HIERARCHICAL IMAGE OBJECT-BASED STRUCTURAL ANALYSIS TOWARD URBAN LAND USE CLASSIFICATION USING HIGH-RESOLUTION IMAGERY AND AIRBORNE LIDAR DATA

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ABSTRACT

High-resolution remotely sensed imagery and airborne laser altimetry data offer exciting possibilities for feature extraction and spatial modelling in urban areas. In this study, hierarchical image objects have been generated by image segmentation based on IKONOS imagery and laser scanning data using semantically meaningful thresholds. Delaunay triangulation and morphological image analysis technique have been applied in deriving spatial relations between image objects and for structural analysis. Land use objects can be inferred at a higher level based on land cover objects and structural information. In this paper, an overview is given of an urban land use classification schema based on hierarchical image objects. The image objects at each level are described, their spatial properties mentioned and the derivation of structural information is outlined. The focus of this paper is on the higher level of spatial clusters and spatial units: land use functions through structural analysis of related features, spatial relations and associated measurements. Finding discriminant functions for identifying land use and its spatial units is a major concern. A number of measurements are introduced and experimental results are compared and evaluated. These experiments are based on different types of data from a study area in southeast Amsterdam.

1 INTRODUCTION

Most conventional pixel-based classifiers such as minimum distance, maximum likelihood, maximum *a posterior*, etc. (Curran, 1985, Campbell, 1987, Richards, 1993), assume parametric statistical models, such as the Gaussian distribution. These methods are not designed to handle data from different sources or of varying accuracy and they cannot cope with non-numerical data. In practice, the data usually do not obey the conditions imposed by these conventional methods that classify pixels via crisp rules (Mertikas and Zervakis, 2001). Urban areas are complicated due to the mix of man-made features and natural features. A higher level of structural information plays a important role in land cover/use classification of an urban area. Additional spatial indicators have to be extracted based on structural analysis in order to understand and identify spatial patterns or the spatial organization of features, especially for man-made features. It is very difficult to extract such spatial patterns by using pixel-based approaches.

A per-field approach using vector data can improve classification accuracy (Aplin et al., 1999a and 1999b, Zhan *et al*, 2000; Aplin & Atkinson, 2001). The per-field approach is good in for extraction and analysis of structural information. In most cases, however, accurate vector data sets are rarely available (Tatem et al., 2001). However, feature boundaries may have changed between the time of producing vector data and acquiring new image data (Zhan *et al*., 2002a). Therefore, a field-boundary extraction approach is proposed in this paper based on image analysis and semantically meaningful image segmentation.

In order to extract structural information, an image object-based structural information analysis schema is presented in this paper. The concepts are tested using high-resolution IKONOS image and airborne laser scanning data of a suburban area in Amsterdam, the Netherlands.

2 STRUCTURAL ANALYSIS SCHEMA

2.1 HIERARCHY OF IMAGE OBJECTS

Urban land use in urban planning context refers to certain functions with related social economic characteristics. For instance, a residential area consists of a number of physical features such as residential buildings, parking space, footpaths, green space, and maybe canals. Quite often, these features are targets of land cover classification. Physical features in general have certain associations with spectral features, so they can be identified by using multi-spectral information from remote sensing images. However, land use cannot be determined by land cover information directly. (Barr & Barnsley, 1997; Zhan et al., 2002b). Land use may be inferred by reasoning on spatial arrangement at land cover level. A hierarchy is proposed for land use classification of 3 levels, namely land use, land cover and pixel level (Fig. 1). Respectively, 3 types of image objects can be created based on the 3-level hierarchy in order to represent spatial coverage and thematic information derived at each level.

Image object at pixel level

Each pixel in an image is regarded as an image object at the lowest level of reasoning. Its geometric coverage is a square covered by a pixel in an image. Its attributes are values from image sources, i.e. intensity of each spectral band of a multi-spectral image, or the height value from laser scanning data. The 4-connected adjacency relationship is defined for its spatial relation in a 2-D image space.

Image object at land cover level

An image object at land cover level is a group of adjacent pixels that are likely to have the same value (homogeneity). Its spatial coverage is derived by image analysis and meaningful image segmentation based on image objects at pixel level (see Zhan *et al*., 2001). Its attributes are the average value of pixels forming the object from different image sources.

Image object at land use level

An image object at land use level is a spatial unit, which contains a number of land-cover objects and present a type of land use.

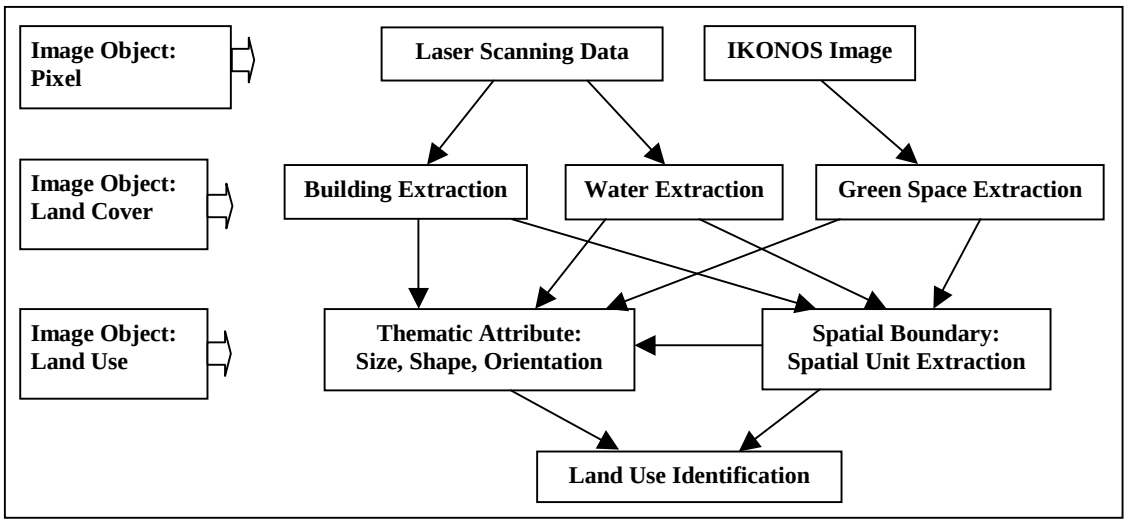

Figure 1. Hierarchy of Image Objects and Working Flow

2.2 STRUCTURAL ANALYSIS SCHEMA TOWARD LAND USE CLASSIFICATION

Before structural analysis can be applied, image objects have to be extracted. Among all the features, which could be extracted from images, buildings, roads, green space and water surfaces are essential ones for land cover/use classification.

In our 3-stage approach we proceed from pixels to land cover objects, and reasoning of spatial coverage for land use and reasoning for land use identification.

In the land cover object extraction stage, image objects are formed based on their physical properties and homogeneity measurements. Building, green space, water will be extracted in this stage. The geometric properties size, shape, orientation etc. are calculated.

Reasoning of spatial coverage for land use will be based on local spatial arrangement of land cover objects. A number of spatial indicators will be extracted as shown in Table 1 and Table 2 for land use classification. The working flow of the proposed land use classification schema is presented in Fig. 1.

3 LAND COVER OBJECT EXTRACTION

Building extraction

Building extraction is a favourite topic of researchers in remote sensing applications. These approaches had been summarised by Shufelt (Shufelt, 2000). Most of them are based on aerial photographs or satellite images. More recently, a number of techniques have been developed based on LIDAR data (Brunn and Weidner, 1997, Lemmens *et al*., 1997 Hug and Wehr, 1997, Haala and Brenner, 1999). However, there are many unsolved problems left. For instance, in an urban area where roads may be above ground floor, they have image characteristics similar to buildings. The proposed approach has been developed to solve this type of problems. It tries to extract buildings through reasoning in a histogram space. Airborne laser altimetry data in raster format are segmented by using several thresholds with 1-meter interval of altitude. These image segments are then labelled. The unique label values are treated as image objects. Hence, a number of properties can be derived based on labelled segments (image objects) such as size, shape and orientation. These properties are used for reasoning in the histogram space. The histogram space is defined by altitude with 1-meter interval as variable the X-axis and geometric properties as functions of altitude the Y-axis. Vertically segmented image objects are linked and inferred vertically. A tree structure is created using links between different layers of segments vertically. Reasoning is based on patterns of these properties on the paths of each branch of the searching tree in the histogram space. A simplified approach for building extraction is applied by using only size differences between vertically segmented image objects. A small part of original image, which is used in the case study, the extracted buildings are shown in Fig. 2 and Fig. 3. Buildings, which are either lower or higher than the roads are extracted properly.

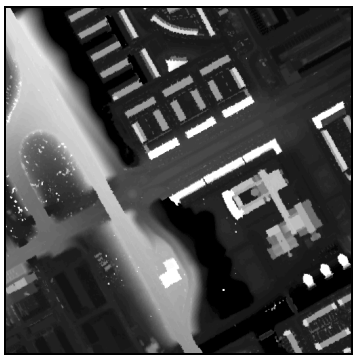

Fig. 2. Laser scanning data

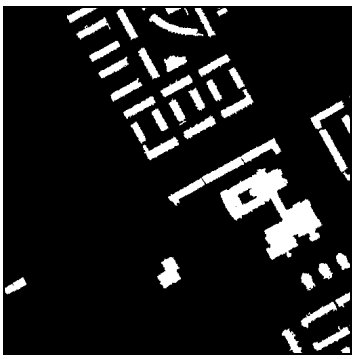

Fig. 3. Buildings extracted by the proposed method

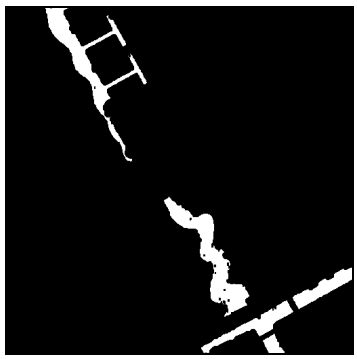

Fig. 4. Extracted water surfaces

Green space extraction

Green space can be extracted based on the normalized difference vegetation index (NDVI) from IKONOS image using the formula: NDVI = (Band4 - Band3) / (Band4 + Band3). A small part of the original IKONOS image and extracted green space are shown in Fig. 5 and Fig. 6 using 0.5 as a threshold for image segmentation.

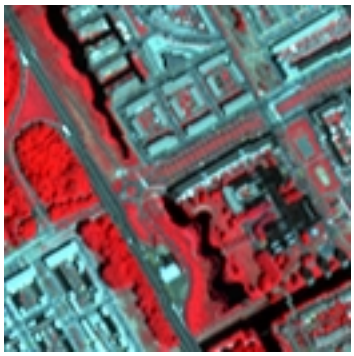

Fig. 5. IKONOS image

Fig. 6. Green space extracted based on NDVI

Water surface extraction

Water surfaces can be extracted based on spectral information in many cases. However, we rather extract from laser scanning data, because no signal can be received by the scanner on water surfaces. Therefore, extracted water surfaces from laser data are likely to give better identification and sharper boundaries than multi-spectral information. It is quite difficult to separate water pixels and pixels falling in a shadow area of a building by using IKONOS image along due to their similarity in spectral space. A small part of the image with extracted water surfaces is shown in Fig. 4. To make sure those ‘missing-value’ pixels from laser are on water surfaces, spectral information should be checked whether they have the spectral properties of water. By the way, noisy pixels and flight gaps should be removed in data preparation phase.

4 STRUCTURAL ANALYSES AND LAND USE OBJECT EXTRACTION

Land use object extraction can be divided into two parts, spatial coverage of a land use object (spatial unit reasoning) and identification (thematic reasoning). These two aspects are presented in following sections.

4.1 EXTRACTION OF SPATIAL UNITS FOR LAND USE CLASSIFICATION

Adjacency relationships play an important role in understanding spatial arrangement and spatial pattern. Delaunay triangulation offers a good tool for analysing adjacency. The morphological image analysis technique provides another option for structural analysis of binary image segments.

Triangulation approach

In triangulation, a binary image is converted to a ‘labelled image’ followed by the raster to vector conversion. Delaunay triangulation is applied then to all points (segment pixels). A matrix is created which indicates adjacent buildings and the shortest distance between them. Detail description of this approach can be found in Zhan *et al*., 2002b. An example is shown in Fig. 7. This approach seeks a global solution using the shortest distance between adjacent segments as a measurement and an optimal threshold to separate different clusters. This method has some difficulties in clustering

segments such as segments that appear partially in the image near the margins or edges of the image. Different types of land use might have different spatial arrangement, etc.

Morphological approach

Since the spatial presentation of an image object in image space is a binary segment, the region adjacency graph (RAG) can be created based on morphological image analysis. The morphological approach is based on operators such as dilation, erosion, opening, closing etc. Dilation can be used to determine how close two adjacent objects are by controlling the repeated application of the dilation operator till two segments merge to one. Street block 1 and 2 in Fig. 9 are two examples, which are produced by morphological image processing.

In this experiment, image segments of buildings, green space and water were combined in a single image (Fig. 8). The process started with opening to remove small segments (smaller than 100 m^2) and make sure no noisy small segments appear along roads. The next step was closing to merge close adjacent segments in blocks formed by side streets. An image labelling operation was employed to identify the size of 4-connected segments. Several operations were applied to divide segments into two groups: small segments (smaller than 1 ha.) and large segments (larger than 1 ha.), which would be treated separately. The next steps aimed at merging small segments to there near by large segments. For every large segment closing was applied to all small segments and the large segment. Another closing was done with a large size of structure element to every large segment to merge as much as possible the small segments and to avoid merging of large segments across a road. A filling operation was applied to fill 'holes' remaining in large segments as the final step.

Integrated approach

The integrated approach consists of two major steps in finding reasonable spatial units for land use classification. The first step is to find 'street blocks' separated mainly by main roads or other linear features. The street blocks can be delineated by morphological approach or simply by using GIS data. In second step, the triangulation approach is applied for reasoning spatial units. A homogeneity check is often necessary to be implemented to determine whether further separation is required after the previous delineation is made.

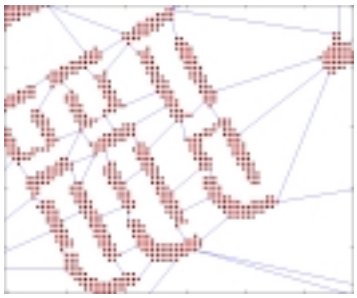

Fig. 7. Adjacent buildings linked with shortest distances between them

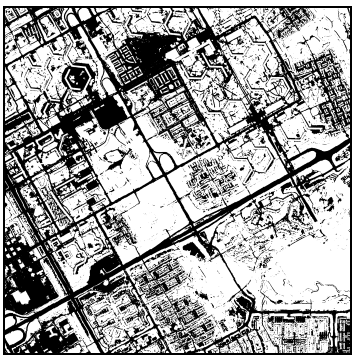

Fig.8. Combined image using image segments of building, green space and water

Fig. 9. Two examples of extracted spatial units (street block) based on morphological analysis (1, 2)

4.2 EXTRACTION OF ATTRIBUTS FOR LAND USE CLASSIFICATION

Numerical and categorical properties

In the following a number of numerical and categorical properties are described, which play an important role in land use classification. E.g., building density, floor space ratio, and green coverage ratio are directly associated with definitions of several land use types. These, and other properties can be derived from image objects when their spatial units are determined:

- Type and proportional composition of land cover objects appear in a land use object.
- Number of buildings, average building size
- Building density (Total area of buildings / Size of spatial unit)
- Floor space ratio (Total area of building floor space / Size of spatial unit)
- Green coverage ratio (Total area of green space / Size of spatial unit)

Geometric properties

Location, size, shape, and orientation are the geometric properties of an image object. These properties can be described by several indicators (van der Heijden, 1994, Shufelt, 2000). A short description and definition is presented in Table 1, which can be derived from image segments. Technical details can be found in User's Guide (The MathWorks, 2001).

Structural properties

Spatial distribution of land cover objects over space of a land use object is an essential element, which can be derived, based on geometric properties of land cover objects shown in Table 1. These geometric properties can also be identified for land use objects and can be treated as structural properties of land use objects.

A number of structural indicators, which are essential for urban land use classification in practice and can be extracted directly from images, are proposed in Table 2. Spatial coverage ratio (SCR), spatial mixture ratio (SMR), and spatial bias ratio (SBR) are useful in determining if further subdivision is required for a spatial unit.

Table 1. Geometric Indicators used for Land Use Classification*

Geometric Indicators		**Description/Definition**
Location	Centroid	The center of mass of the region.
Size	Size	The actual number of pixels in the region.
	FilledArea	The number of on pixels in FilledImage.
	Extent	The proportion of the pixels in the bounding box that are also in the region.
	ConvexArea	The number of pixels in 'ConvexImage'.
	Solidity	The proportion of the pixels in the convex hull that are also in the region.
Shape	MajorAxisLength	The length (in pixels) of the major axis of the ellipse that has the same second-moments as the region.
	MinorAxisLength	The length (in pixels) of the minor axis of the ellipse that has the same second-moments as the region.
	Eccentricity	The eccentricity of the ellipse that has the same second-moments as the region. The eccentricity is the ratio of the distance between the foci of the ellipse and its major axis length.
	EquivDiameter	The diameter of a circle with the same area as the region. Computed as sqrt(4*Area/pi).
Orientation	Orientation	The angle (in degrees) between the x-axis and the major axis of the ellipse that has the same second-moments as the region.

* These indicators are available in the Image Processing Toolbox as an extension of Matlab.

Table 2. Structural indicators in terms of spatial distribution

Structural Indicators	Formula	Description/Definition	Application/Example
Spatial coverage ratio	ConvexArea / Size of a spatial unit	Spatial distribution of certain land cover feature in a spatial unit	Spatial distribution of certain feature over a space
Spatial mixture ratio	Overlay of convex / Union of convex	Degree of overlay in spatial distribution of different features	Check out if different types features are mixed in a space
Spatial bias ratio	2 * |F_cen – B_cen| / EquivDiameter_B	Distance between feature centre and block centre divide by equivalent radius of a block	Check out if features are equally distributed over a space or on concentrated in certain parts of space

4.3 LAND USE IDENTIFICATION

The land use identification consists following components:

Thematic aspects

- Composition: type of land cover objects, which appear in a land use object
- Proportion: percentage of spatial coverage of different land cover types
- Homogeneity: size and deviation or outliers

Spatial aspects (spatial distribution)

Given the information as obtained from the processes described before, many classification methods can be used in the final stage of land use classification. The classifiers, however must not conflict with the nature of the data. Classifiers to consider for land use are fuzzy logic, nearest neighbour classifier, tree-based classifier, etc. A land use classification example based on fuzzy logic can be found in another paper published by authors (Zhan *et al*., 2000).

5 CONCLUSIONS

A concept of urban land use classification based on high-resolution remote sensing image is proposed in this paper. The experimental results produced for various stages of the process show that progress has been made in urban land use classification by applying hierarchical image objects and structural image analysis techniques. Since urban areas are complicated, a comprehensive approach is needed and different settings have to be investigated to cope with different types of urban areas and to different types of cities.

The experiments show that hierarchically formed image objects are useful tools for image analysis and spatial modelling and more successful than were to pixel-based approaches. Structural information derived from hierarchical image objects plays an important role in land use classification in urban areas. The combination of high spatial resolution airborne LIDAR and IKONOS imagery offers great application opportunities, especially in urban areas.

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