Inventorying urban areas with Very High Resolution Satellite Images

Tim Van de Voorde[1], Marc Binard[2], Tom Op 't Eyndt[3]
[1] Center for Cartography and GIS, Vrije Universiteit Brussel
[2] Laboratoires SURFACES, Université de Liège
[3] Ondersteunend Centrum GIS Vlaanderen, Vlaamse Landmaatschappij

Introduction

Prior to the commercial availability of Very High Resolution (VHR) satellite imagery, the applicability of Earth Observation data in the urban planning sector was very limited. The spatial resolution of the imagery, supplied by platforms like Landsat TM and SPOT HRV, was too coarse to be of real practical use to urban planners and their applications. Satellite images of urban or sub-urban areas are characterized by large radiometric variations due to the small size and the diversity of the objects. This in turn causes a radiometric contamination between neighbouring pixels which renders object recognition nearly impossible. Satellite images with a higher resolution might alleviate this problem. The dawn of the VHR era was thus anticipated with great aspiration by urban remote sensing researchers.

In the framework of a DWTC/OSTC Telsat 4 pilot project we proposed a methodology to employ IKONOS-2[1] imagery to develop an inventory of built-up, and un-built areas in Belgium's Flemish region. Such an inventory can be of use to regional planning agencies that are responsible for the implementation of the government's planning policies. In Flanders, AROHM (Administration of Spatial Planning, Housing, Monuments and landscapes) records, monitors, and evaluates the built-up areas. To do this, they need an extensive data input from the communities, which requires a lot of time and effort. A reliable and swift technique, based on earth observation data, and applicable for each residential area in Flanders, would be of great value to them. Not only would it allow them to make swift assessments more frequently, they could also double-check incoming data from the communities.

The aforementioned project consisted of three parts : the visual interpretation of two study areas (Hasselt and Ghent), the automatic classification of these areas using both Maximum Likelihood and Neural Network classifiers, and the development of GIS procedures to transform the classified images into thematic maps like, for instance, a map of building densities.

Preparatory steps

Study Area Delimitation

Two study areas were selected on two separate Ikonos-2 images. One image was registered on April 18th 2000, and contains a part of the municipal territory of Hasselt and some neighbouring towns. The second image was collected on May 9th 2000, and covers the city of Ghent. The first study area contains the high density building from Hasselt's city center, residential areas outside the beltway, pastures, agricultural fields, and small forest patches. The coordinates of the corners (Belgian Lambert Projection) are (216.400; 182.545) for the ULC, and (219.800 ; 178.600) for the LRC. The second study area is part of the Dampoort neighbourhood of the city of Ghent, and contains mostly high density urban building. Corner coordinates are (104.983 ; 193.491) ULC and (106.604 ; 192.234) LRC. The study areas were chosen taking into account shadows, cloud cover and the availability of ancillary data.

Acquisition and tailoring of ancillary data

For both cities different types of ancillary data were available. For Hasselt we used digital black and white orthophoto-plans from the Belgian National Geographical Institute, resampled to 1m resolution, to geometrically correct the Ikonos-2 image. These plans were created from aerial photographs, and have a scale of roughly 1/40 000. We also used vector data of houses and parcels for verification and accuracy assessments of built-up areas. These data were made available by the Hasselt city council. For Ghent we used recent high resolution aerial photography (March 2000) and vector data of houses and parcels.

A GIS database was set up to contain both visually interpreted data and comparative ancillary data sets, and to study the accuracy of both the semi-automated and the visual interpretation techniques.

[1] Ikonos-2 images have a spatial resolution of 1m for the panchromatic channel and 4m for the multispectral channels (blue, red, green, infrared).

Pre-processing of satellite images

The Hasselt image was geometrically corrected with a second order polynomial function, using the NGI orthophoto-plans as reference data. The RMS error was 2.343 meters with 23 points. It is important to note that these points have been measured at ground level, and do not take into account the displacement of building tops caused by the inclination angle of 26 degrees. This displacement complicates and limits the visual interpretation and the image classification, and calls for the development of more exhaustive correction techniques. When Ikonos-2 stereo couples become available, it will be possible to construct a DEM from the images which will allow to correct them in three dimensions. For the Ghent area the geometrical correction using the geometrically accurate vectorial cadastre data yielded a RMS error of 2.045 meters. The Ghent image was registered with an inclination angle of roughly 14 degrees.
For both areas, the multispectral true colour image (RGB) was fused with the panchromatic image with the Local Mean and Variance Matching Algorithm (Muller et al., 2000). This image was used only for the visual interpretation.

Visual Interpretation (Computer Aided Image Interpretation)

The interpretation was digitized on the panchromatic Ikonos-2 images, with the fused RGB image, and often with ancillary data as reference. Four classes were extracted : "built-up areas", "roads and parking", "water", and "railways". The fifth class: "un-built areas", corresponds to what remains unclassified. The fusion of the panchromatic and multi spectral channels was found to be very useful to the image interpreter.

The impediments of the CAII are very closely related to those of a traditional photo-interpretation: shadows, slant effects, radiometric variations due to the solar aspect, and the typical land use/land cover problem. The latter arises because the spectral signature is characteristic for the constituent materials, but not for the object's actual use (e.g. asphalted road versus roofing).

It is important to note that the un-built areas in the interpretation do not necessarily correspond to the actual vacant plots for new constructions. They also contain plots of land that are too narrow or that have a slope that is too steep, zones in danger of flooding, etc…

The accuracy of the visual interpretation was assessed by comparing it with the cadastral data using a union procedure. Maps that visualise the admission and commission errors for both study areas were made. The user's accuracies were 72% for Hasselt, and 84% for Ghent. Admission errors correspond to areas that are new buildings, omission errors correspond to built-up areas that are not interpreted as such. The main reasons for the differences between the two files are:

- The geometrical qualities of the cadastral vector file vary strongly from sheet to sheet. On top of that, national cadastral data are recorded in a local coordinate system and have to be transformed to the Lambert projection if they need to be combined with other data. This process introduces inaccuracies which causes a shift of building objects. Sometimes these shifts are modest, in other cases they can be significant.
- The satellite image is more recent than the cadastral data. Sometimes new buildings were put up. This is considered to be an error in this analysis while it really is the most important information that can be deduced from the Ikonos images.
- Errors can be introduced during the class allocation of polygons after the topology creation.
- There are also thematic errors present in the cadastral files. The correction of these errors is another added value of the Ikonos images.

The visual interpretation was time consuming. Interpreting the 181 ha. of the Ghent pilot study area took 21 hours. The density of the study area increased the required time significantly. Topology building and error correction took another 8 hours.

Automatic Classification

Because the CAII method is time consuming, part of this project aimed to obtain a mask of built-up space by automatic classification techniques. Several approaches were tested, taking the spectrally heterogeneous nature of urban areas into account.

Automatically classifying satellite images is about allocating every image pixel we want to classify, to a certain type of land cover. In this particular case we want to initially distinguish built-up from un-built land.

Several automated classification strategies have thus far been extensively studied and applied, and were documented in remote sensing periodicals. We applied two classifiers on the Ikonos data. One of the better known ones is the so-called Maximum Likelihood (ML) Classifier, which is a parametric statistical classifier that decides to which class a pixel belongs based on it's scores on a number of variables. These are usually the grey levels in a particular image band, which in turn represent the reflectance of solar light in a particular range of the electromagnetic spectrum. Another, emerging, classification strategy is the Artificial Neural Network (ANN). This technique uses a network architecture consisting of several layers of interconnected nodes to make a mapping of one dataset onto another, by adjusting the weights of the interconnections between the nodes. No statistical model underlies this classifier (Atkinson, P.M., 1996).

Besides testing these two classifiers for per pixel classifications alone, we also included texture measures into the classification process. Urban land cover is heterogeneous in nature. Combined with the high resolution of the Ikonos images this result in image pixels that are spectrally very different, although they are all part of the same land cover class. This inhibits the classification procedure from achieving high per pixel accuracies (Karathanassi, 2000). After all, for the human eye it is also very difficult to see what a pixel of 1m² represents if we look at the pixel alone.

We can extend the spectral variables with so-called neo-channels in an attempt to increase the classification performance. A neo channel could consist of derived values like the NDVI or of textural properties of a subset of the image. In this research we attempted to increase the performance of the ML and ANN classifiers by adding textural measures as neo-channels. The measures we tested are based on Spatial Coocurance matrices, e.g. *Haralick Contrast* (Haralick et al., 1973). We also used Moran's I, a measure of spatial autocorrelation (Moran P.A.P, 1950; Emerson, 1999) . We calculated one textural measure for an image subset. This subset is typically a window ranging from 5 by 5 to 101 by 101 pixels centred around the pixel for which we wish to obtain a value. This window is moved around the Ikonos image. The result is a derived "image" with textural values (Franklin et al., 1996).

The visual interpretation was used to collect training samples and to validate the classifiers.

We achieved about 78% overall accuracy for Hasselt, and 89% for Ghent when we compared the mask of built-up areas derived from the automated classification with the visual interpretation. This is reasonable, but insufficient for practical purposes. Especially the results obtained by the textural measures were disappointing. Future research has to be conducted to improve the method by which the textural measures are implemented. No significant differences in performance between the ML and the ANN were noted.

Building density and inventory of (un)built parcels

Two different approaches to visualise the building density were tested. One approach deploys a window of 100 by 100 pixels that moves across the built-up image, and that assigns a value to the central pixel, based on the fraction of built-up area inside it's perimeter. This approach makes it possible to visualise building density in a more continuous way. The second approach visualises the building density per cadastral parcel. Simply, the percentage of the parcel that is occupied by built-up area represents the density. This approach is a more discrete visualisation. Both techniques show fairly the same picture. When assessing the error of the building density for the second approach, it appeared that this error is dependent on the parcel size.

The inventory of the (un)built parcels is derived from the cadastral representation of the building density map. Simply, parcels with zero building density are regarded as non-built. Several thresholds were tested, since shifts can introduce a certain amount of built-up area in a parcel that is actually vacant. However, the 0 threshold performed best. When comparing the inventory with a similar inventory based on the cadastral information, an accuracy of 84 % was obtained, good but not good enough for operational applications.

Conclusions

Although the obtained classification results were encouraging, and certainly prove that there exists a potential for the use of VHR satellite imagery for urban planning purposes, several shortcomings hamper an immediate application. Firstly, the displacements that are caused by the large inclination angles significantly compromise both the visual interpretation and any overlay with ancillary data. An extensive geometrical correction, maybe using VHR stereo couples, is warranted. Secondly, the visual interpretation is too time consuming to be used for large regions. The automated classification is much more economical, but also less accurate. Thirdly, if we want to implement the inventorying of built-up parcels from VHR satellite images region-wide, images will have to be available for the entire territory, and will have to be regularly updated. These conditions are currently not met. The single Ikonos satellite provides only a limited timeframe for observing each region under good conditions. Especially in cloudy Belgium this is a problem, the long delays and low availability of cloud free images during the course of this project are an example. Furthermore, the cost of image acquisition is prohibiting. The scheduled launch of two new VHR satellite platforms by competing companies might bring some relief.

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