Per-Parcel Classification of Urban Ikonos Imagery

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SUMMARY

For some years high resolution imagery like Ikonos and Quickbird has come available to the public. In contrast to our commons sense the increase in spatial resolution does not automatically lead to improved classification accuracy, in particular in urban areas. The automatic classification of land cover classes often requires an object-based approach where classification is not any more based on individual pixels but on homogenous objects. But as traditional image analysis software is not adapted to this new methodology, the user is forced to invest in expensive new software or to develop own algorithms. This paper presents an alternative classification method, parcel-based, in order to overcome these obstacles. In a first phase an ordinary per-pixel classification is performed and the results are then summarized and assigned to land parcels. In the next phase the land parcels are classified into final land use classes by means of a discriminant analysis of the parcels.

KEYWORDS: *high resolution imagery, Ikonos, classification, per-parcel, urban land use*

DESCRIPTION OF THE LAND USE CLASSIFICATION PROBLEM

One of the interesting applications of satellite imagery is the regular update of spatial databases at a low cost. In particular in dynamic urban environments a fully automated update process can save considerable time and money in comparison with human interpretation of images. With the introduction of high resolution satellite imagery[33], the regular update of large scale city maps seems very close. Indeed, imagery like Ikonos provides a lot of detail in comparison with the images of the 'Landsat generation': many individual objects like trees, cars, zebra-crossings etc. are visible on urban images. However, automatic classification seems to be more difficult than it used to be. We will focus on these classification problems in the context of urban land use and propose a possible methodology to classify urban land use.

One major problem with high resolution images is the high resolution itself because for general classification purposes they contain too much detail:

Desired land cover object	*Land cover sub-objects in image*
Street	surface + cars + zebra crossings + pavement
Building	façade + roof parts with different reflection
Built up area	buildings + back yards + parking places

Such high details obscure a direct relationship between the desired land cover objects and the spectral response of the pixels whereas with medium resolution imagery there was a much better relation between land cover objects and their spectral response. With Ikonos many small individual land cover objects are visible and they only make sense as a whole or within their spatial context. Unlike the human eye, which

[33] Ikonos sensor, launched in 1999, spatial resolution of 1 meter Quickbird sensor, launched in 2001, spatial resolution of 0.62 meter

is very skilled in recognizing these spatial patterns as meaningful objects, the traditional image classification software is not used in 'thinking' this way. The fact that the objects of interests are much larger than the pixel size and that they are composed of many individual sub-objects leads to difficulties when applying a standard per-pixel classification strategy. In addition the high detail will lead to a huge salt'n pepper effect and thus it is clear that very high resolution imagery requires an adapted classification technique with specific attention for the spatial context. One way to deal with this problem is to build 'meaningful objects' at different hierarchical levels through the process of image segmentation (Blaschke et al., 2000). By creating such homogeneous objects at an appropriate scale one can already reduce unwanted spatial detail at this scale. The subsequent classification is applied to the objects which hold spectral parameters (mean spectral response, texture, etc.) as well as spatial parameters (shape, compactness). While this is a robust and appealing approach it requires specific and expensive software (e.g. *eCognition*, Definiens Imaging). Less complex is the per-parcel method (Aplin et al. 1999) which assumes that object boundaries exist a priori (e.g. land parcels) and serve as the units for classification. The methodology to be developed in this paper follows the per-parcel method.

A second major problem concerns the identification of the *land use,* which is a step beyond standard land cover classification. Whilst land cover is related to the physical characteristics of the earth's surface and can fairly easily be classified, land use is related to the socio-economic occupation of the earth's surface and its classification is more problematic. Land use is first of all defined in terms of function but it can be inferred more or less from its form (Barnsley & Barr, 1996). Spatial patterns and relations (between land cover objects) must be taken into account to infer the land use and an object-oriented approach is necessary. Barnsley and Barr (1997) constructed a Structural Analysis and Mapping System (SAMS) that is able to 'understand' urban land use in terms of the structural composition of the land cover objects. eCognition also provides a framework to construct relations between land cover objects in order to determine the land use class. While these methods explicitly search for spatial relations (e.g. adjacency of land cover objects) and try to understand the spatial structure between land cover objects, we propose a more black-box oriented method that is feasible with an average statistical software package. Within the framework of the per-parcel classification method we statistically examine the land cover information to determine the land use of the parcel.

DATA AND METHODOLOGY

In this research we worked with an Ikonos image of Brussels, captured in 2001 (*Figure 5*). The resolution for the panchromatic band is 1 x 1 meter and the four multispectral bands have a resolution of 4 x 4 meter. The image covered the southeastern part of the Brussels Capital Region, with different land occupation ranging from peri-urban land use to the typical high density land use occupation in the city centre. *Figure 5* shows a part of the European district with its large buildings, parking lots, some green elements and avenues. This view illustrates the complexity of very high resolution urban imagery. The image was rectified but not orthorectified resulting in slight planar deviations (up to 20 m) due to the relief in Brussels (height differences up to 100 m). A large scale base map was available which contained accurate information on streets, physical blocks, buildings etc. The Corine Land Cover Map was used as a medium scale reference layer for accuracy assessment.

A number of steps are performed to achieve the final land use classification. First, the image needs some geometric as well as spectral preprocessing. Geometric correction of the image is necessary to get a better match between image and vector layer so that the land parcel boundaries match exactly those on the image. Next, the four multispectral bands were merged with the panchromatic band to produce four new 1 x 1 meter multispectral bands. Classification is a two-stage process: first the relevant land cover objects are derived and in the second stage this information is summarized per parcel and these parcels are then classified. Land cover is classified with a per-pixel maximum likelihood classifier in Erdas Imagine and ArcGIS is used to assign this land cover information to the land parcels. Then the land parcels are profiled and classified into land use classes with the "Discriminant Analysis module" of Statistica and final post-processing is done in ArcGIS.

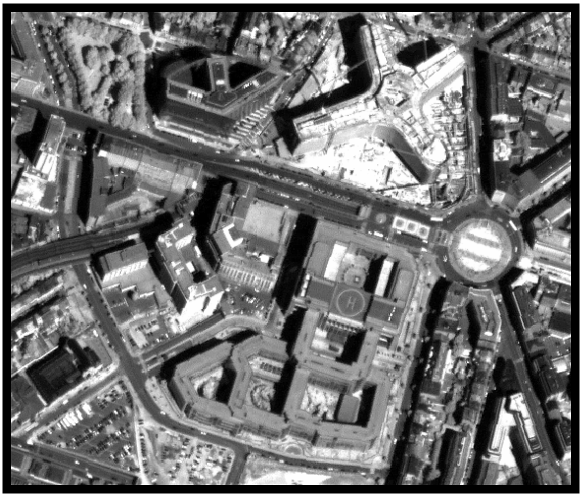

Figure 5: detail of Ikonos panchromatic band; European district, Brussels

PRE-PROCESSING STEPS

Rectification

Ikonos imagery exists at the different geometric quality levels and our image was of moderate geometric quality. When overlaid with a high precision vectormap several displacements could be observed and these errors must be corrected before all other processing can take place. Best results were achieved with rubber sheeting technique and a lot of ground control points. The reference parcel polygons matched very well with the boundaries on the images (street sides) and thus it was allowed to “cut” the image into land parcels (Figure 2).. A good geometric match between image and parcel layer is necessary to avoid that the parcels get ‘contaminated’ with external spectral information.

Data Fusion[34]

Next an appropriate method for merging the multispectral bands with the high resolution panchromatic band was applied. Adaptive Image Fusion is a data fusion method using filter techniques that acts as a pre-segmentation on the image (Steinnocher, 1999). The goal is not only to sharpen the multispectral image but also to get the objects in the new image more homogeneous (Figure 2). The more the objects are homogenous the less salt’n pepper will show up in the classification. Adaptive Image Fusion also preserves the spectral characteristics of the original low resolution image to a high extent (Steinnocher, 1999). The fused image (Figure 2, right) is sharpened as can be noticed on the edges of buildings but the buildings themselves are far more homogenous than on the original multispectral (Figure 2, left) or panchromatic (*Figure 5*) images.

[34] “Adaptive image fusion” software was provided by Klaus Steinnocher (Klaus.Steinnocher@arcs.ac.at)

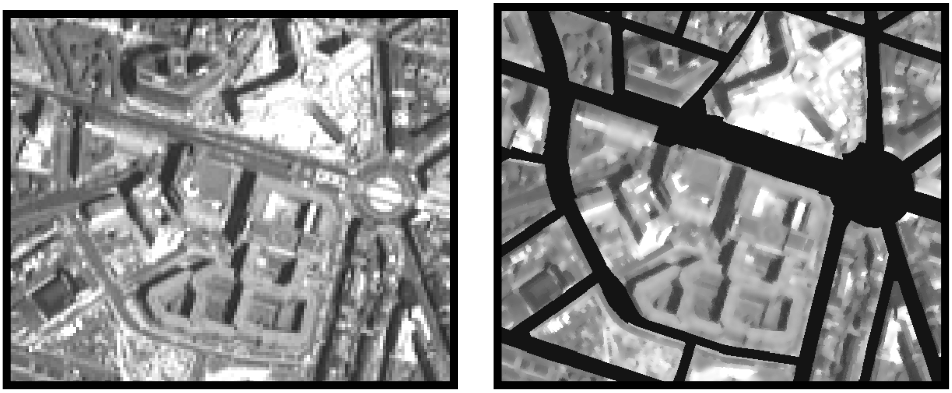

Figure 6: Ikonos false colors 4 x 4 m multispectral image and AIF fused 1 x 1 m image

CLASSIFICATION

Per-pixel classification

A supervised per-pixel maximum likelihood classification was performed on the basis of several land cover class signatures that were derived by a preliminary unsupervised classification and by human interpretation. First an unsupervised classification was run on a representative subset of the city centre – which contained most of the land cover classes – resulting in about 30 classes. Some of these classes were merged with the aid of separability measures and visual interpretation. Then, from another subset, situated near the peri-urban transition zone some additional classes were selected to complete the existing classes. Finally the image was classified using 12 land cover classes: a shadow class, several “built”- classes, soil, water, vegetation, roofs, grass-arable land etc. Salt’n pepper was eliminated to some extent with a majority filter and Erdas’ elimination module (elimination of small contiguous blocks of pixels). The resultant land cover map contains many land cover objects and has consequently only a moderate readability (*Figure 7*). The quality of the land cover map is crucial because it is the basis for the second, land use classification. Accuracy assessment on this map was not performed but we certainly expect errors. An example is the presence of several water objects in the middle and top left part of the image. In this case, water has been confused with shadow. Indeed shadow is difficult to classify and sadly enough shadow is omnipresent in cities due to the high buildings. Shadow pixels were eliminated to some degree by means of shadow-specific majority filter.

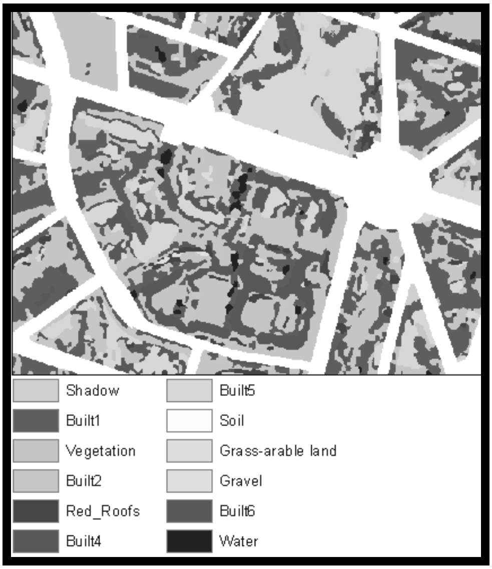

Figure 7: Land Cover, per-pixel classification, European district

Per-parcel classification

For every parcel several land cover parameters were summarized:

- total area per land cover class
- mean area per land cover class object
- number of land cover class objects
- standard deviation for perimeter and area for all land cover objects

This resulted in 35 land cover parameters for every parcel upon which a discriminant analysis was conducted with the statistical software package Statistica. Discriminant analysis is used to determine which variables discriminated between two or more groups. The "best" variables are then used to predict group membership (of new cases): 24 out of the 35 variables were used in the discriminant analysis model. In fact these variables are transformed to fewer new variables – canonical roots - in such a way that these roots discriminate most between the groups. In our case the groups are the land use classes: high density built area or central city land use, medium density residential area, low density residential area, offices and industrial area and 'green' area. The last class is not really land *use* but more land cover, however since we are interested in urban land use we didn't focus on differentiating 'green land use'. For each of the land use classes some typical reference parcels were selected on which the discriminant and canonical correlation analysis was done.

*Figure **8*** shows examples of a typical low density residential class and a high density built area class. It is clear that these two parcels differ from each other on a number of land cover parameters such as total green area, number of built land cover objects, mean area of built land cover objects etc. We expect these different land cover structures to be discovered in the canonical correlation analysis and the resulting canonical roots will describe these structures. The final result is a set of classification functions which allows us to classify all other parcels (over 2000 parcels) according to their scores on the roots.

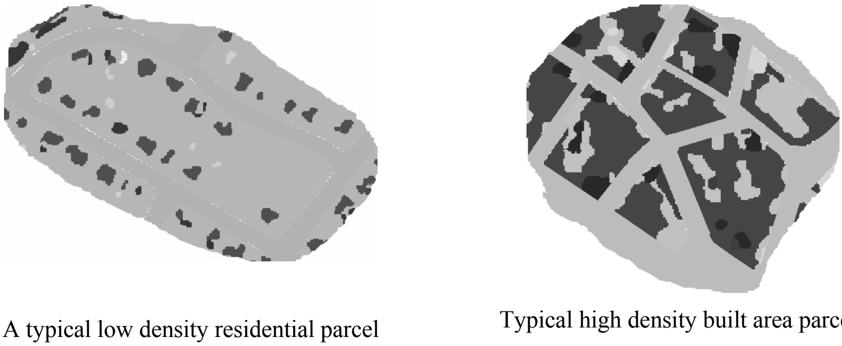

Figure 8: Typical land use classes

Four canonical roots are calculated of which the first two explain the different land use very well (*Figure 9*). There are however two reference parcels of the type "offices and industrial" which tend more to type of "high density built" parcels. This distortion is also present in the third and fourth roots and possibly points out that these parcels represent an extra class between the two other classes. Another hypothesis is that these two parcels are merely outliers and should be neglected, thus accepting that they will be classified wrongly.

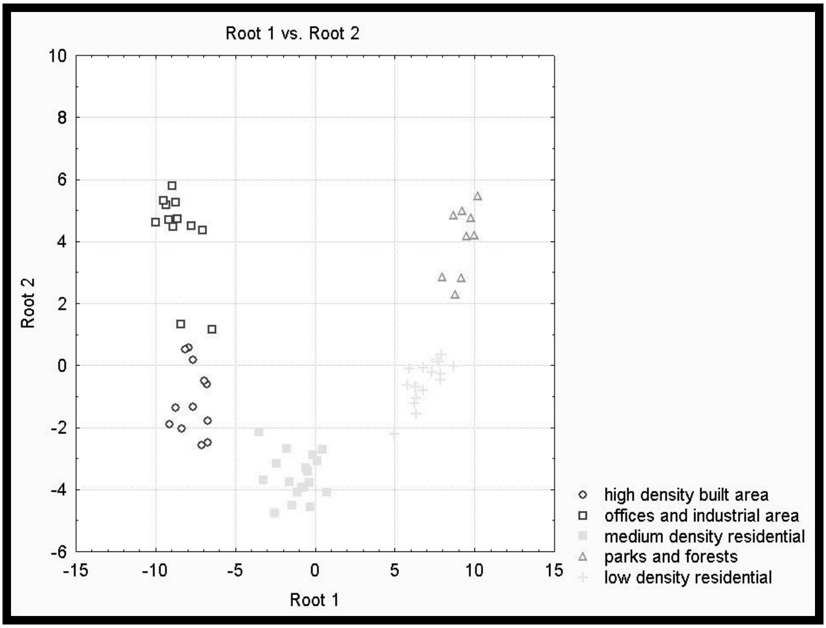

Figure 9: Root graph showing the five types of land use reference parcels

We can draw some conclusions concerning the interpretation of the first two roots. It is obvious that root 1 correlates with the level of morphological urbanization because on this root the land use classes can be ordered with decreasing level built up area. Thus, root 1 can be characterized as a “greenness axis”: the higher its value, the more “green” the land parcel is or the less urbanized it is. The second root contrasts “offices and industrial area” and “parks and forests” on the one hand with “high density built area” and both residential classes on the other hand. In fact this root distinguishes between non-residential land use (the former) and residential land use (the latter) and represents a “residential axis”. This is further confirmed because the root is mainly correlated with the “red roofs” land cover parameters which are typical for (suburban) residential land use. The third and fourth roots discriminate less between the land use classes and are more difficult to interpret.

Post-processing and results

After automatic classification of the five land use classes, two more land use classes, railway infrastructure and the canal were manually added. These two classes were not automatically classified because there were too few parcels involved making it much faster to add these classes manually. Then, some parcels with a low probability of being correctly classified were reclassified according to the land use of their neighbouring parcels. Suppose an office/industrial land parcel with low classification probability is surrounded by medium density residential parcels, then the central parcel would have been reclassified to medium density residential. This ‘cleaning’ process improved the map’s readability but the effect on the classification accuracy was not tested. Finally a vector road layer was added to complete the map (*Figure 10*).

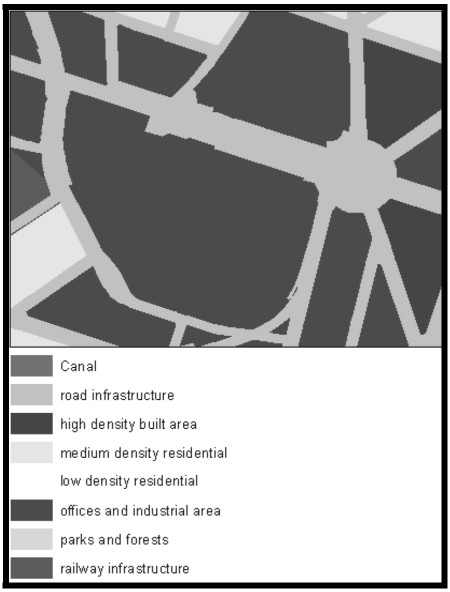

Figure 10: Land use map, per-parcel classification, European District

Classification accuracy is low, only 73%, which we believe is due to the fact of typical urban land use, which is more difficult to classify than non-urban land use (*Table 4*). In the accuracy analysis low and medium density built classes were merged because they were not separate classes in the reference layer (Corine Land Cover Map). Although the producer’s accuracy (the percentage correctly classified reference parcels) is rather the same for all classes this is not the case for the user’s accuracy which indicates that high density built area and offices and industrial area are the least well classified. This stresses again the difficulty of classifying urban areas where it is difficult to 1) produce a good quality land cover classification and 2) distinguish between offices/industrial land use and high density built areas. The distinction between those two land use classes is not completely clear as could be seen on the canonical root graph in *Figure 9*. Classifying urban land use is in many studies problematic and gives low accuracies (e.g. Aplin, 1999). Care should be taken when addressing all classification errors to the per-parcel classification technique because that is probably not the case. Improvements in the initial land cover classification and image quality (e.g. less oblique view angle, less shadows etc.) will have a substantial effect on the final land use classification. In addition the reference data' s accuracy is questionable as the Corine Land Cover Map is small scale data compared to our land use classification. For the study region exists a more accurate large scale map but it is less applicable because the land use classes do not overlap well with our classes.

	Producer's accuracy (%)	User's accuracy (%)
High density built area	72	60
Low & medium density built area*	73	83
Offices and industrial area	72	55
Parks and forests	76	89

* low and medium classes are grouped because they are not separate classes in the reference layer

Table 4: Producer's and user's accuracies for per-parcel classification

CONCLUSIONS

With the introduction of very high resolution satellite imagery the interest in automatic derivation of high quality land cover or land use maps has increased. However it is clear that a standard per-pixel multispectral classification cannot produce satisfying results, in particular due to the very high resolution. With the arrival of the high resolution there are so many small objects visible which result in a high amount of unwanted spatial detail. Combined with the salt'n pepper effect in a per-pixel classification, the result will be of low quality, especially in an urban environment. Another problem is the transition from land cover to land use and this requires some notion of spatial context and understanding of spatial relations and configuration between land cover objects. Therefore we presented a two-stage classification approach: a standard per-pixel classification was followed by a per-parcel classification. We believe that this method can better discriminate between land use types because the spatial configuration of all land cover objects within a parcel is taken into consideration.

Our main conclusion is that using a per-parcel classification approach to classify very high resolution imagery like Ikonos provides some major advantages against a per-pixel approach. Using parcels it is now possible to determine the land use whereas with a per-pixel approach the information extracted is limited to land cover or the physical characteristic of the earth's surface. Second, the end product is of better cartographic quality then would have been with per-pixel method only (no salt'n pepper, better readability). Third, the accuracy differences between per-pixel and per-parcel results are not evaluated because 1) they are two different products and 2) the per-pixel classification acts as an intermediate result and consequently per-pixel errors might be reproduced in the per-parcel classification.

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