Land cover detection in urban environment

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Abstract — **The town planning and city management requires wide spectrum of topographical, environmental, infrastructure and several other information as well. High-resolution satellite images provide an important data source for many fields of research. The difficulty of mapping land cover in urban environment is not due to the classification methods (algorithms). The problem is related to the creation and selection of features. It is very difficult to find out the representative training samples or features for man-made objects. The present study aims at finding an appropriate classification method in order to map urban land cover based on high resolution remote sensing data. This paper deals with object-oriented image analysis applied for an urban area. Very high-resolution aerial photos and satellite images in conjunction with object-oriented image analysis have been used for land cover detection. Using the eCognition software with object-oriented methods, not only the spectral information but also the shape, compactness and other parameters can be used to extract meaningful objects. The spectral and geometric diversity of urban surfaces is a very complex research issue. It is the main reason why additional information is needed to improve the outcome of classification. The most consistent and relevant characteristic of buildings is their height. The elevation data are suitable for building and the different vegetation levels extraction, segmentation and classification. Today the best resolution elevation model can be produced by LIDAR technology. The model based on LIDAR measured points contains the high of the natural and artificial objects, and it is called Digital Surface Model (DSM). The orthophoto based on DSM is called true orthophoto. It shows the objects at their actual orthogonal projected position. Vertical walls will not appear on the image as a spectral noise, so the true orthophoto is suitable for classification.**

I. INTRODUCTION

High-resolution satellite imagery provides an important data source for many fields of research. This study deals with object-oriented image analysis applied for an urban area. The aim of this paper is to describe object-based image analysis for land cover mapping in the urban area of Székesfehérvár city. Urban land cover and land use data play an important role in ecological and environmental investigations. In several studies remote sensing data are used as a source, but the results are not quite satisfying for detailed land use detection in urban areas (ZHOU et al. 2009, LU at al. 2010, PU et al. 2011). Many studies have been carried out to find an appropriate method to classify the high resolution remote sensing data (ZHANG 1999, FEKETE at al. 2008, MYINT et al. 2011, WENG 2012). The difficulty of mapping land cover in urban environment is not due to the classification methods (algorithms). The problem is related to the creation and selection of features. It is very difficult to find out the representative features or training samples for man-made objects. Recent sensor development including high spatial and spectral resolution like WorldView sensors have the potential for more detailed and accurate mapping of urban land cover and land use. A large number of studies have focused on the issues of spectral properties of urban materials and their representation and mapping from remote sensing data. The results indicate highly complex and diverse spectral properties of urban land cover types. The spectral separability of urban land cover types is strongly dependent on spectral sensor characteristics (HEROLD 2004). The development of classification methodologies for analysis of high resolution satellite imagery is relevant to studies related with mapping of urban environments (WENG 2012).

We have integrated high resolution satellite images and high resolution and vertical accuracy Lidar data.

II. MATERIALS

A. Study area

Székesfehérvár is situated in central Hungary and one of the largest settlements in Transdanubia. It is the county seat, the cultural and economic centre of Fejér County. According to the historical documents the place has been inhabited since the 5th century BC, but Székesfehérvár was first mentioned in 1009, as Alba Civitas. After World War II the city was subject to industrialization. Parallel with industrialization the population was also growing. By the 1970s Székesfehérvár had swelled to more than 100 000 inhabitants (in 1945 it had only about 35 000.) The city and its surroundings were the most dynamically growing regions of Hungary in the 1990's. A number of new housing estates were built, but the city centre was able to preserve its Baroque character. It is inhabited by 99 060 people (KSH 2014. 01.01.), the density of population is 595-person/sq km and ranks among the middle-sized cities of the country. With a total area of 170.9 sq km it is the second largest county centre in the Transdanubian region.

B. Dataset

The study used the following remote sensing data:

- WorldView2 satellite image (2011)
- Airborne photographs (2008, 2009)
- LIDAR data (2008)

WorldView-2 developed by DigitalGlobe, USA, in 2009, is the first high resolution multispectral commercial satellite having eight spectral sensors from the visible to near-infrared range. Spatial resolution of the Pan is 0.5 m and of MS sensors is 2.0 m. WorldView-2 image was acquired on July 11, 2011.

In 2008 the inner part of the city Székesfehérvár was laser scanned and in parallel with the laser scanning a digital airborne photographs were taken in visible and in NIR spectra. The images cover an area of 5 km^2. The air photo made in 2009 covered all study area. Both of the airborne datasets were acquired in similar spatial resolution of approximately 0.5 m. The Lidar points measured directly from the field, their point original density is 6-8 point/m2, and the absolute horizontal accuracy is 0,5 m, the vertical accuracy is ±0,15 m (TABLE I., Fig. II-1). We have integrated high resolution satellite images and high resolution and vertical accuracy Lidar data (BALÁZSIK at al.2012)

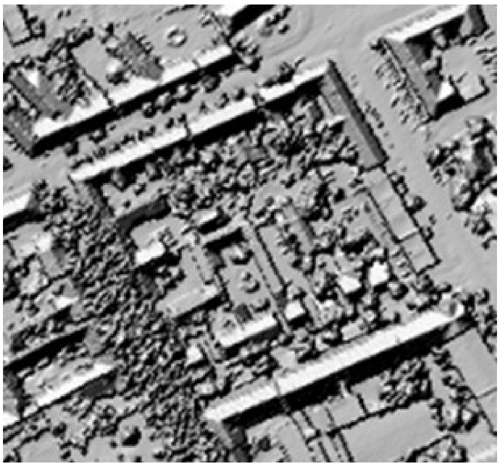

Figure II-1 Digital Surface model based on Lidar points

Other data sources used for investigation: field reference data (GPS), vector data from Cadastre maps, attribute data gained from the municipalities and other statistical data. Ground reference data were acquired to characterize the spectral properties of urban surfaces and to develop a basis for the validation of the image classification.

TABLE I.
THE SPECIFICATION OF REMOTE SENSING DATA

Datasets	Spectral resolution	Other specification
WorlView2 (2011)	Multispectral (400-1040 nm) band 1 (coastal blue), band 2 (blue), band 3 (green), band 4 (yellow), band 5 (red), band 6 (red edge), band 7 (NIR 1), band 8 (NIR 2). Panchromatic	Spatial Resolution: PAN – 0,5 m MS – 2 m Quantization Level: 11 Bits
Aerial photographs (2008)	visible/infrared	Spatial Resolution: 0,5 m
LIDAR (2008)		LIDAR point cloud FE/LE Absolute accuracy: horizontal < ±0.50 m; height < ±0.15 m

III. METHODS

One of the main objectives of this study was to develop a methodology to generate land cover classes of urban area from high spatial resolution satellite images through object-based classification. Using the eCognition software not only the spectral information but also the shape, compactness and other parameters can be employed for mapping. To extract buildings a combination of spectral (WorldView2) and LIDAR data contains elevation information were applied. The most relevant information about buildings is their different elevation compared to their surroundings. We used an object-oriented approach, which allowed context consideration during the classification process. A consideration of spatial context is very important for correct identification and classification of objects.

A. Object-based image classification

Defining the land cover classes the next main view-pionts were considered: to give names to categories by simply using accepted terminology, to use remote sensing as the primary data source. Object-based image analysis (OBIA) technique offers an efficient solution for high spatial resolution mapping. The classification process considered spectral value and spatial characteristics of objects and it included the following steps:

- Segmentation
- Feature extraction
- Object classification
- Refinement of classification based on spectral value and spatial characteristics of objects
- Final identification of categories
- Accuracy assessment

B. Segmentation and feature extraction

Segmentation of images is one of the main steps that have to be solved in the object-based classification (BURNETT - BLASCHKE 2003). Segmentation is a process by which pixels are grouped into segments according to their spectral similarity and other criteria (shape, area, position etc.) (SCHÖPFER et al. 2010). At the beginning of segmentation the heterogeneity criterion is thresholded by the user. This is done by choosing a scale factor and by fixing the weights of the colour and shape criteria, and the smoothness and compactness criterions as well. The multiresolution segmentation algorithm was run with different scale factors (10, 20, 30, and 40) while all other parameters were held constant (shape: 0.1 and compactness: 0.5; shape: 0.4 and compactness: 0.5). In general, a scale factor of 10 a shape factor of 0.1 and compactness of 0.5 produced the best results. The algorithm spectral difference was used to refine existing segmentation results by merging spectrally similar image objects (Fig.III-1).

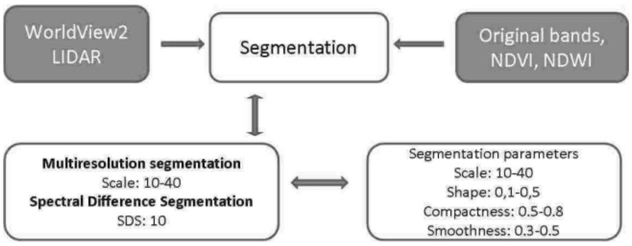

Figure III-1 Segmentation scheme

One of the critical steps in image analysis is to determine the most relevant features and algorithms to be used in classification (BLASCHKE 2010). The eCognition works with objects and information of whole objects like as the spectral signature, the shape and size or context is available. All these attributes can be applied and combined for classification. Features usually define the upper and lower limits of a range measure of characteristics of image objects. Image objects within the defined limits are assigned to a specific class, while those outside of the feature range are assigned to a different class (or left unclassified). The TABLE 2. summarizes the features used to aid the classification process.

TABLE II
THE FEATURES USED TO AID THE CLASSIFICATION PROCESS

Class	Main features	Other features
Vegetation (trees, brushy, grass, barren)	NDVI	context: rel. Border to trees
Building	Height information	Spectral features, NDVI, context (Rel. Border to buliding), size information
Other man-made (road, other)	Spectral information (NDWI, NDVI)	size: area, length to width ratio
Parking place (big area)	Spectral information (NDVI, NDWI)	Shape: rectangular fit, shape index; size: area, length to width ratio, context: rel. Border to parking place)
Water*	Spectral information (NDWI)	
Shadows*	Spectral information (NDWI)	

* At the end of classification the segments of shadow class were reclassed to the road and other man-made classes according to the shape. The water in not included in presented study area.

C. *Rule set based classification*

The classification of urban areas was done in two levels. In the first one the main categories of land cover were determined by taking advantage of spectral properties of WorldView2 image. In this process some normalized difference index was created according to the spectral mean data of determined classes in different bands. Normalized Difference Vegetation Index (NDVI) was used to select vegetation and no-vegetation and to investigate different kind of vegetations. Other indices also were developed and utilized during the classification (eg. NDWI Normalized Difference Water Index). In the second level during the building extraction the elevation data was used as the most relevant characteristic of buildings. Additionally the spectral and context features were employed to clarify the classification. The TABLE II and Fig.III-2 summarize the features, which were utilized to reveal the appropriate land cover classes.

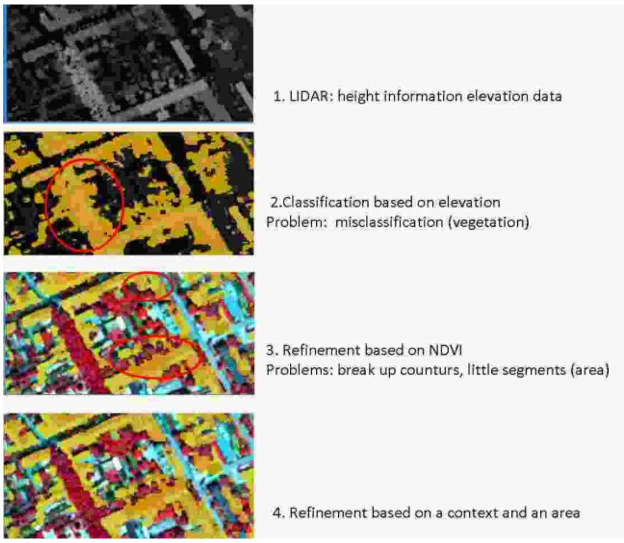

Figure III-2 Building extraction: steps and results

IV. RESULTS

The outcome of our research confirms the original assumption that additional data like LIDAR can effectively improve the classification result of VHR data. The result of classification is shown in Fig. IV-1. The TABLE III includes statistical data of the classification (VERŐNÉ WOJTASZEK-RONCZYK 2012).

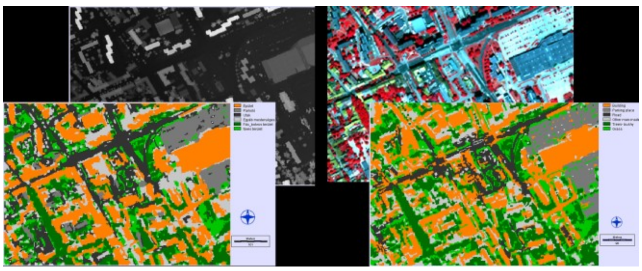
Figure IV-1 The result of classification

The Fig.IV-2 shows the subset of land cover map generated by classification of integrated data (WorldView2, LIDAR points). The next figure (Fig. IV-3) shows the classes draped on DSM in perspective view.

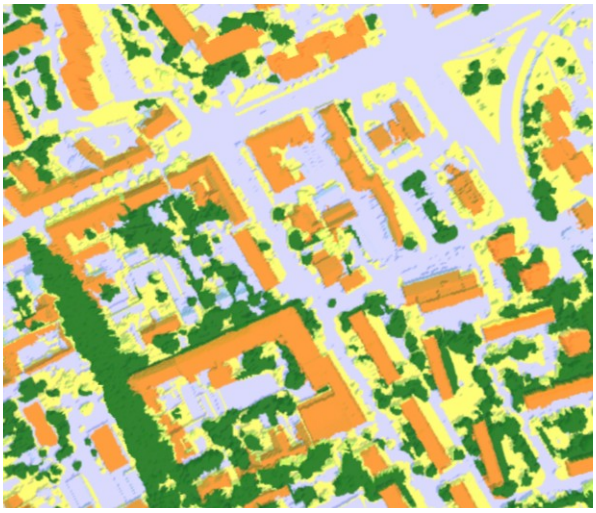

Figure IV-2 WorldView2 and LIDAR based-classification

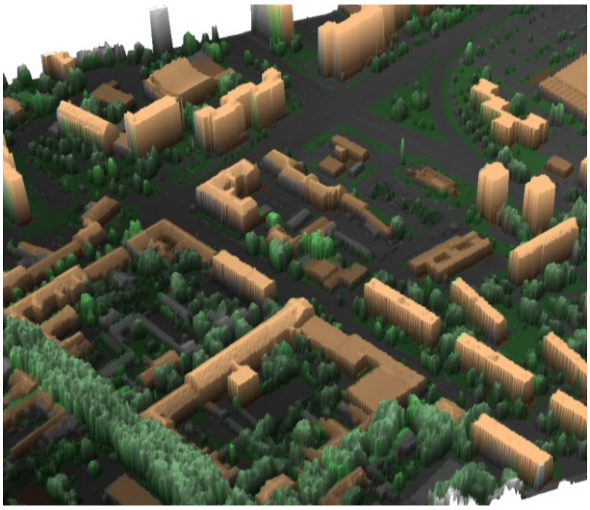

Figure IV-3 The results of classification draped on DSM

TABLE III
THE RESULTS OF CLASSIFICATION

Class	WorldView2 and LIDAR based-classification (m^2)	WorldView2 based classification (m^2)
Building	107031	109077
Parking place	26116	23793
Road	65411	34191
Other man-made	55360	49477
Trees and bushy	61372	74438
Grass	35309	58976

A. *Performing accuracy assessment*

The results of the land cover classifications derived from remotely sensed data are compared by an accuracy assessment. An accuracy assessment analysis was performed by producing an error matrix that compared the interpreted land cover map and a map contains the result of ground truth investigation. The most important outputs from the accuracy assessment included an error matrix, errors of omission and commission, both for all classes and on a per category basis. The assessment indicates the producer's and user's and overall accuracy (TABLE IV).

TABLE IV
ACCURACY ASSESSMENT

Class	WorldView -based classification		LIDAR and WorldView based classification	
	Producer's accu-racy %	user's accu-racy %	Producer's accu-racy %	user's accuracy %
1. Building	78	84	88	99
2. Parking place	99	97	96	99
3. Road	54	86	67	92
4. Other man-made	48	37	97	26
5. Trees-bush	94	62	98	54
6. Grass	84	58	94	51
	Overall accuracy: 71		Overall accuracy: 82	

V. CONCLUSION

An urban ecosystem presents a wide structural diversity and consequently spectral variability therefore the process of classification needs not only spectral information but other information like context or geometry as well. In the paper we tried to analyze the fusion of remote sensing techniques (imagery and aerial lidar) which offers an efficient way to map and update GIS ready land cover information. Using enhanced data source and object based image analysis accurate results could be obtained.

Accuracy measures have shown that the use of elvation parameters leads to significant improvments in comparison to only spectral bands classifications. However, the best classification results were reached with the application of combined dataset of spectral and elevation features, we need further studies in this field. The accuracy of this method can be increased by integrated using high resolution aerial photos and Digital Surface Model (DSM). For the image processing first we had to eliminate the distortions of the image. The Digital Elevation Model (DEM) contains only the terrain surface without objects, as the result of the ortorectification the vertical walls of the buildings are visible sloped away from the nadir point (~centre of the image). (Figure. II-1) The reason is that the elevation data of the objects are not known. These orthophotos are not suitable for image processing based on the spectral content. To correct these anomalies if DSM is used instead of DEM. This kind of digital model contains all the natural and artificial objects of the surface, therefore the vegetation and the buildings, all that reflected the laser beam.

V-1 Orthophoto based on DEM and based on DSM

The true orthophoto (Figure V-1 on the right) – based on DSM - shows the objects at their actual orthogonal position (VALBUENA at al. 2008). Vertical walls will not appear on the image as a spectral noise, appear only as a few pixels, which can be eliminated by a procedure of the image analysis. The horizontal accuracy of orthophotos based on high-resolution Lidar surface model can be characterized by size of a pixel or less.
Fort he improvement of recent results, complete cover of urban environment classes and the use of other classification algorithms (membership function based classification) have to bo analysed in the further research.

ACKNOWLEDGMENT

We wish to thank for supporting of TÉT_12_CN-1-2012-0026 project.

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