FINDING SPATIAL UNITS FOR LAND USE CLASSIFICATION BASED ON HIERARCHICAL IMAGE OBJECTS

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ABSTRACT:

Remote sensing in urban areas has been a challenger for quite some time due to their complexity and fragment with combination of man-made features and natural features. High-resolution satellite images and airborne laser altimetry data offered potential possibilities for feature extraction and spatial modelling in urban areas. Land use classification of urban areas may become possible by exploiting current high-resolution sensor data. The proposed approach incorporates spectral information from multi-spectral IKONOS images and height information from laser scanning data in hierarchical image segmentation based on semantically meaningful thresholds. By image segmentation, we obtain image objects at several levels with certain properties, which make it possible to include the spatial relations between adjacent image objects. Land cover classification and identification of image objects can be carried out mainly according to their properties. Land use classification at a higher level need to be inferred based on land cover objects and structural information at lower levels. We use Delaunay triangulation for deriving spatial relations between image objects and for structural analysis. Based on adjacency relationships of image objects, human settlements and other urban spaces are formed that create a base for land use identification as well as for structural analysis of urban areas. In this paper, the hierarchical image segmentation schema and the corresponding semantic-based thresholds are presented. To test the approach, we selected a site in a suburban area in Amsterdam, the Netherlands. The experiments show that hierarchically formed image objects are useful tools for image analysis and spatial modelling as compared to pixel-based approaches. Structural information can be derived based on hierarchical image objects, which plays an important role in land use classification in urban areas. We could cluster 704 image objects (buildings) into 82 spatial units for land use classification based on the measurement of shortest distance between adjacent buildings.

1. INTRODUCTION

Increasing availability of high spatial-resolution remote sensing images and airborne laser altimetry data offers new opportunities, especially for urban planning. However, it seems desirable to make progress in automating high-level information extraction on urban land use (Barr and Barnsley, 1995, 1997). 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 of remote sensing images. However, land use cannot be determined by land cover information directly. For instance, a building can be a residential house, a shop or a warehouse. Green space can be found in a park, a residential area or even in a commercial area. Therefore, in land use identification, additional information or evidences have to be found on top of land cover information. Furthermore, a reasonable spatial unit has to be delineated to represent the spatial extend of certain land use although this type of boundary is often vague. This research is intended to find the way to delineate areas of different land use and identify the land use type in every delineated area. Delaunay triangulation is deployed in creating spatial associations and structural analysis toward spatial clustering of physical features in image space with the aim of identifying land use. Delaunay triangulation has been widely used in spatial analysis and spatial modelling (Bundy *et al*., 1995). However, most applications are based on vector data. In this research, we deploy Delaunay triangulation on lattice (image) data. The test image we used in our triangulation is a binary image; showing all the buildings with value 1 against everything else 0. The approach of deriving such building segments is presented in section 2. A detail description for finding spatial units can then be found in section 3. The experimental results in finding spatial units for land use identification are presented in section 4.

2. IMAGE SEGMENTATION AND IMAGE OBJECT

Airborne lasers scanning data and high-resolution multi-spectral remote sensing images are expected to have great potential use in feature extraction, especially for urban areas. Semantic-based image segmentation introduced by Zhan shows that many man made objects can effectively be derived from laser scanning data and multi-spectral remote sensing images. Detailed description of the image segmentation schema applied in this research can be found in Zhan *et al*. (2001). Some related approaches can be found in other literatures as well (Brunn and

Weidner, 1997; Haala and Brenner, 1999; Hug and Wehr, 1997; Lemmens *et al*., 1997).
We used high-resolution IKONOS imagery and airborne laser scanning data in this case study presented here. The laser scanning data we took, the 5-meter resolution raster product of AHN (Actual Height of the Netherlands), were resampled to 4-meter grid image to match the resolution of IKONOS multi-spectral image. The NDVI (the Normalised Difference Vegetation Index) image was created based on Band 3 and Band 4 of the IKONOS image in order to get semantically meaningful data (i.e. vegetation etc.) and reduce the amount of data.

Based on knowledge of the test site and careful study of related data, we segmented the AHN data with a threshold of 0-meter in altitude (i.e. mean sea level). The study area and its surroundings are reclaimed from a lake (Bijlmermeer). Most of ground floors are around 3 meters below sea level and the area is flat in general. 3 meters above ground floors is also a good threshold for finding buildings and other high objects such as trees. Therefore, the first segmentation was applied with threshold of 0-meter on AHN data. The result shows that not only buildings and trees are segmented but also most of main roads and parking garages. Hence, additional separation has to be made by using size of objects to separate raised roads from buildings. Subsequent segmentations are mainly based on the NDVI data for each branch of the hierarchical tree structure according to Zhan *et al*. (2001). Thresholds of 0.75 and 0.65 are based on the sample study of built-up area, green space and water as well as efforts in finding lowest possible valleys in the histogram space of NDVI data. This resulted in separating trees from buildings.

Urban space has been planned and constructed in certain ways that enable serving certain functions of usage. Some spatial arrangements have been applied in spatial organization. Therefore, we believe that structural information and spatial pattern can play an important role in finding out the spatial extends of certain land use. In this stage, only building segments ($S_{Building}$) were used in this experiment. Fig. 1 shows the building segments of a sub area of the total test site. The building segments were derived based on following thresholds:

$$S_{Building}\{AHN(0,\max), Size(\min,\ 1\ ha.), NDVI(\min,0.65),\ \ \forall\ s_i \in I\}$$

where image space $I\ \{AHN,\ NDVI,\ ...,\forall\ pixel\ p_i \in I\}$

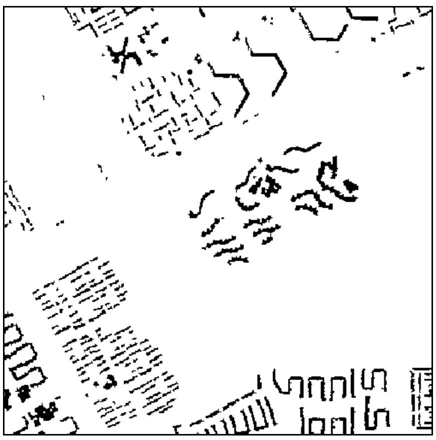

Fig. 1 Image objects (buildings) derived from image analysis

3. SPATIAL CLUSTERING

3.1 Spatial Clustering Based on Distance between Adjacent Buildings

Based on the assumption that buildings, which are close to each other, are used for similar function, we use the shortest distance between adjacent buildings as a measurement in spatial clustering. A threshold is needed for distance as criterion for similar type of land use. This threshold is to be inferred in an optimisation process based on number of spatial clusters and other indicators.

3.2 Delaunay Triangulation

In order to find out possible links between adjacent buildings and the shortest distance, we developed a Delaunay triangulation algorithm based on the Quickhull Algorithm (Barber at al 1996).

The binary image is converted to a 'labelled image'. By checking the 4-connection, individual labelling are identified and uniquely labelled. The next step in raster to vector conversion of the labelled image, the centre of building pixel becomes a point.

Delaunay triangulation is applied then to all points (building pixels). Since we are interested in find relations between adjacent buildings, we delete all the triangles that have the same label value. From the remaining triangles, we create a matrix, which indicates the links between adjacent buildings and the shortest distance between them.

3.3 Reasoning for Spatial Clustering

Threshold (MaxDist) is defined as the largest possible distance between adjacent buildings to be considered as in the same cluster (spatial unit of a land use type candidate). All links between adjacent buildings will be broken if they are apart by more than the threshold.

In order to determine the threshold, spatial clustering is done in a loop using trial thresholds from 5 meters to 250 meters. A threshold of 5 meters will generate a cluster for each building. A threshold of 250 meters will group all buildings in only one cluster. An optimised threshold can be determined based on checking several cluster-related indicators such as number of spatial clusters, maximum number of buildings in a cluster, minimum number of buildings in a cluster, number of isolated buildings, and average number of buildings per cluster. The definitions of these indicators with short explanations are:

- Number of spatial clusters (NoCluster)

  The umber of spatial clusters is counted according to number of separated clusters (no link between them) when a threshold was applied. When the threshold increases the number of spatial clusters decreases.

- Maximum number of buildings in a cluster (MaxNoObjects)

  The maximum number of buildings in a cluster indicates highest number of buildings among all clusters. When the threshold increases the maximum number of buildings in a cluster increases.

– Minimum number of buildings in a cluster (MinNoObjects)

The minimum number of buildings in a cluster indicates the lowest number of buildings among all clusters. When the threshold increases, the minimum number of buildings in a cluster increases as well but with different rate as compared to the maximum number of buildings in a cluster.

– Number of isolated buildings (NoIsolatedObjects)

The number of isolated buildings is taken from the number of clusters that consist of only one building. When the threshold increases the number of isolated buildings decreases.

– Average number of buildings per cluster (AvNoObjectsPerCluster)

The average number of buildings per cluster is calculated as the total number of buildings divided by the number of clusters. When the threshold increases, the average number of buildings per cluster increases. The rate of increase is in a range between maximum and minimum number of buildings in a cluster.

3.4 Creating Convex Hull of Land Use Clusters

The next step is to assign each building to one of clusters found in previous steps and to delineate the convex hull for each cluster using the convex hull algorithm (Barber *at al.*, 1996). The derived convex hulls will be used in identifying the land use type at a higher level of reasoning.

4. CASE STUDY

4.1 Study Area and Data used in this Study

A 9 km^2 (3 km × 3 km) area, Southeast of Amsterdam, was selected for the experiment (see Fig. 2). Approximately 200,000 people live in this sub-urban district. Several types of residential as well as commercial areas, parks, lakes and canals can be found in the study area. Built-up area, green space and water are the three end-member land cover classes in this study. However, to avoid additional complexity, a test image was prepared that consists of image objects, which are exclusively buildings (derived from image analysis and edited with reference to the 1:1000 scale cadastral maps (see Fig. 4)). Other image objects would have to be used in other stages of the total process.

Data used in case study are listed in Table 1. The laser scanning data is shown in Fig. 3.

Type of Data	Date	Band/Colour	Resolution or Scale
Laser scanning data	March 1998	Height in real value	5 m
IKONOS image	June 2000	Multi-spectral	4 m
Topographic map	May 1999	Black & White	1:1,000

Table 1. List of data used in the experiments

Fig. 2 Location of the study area (Southeast, Amsterdam)

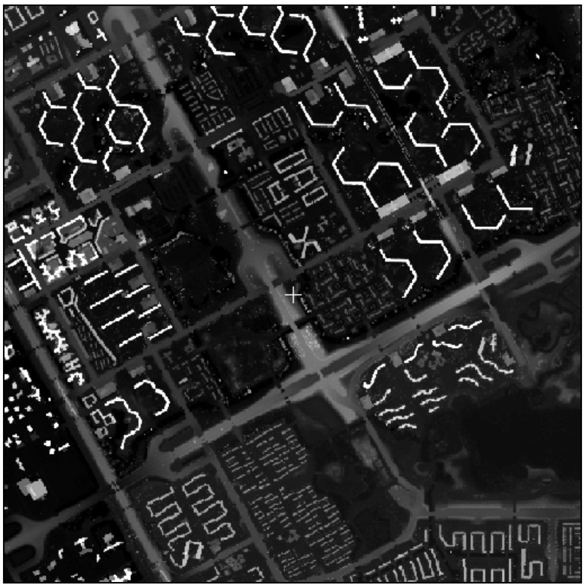

Fig. 3 The AHN image (Light tone refers to higher objects)

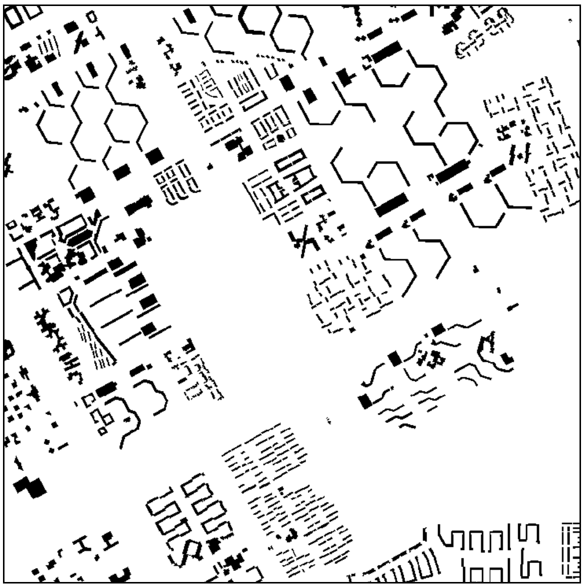

Fig. 4 The test image (a binary image with all building pixels)

4.2 Determining Shortest Distance between Adjacent Buildings

The result obtained from the Delaunay triangulation on building pixels can be seen in Fig. 5 (showing a portion of the total area of Fig. 4 and it corresponding to a area in Fig. 10 where cluster 7, 26 and 30 are located). Removing the links based on the shortest distance between adjacent buildings produces a result as shown in Fig. 6. An output shown in Fig. 7 is a result of using 40 meters as a threshold.

Based on the reasoning approach outlined in the previous section, a test run was initiated in finding a reasonable number of spatial clusters using the following indicators. The shortest distance between adjacent buildings was used as criterion to link adjacent buildings. The shortest distances between buildings were checked against the threshold. Using the indicators described in the previous section lead to the results plotted out in Fig. 8.

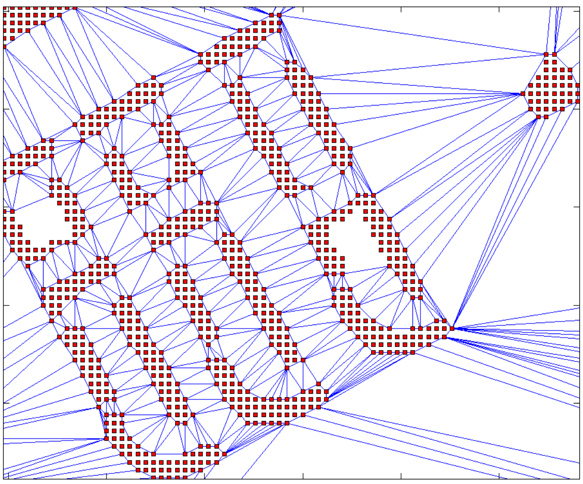

Fig. 5 Adjacent buildings linked by triangles (Portion)

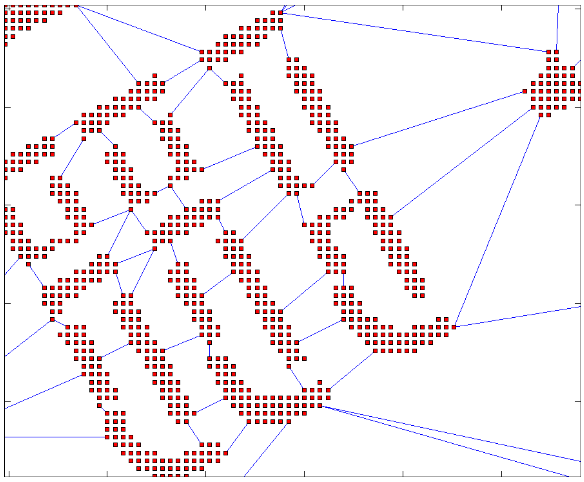

Fig. 6 Adjacent buildings linked with shortest distances between them (Portion)

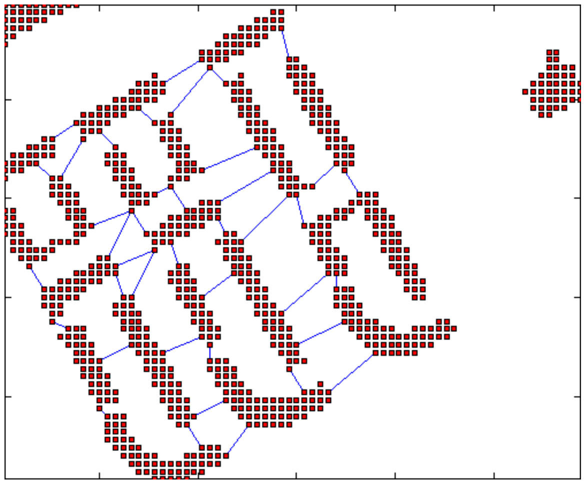

Fig. 7 Linked buildings with the threshold value of 40 meters (Portion)

4.3 Determining the Number of Clusters

Fig.8 shows that the number of spatial clusters (NoCluster) and the number of isolated buildings (NoIsolatedObjects) decrease sharply when the threshold increases in the range of 5-meter to 30-meter. The rate of decrease becomes stable when the threshold follow increased.

On the other hand, the maximum number of buildings in a cluster (MaxNoObjects), the minimum number of buildings in a cluster (MinNoObjects) and the average number of buildings per cluster (AvNoObjectsPerCluster) increase when the threshold increases but with different rates of increase. MinNoObjects increases sharply when there is no isolated building found. This is not a good indicator since there are buildings such as gasoline stations etc. that should not be included in clusters with many buildings surrounding. However, we consider that AvNoObjectsPerCluster is not a proper indicator either, since it mixes up many different types of spatial clusters such as clusters with many buildings inside and clusters containing only one building.

The test results show that number of spatial clusters (NoCluster) and maximum number of buildings in a cluster (MaxNoObjects) gives the best indication in finding number of spatial clusters in this case study (see Fig. 8). Since MaxNoObjects shows as a continuous curve in Fig. 8, but it is not a smooth curve and it may behaves differently in different types of urban areas, further investigations have to be made in finding better indicators. However, clustered regions created by the proposed approach can be used as a base for additional analysis such as removing outliers in each spatial unit and combining similar clusters using other measurement for instance size, shape, height etc.

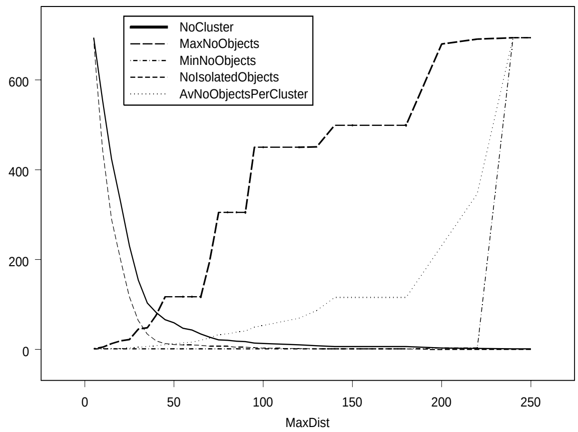

Fig. 8 Proposed indicators change in corresponding to different thresholds used for determining reasonable number of clusters

4.4 Classifying Buildings into Spatial Clusters and Delineation of Cluster Boundaries

Once the best threshold is determined, individual buildings are grouped based on the links that survive (see Fig. 7). Clustered buildings can be represented in image space again assigning the spatial cluster numbers to building pixels, replacing the label numbers. A part of the respective output image is shown in Fig. 9. The clusters shown in Fig. 9 correspond to the clusters 65, 67, 69 and 74 in Fig. 10. The cluster boundaries as shown in Fig. 10 for the entire test site were delineated by using the convex hull algorithm.

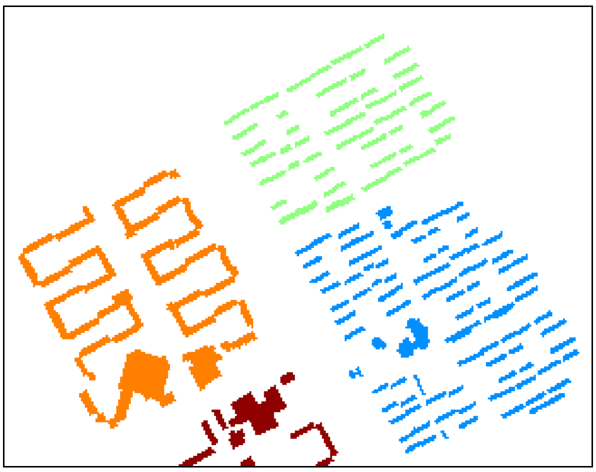

Fig. 9 Clustered buildings with threshold of 40 meters (Portion)

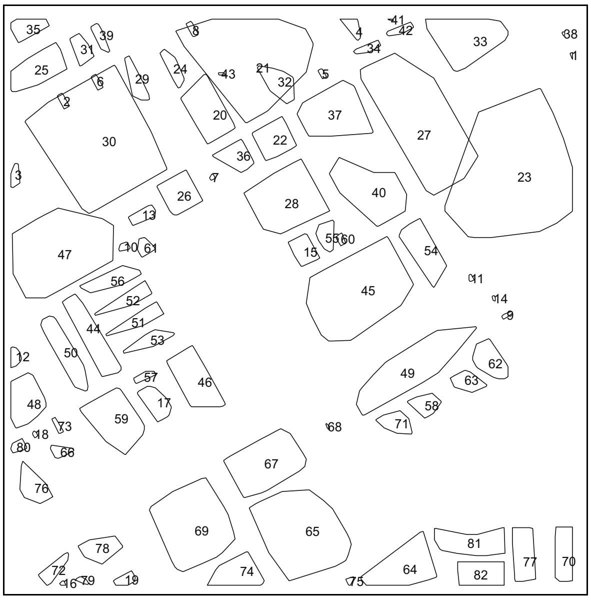

Fig. 10 Convex hulls of clustered regions (Land use units)

5. CONCLUSIONS

The experimental results support the expectation that higher-level structural information can be obtained from spatial reasoning on segmented data. Structural information is useful in image understanding as well.

Hierarchical image segmentation and hierarchical image objects are useful tools for image analysis and classification especially in urban areas. This opens new possibilities to incorporate rules in image understanding, classification and aggregation. The results presented in this paper are just a beginning of referencing higher level of structural information. Only building pixels were used at this stage. More complicated structural information are expected to be derived when using additional information such as size, shape, height, etc of buildings and including vegetation and water pixels. These types of information have been derived already during image analysis and hierarchical image segmentation. We expect that the current approach is quite suitable in finding different types of residential and commercial areas.

There are a number of issues for further investigation such as finding better indicators to replace the maximum number of buildings in clusters, i.e. to include size, height of buildings, etc. A check on outliers in each clustered region will lead to further improvement.

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