

Object-based updating of land-use maps of urban areas using satellite remote sensing

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Geographical information in the form of maps is continuously subjected to change, especially in urban areas. Therefore maps have to be updated, which can be done using satellite remote sensing techniques since many satellites are in orbit today. In this paper several object-based classification and change detection techniques are investigated. An important aspect in map-updating is the translation from land cover (image domain) to land use (map domain). To study the results of several techniques, data of Landsat 5 TM (30 m), ERS 1 (30 m), Ikonos (4 m) and PHARUS (4 m) were used. The focus was on data of urban areas in the Netherlands. Classification of the images was done using spectral information, texture and in one case information on the relation between adjacent objects. Non-parametric techniques were applied because most textures appeared to be non-Gaussian distributed. The classification accuracy of Landsat 5 TM was best, second was ERS 1 and third were the results of PHARUS and Ikonos. Several reasons are given, but classifying high-resolution images is clearly more difficult than classifying low-resolution images. In case of change detection, pre-classification techniques were preferred. Although the methods can be improved, more information is required, e.g. from combining sensors or from the map to be updated. Map updating may not become fully automatic, but the job of a human operator can be made easier using the techniques investigated in this paper.

Introduction

The world is rich of geographical information in the form of maps. We all know paper maps but today, more and more maps become available digitally. Examples of such maps are the Digital Chart of the World (DCW), the Vector Map (VMap) product series and national digital maps as the TOPvector product series of the Topografische Dienst Kadaster, Netherlands national mapping agency. The areas of applications of those maps are various: environmental planning, agriculture, forestry, tourism, defence, and many more. Because the Earth's surface, that maps attempt to describe, develops, maps are continuously subjected to change, especially in urban areas where the pace of development is rela-

tively high. To keep maps up to date, it is important to know where the change took place, what has changed, how it is changed and if it is relevant for the map. To answer these questions satellite remote sensing techniques can be used, since many commercial satellites are currently in orbit. Examples are Landsat, Spot, Ikonos, Quickbird, ERS, Envisat, and Radarsat. More are planned.

The remote sensing techniques that are discussed in this paper focus on land-use classification and change detection. An important development in these techniques that is addressed here is object orientation. For evaluation some of these techniques were applied to satellite data of several areas in the Netherlands, including data of Landsat 5 TM (30 m), ERS 1 (30 m), Ikonos (4 m) and PHARUS (4

m). Landsat 5 and Ikonos are optical/infrared satellites. ERS 1 is a radar satellite. PHARUS (Griedanus et al. 1996) is an airborne imaging radar representing the future generation of radar satellites which is planned to be in orbit from 2005 (e.g. Radarsat 2, Cosmo/SkyMed and TerraSAR). This paper is based on an earlier publication by the author ([6]).

Land Cover and Land Use

An important aspect in translating satellite images into maps is that satellites give a physical description of the earth's surface (materials, surface roughness, structure), while most maps give a functional (socio-economic) description. Both descriptions are referred to as land cover and land use respectively and are often mixed up ([1], [9]). Examples of land cover are grass, trees, building and asphalt. Examples of land use are agricultural, residential, commercial and industrial. Most land use classes are composed of several land cover types, and have often a many-to-many relationship ([11], [4], [9]), see also figure 1.

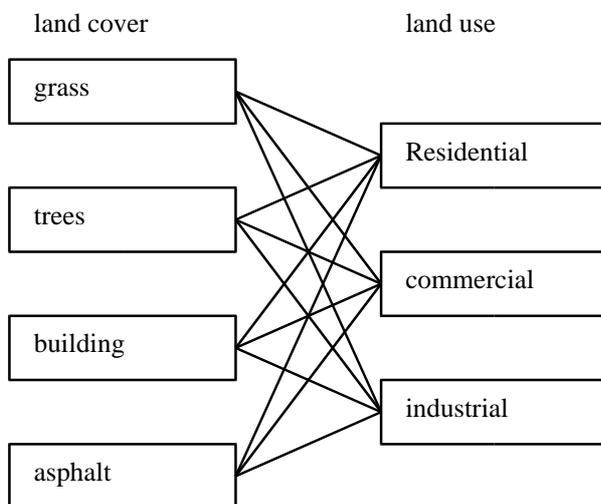


Figure 1: Many-to-many relationship between land cover and land use (Fisher et al. 2002).

Test Areas and Data

In this paper classification and change detection is applied to satellite images of the Netherlands. The Netherlands can be characterised as a well-planned

country: almost every acre has a function. Compared to many other countries the Netherlands is quite urbanised, especially in the west and south. Three test areas were selected:

- Zwolle and Veluwe, in the centre to the East of the Netherlands, is a less dense urban area. It is dominated by meadow and forest (Veluwe).
- Randstad Holland, a dispersed but dense urban area in the west of the Netherlands. It contains residential areas, industry, greenhouses, pasture, arable land, and some forest. The area includes two of the four largest cities in the Netherlands, Rotterdam and The Hague.
- The Hague, in the west of the Randstad Holland by the North Sea is quite a green city. It contains much forest and is built against a (natural) sand dune area that protects a large part of the Netherlands from the sea. This area is chosen to study higher resolution data.

The maps of the first two areas are from VMap level 1 of the Netherlands (1:250,000) that was produced in 1998. The information model behind VMap is the Digital Geographic Information Exchange Standard - Feature Attribute Coding Catalogue ([8]) which was developed by the Digital Geographic Information Working Group ([8]). About 150 types of entities are included. Because some VMap level 1 land-use types are rather close, the map was conceptually generalised by merging areas with different codes into a map with less classes. For instance, forest includes the classes orchard/plantation and trees, which is conceptually valid in the Netherlands. Unfortunately, VMap level 1 does not show areas that contain industrial activity only, if reproduced these are included in urban. Figure 2 shows the map of the area of Zwolle and Veluwe. The map of The Hague comes from the TOP10vector series of the Netherlands (1:10,000). It was updated in 1999. Due to the large number of land-use classes the TOP10vector was conceptually generalised as well. It is shown in Figure 3. The satellite data are summarised in table 1. There is no relation between useful resolution and pixel spacing (i.e. sampling distance). If the resolution is higher than the pixel spacing, this means that the images are oversampled. The number of looks is a measure for the speckle-noise reduction. For instance, when the number of looks is three, this means that the speckle-noise is reduced by averaging three independent images (the band-

width of one image corresponds to one-third of the antenna beam). The polarisation stands for the orientation of the radar waves. The backscatter prop-

erties of objects can be different for different polarisations. Some acquisitions are previous to the map updates but the differences in land use are small.

sensor	Landsat 5 TM	ERS 1	Ikonos	PHARUS
type	optical/infrared	radar	optical/infrared	radar (airborne)
altitude	705 km	785 km	681 km	6 km
useful resolution	30 m	30 m	4 m	4 m
useful bands	6 (0.45-2.35 μm)	1 (5.3 cm)	4 (0.45-0.88 μm)	1 (5.3 cm)
visual	3	-	3	-
infrared	3	-	1	-
microwave	-	1	-	1
number of images	1	1	1	2
number of looks	N/A	3	N/A	5
polarisation (used)	N/A	VV	N/A	HH
test area	Zwolle and Veluwe	Randstad Holland	The Hague	The Hague
acquisition data	18 October 1993	23 June 1995	23 September 2000	26 April 1996 27 January 1998
pixel spacing	20 m	20 m	2 m	2 m
size	1500x1500 pixels 30x30 km	3209x3273 pixels 64x65 km	1353x1825 pixels 2.7x3.7 km	1353x1825 pixels 2.7x3.7 km

Table 1: Overview of satellite data of the three test areas.

Classification Techniques

Classification techniques, how to translate a satellite image into land cover or even land use, can be divided in various categories. Two are described: feature-based and knowledge-based (i.e. rule-based) techniques. In feature-based classification images are classified based on a set of distinguishing characteristics or features. A feature can be the spectral intensity, texture, polarimetric information, etc. Texture can become important if only one spectral band is available, e.g. in case of the radar images. Therefore a set of texture measures was investigated with respect to their separability of land use in the ERS 1 image of the Randstad Holland ([6]). The measures that performed best were mean intensity (actually no texture), variance, weighted-rank fill ratio and semivariograms. The weighted-rank fill ratio is an order-statistic, which is defined as the ratio of the power of the 5% brightest pixels of an object and the total power of all pixels. The semivariogram is a eo-statistic measure, which is an indicator of the geospatial distribution of textures (e.g. repeatability, depth).

The most popular feature-based classifiers are para-

metric, meaning that they decide if a feature-vector belongs to a certain class, based on the parameters of the class probability-density-function (e.g. mean and standard deviation). A problem with these classifiers is that most assume the features to be normally distributed. Although other classifiers can be designed, there can still be the problem of features having different distributions. Linking up these distributions is sometimes possible by applying variable transformations, but not always. Another solution is to apply non-parametric techniques, which consider the whole population and not only the mean and standard deviation. An example of a non-parametric classifier is the k -nearest neighbour (k NN) classifier which is based on the following distance ([10]):

$$d_i^2 = (X - X_{i,NN})^T \Sigma_i^{-1} (X - X_{i,NN})$$

Here $X_{i,NN}$ is the k -th nearest neighbour of class i to feature vector X under test and Σ_i the covariance matrix of class i . The smallest distance determines the class. This procedure is also referred to as the volumetric k NN procedure. For computational reasons (1) can be simplified to:

$$d_i^2 = \sum_{j=1}^n \frac{(x_j - x_{ij,NN})^2}{\sigma_{ij}^2}$$

Here x_j is the j -th element of feature vector X with dimension n . $x_{ij,NN}$ is the j -th element of the k -th nearest neighbour $X_{i,NN}$ and σ_{ij} is the standard deviation of all j -th elements of all sample feature vectors of class i .

Another example of a non-parametric classifier is the knowledge-based or rule-based classifier ([11], [15]). The most common rule in such classification is the *if-then* rule: *if condition then inference*. Fuzzy rule-based systems follow the same rules, except that conditions are not hard. In a basic rule-based system for instance the condition if a radar tone is dark, is determined by a hard threshold on the radar backscatter. In a fuzzy rule-based system this condition is determined by a membership function which describes the degree of membership to a fuzzy set ([2]). Because land cover and land use have many-to-many relationships, knowledge-based or rule-based classification systems are ideal to convert one to another ([11], [4]).

The classification techniques that were discussed, can be applied to pixels or objects. From a land-cover point of view, an object is a region or segment in which the feature space is homogeneous to some degree, so it fits one (physical) description. From a land-use point of view an object fits one function. In general, object-based classification is preferred to pixel-based classification (i.e. pixel-by-pixel classification) because it is more accurate ([13]). Objects can be extracted from the satellite image using segmentation techniques ([14], [2]).

Change Detection Techniques

Change detection is useful when we have to update a map of an area and do not know which parts have changed. Several techniques exist which can be divided into two categories: pre-classification and post-classification change detection. The basic pre-classification methods are image differencing and image ratioing ([17], [16]), which compare the images directly, before classification. Image differencing is subtracting the before image from the after image. Image ratioing is dividing the first by the latter. Generally, image ratioing is less sensitive to radiometric errors, and preferred in case of radar change detection due to the radar image statistics. Other pre-classification methods, based on image differencing and ratioing, have been designed ([17],

[5]). One of them, especially designed for radar images, applies an adaptive filter to the ratio image, to reduce the speckle-noise which is typical for radar images.

Post-classification change detection is applied to the classification results of images. The advantage of this method is that it applies to information from sources that are difficult to combine before classification (e.g. optical/infrared, radar, digital maps). A disadvantage of this method is that it is sensitive to classification errors.

The change detection techniques discussed can be applied to pixels and objects as well. Matching the results with existing map objects will show which areas or objects have changed. In object-based change detection it is important that the boundaries of the object under test are the same. Otherwise sliver or larger polygons that indicate false change may occur. One way to overcome this problem is to apply multi-channel segmentation in which both images are input to the segmentation process ([3], [18]).

Results and Discussion

To investigate the effects of these classification and change detection techniques, several were applied to the objects that were recognised from data that were discussed. Addressed were spectral and textural features. Non-parametric techniques were applied because most features, especially the texture measures, appeared to be non-Gaussian distributed. The classifiers were trained manually by selecting a number of appropriate training objects. Table 2 gives an overview of the results.

Land use classification of Landsat 5 TM was done using a fuzzy rule-base which included rules based on the spectral intensities, texture (i.e. standard deviation) and some rules considering the relation between adjacent objects. Figures 2 and 3 shows the result. The relatively high percentage of correct classification (Pcc) is mainly due to the high number of bands compared to the low number of classes. Besides, this area is less complex because it is dominated by natural land cover instead of urban. The effect of using a fuzzy classifier must not be overestimated. The rules on the spectral intensities and texture are based on training sample-areas, as with the Nearest Neighbour (NN) classifier.

sensor	nr.of bands	res.	map	scale	classifier	texture	nr.of class.	Pcc	kappa
Landsat 5TM	6	30m	vMap1	250K	fuzzy	yes	4	82.9	59.6
ERS 1	1	30m	VMap1	250K	NN	yes	5	52.1	36.3
Ikonos	4	4m	TOP10	10K	NN	no	5	42.4	26.8
PHARUS	1	4m	TOP10	10K	NN	yes	3	48.3	29.4

Table 2: Overview of land-use classification experiments.

The ERS 1 image was classified using different texture measures because only one band was available. The best performing texture measures (i.e. mean intensity, variance, weighted-rank fill ratio and semi-variograms) were applied. The results show that the textures improve classification but the results are not optimal. This is due to the fact that (i) the class definitions between the map (land use) and the image (land cover) are not exactly the same, (ii) the fact that the map shows deficiencies, and (iii) the fact that the land-cover information content of ERS 1 leaves something to be desired.

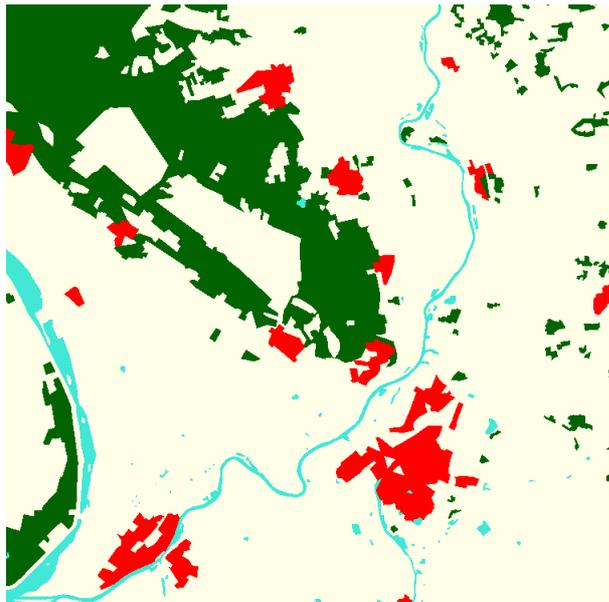


Figure 2: Classification of the test area Zwolle and Veluwe. Urban = red; forest = green; water = blue; other = light yellow; unclassified = black.

The classification result of Ikonos shows the lowest Pcc. The reason for this was found in the facts that different land covers are made up of the same materials (e.g. roofs and roads are often made up of tarmac) and that the map that was used showed deficiencies as well. Using texture did not improve

the result. The result is worse than that of Landsat 5 TM which is due to the lower number of bands, the higher complexity of the scene, and the higher number of classes. Again, it can not be fully ascribed to the classifier.

The classification accuracy of PHARUS, using the same map, was slightly better. The best performing texture measures were applied here as well. However, the result was not better than that of ERS 1. Besides the reasons mentioned with the classification of ERS 1, this was caused by the fact that radar reflections are often due to parts of buildings instead of the whole building (e.g. wall-ground reflections).

The NN classification of the high-resolution sensors Ikonos and PHARUS is not optimal. Classifying high-resolution imagery is clearly more difficult than classifying low-resolution images. On the other hand, different maps were used for different resolutions.

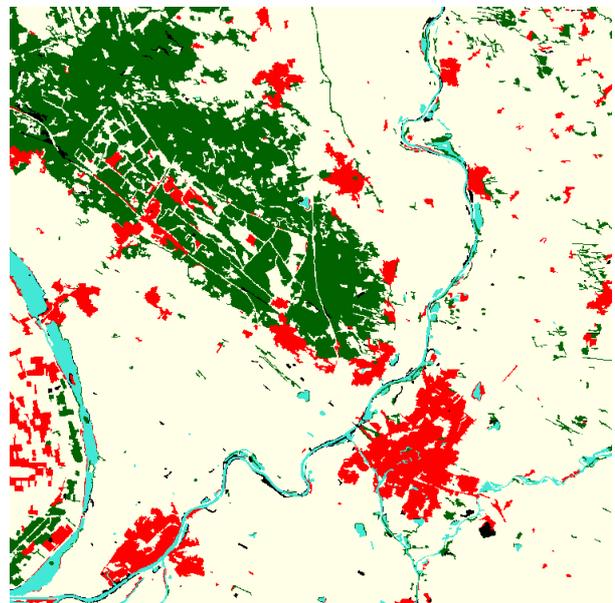


Figure 3: VMap level 1 of the test area Zwolle and Veluwe (source: Topografische Dienst Kadaster) Landsat 5 TM image.

In case of the change detection techniques, three were applied to the two PHARUS images:

- Pre-classification change detection applied to the ratio image using an adaptive filter
- Pre-classification change detection by multi-channel segmentation
- Post-classification change detection

Pre-classification techniques are preferred to post-classification change detection, unless the classification is accurate but this was not the case, see table 2. The difference between pre-classification change detection applied to the filtered ratio image and by multi-channel segmentation is small. The first slightly better preserves smaller objects, while the latter better reproduces the shape of the changed objects. The main reason for that is found in the fact that the speckle in the PHARUS images was already quite low due to its relatively high number of looks.

Conclusions

Despite the fact that it is not easy to make a good comparison between the sensors due to different numbers of bands, areas, maps, scales and numbers of classes, the results are indicative for what can be achieved in image classification and change detection today. Although the methods can be improved, more information is required in the map-updating process. Instead of using a single sensor, images from multiple sensors covering different parts of the spectrum can be applied (e.g. combine optical/infrared with radar). Another possibility is to include information on the relation between adjacent objects (this was only done for Landsat 5 TM) or information from the map that has to be updated. Techniques that improve the vector results of classification may be required as well.

Map updating may not become fully automatic, but the job of a human operator can be made easier using the techniques investigated in this paper. Change detection will reduce the number of areas an operator has to check for changes, and object-based classification of those areas will provide the operator with the new map objects. And although the objects may not all be perfectly shaped and classified, the operator does not have to do all the work, especially when the percentage of correct classification is high.



Figure 4: Classification of the generalised TOP10vector of The Hague. Buildings = red; roads/bare soil = light yellow; low vegetation = light green; trees = dark green; water = blue; other land use = white, shadow/unclassified = black.

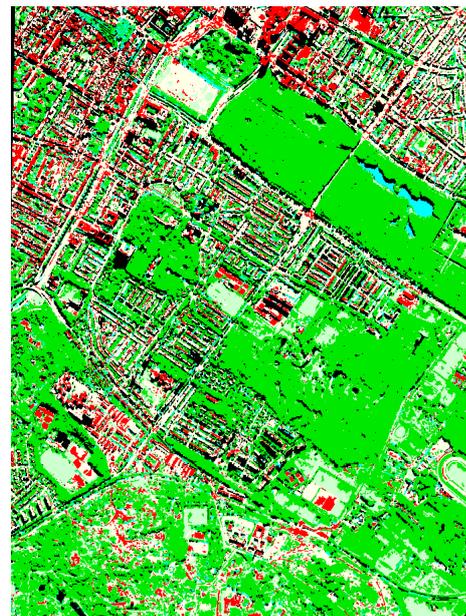


Figure 5: Generalised TOP10vector of The Hague (source: Topografische Dienst Kadaster) Ikonos image.

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