sensor has four bands, which are red (0.61~0.69µ m), green (0.52 ~ 0.60 µ m), blue (0.42 ~ 0.50 µ m), NIR (0.76 ~ 0.89 µ m).

The AVNIR-2 multi-spectral data with middle resolution of 10m and the PRISM high spatial resolution data of 2.5m at panchromatic spectral (0.52~0.77 µ m) were applied to change detection in this study. CCD multi-spectral data and high resolution panchromatic data from ALOS were captured on December 23, 2006 and November 12, 2008 respectively. After radiometric correction, image registration was done by image to image mode, and the pixel errors from ALOS images went down to 0.3 pixels .
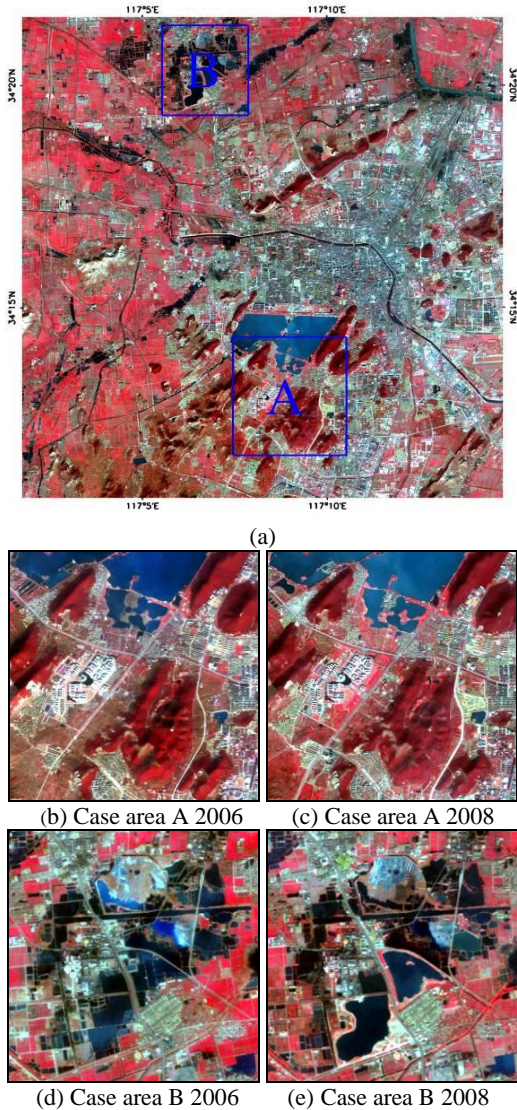

(a)

(b) Case area A 2006   (c) Case area A 2008

(d) Case area B 2006   (e) Case area B 2008

Figure1. Location of two case study area and their false composite images

3. OBJECT-ORIENTED METHOD

The methodology for gaining the change map consists of five steps: (1) remotely sensed images preprocessing, including radiometric correction and geographical registration; (2) data fusion by Brovey transform; (3) multiresolution segmentation and object description by spectral, texture and shape features in

eCognition software, and object attribute exporting as .shp files; (4) overlaying two-date segmented polygon layers to create a new polygon layer in ArcGIS; (5) attribute analysis and threshold selection to obtain the changed and unchanged polygons. The methodology of object-oriented change detection is illustrated in Figure 2.
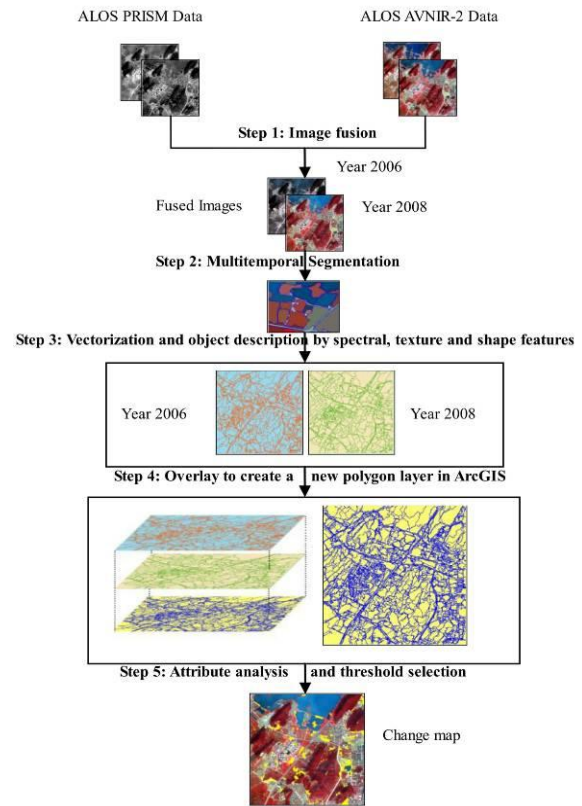

Figure 2. Flowchart of the object-oriented change detection methodology

3.1 Multi-resolution Segmentation

Image segmentation is the subdivision of a digital image into some small separated regions represented by basic unclassified image objects according to the given criteria. Usually the objects we want to identify in remotely sensed images have different sizes, so the image must be processed at different resolutions which contain different level of detail information. It is natural to analyze the image content at a coarse resolution and then gradually increase the resolution to observe more details (Mallat, 1989). The process of multi-resolution segmentation algorithm is shown in Figure 3.
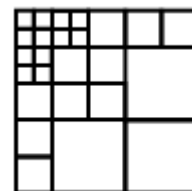

Figure 3. The process of multi-resolution segmentation algorithm (Definiens, 2007)

Image segmentation was conducted in object-oriented software eCognition, to form a series of relatively homogeneous polygons.

3.2 Object Operation and Analysis

The image objects in eCognition software could be described with the gray, texture, shape, hierarchy and thematic features. In this work, two segmented polygon layers derived from two-date remote sensed images and their 12 representative features including mean, brightness, Standard deviation (std), shape index, density, main direction, compactness, asymmetric and homogeneity derived from GLCM (Gray Level Co-occurrence Matrix) were exported as *.shp files of ArcGIS. Then the two polygon layers were overlapped to create a new polygon layer in ArcGIS, and the attributes of each polygon in this new layer were obtained. Change detection was conducted on this new layer based on the attributes of each polygon.

3.3 Change Detection

In the attribute table of this new layer, there was double number of attributes comparing with the previous two polygon layers. Difference comparison was used to determine the threshold. Simple operation was conducted in ArcMap's *Field Calculator*, in each polygon object, and 12 new attributes were created by subtracting attributes of layer 2006 from those of layer 2008. Those abnormal distributions of polygons in each feature were found and the change thresholds were determined. Finally, the range of changed areas was detected by the combination analysis of multi-threshold.

3.4 Accuracy assessment

Ground truth was used to assess the accuracy of object-oriented change detection. Ground truth samples were obtained by visual interpretation and field investigation. An error matrix was built to compute several accuracy indicators (Table 1).

Detection results/ Ground truth data	Changed (c)	Unchanged (u)	Total (T)
Detected changed(C)	Cc	Cu	TC
Detected unchanged(U)	Uc	Uu	TU
Total(T)	Tc	Tu	T

Table 1. Error matrix

Overall accuracy and *Kappa coefficient* was computed according to the error matrix. *Overall accuracy* is the ratio number of correctly detected samples to total sample number, defined as:

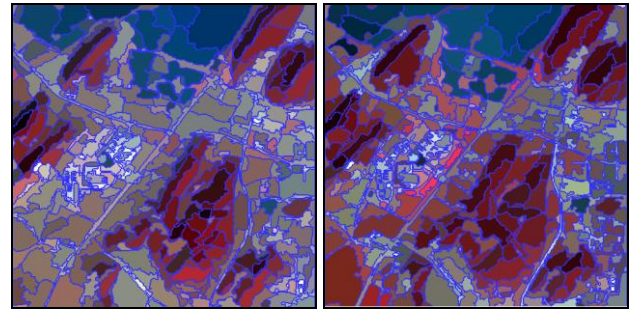$$OA = \frac{Cc + Uu}{T} \times 100\% \qquad (1)$$

Kappa coefficient is the internal consistency of detected results. It is expressed as:

$$Kappa = \frac{T(Cc + Uu) - (TC \times Tc + TU \times Tu)}{T^2 - (TC \times Tc + TU \times Tu)} \qquad (2)$$

4. EXPERIMENTS AND ANALYSES

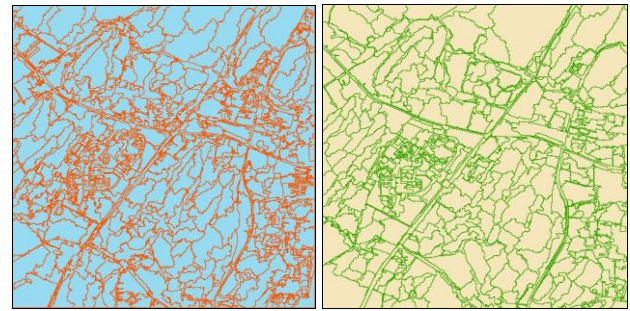### 4.1 Experiment on Case area A: Urban areas around CUMT

In the first case study area, the segmentation scales of 2006 and 2008 were 65 and 55 in the eCognition, by which 437 and 473 objects were generated respectively (Figure 4). Then the two polygon layers were overlapped to create a new polygon layer in ArcGIS. This new layer has a total of 2665 polygon objects (Figure 5).
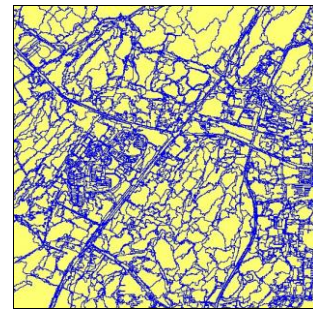

(a) 2006   (b) 2008

Figure 4. Multi-resolution segmentation results

(a) Polygon layer in 2006   (b) Polygon layer in 2008

(c) Overlapped layer of (a) and (b)

Figure 5. Two polygon layers and the overlapped new layer in ArcGIS

After repeated experiments and subtraction threshold selection, the thresholds of changed polygons were determined as：Difference of mean value of three band (-8.80, 10.54), (-17.0, 27.88) and (14.94, 26.83); Difference of brightness value (-15.24, -0.17) and (2.80, 17.82); Difference of compactness value (-9.50, -0.37) and (0.98, 3.30); Difference of shape index value (-2.68, -0.10) and (1.25, 5.34); Difference of density value (-0.50, 0.87); Difference of main direction value (-175.82, -120.0) and (-40.0,169.5); Difference of GLCM homogeneity value (-0.02, 0.48) and so on. Combining all these thresholds

with the "∩" intersection operation, the final changed areas were obtained.

In order to evaluate the accuracy of this proposed method, a conventional pixel-based method, Principal component analysis (PCA) was experimented in the same dataset (Singh, 1989; Fung and LeDrew, 1987; Coppin et al, 2004). The final results are shown in Figure 6 (a~b). Figure 6(c~d) demonstrates the final changed areas extracted from ArcMap using the proposed method. There were 213 polygon samples from the change category and 276 polygon samples from the unchanged category in order to build the error matrix.
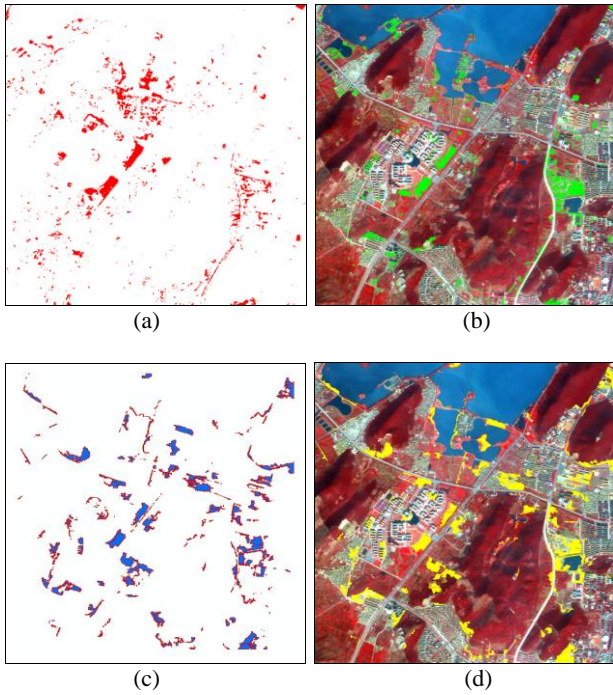

(a)

(b)

(c)

(d)

Figure 6. Change map obtained from PCA (a~b) and object-oriented method(c~d)

Method	Overall Acc.	Kappa
PCA	85.4%	0.644
Object-oriented	86.9%	0.732

Table 2. Changed detection Accuracies of PCA and Object-oriented Method

Method	Changed Areas (%)	Unchanged Areas (%)	Total (%)
PCA	4.286	95.714	100
Object-oriented	4.750	95.250	100

Table 3. The results in the proportion of the total study area

By computation, *overall accuracy* and *Kappa coefficient* of PCA and object-oriented method were listed in Table 2 according to Equation (1) and Equation(2). It is concluded that both PCA and object-oriented methods are suitable for change detection of land cover over urban areas. Object-oriented approach performs better than PCA method. Table 3 shows the proportion of changed area to the total study area. Object-

oriented method detects about 0.464% more than PCA, and those changed polygons can be found and used for further analysis, including identifying their type of land cover(from what to what) and their accurate occurrence location.

4.2 Experiment on Case area B: Pangzhuang Mining Area

With the same methodology, the second case study area located in Pangzhuang mining area was experimented to test the proposed object-oriented change detection approach. The segmentation thresholds of 2006 and 2008 were selected as 53 and 64, and 708 and 796 objects were generated respectively (Figure 7). The new layer created by overlapping of the two polygons has a total of 4411 polygon objects, (Figure 8).
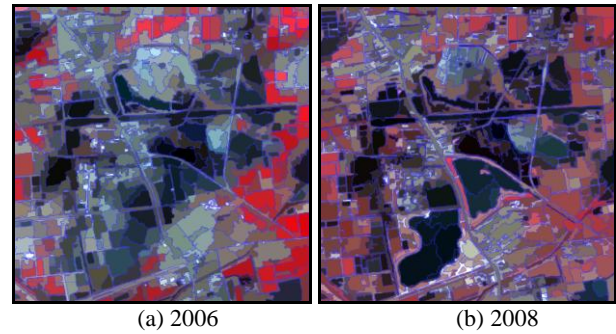

(a) 2006

(b) 2008

Figure 7. Multi-resolution segmentation result

(a) Polygon layer in 2006
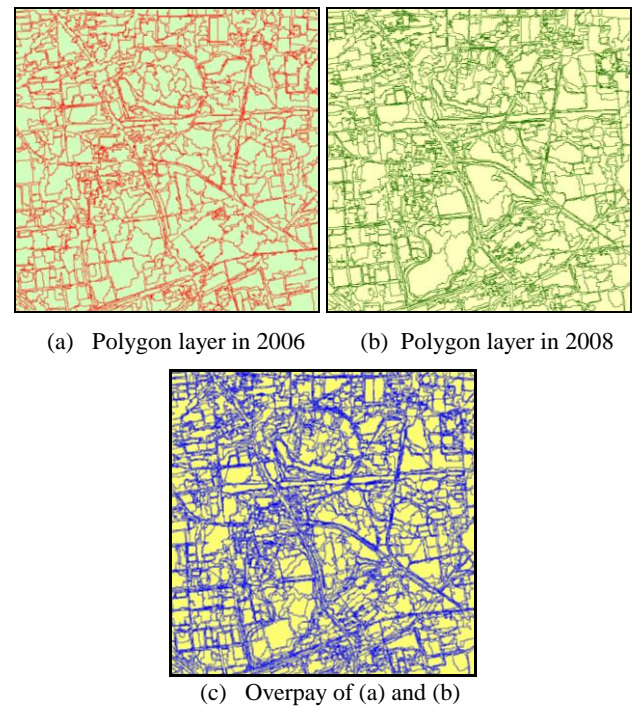
(b) Polygon layer in 2008

(c) Overpay of (a) and (b)

Figure 8. Two polygon layers and the overlapped new layer in ArcGIS

The thresholds of the changed polygons in case area 2 were determined as：Difference of mean value of three band (-25.0, 28.5), (-33.0, 47.4) and (-24.0, 37.6), respectively; Difference of Standard deviation (std) value of three band (-6.0, 15.2), (-4.0, 15.0) and (-5.0, 13.6); Difference of brightness value (-26.4, 39); Difference of compactness value (-20.0, 17.3); Difference of shape index value (-2.8, 4.6); Difference of density value (-1.70, 1.60); Difference of main direction value (-125.0,130.4);

Difference of GLCM homogeneity value (-0.34, 0.17) and Difference of asymmetry value (-0.65, 0.7). Combining all these thresholds with the "∩" intersection operation, the final changed areas were detected. Figure 9 (a~b) show the object-oriented change detection result.

Here the conventional pixel-based method, Change Vector Analysis (CVA) was experimented in the same dataset (Lambin, 1994; Malila, 1980; Johnson and Kasischke, 1998). The final results are shown in Figure 9 (c~d). There were 238 polygon samples from the change category and 294 polygon samples from the unchanged category in order to build the error matrix.
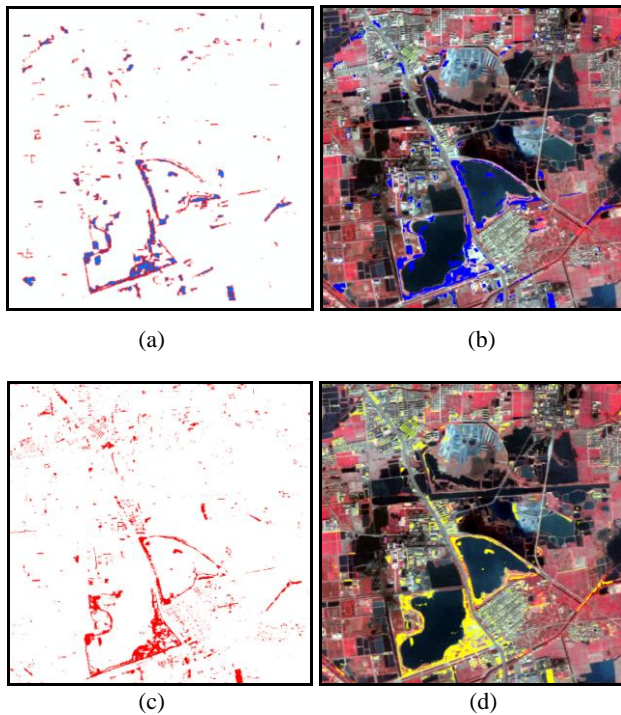

(a)   (b)

(c)   (d)

Figure 9. Change map obtained from object-oriented method (a~b) and CVA (c~d)

Method	*Overall Acc.*	*Kappa*
CVA	87.7%	0.754
Object-oriented	86.2%	0.724

Table 4. Changed detection Accuracies of CVA and Object-oriented Method

Method	Changed Areas (%)	Unchanged Areas (%)	Total (%)
CVA	4.184	95.816	100
Object-oriented	3.309	96.691	100

Table 5. The results in the proportion of the total study area

Overall accuracy and *Kappa coefficient* of CVA and object-oriented method were listed in Table 4. From the table, it is concluded that the two methods are suitable for change detection of land cover in mining areas. The final detection results are very close. CVA performs a bit better than Object-

oriented approach method. Table 5 shows the proportion of changed area to the total study area. CVA detects about 0.875 percentages more changed areas than Object-oriented method, which including some false detected build-up areas, so called "commission error". Also, these changed polygons would be used for further analysis.

In contrast with the pixel-based change detection results, the object-based approach takes advantage of the image segmentation to remove a lot of noises; accordingly, the edge of the changed regions becomes more complete and smoother. But the segmentation procedure would make more changed region be detected inside an object, so it caused the emergence of a large number of "commission" areas.

5. CONCLUSION

In this paper, multi-temporal ALOS remotely sensed images were used to detect and analyze land cover change in Xuzhou city. A new method was proposed to test its feasibility. The proposed object-oriented change detection approach is no more the pixel-based comparison and operation, but a procedure of attributes analysis and extraction towards each object in GIS database. Using the homogeneous objects as analytical unit decreases the spectral variability between pixels. And the spatial and context information could also be obtained. At the same time, the object-oriented change detection effectively restrains the "Salt and Pepper Effects" normally caused by pixel-based change detection, which takes up most of the "commission" areas.

On the other side, the new approach suffers from two main problems. First, it is easy to smooth the discrete boundary between the different types, which requires repeated segmentation threshold selection, till the optimal segmentation image is obtained. Second, there are a lot of attributes in the vector layer exported, so how to select the available attributes and determine the threshold to extract changed areas requires repeated experiments and artificial interpretation.

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