TRACKING LAND COVER CHANGE USING HIGH RESOLUATION ORBITAL IMAGERY

In Hun, Jeong[1] Jung Rack, Kim*[2] and Sang Jin, Lee [3]

[1]Graduate Student, Department of Geoinformatics, University Of Seoul
Seoulsiripdaero 163., Dongdaemum-gu, Seoul,130-743, Korea; Tel: + phone (+82) 0*222105073*
E-mail: easystudio@uos.ac.kr
[2*]Research Professor, Department of Geoinformatics, University Of Seoul
Seoulsiripdaero 163., Dongdaemum-gu, Seoul,130-743, Korea; Tel: + phone (+82) 07082533008
Email: kjrr001@gmail.com
[3] Graduate Student, Department of Geoinformatics, University Of Seoul
Seoulsiripdaero 163., Dongdaemum-gu, Seoul,130-743, Korea; Tel: + phone (+82) 0*222105073*
E-mail: lsj@uos.ac.kr

KEY WORDS: Change detection, Land cover, High resolution image, RapidEye

ABSTRACT: With the increasing demand of landcover information for the corresponding authorities, the temporal tracing of landcover change is also being required for many proposes such as local development, social infrastructure planning and environment management. Replacing the ground survey which consumes huge resources and time, the employment of satellite imagery became a highly efficient method for many applications. Instead of the conventional change detection algorithms not any more adequate with the contemporary high and very high resolution satellite images, we hereby proposed a two stages landcover tracing scheme utilizing the object oriented approach and ANN (Artificial neural network). The test processing proved the robustness of the algorithms. However, the improvements in the current processor will be further promoted using the more sophisticated image manipulation method as there are still unresolved problems, for example image registration issue.

1. Introduction

The environmental impacts of anthropogenic activities became more significant causing comprehensive and rapid land cover variation. However, the tools for instantly monitoring such land cover change and tracking its details in time domain are quite limited. For instance, the global land cover using MODIS (Moderate Resolution Imaging Spectroradiometer, http://modis.gsfc.nasa.gov/data/dataprod/dataproducts.php?MOD_NUMBER=12) which has been processed annually is not suitable for the applications in regional issues. Hence, the spatial information infrastructures including the regional land cover are infrequently updated so that it results in the inappropriate policy decision sometimes.

In this study, we employed high and very high resolution satellite imagery and tested an automated approach to trace multi-temporal thematic information in the regional land cover changes. The test data set consists of two high resolution RapidEye and a KOMPSAT-2 images. Especially, RapidEye is an ideal sensor for the purposes of this research due to the 5 multi spectral bands and relatively high spatial resolution together with the short revisiting time. The main technical challenges are i) tracking algorithms for the details of land cover change as well as the changed area identification; ii) the strategy for the co-registration between image sequence in 1-5 metre spatial resolution. The issues were tackled with the Rational Polynomial Coefficient improvement to attain maximum geodetic accuracies and the object oriented change tracing strategy. The main components of change tracking algorithms are based on the Artificial Neural Network (ANN) to evaluate the translations of spectral signatures between the homogeneous object segments combining a translation matrix. The test processing retrieving the land cover changes between RapidEye and KOMPSAT hybrid image sequence were demonstrated.

The results showed a clear potential possibility to replace the land cover change tracking scheme by the ground survey with the automated processor employing orbital EO imagery.

2. Background

Change detection is the process identifying differences in the state of an object or phenomenon by observing it at different times (Singh 1989).

Types of change Detection are categorized into two classes. One is "post classification" and the other is "image operations". Simply post-classification type is performed by tracing a sequence of classification results. On the other hands, image operation type is based on the continuous spectral/intensity operation of images and the subsequent thresholding. Hence, the post classification type is able to provide the information concerning "changed pixel properties" which means prior and posterior landcover classes of the changed pixels. It is huge merits in the end user's point of view. However, the accuracy of the tracing result is proportional to the multiplication of all relevant classification accuracies. Considering that the most advanced classification algorithm has a bit better accuracy than 80% normally, the post classification method is very inappropriate for the many application purposes. Contrastively, the image operation approaches provided only the information of “which pixel a changed with what possibility”. For the most application topics, it is not enough. Therefore, we tried to implement a change detection /tracing scheme which possesses the merits of both approaches, i.e. the robustness of “image operation” method and the capability of the comprehensive spatial information providing of “post classification” method.

2.1 Data sets

For the trace of temporal variation in landcover using satellite imagery, the first topic to be addressed is the target image selection. Even though the contemporary commercial satellite’s revisiting time and coverage are rapidly improving, it is not easy task acquiring the suitable image in the appropriate time, because of the other external conditions such as the climate factors and the acquisition cost. It was tackled with two ways in this study. First of all, the images from satellite constellation were employed. Locating a serious of image sensors in orbit, the revisiting time is highly improved so that the processors for change detection can be handled with more stable image qualities. Secondary, the change detection algorithms were designed with the hybrid image basis. For example, if the algorithm is organized not depending on the specific image sensor, the flexibility of the target image selection is largely improved. In such bases, the RapidEye which has five satellites constellation and 5.5 days revisiting time were chosen as the primary data source. Together with the orbital characteristics, Rapideye image has five multispectral bands (R-G-B-RedEdge-NearIR) and 6.5m GSD (ground sampling distance) which are very beneficial for the landcover analysis. Specially, 6.5m GSD in Rapideye is highly promising for the change detection, as it is a compromising value between the conventional spatial resolution of very high resolution satellite image and the medium resolution earth observation sensor. Sub deca-metre resolution of Rapideye can deliver the texture of individual landscape object but does not require complicate algorithms to manipulate the spatial properties of individual entity. In addition, KOMPSAT-2 with 1m panchromatic and 4m multi spectral resolutions was also employed to fill the time gap of Rapideye image acquisitions.
The target image sequences consisting of KOMSAT and Rapideye imagery is a very realistic situation because the continuous focusing by an EO sensor over specific target area is not usually feasible.

2.2 Pre-processing

Considering the geometric and radiometric variation in multi-temporal and multi-sensor images, the suitable pre-processing of target imagery is highly required. Pre-processing is usually performed in a series of sequential operations, including atmospheric correction, geometric correction, and image registration. To take into account the difference atmospheric conditions and the resulting the reflectance values or digital numbers (DN) of satellite images, the images have be normalized or corrected. The goal of atmospheric correction conveniently is that all images should appear as if they were acquired from the same sensor (Baboo and Devi, 2011). However, in technical point of view, it is not easily achievable especially in the hybrid image mode of this study. The introduction of post classification approach is supposed to be the simple solution to avoid the difficulty of the radiometric correction.
The geometric correction and registration are the most important part of preprocessing. Theoretically, the requirement for the robust algorithm application is sub pixel level co-registration between the target images. It is not attainable with the positioning accuracies of pre-georectified image products by the data provider because of the different base DEM(Digital Elevation Model) and the ground control for ortho rectification as well as the different indigenous senor modeling accuracies. The senor model in the test imagery is RPC(Rational Polynomial coefficient) which is now being the industrial standard (Tao and Hu, 2001). Compared with the rigorous sensor models widely used, RPC is essentially a more generic and expressive form. In order to co-registrate KOMPSAT and two Rapideye images, the bias compensation of RPC were applied with the maximum 12 GCPs (Ground Control Point) and ASTER 30m DEM (http://www.gdem.aster.ersdac.or.jp/). According to our experience, KOMPSAT-2 RPC was updated up to 6-12m horizontal error for whole image coverage. It means the un-directional positioning error in KOMPSAT-2 was not fully addressed by the bias compensation of RPC. Rapideye revealed the same amount of positioning error in spite of the scrupulous ortho rectification using the same GCPs and base DEM with KOMPSAT-2. Conclusively, the pixel-by-pixel comparison in changed detection algorithms was not accomplished with those photogrammetric accuracies.
Rather than further manipulation in the sensor models, it was proposed to exploit the object oriented processing. The processing of image patches rather than individual pixel which is more likely “ill-located” during the change detection operation, is able to compensate positioning errors better.

2.3 Target area

The test area for the algorithms developments is located in the Western Korean, Boryeong providence (36.3N, 126.6E). The area included densely populated urban areas together with the natural forests and the cultivated lands.

The rapid landcover change is undergoing in the test site due to the regional developments. This area was covered with two Rapideye-2 and a KOMPSAT whose specifications were shown in Table 1.

image	Technical specifications	Image acquisition time
KOMPSAT-2	Resolution : 1 m panchromatic, 4 m multispectral, Four multispectral bands (R-G-B-Near IR), Swath Width : 15km approx.	2008-08-26
Rapideye	Resolution : 6.5m GSD, Five multispectral bands (R-G-B-Rededge-Near IR), Swath Width : 77km	2010-06-23 and 2010-09-18

Table 1. The test images for the change detection

3. Algorithm design

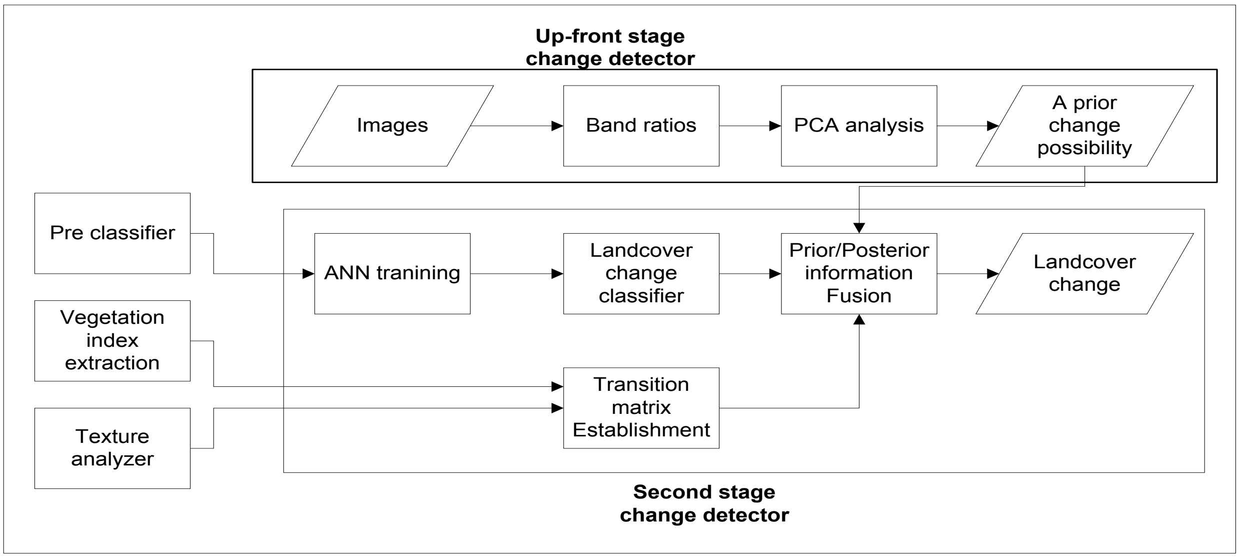


Figure 1. The algorithms design

The outline of change detection algorithms is shown in Figure 1. The purposes of such algorithm implementation are the organization of robust S/W scheme working with any hybrid image combination. Also it should be capable of providing the contents of landcover changes.

For the full exploitation of both post classification and image operation merits, it consists of two stage processors. The up-front stage processor takes a role for extracting a prior possibility of landcover changes based on the conventional PCA (Principle Component Analysis) analysis and the band rationing (Prakash and Gupta, 1998) which are simple but not robust to trace landcover change with a certainty. The underlying idea is that the combination of both algorithms became stable to estimate a prior possibility of landcover change. The corresponding band ratio between Rapideye and KOMPSAT-2 R-G-B-NIR, were feed-forwarded into PCA analysis (Byrne et al., 1980). Then the first PCA components provided the prior possibility of landcover change with quite high accuracy.

Given the fact that there are prohibited landcover changes contextually, it is very helpful to build a translation matrix between landcover types. Also together with the transition matrix establishment, the introduction of quantitative criteria for possible landcover change is certainly of use. Vegetation index and image texture extractions are very promising to measure the landcover translation possibility even with the hybrid satellite images. For example, the landcover transition from the forest to the built-up area is not valid if the vegetation index in corresponding area is decreased. In the same manner, the change from buildup area to barren field with the decrease of texture is not possible. The EVI (Enhanced Vegetation Index, Liu and Huete, 1995) and GLCM (Gray-Level Co-occurrence Matrix) texture analysis with subsequent MNF (Minimum Noise Fraction, Boardman and Kruse, 1999) transformation were employed as vegetation and texture variation indexes.

All outputs from the up-front change detector and the auxiliary data such as transition matrix were then delivered to the main body of landcover change classifier based on the ANN. The main issue of the landcover change classifier is the training data selection prior to the clear definition of changed areas. Our strategy for such ill-posed problem is the employment of landcover classification of the individual target image as the landcover combinations between the individual target images can be used for the learning of ANN as long as the complexity of landcover section is avoidable. In this stage, the transition matrix and the changing criteria was employed to reduce the complexity in ANN learning and provided the robustness of training vector.

The output of ANN which presents the probability function of individual landcover change, were then multiplied by the prior change possibility and the step function from the changing criteria. Hence, it provided the higher accuracy in regard of the uncertainty removal of the final output.

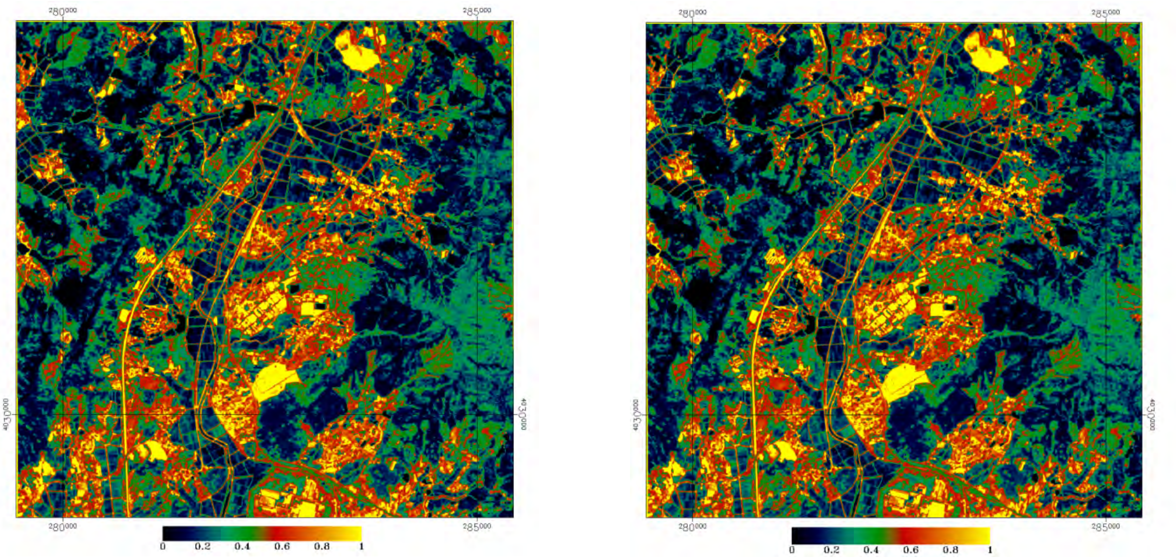
Overall, the scheme of this study aims the integration of a variety of information and the detailed tracing of landcover change contents. It should be noted that all the classification and threshold operations of the criteria was performed with the image patch units, so called image objects, to reduce the influence of geomatic co-registration errors.

4. Results and Discussion

The test processing was performed in the two cases between a KOMSAT and two Rapideye images. The landcover change between two Rapideye image acquisition times doesn’t exist because the time gap of two Rapideye images was too close to produce meaningful landcover changes.

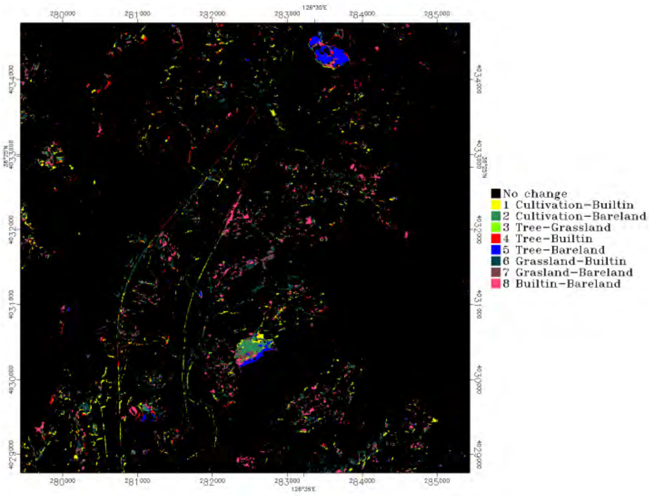
Figure 2 showed the input images and the intermediate products of test processing. The prior possibility from PCA analysis in Figure 2 (b) demonstrated high accuracy even though it didn’t have any clues about the contents of landcover changes.

(a) KOMPSAT-2 image (left), Rapideye in 2010/06/23 (middle) Rapideye in 2010/09/18 (right)

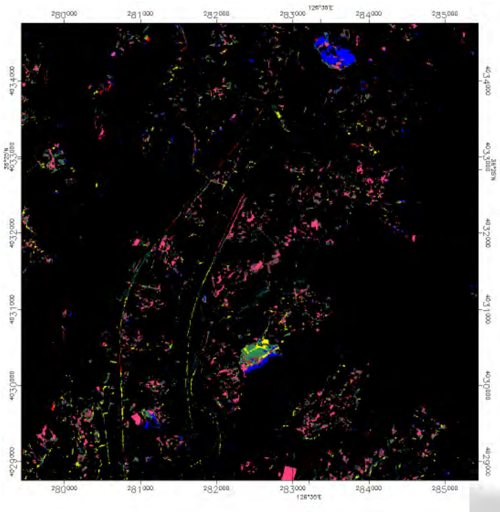


(b) Change possibility between KOMPSAT-2 and Rapideye in 2010/06/23 (left) and KOMPSAT-2 and Rapideye in 2010/09/18. Note the obvious similarity between two.

Figure 2. The input sample images and the intimidate results.



(a) Landcover change map from KOMPSAT-2 in 2008-08- to Rapideye in 2010/06/23



(b) Landcover change map from KOMPSAT-2 in 2008-08-to Rapideye in 2010/09/18

Figure 3. The final change detection results

The final result in Figure 3 clearly showed the contents of landcover change were successfully recovered by the employed algorithms. In the rough visual inspection, even relatively small scale changes were successfully traced. Given the fact that two tracing results of landcover changes are similar to each other, the performance of constructed algorithm was well proven.
The unresolved problem in the scheme is the geomatic co-registration error. The test images were chosen from the subset area where the co-registration is well established so that the object oriented processing scheme compensated the un-directional errors of the sensor models. Some exceptions were observed around the thin landscape entities such as road lines, image patch boundaries and riversides in Figure 3. However, it should be noted the relative geomatic positioning error can be extended up to few tens meters in some cases. Then the error level is not manageable with the current processing scheme. It is supposed that the hierarchical object construction is a solution but the processing scheme employing hierarchical object construction will be more complicated.
The balancing between the algorithm robustness and the solution of geomatic co-registration error is quite contradictional topic. Apart from the sensor model updating by image provider, it requires the introduction of far sophisticated algorithms.

5. Conclusion

In this study, we developed a processing scheme differentiated from the existing solutions providing the contents of landcover change as well as the identification of changed landcover area. The scheme consisting of two stage landcover change tracer and the auxiliary data extractor successfully retrieved the detailed landcover change information.
The biggest technical barrier to apply the scheme for full coverage of very high resolution satellite imagery is the geomatic registration error originated from incomplete sensor model. The temporal solution exploiting the image objects can only manipulate small directional error. Considering the contemporary very high resolution satellite imagery includes a large amount of unidirectional error, the advanced processing hierarchy should be developed.

Acknowledgements

The first and third authors' researches in this study were supported by Project to Educate GIS Experts.

Reference

Boardman, J. W., and Kruse, F. A., 1994, Automated spectral analysis: a geological example using AVIRIS data, north Grapevine Mountains, Nevada: in *Proceedings, ERIM Tenth Thematic Conference on Geologic Remote Sensing*, Environmental Research Institute of Michigan, Ann Arbor, MI, pp. I-407 - I-418.

Byrne, G. F., Crapper, P. F., and Mayo, K. K., 1980, Monitoring land cover change by principal component analysis of multitemporal Landsat data. Remote Sensing of Environment, 10, 175–184.

Chan, J,C., Chan, K.P., and Yeh, A.G., 2001. Detecting the Nature of Change in an Urban Enviroment : A Comparison of Machine Learning Algorithms. Photogrammetric Engineering & Remote Sensing, vol. 67, No.2, pp.213-225.

Liu, H.Q.; Huete, A.R., 1995, A feedback based modification of the NDV I to minimize canopy background and atmospheric noise. IEEE Transactions on Geoscience and Remote Sensing, 33, 457-465.

Prakash, A., and Gupta, R. P., 1998, Land-use mapping and change detection in a coal mining area—a case study in the Jharia coalfield, India. International Journal of Remote Sensing, 19, 391–410.

Singh A, 1989. Digital change detection techniques using remotely sensed data. International Journal of Remote Sensing, 10, pp.989-1003.

Tao, C.V., Hu, Y., 2001. A comprehensive study of the rational function model for photogrammetric processing. Photogrammetric Engineering & Remote Sensing, 67 (12), 13471357.