URBAN EXPANSION DETECTION WITH SPOT5 PANCHROMATIC IMAGES USING TEXTURAL FEATURES AND PCA

Linlin Lu1, Qingting Li1*, Huadong Guo1, Martino Pesaresi2, Daniele Ehrlich2

1Center for Earth Observation and Digital Earth, Chinese Academy of Sciences, Beijing, China, lllu@ceode.ac.cn

2Institute for the Protection and Security of the Citizen, European Commission, Joint Research Centre, Ispra(VA), Italy

ABSTRACT

Remote sensing is an effective tool in urban extent mapping and monitoring. In this study, a procedure to detect urban expansion is presented using SPOT5 panchromatic image with 2.5m resolution. First of all, the urban extents of different images are extracted with a PANTEX methodology, which use the anisotropic rotation-invariant textural grey-level co-occurrence measures as the presence of built-up areas. The change detection is performed on the two built-up index images using principal component analysis technique. Finally, the accuracy of this procedure is assessed with visual analysis results. The method shows good performance according to the overall accuracy of 91.18% (Kappa coefficient=0.8719).

Index Terms— Urban expansion, PANTEX, principal components analysis (PCA), textural feature

1. INTRODUCTION

Urban expansion has accelerated in developing countries all over the world since the end of last century. China, as the largest developing country of the world, has endured a rapid process of urbanization [1]. Accurate and timely monitoring of the urban extent and change is essential for governments, planners and researchers to understand the impact of human activity on urban ecological and environmental conditions.

Due to its capacity in continuous observations with high temporal and spatial resolution, remote sensing is an effective tool in urban extent mapping and monitoring. The spatial resolution required to define adequately the high diversity of the urban scene details ranges from 0.5m to 10m instantaneous field-of-view(IFOV)[2]. Since the launch of high spatial resolution(HR) space-based systems such as SPOT, IKONOS and QuickBird, the potential for detailed and

accurate mapping of urban area with remote sensing data has been further explored[3,4].

However, only panchromatic band are available for several HR satellite systems, which limits the acquisition and usage of image information. Textural feature of an image is playing an increasingly important role in high resolution image classification and pattern reorganization applications [5-7]. The objective of this study is to apply and assess a change detection strategy to monitor urban expansion with SPOT panchromatic images based on the unique textural feature of built-up. It is exemplified using Tangshan, a medium-sized city of China which has experienced a tremendous urbanization process from 2003 to 2008[8].

2. DATASET AND STUDY AREA

Tangshan is a largely industrial prefecture-level city in Hebei province, People's Republic of China. It is adjacent to the Capital Beijing and belongs to Jing-Jin-Tang urban agglomeration. It has become known for the 1976 Tangshan earthquake which measured 7.8 on the Richter scale and killed at least 255,000 residents. The city has been rebuilt and become a tourist attraction. Urbanization in this area includes expansion of old counties, emergence of new towns and rebuilt of traffic infrastructure.

The panchromatic (black and white) spectral band on SPOT-5, available since mid-2002, is 0.51-0.73 µm and 5 m spatial resolution with a super-resolution mode at 2.5 m. Two level 2A images with ground sample distance of 2.5m distributed by Spot Image Corp. are used in this study. They were acquired on May 3, 2003 and October 31, 2008 respectively covering part of Tang Shan prefecture. A subset of 9000*9000pixels from original scene(14446*14408 pixels) with fine quality is extracted and used for urban extension analysis.

3. METHODOLOGY

The workflow of urban expansion detection includes several steps as illustrated in Figure 1. The two images of year 2003 and 2008 are georeferenced at first. Built-up areas are extracted from satellite images using textual information for SPOT panchromatic images. The change information of built-up areas is derived with a general transformation method, principal components analysis. Finally, a vector layer showing the urban expansion pattern of the study area is automatically detected and exported. Accuracy assessment is conducted in comparison with the result of visual interpretation.

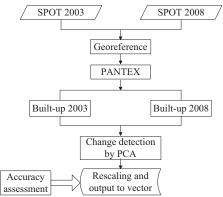


Figure 1. Workflow for detecting urban expansion pattern with SPOT panchromatic images.

3.1. Built-up presence index

The built-up area is extracted by calculating a texture-derived built-up presence index (PanTex) for discriminating the presence of built-up structures on panchromatic images, which is introduced by Pesaresi et al[9,10]. It has been tested to retrieve global human settlements from high resolution images at global scale[11]. The calculation of t built-up presence index is based on fuzzy rule-based composition of anisotropic textural measures derived from the satellite data by the gray-level co-occurrence matrix (GLCM). The goal of this method based on the GLCM is to take into account the different directional components of the textural measure and produce a compact "built-up-presence" index. This index is able to capture effectively a basic structural characteristic of buildings. Two scenes of SPOT data are georeferenced and input to PanTex. Built-up index images are calculated using specific parameters of window size as 21pixels and tolerance as 0.01.

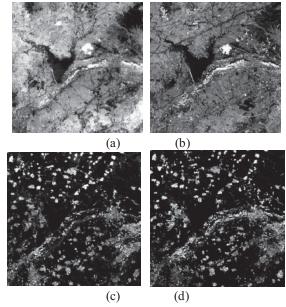
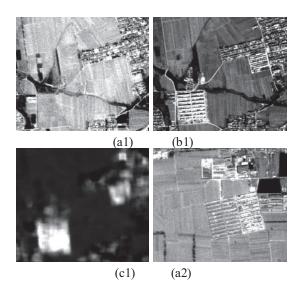


Figure 2. SPOT panchromatic image of Tangshan are displayed in (a)2003 and (b)2008 and corresponding built-up indicators in (c)2003 and (d) 2008.

3.2. Principal Components Analysis (PCA)

Change detection is a general remote sensing technique that compares imagery collected over the same area at different times and detects features that have changed. The Principal Components Analysis (PCA) method is used to highlight changed areas. Principal components is used to produce uncorrelated output bands by finding a new set of orthogonal axes that have their origin at the data mean and that are rotated so the data variance is maximized[12]. PC bands are linear combinations of the original spectral bands and are uncorrelated. Built-up presence index images at different times are input to PCA and change indicators are produced.



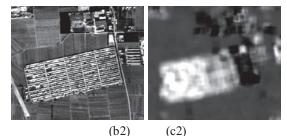


Figure 3. Subsets of typical changed areas, (a)image 2003, (b)image 2008, and (c)corresponding change indicator.

3.3. Validation

Finally, the change detection result of 2.5m resolution is aggregated to 10m. It is extracted to a shape file of polygons using a manual-defined threshold. This threshold is determined through inspection of changed areas along random image transects. This shape file, as the final product of change detection, shows the urban expansion spatial pattern. The accuracy assessment is conducted in ArcGIS 9.3. A fishnet of grids(50m*50m) is created covering the whole dataset and 2200 grids are randomly selected as reference dataset used in validation. The reference dataset is composed of 371 changed and 1829 unchanged. It corresponds to 5.5 square km in total. In particular, changes caused by different crop fields, new mining areas, extended dump sites and river banks are not included in the "changed" class of the reference database, even though there are built-up structures inside or show similar textural characteristics. Only new settlements and roads are defined as new built-ups.

4. RESULTS AND DISCUSSION

Table1 shows the results of the confusion matrix obtained by comparing the results of change detection with the reference dataset, while the Table2 shows the estimation of the commission, omission errors and of the producer, user accuracy. The overall accuracy and Kappa-coefficient were also calculated.

Table 1 Confusion matrix

Output class	Change	Notchange	Total
Changed	329	42	371
Notchanged	152	1677	1829
Total	481	1719	2200

Overall accuracy=91.18% Kappa coefficient=0.8719

Table2 Commission, omission errors, and producer user accuracy

Output class	Commission	Omission	Prod.	User
	(Percent)	(Percent)	Acc.	Acc.
	(1 creent)	(1 creent)	(Percent)	

Changed	8.73	31.6	68.4	88.68
NotChanged	8.84	2.44	97.56	91.69

The method shows good performance according to the user's accuracy estimation of the not changed areas with more than 90% of estimated accuracy. Also the producer's accuracy of the not changed areas is quite good showing more than 90% accuracy. The user's accuracy of the change areas estimation is quite good being above 85% for two years and slightly above 90%. More problematic seems the change producer's accuracy that falls to circa 70%.

The most important problem arising from this validation exercise seems to be the omission error associated with estimation of the change areas (proportion of pixels that are classified as not changed whereas they are changed) from the change detection method. This omission error is estimated as 31.6%. For the omission error, pixels of newlybuilt small roads and buildings with small size are mistakenly missed. Another possible reason can be attributed to the threshold parameter for change polygon exportation. Adequate reference samples are necessary in order to choose appropriate threshold for each scene. The sensitivity of change detection results to threshold definition can be investigated in future study.

5. CONCLUSION

The study presented a workflow to map and monitor the spatial pattern of urban expansion using SPOT5 panchromatic imageries. It has been tested using images acquired for Tangshan, China in year 2003 and 2008. This method detects the change of built-up areas using textural information of high resolution panchromatic image and PCA. Comparing with visual interpretation results, the achieved accuracies are satisfying considering the complexity of the urban landscape. With regard to the rapid global urbanization process, our approach represents an operational methodology to map urban growth with remote sensing data. But this method is only tested on image subsets with good quality. It is necessary to apply the method to extensive dataset including degraded and hazecovered images for its improvement, robustness and consistency.

6. ACKNOWLEDGEMENTS

This research is supported by the Major International Cooperation and Exchange Project of National Natural Science Foundation of China "Comparative study on global environmental change using remote sensing technology" under grant NO. 41120114001 and 973 project "Earth observation for sensitive factors of global change: mechanisms and methodologies" under grant

NO.2009CB723906 from Ministry of Science and Technology of China.

7. REFERENCES

- [1] E.F. Lambin, and H. Geist, "Global land use and land cover change: what have we learned so far?," *Global Change News Letter*, vol. 46, pp. 27–30, 2001.
- [2] R.Welch, "Spatial resolution requirements for urban studies," International Journal of Remote Sensing, vol. 3, no. 2, pp. 138–146. 1982
- [3] M. Herold, C.N. Goldstein, and C.K. Clarke, "The role of spatial metrics in the analysis and modeling of urban land use change," *Computer, Environment and Urban System*, vol. 29, pp. 369-399, 2003.
- [4] A. P. Carleer, and E. Wolff, "Urban land cover multi-level region-based classification of VHR data by selecting relevant features," *International Journal of Remote Sensing*, vol. 27, no.6, pp.1035–1051, Mar. 2006.
- [5] F. Agüera, F.J. Aguilar, and M.A. Aguilar, "Using texture analysis to improve perpixel classification of very high resolution images for mapping plastic greenhouses," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 63, no.6, pp. 635-646, 2008.
- [6] F. Pacifici, M. Chini, and W. J. Emery, "A neural network approach using multi-scale textural metrics from very highresolution panchromatic imagery for urban land-use classification," *Remote Sensing of Environment*, vol. 113, no.6, pp. 1276-1292, 2009.
- [7] P. Gong, D.J. Marceau, P.J. Howarth, "A comparison of spatial feature extraction algorithms for land-use classification with SPOT HRV data," *Remote Sensing of Environment*. vol.40, pp. 137–151, 1992.
- [8] L. Lu, H. Guo, and X. Li. "Monitoring the decadal development of urban agglomeration with remote sensing images in Jing-Jin-Tang area, China," *Journal of Applied Remote Sensing* (submitted)
- [9] M. Pesaresi, "An optimized procedure to built space automatic recognition via Spot HRV panchromatic satellite data processing, in proceedings of ISTAT-EUROSTAT seminar," in *Proc. The Impact of Remote Sensing on the European Statistical Information System*, Rome, Italy, pp. 27–29, 1995.
- [10] M. Pesaresi, A. Gerhardinger, and F. Kayitakire, "A robust built-up area presence index by anisotropic rotation-invariant textural measure," *Ieee Journal of Selected Topics In Applied Earth Observations and Remote Sensing*, vol.1, no.3, pp.180-192, 2008,
- [11] M. Pesaresi, D. Ehrlich, and I .Caravaggi, "Toward global automatic built-up area recognition using optical VHR Imagery," *Ieee Journal of Selected Topics in Applied Earth* Observations and Remote Sensing, vol.4, no.4,pp.923-934
- [12] J.A. Richards, *Remote Sensing Digital Image Analysis: An Introduction*, Springer-Verlag, Berlin, Germany, 1999.