Object-based Urban Land Cover Classification with RADARSAT-2 Ultra-Fine-Beam SAR Data

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April 7, 2009

Introduction

- Background
  - The civil space borne SAR systems are now providing SAR imagery with a spatial resolution comparable to high-resolution optical systems.
  - Although SAR data is more reliably available than optical data, it takes more effort to employ high-resolution SAR imagery for urban applications.
- Objective
  - to develop effective object-based classification method for high-resolution SAR imagery over urban areas.

Study Area

- The major landuse/land-cover classes
  - high-density built-up areas, low-density built-up areas, roads, forests, parks, golf courses, water and four types of agricultural lands.
- These 11 classes were chosen to characterize the complex landuse/landcover types in the rural-urban fringe of the GTA

Data Description

RADARSAT-2 SAR Data

Acquisition date of SAR	Beam modes	Orbit	Incidence angles
Jun 25,2008	Ultra-fine	Ascending	30.61-32.04
Aug 12, 2008	Ultra-fine	Ascending	30.62-32.04
Sep 05, 2008	Ultra-fine	Ascending	30.61-32.02

Other Data

- DEM
- National Topographic Database (NTDB) vector data
- Filed Data were collected during each satellite overpass

Methodologies

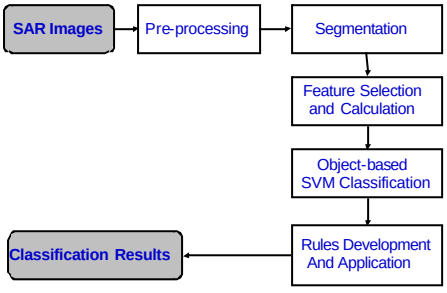


Image Pre-processing

- Orthorectification
- Image filtering
  - Intensity-Driven Adaptive-Neighborhood and the locally linear minimum mean-squared error (LLMMSE) estimator
- Data transformation
  - From 16-bit unsigned depth to 8-bit unsigned depth
  - The simple linear rescale min-max algorithm is used. The max value is set equal to the mean value plus two times the standard deviation value. The min value is the minimum pixel value.

Image Segmentation

- Multi-resolution segmentation algorithm, implemented in Definiens eCognition, is used.
- Two segmentation levels are created using the parameters shown in the table. The lower level (level 1) contains 131,251 image objects and the higher level (level2) 25,354.

	Scale Para-meter	Homogeneity		Shape Ratio	
		Colour	Shape	Compactness	Smoothness
Level 1	50	0.5	0.5	0.5	0.5
Level 2	120	0.5	0.5	0.5	0.5

Selected Features

Spectral features (backscatter characteristics)	Geometrical features	Texture features
Mean	Area	GLCM Homogeneity
Standard deviation	Border index	GLCM Contrast
Mean difference to neighbours	Compactness	GLCM Dissimilarity
Mean difference to neighbours (abs)	Density	GLCM Entropy
Mean difference to darker neighbours	Shape index	GLCM Mean
Mean difference to brighter neighbours	Length of main line	GLCM StdDev
	Length/Width	GLCM Correlation
	Width	Mean of sub-objects: stddev (only on level 2)

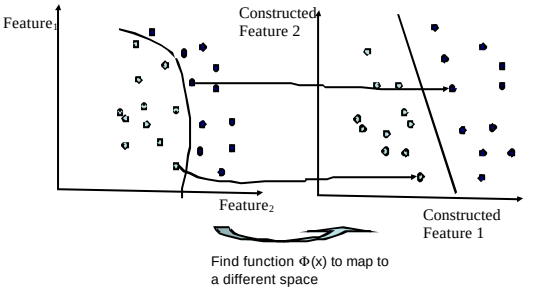
Feature Calculation and Inheritance

- These features are calculated for each object on both segmentation levels.
- Texture and contextual information is often very important for a successful classification.
- The image objects on level 1 inherit features from their super objects on level 2. The inherited features will give image objects on level 1 more information about their neighbouring objects and their context.
- Classification takes place on the lower level (level 1).

Support Vector Classification

- The Support Vector Machine (SVM) is an advanced machine learning methodology which was derived from statistical learning theory.
- SVM can map the input data features into a high dimensional feature space by a transformation function and construct the optimal separating hyperplane (linear surface) in that space.

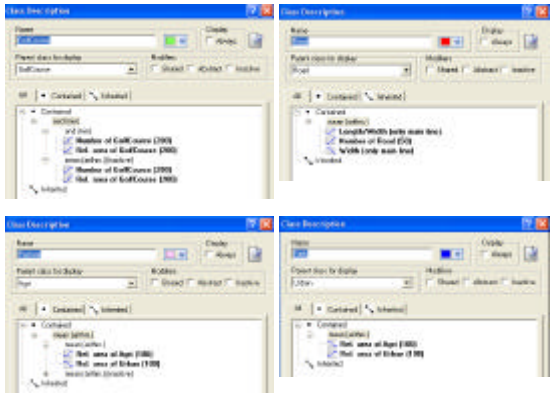
Linear Classifiers in High-Dimensional Spaces



- A widely used SVM program called LIBSVM is chosen to perform the classification.
- About twenty image objects are selected as training objects for each class on level 1.
- All calculated and inherited features are exported from eCognition and imported into LIBSVM.
- The classes of image objects on level 1 are predicted using LIBSVM.

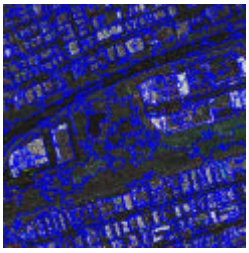
Rules Development

- Confusions exist in the initial classification result
  - Golf courses, roads, pasture and parks
  - Forests and wheat
  - High-density built-up and Low-density built-up
- Develop rules to resolve the confusions
  - Spatial relationship and shape features are used.

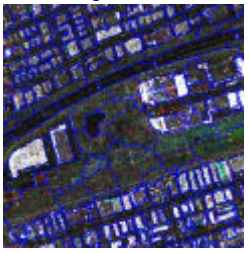


Results

- The effect of data transformation on segmentation



Segmentation result using original SAR images



Segmentation result using images derived from 8-bit transformation

Results - Classification

- The overall classification accuracy is 81% with kappa of 0.79.
- Confusions still exist between some classes

Confusion Matrix

	Reference Data											
Classified Data	Soya	Corn	Wheat	Pasture	Forests	GC	HDB	LDB	Parks	Roads	Water	User's Accu.
Soya	19520	0	0	0	0	0	0	0	0	0	0	1
Corn	0	41563	2	0	0	0	0	0	0	0	0	1
Wheat	2343	15990	53901	5981	4776	0	0	0	0	0	0	0.65
Pasture	0	0	2958	61387	0	1606	0	0	5983	5522	0	0.79
Forests	0	0	17523	0	73866	0	0	1913	5019	1681	0	0.74
GC	0	0	0	0	0	53953	0	0	0	2570	0	0.95
HDB	0	0	0	0	0	0	23865	4563	0	0	0	0.84
LDB	0	0	0	0	0	0	7794	39505	0	470	0	0.83
Parks	0	0	0	5800	0	6675	0	1564	40970	8602	0	0.64
Roads	0	0	0	6994	0	1646	0	1784	0	68803	0	0.87
Water	0	0	0	0	0	62	0	0	0	0	39175	1
Sum	21863	57553	74382	80162	78662	63880	31659	49329	51972	87648	39175	
Producer's Accu.	0.89	0.72	0.72	0.77	0.94	0.84	0.75	0.80	0.79	0.78	1	

SAR Imagery & Classification Result

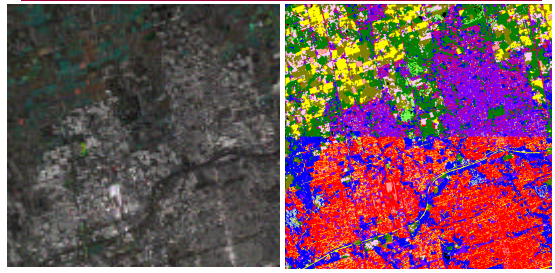
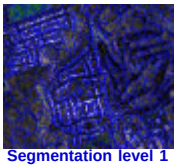
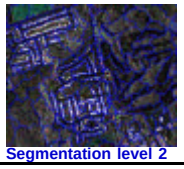


Image Segmentation and Classification

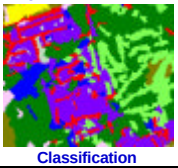
SAR image



Segmentation level 1



Segmentation level 2



Classification

Conclusions

- Object-based approach has potential to classify high-resolution SAR imagery in urban areas.
- Major confusions could be resolved by knowledge-based rules.

Thank you for your attention!