

MAPPING OF URBAN GREEN COVER USING DIFFERENT IMAGE PROCESSING TECHNIQUES ON VHR SATELLITE DATA

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ABSTRACT:

Green areas are important parts of urban sprawl with environmental and social effects. Mapping of urban green is a basic condition for effective management and protection. Fast growing of settlements and rising of ecological problems in urban zones lead to larger use of advanced technologies of Remote Sensing to acquire detailed and accurate information about land use for management and planning. Remote Sensing data and its software processing represents powerful tool for creation of thematic maps. There are several satellites which provide image data. Ikonos and QuickBird images are included among data with very high resolution (VHR). Each of them has different characteristics; above all it is spatial resolution. There are two basic ways how image processing software treats the images: per-pixel and object-oriented approaches. This paper is focused on comparison of different classification techniques used on various satellite images and oriented to map vegetation. Subsets of both scenes were chosen for the analyses. Area of interest displays Brno city quarter Lesná (CZ) as it represents typical residential quarter with single houses, blocks of flats and large green areas.

1. INTRODUCTION

Green vegetation has significant position within cities. Trees play important role in cleaning pollution, equilibration of water cycle and climate stability of the environment. They have influence on physical health of citizens – parks are used as recreational areas. The management of vegetated areas by urban planners relies on detailed and updated knowledge of their nature and distribution. (Mathieu and Aryal 2005) Ground survey mapping provide outputs of high accuracy and detail but it is very time consuming and in some cases such detailed information is not needed. Then, here comes the place for remote sensing techniques. One of its methods could be manual photo-interpretation of aerial photographs. This approach is efficient, but also time consuming (Mathieu and Aryal 2005). Recently, satellites provide image data of very high resolution; it means spatial resolution less than 5m. This type of data offers e.g. satellites Ikonos and QuickBird. Both provide four multispectral bands and one panchromatic band with even higher spatial resolution. Then, image fusion (pan-sharpening) techniques produce multispectral data with 1m respective 0.6m resolution. This is very good source for urban vegetation mapping on certain level of detail. Other important characteristic is that both data include near infrared (NIR) band which is the basic supposition for every vegetation analysis. We can monitor health condition of those vegetated areas. By remote sensing and image processing, vegetation condition can be assessed and monitored at a range of scales from site to regional and broader, depending on one's goals (Briggs and Freudenberger 2006).

In this paper, three different techniques of image classification in the context of urban vegetation mapping were compared. They were per pixel classification approach (maximum likelihood algorithm), classification by neural network algorithm (multi-layer perceptron) and object oriented classification method (nearest neighbor algorithm and

membership functions). Validation was made on basis of ground survey using Global Positioning System (GPS).

2. DATA

The project was based on two types of VHR data; they were Ikonos and QuickBird imagery. Subsets of each scene were chosen. They represent the same area of interest: Brno city quarter "Lesna" in the north of the city.

Sattelite	Date of acquisition	Channels	Spatial resolution
			[m]
Ikonos-2	March 2002	R, G, B, NIR	4
		PAN	1
QuickBird	August 2003	R, G, B, NIR	2.44
		PAN	0.61

Table 1. Basic parameters of used data



Figure 2. Area of interest. Upper-right: Ikonos (4,3,2 composition), lower-right: QuickBird (4,3,2 composition)

3. METHODS

3.1 Pre-processing

Image fusion became usual technique of pre-processing as it improves the detail of information which can be acquired from the satellite data. The objective is to obtain a high-resolution multispectral image that combines the spectral characteristic of the low-resolution data with the spatial resolution of the panchromatic image (Grassi and Radicioni 2005). The algorithms of pan-sharpening improve continually, so the change of spectral characteristics is minimal.

3.2 Classification

Three methods of supervised classification were used: traditional per-pixel approach with maximum likelihood algorithm, neural network with multi-layer perceptron classifier and object-oriented classification using nearest neighbour algorithm and membership functions.

Maximum likelihood procedure is based on Bayesian probability theory. It uses information from a set of training sites to estimate the posterior probability that a pixel belongs to each class. Multi-layer perceptron neural network uses back propagation and the calculation is based on information from training sites. (Eastman 2006). The operation has two stages: training of the network and classification itself. Training fields were done for nine classes: *coniferous*, *deciduous*, *grass*, *bare soil*, *road*, *red roof*, *grey roof*, *white roof* and *shadow*. The same set of signatures was used for maximum likelihood classifier and neural network classifier. Nine classes were then merged to form four main classes of interest: *coniferous*, *deciduous*, *grass* and *urban area*.

Image processing using object-oriented classification had different steps. At first, the image had to be segmented into meaningful objects. Segmentation is the subdivision of an image into separated regions, then multitude of additional information can be derived based on image objects (Batz, Benz et al. 2004). After the segmentation, the images were divided into two classes – vegetated and non-vegetated area – by NDVI (Normalised Difference Vegetation Index) ratio. Then the classification was performed only on the segments which represent vegetated area. Four classes were made: *coniferous*, *deciduous*, *grass* and *urban area*, which included segments omitted by NDVI ratio. Nearest neighbor algorithm was used to classify the image. Improvements of the classification were made using membership functions.

3.3 Validation

Ground truth survey was done to gain data for validation of semi-automated image processing. Four validation squares, each 150 m x 150 m, were mapped in detail. Mapping and digitization were made as a single process using Personal Digital Assistant (PDA) with GPS. This vector data were then modified into the final form. Error matrix was computed for each classification output based on ground truth data.

4. RESULTS

Both images were classified with high accuracy. Exact numbers can be seen in table 4. The best classification result of Ikonos subset provided object-oriented approach with average accuracy

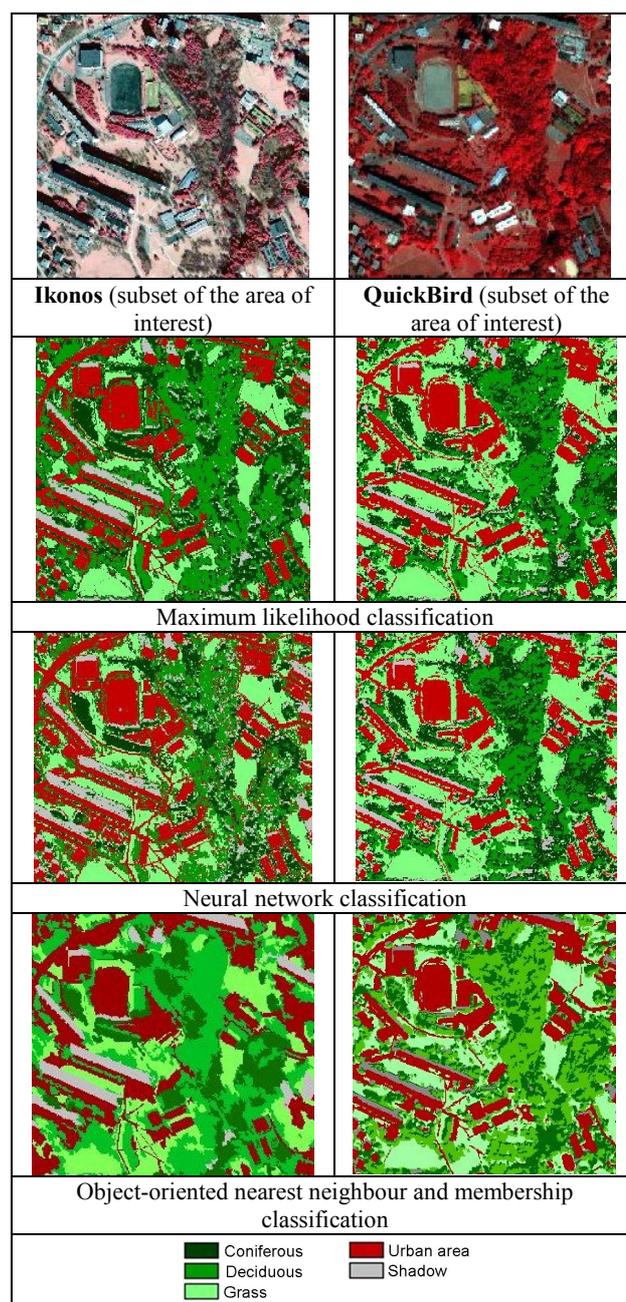


Figure 3. Results of image classification

of 95.3%. Some misclassifications can be seen. The most important is confusion between classes *deciduous* and *urban area* (barren surface), when pixels or objects of barren land are assigned to the class *deciduous*. Deciduous trees are without leaves in this Ikonos image, so the barren surface can be seen through bald canopy. The class with almost no problems of assignment in all three methods was the class *grass*. Average accuracy of QuickBird image subset was very high in all three cases of classification, while the best result was 98.7% of per-pixel maximum likelihood algorithm. The majority of misclassifications can be seen in class *coniferous*. Some pixels of coniferous trees were assigned to classes *deciduous* and *shadow*. Misclassifications between coniferous trees and shadow constitute usual problem, especially in case of per-pixel classification. The lowest accuracy value of object-oriented

method was caused on account of performed misclassifications of the class *grass*. Almost 9% of *grass* ground truth data was assigned to other classes. The reason can be confusion with barren surface regarding the condition of grass in August, when the temperature is high and precipitations low, so the large lawns are quite dry and transparent in benefit to soil. Next, edge areas of the lawns could be jointed to the class *deciduous* during segmentation process and then, whole objects were classified as *deciduous*.

Classification	Accuracy [%]	Ikonos	QuickBird
Maximum likelihood	Average a.	89.16	98.72
	Kappa index	86.21	98.24
Neural network	Average a.	94.61	98.40
	Kappa index	93.16	97.80
Object-oriented (NN, MF)	Average a.	95.25	95.04
	Kappa index	93.85	93.54

Table 4. Average accuracies from error matrixes of both images and three methods of classification

5. DISCUSSION AND CONCLUSION

The aim of the presented paper was to map effectively vegetated area within town residential area. Urban sprawl is very heterogeneous area where land use change rapidly over the scene. Other typical characteristic of urban green areas is that number of wood species is very high, exotic species are often planted for the esthetic purpose

All performed image classifications give good results. The best of them according average accuracy values was maximum likelihood algorithm on QuickBird image data. Computing process is fast so then the hardest point is searching and digitization of training fields. Above all, there is a condition of homogeneity of those training fields. User has to define every class carefully and also has to divide some classes into few more detailed. Neural network multi-layer perceptron algorithm requires training fields which are formed the same way. But the processes of training network and then the classification itself take a long time to process. In addition, settings of the algorithm are more complicated and require good knowledge of artificial neural network background. Then it is not so comfortable for a common end user who should be able to product the thematic map easily. Object-oriented classification usually gives very good results (Mittelberg 2002). The first step is to segment the image, but there are no clear suggestions for the usage of segmentation parameters, as they should be determined on an "ad hoc" basis (Hurskainen and Pellikka 2004). Scale parameter (size of segments) is an important parameter. This paper was focused on almost every single tree, so the segments had to be quite small. It means that the segmentation process was long and required good hardware equipment. Forming of classification rule set could be labeled as easy because of lots of supporting tools. Description of each class may be or even should be heterogeneous; it means we can create just one class "urban area" without dividing it into several classes depending on the material of buildings' roofs. The process of classification itself is then very quick.

Comparison of the two images is burdened with the fact that they were acquired in different season of the year, so the vegetation didn't have the same spectral response because of diverse phenological phase. Deciduous trees are without leaves in the Ikonos image, which was acquired in March. On the other

hand, it could facilitate distinction between deciduous and coniferous trees within the image.

Presence of shadow within VHR image data is another classification problem. In this paper shadow was classified as a singular class without further analysis. Only in case of object-oriented classification some objects were assigned to the proper class using membership functions. Classification of shadow with maximum likelihood algorithm as well as with object-oriented approach will follow in next work.

In conclusion, per-pixel maximum likelihood method of creation thematic map focused on vegetated areas within urban sprawl could be recommended to inexperienced user. Object-oriented approach is also good alternative but it requires more knowledge of the software and fundamentals of remote sensing. Further work in consequence of this paper is to improve result of object-oriented classification, mainly by more detailed classification of shadows.

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