URBAN LAND-COVER MAPPING AND CHANGE DETECTION WITH RADARSAT SAR DATA USING NEURAL NETWORK AND RULE-BASED CLASSIFIERS

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ABSTRACT:

This paper presents a new approach to extract urban landuse/land-cover information from high-resolution radar satellite data. Five-date RADARSAT fine-beam SAR images over the rural-urban fringe of the Greater Toronto Area were acquired during May to August in 2002. One scene of Landsat TM imagery was acquired in 1988 for change detection. The major landuse/land-cover classes were high-density built-up areas, low-density built-up areas, roads, forests, parks, golf courses, water and four types of agricultural crops (soybeans, corn, winter wheat/rye and pasture). The proposed approach to classify SAR images consisted of three steps: 1) image segmentation, 2) feature selection and object-based neural network classification, 3) rule set development to improve classification accuracy. Post-classification change detections were then performed using the final classification result of RADARSAT SAR images and the classification result of Landsat TM imagery. The results showed that the proposed approach achieved very good classification accuracy (overall: 87.9%; kappa: 0.867). The change detection procedure was able to identify the areas of significant changes, for example, new built-up areas, even though the overall accuracy of the change detection was not high.

1. INTRODUCTION

A large number of cities around the world are undergoing rapid expansion and massive changes. Mapping urban landuse/ land-cover and their changes regularly and accurately is thus important for urban planning and sustainable management of land resources. Maintaining up-to-date landuse/land-cover information is both costly and time-consuming using traditional field and air photo methods. Remote sensing technology provides an efficient and less-expensive way for landuse/land-cover mapping. During the past decades, a large number of researches were conducted on urban landuse/land-cover mapping and change detection using optical satellite data (e.g., Wang, 1993; Van Teeffelen et al. 2001; Martinez et al. 2007).

Due to frequent cloud cover, smog, haze and winter darkness, optical data may not be available or of high quality during critical monitoring cycle. With its all-weather and day/night capability and its unique information content, Synthetic aperture radar (SAR) data is an attractive data source for mapping urban landuse/land-cover. The advent of high-resolution spaceborne SAR data makes it possible to extract detailed urban land-cover information from SAR data (e.g., Ban and Wu, 2005; Ban and Hu, 2007). These researches showed that RADARSAT fine-beam SAR data has the potential for operational urban land-use/land-cover mapping and change detection.

This objective of this research is to develop a new approach to extract information on urban landuse/land-cover and their changes from multitemporal RADARSAT fine-beam SAR imagery.

2. STUDY AREA AND DATA DESCRIPTION

The study area is located in the north and northwest part of the GTA, Ontario, Canada, where rapid urban expansion and sprawl has encroached onto the Oak Ridges Moraine, one of the most distinct and environmentally significant landforms in southern Ontario. The major landuse/land-cover classes were high-density built-up areas (HDB), low-density built-up areas (LDB), roads, forests, parks, golf courses (GC), water and four types of agricultural lands (soybeans, corn, winter wheat/rye and pasture).
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Acquisition date	Beam position	Orbit	Incidence angle range (degree)
May 14 2002	Fine 2 Far	Ascending	39.5-42.5
Jul. 1 2002	Fine 2	Ascending	39.3-42.1
Jul. 16 2002	Fine 4 Near	Descending	43.2-45.5
Aug. 9 2002	Fine 4 Near	Descending	43.2-45.5
Aug. 18 2002	Fine 2	Ascending	39.3-42.1

Table 1. RADARSAT Fine-Beam SAR Imagery

Five-date RADARSAT fine-beam C-HH SAR images with a spatial resolution of 10 meters and a pixel spacing of 6.25 meter were acquired during May to August in 2002. The detailed descriptions of these images are given in Table 1

Field data on various landuse/land-cover types, their roughness and moisture conditions, vegetation heights, gound-coverages were collected during each satellite overpass. Photographs were taken during fieldwork to assist image interpretation and analysis. Other sources of data were also used to georeference SAR data and to assist selecting ground reference data for classification calibration and validation and they include:

- Landsat ETM+ data, 2002
- Orthophotos at 0.5 meter resolution, 1999
- National Topographic Database (NTDB) vector data
- DEM, 30m resolution

3. METHODOLOGY

The proposed approach to classify SAR images consisted of three steps: 1) image segmentation, 2) feature selection and object-based Neural Network (NN) classification, 3) rule set development to improve classification accuracy. In the first step, the object-based image analysis software Definiens eCognition was used to segment SAR images. A number of spectral, shape and contextual features were then calculated to characterize image objects. In the second step, the feature selection method, "minimum-Redundancy-Maximum-Relevance", was used to remove irrelevant and redundant features of image objects, which helped improve the performance of neural network learning model. An object-based neural network classification was then undertaken to generate a preliminary classification result of the SAR images. In the third step, knowledge-based rules were developed to refine the NN classification result.

3.1 Orthorectification of SAR Images

To remove the relief displacements in SAR data and bring the five images from two opposite look-directions to the same database, multi-temporal RADARSAT SAR imagery were orthorectifed to the NTDB database using satellite orbital models and a DEM at 30m resolution.

3.2 Data Compression

In this study, RADARSAT SAR images were first converted from 16-bit unsigned depth to 8-bit unsigned depth, as the resulting images were less time-consuming and may lead to better segmentation. Examination of the histograms of SAR images showed that most of brightness values in the images were concentrated in the first fifth of 16-bit range. Very high values were usually caused by some point targets in the image. The simple linear rescale min-max algorithm was used with the max value set equal to the mean value plus two times the standard deviation value, which represented over 98% of the data distribution. Such a transformation not only significantly saved the computation time of subsequent processes, but also made the segmentation algorithm perform better, for the dissimilarity of pixel values of an object was greatly reduced.

3.3 Segmentation

Image Segmentation is widely used in the fields of machine vision and pattern recognition. Image segmentation is the division of an image into spatially continuous, disjoint and homogeneous regions. Traditional image segmentation methods have been commonly divided into three approaches: pixel-, edge and region based segmentation methods (Blaschke et al. 2005).

In this study, SAR image objects were created by means of the multi-resolution segmentation algorithm introduced by Baatz and Schape (2000), which is implemented in the commercial image analysis software, Definiens eCognition. The procedure for the multi-scale image segmentation can be described as a bottom-up region merging technique and is therefore regarded as a region based segmentation method. It starts with each pixel which is assumed to be an image object. Pairs of objects are merged to form larger object based on a homogeneity criterion. A ‘merging cost’ is assigned to each possible merge. A merge takes place if the merging cost is less than a user-specified threshold, which is scale parameter in eCognition. The procedure stops when there are no more possible merges.

The selection of scale parameter and homogeneity criterion factors in this study was based on trials with the segmentation procedure. The scale parameter was set to 25. Both the colour vs. shape weight and the smoothness vs. compactness weight are 0.5:0.5. The weight in segmentation is equal for each image layer. A segmentation level was created containing 44,123 image objects.

The image objects can be characterized by calculating spectral, shape and textural features. A classifier can then utilize the features values to classify each image object as a whole (the so-called object-based classification). A total of 68 features were selected and calculated in the study. The spectral features were image layer means, standard deviations, mean differences to neighbours, mean differences to darker neighbours and mean differences to brighter neighbours. The shape features included area, border index, compactness, density, length, length/width, shape index, width, length of main line, length/width (only main line) and width (only main line). The texture measures were derived from the Grey-Level Co-occurrence Matrix (GLCM) and the following GLCM measures were chosen: homogeneity, contrast, dissimilarity, entropy, mean, standard deviation, correlation. For the definition of these features, see Definiens eCognition Reference Book.

3.4 Feature Selection

Instead of using all available features or attributes in the data, one can select a subset of features when classifying images. Feature selection has demonstrated several advantages: dimension reduction to reduce the computational cost, noise reduction to improve classification accuracy, and more interpretable features.

Feature category	Object features
Spectral	Mean SAR-20020701
	Mean SAR-20020809
	Mean SAR-20020818
	Standard Deviation SAR-20020701
	Standard Deviation SAR-20020809
	Standard Deviation SAR-20020818
	Mean Diff. to Bright Neighbours SAR-20020809
Shape	Width (only main line)
Texture (GLCM)	Standard Deviation SAR-20020514
	Standard Deviation SAR-20020716
	Standard Deviation SAR-20020818
	Mean SAR-20020701
	Entropy SAR-20020809
	Contrast SAR-20020809
	Contrast SAR-20020818
	Dissimilarity SAR-20020514

Table 2. 16 selected features

Minimum-redundancy-maximum-relevance (mRMR) feature selection, proposed by Peng et al. (2005), was used here to determine the best combinations of features. This method selects features that are both minimally redundant among themselves and maximally relevant to the target classes. The emphasis is direct, explicit minimization of redundancy. mRMR feature selection method does not convolve with specific classifiers and can be combined with a particular classification method.

Training objects of each class with all 68 features were exported from eCognition to mRMR program and 16 features were selected using nRMR. They are listed in Table 2.

3.5 Object-based NN Classification

Neural network classifiers are computer programs designed to simulate human learning process through establishment and reinforcement of linkages between input data and output data. NN presents a non-parametric, distribution-free approach to image classification. NN classifiers have been applied to multi-source, multi-dimension data to overcome the limits of classical classifiers such as Maximum Likelihood Classifier (MLC), which is based on some untenable assumptions about the dataset such as the normal distribution of the data (Ban, 2005).

10 image objects were selected as training objects for each class, except 25 for forests and 33 for HDB as forests and HDB exhibit great backscatter variation. The number of validation objects for each class is between 15 and 20.

Training objects of each class with the 16 selected features were exported from eCognition and then imported to PCI Geomatica to train the neural network. Afterwards, all image objects with the 16 selected features were classified using trained neural network layers.

3.6 Rule Set Development

As some classes have very similar backscatter values on the SAR images, they could not be well separated in object-based NN classification. To differentiate these classes, special rules were developed and applied.

Golf courses, roads, pasture and parks all exhibit low backscatter and some objects of these classes were misclassified in object-based NN classification result. Spatial relationship could be used here to reduce misclassification. An object of roads, pasture or parks was assigned to golf courses if the number and area of objects of golf courses within a specific distance from the object reached a certain threshold. Shape features, like compactness and length/width, were used to reduce misclassification of roads objects. Pasture was located in rural areas while parks were not far from built-up areas.

Spatial relationship was also used to resolve the confusion between forests and low-density built-up areas (LDB), for LDB owned more neighbouring objects belonging to built-up areas.

3.7 Classification Accuracy Assessment

To assess the quality of the image classifications, various measures including overall accuracy and Kappa coefficient of agreement (or Kappa) were analyzed to compare classification results with the validation or reference data in confusion matrices.

3.8 Post-Classification Change Detection

Landsat TM image from 1988 was classified with several unsupervised classifiers like k-means clustering and ISODATA clustering. Supervised classifiers were not applicable because of the lack of reference data from 1988.

The final classification result of SAR images contained eleven classes, four of which were agricultural lands. However, detailed agriculture types could not be identified in TM image. The classified TM image only contained 8 classes and all agricultural lands were classified as agriculture. In order to perform post-classification change detection, the four types of agricultural lands in classified SAR imagery were merged to one class – agriculture.

Post-classification change detections were performed using the classification result of RADARSAT SAR data from 2002 and the best classification result of Landsat TM image from 1988 using image differencing.

4. RESULTS AND DISCUSSION

4.1 Orthorectification of SAR Images

The five SAR images were ortho-rectified into the NTDB/ETM+ database and the RMSs for both x and y directions were less than 1.4 pixels (pixel spacing is 6.25m).

4.2 Segmentation

Only one segmentation level was created in this study. Most objects could be delineated on the segmentation result, except some very narrow roads and tiny objects.

It is hard to get smooth boundaries between image objects when segmenting SAR images due to the complexity of the images. However, segmenting images derived from 8-bit transformation produced better segmentation result from visual interpretation, as shown in Figure 1. The two segmentation results contain almost the same number of image objects, but the left result appears more compact and approximates to the real boundaries.

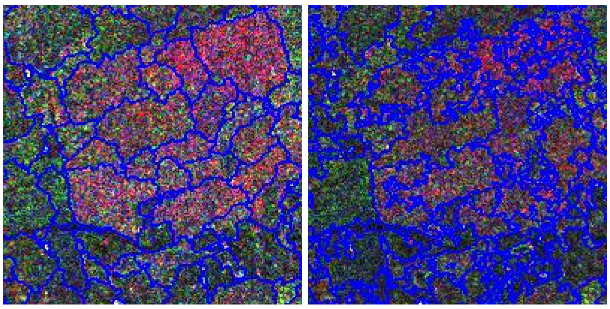

Figure 1. Comparison of segmentation results. Left: segmentation result using images derived from 8-bit transformation; Right: segmentation result using original SAR images

4.3 Classification

Eleven land use classes were extracted using objected-based NN classification and the overall accuracy was 67.9% with kappa of 0.647. The relatively low classification accuracy may be in part due to the feature selection process where important images/features, such as multitemporal information from SAR images acquired on May 14 and July 16, were omitted. Another possible cause was the compression from 16 bits to 8 bits that might have resulted in lower contrast among some classes, even though the method improved segmentation results.

Table 3 shows that soybeans, corn, high-density built-up areas and water were classified with very good results (over 80% accuracy). Low-density built-up areas were confused with forests while pasture, golf courses, , parks and roads, however, were confused with one another due to their similar backscatter characteristics, thus had very low accuracies.

After applying well-designed rule sets, the overall classification accuracy reached 87.9% and kappa reached 0.867. Table 4 shows the confusion matrix of final classification result. Omission errors and commission errors were considerably reduced and confusions between classes were well resolved. Forests classification accuracy improved from 77.1% to 95.5% while that of parks improved from 64.2% to 92.1%. The accuracy of golf courses increased 33.5% and the accuracy of pasture, LDB and Roads increased over 40%.

	Reference Data										
Classified Data	Soybeans %	Wheat %	Corn %	Pasture %	Forests %	GC %	HDB %	LDB %	Parks %	Roads %	Water %
Soybeans	86.6	13.6	0	7.6	0	0	0	0	0	0	0
Wheat	6.2	75.4	0	0	0	0	0	0	0	0	0
Corn	0	0	85.9	0	0	0	0	0	0	0	0
Pasture	0	0	2.1	52.2	0	25.9	0	0	31.9	0	0
Forests	7.2	11.0	12.0	0	77.1	0	0	46.3	0	0	0
GC	0	0	0	9.9	0	59.1	0	0	0	32.0	2.3
HDB	0	0	0	0	0	0	81.4	10.3	0	0	0
LDB	0	0	0	0	22.9	0	17.9	43.4	0	0	0
Parks	0	0	0	23.0	0	7.5	0	0	64.2	33.4	0
Roads	0	0	0	7.3	0	7.5	0.7	0	3.9	34.6	0
Water	0	0	0	0	0	0	0	0	0	0	97.7

Table 3. Confusion matrix: Object-based NN classification

	Reference Data										
Classified Data	Soybeans %	Wheat %	Corn %	Pasture %	Forests %	GC %	HDB %	LDB %	Parks %	Roads %	Water %
Soybeans	86.6	13.6	0	7.6	0	0	0	0	0	0	0
Wheat	6.2	75.4	0	0	0	0	0	0	0	0	0
Corn	7.2	6.8	91.6	0	4.5	0	0	0	0	0	0
Pasture	0	0	2.0	92.4	0	0	0	0	4.0	0	2.3
Forests	0	4.2	6.4	0	95.5	0	0	2.4	0	0	0
GC	0	0	0	0	0	92.6	0	0	0	4.3	0
HDB	0	0	0	0	0	0	81.4	10.3	0	0	0
LDB	0	0	0	0	0	0	17.9	87.3	0	0	0
Parks	0	0	0	0	0	2.3	0	0	92.1	19.1	0
Roads	0	0	0	0	0	5.1	0.7	0	3.9	76.6	0
Water	0	0	0	0	0	0	0	0	0	0	97.7

Table 4. Confusion matrix: Integration of object-based neural network classifier and rule-based classifier

4.4 Change Detection

The classification result of RADARSAT SAR images were subtracted from the classified TM image. The change map has large amount of noise. This is mainly due to the misclassifications of RADARSAT SAR images and Landsat TM images. In TM classification, high-density built-up, low-density built-up areas, golf courses, and agriculture had certain amount of misclassification. Therefore, in the change detection process, these areas were identified as changed areas. In general, post-classification change detection is largely dependent on the classification accuracy of the images. The commission and omission error present in the SAR and TM images had a significant impact on the overall quality of the change detection.

The change detection procedure, however, was able to identify the areas of significant change, for example, new low-density and high-density built-up areas, major new roads and golf courses (Figures 2).

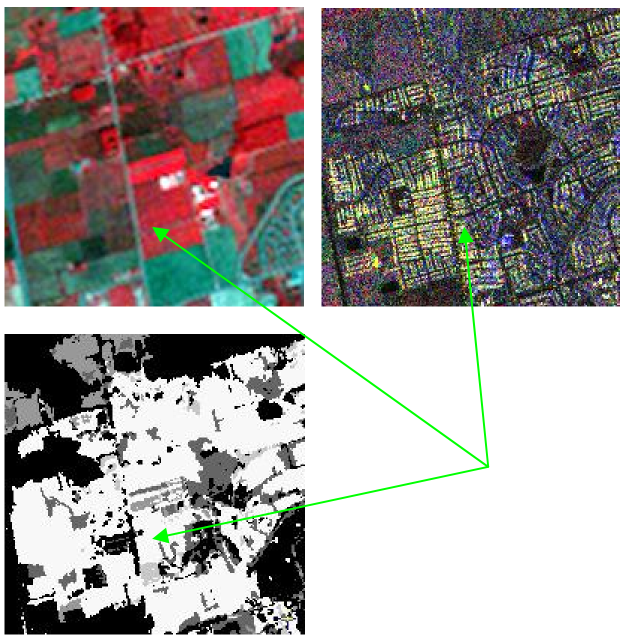

Figure 2. New built-up areas. Upper-Left: TM image, 1988; Upper-Right: SAR image, 2002; Lower-Left: Change map.

5. CONCLUSION

A new approach to extract urban landuse/land-cover information from RADARSAT fine-beam SAR imagery was presented in this paper. The proposed three-step routine produced good classification result for RADARSAT SAR imagery. The compression of SAR images from 16-bit depth to 8-bit improved segmentation performance and made consequent processes less time-consuming. Confusions existed between some classes in object-based neural network classification result. The application of well-developed rule set significantly improved the overall classification accuracy.

The post-classification change detection was able to identify the areas of significant change, for example, new low-density and high-density builtup areas, major new roads, and golf courses, even though the change detection results contained large amount of noise due to classification errors of individual images.

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