# OBJECT-ORIENTED CLASSIFICATION OF REMOTE SENSING DATA FOR THE IDENTIFICATION OF TREE SPECIES COMPOSITION

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## ABSTRACT

This paper deals with the classification of tree species composition from Ikonos imagery (4m resolution) based on the object-oriented image analysis in eCogniton software. The image was acquired over a man-planted forest area with proportion of various forest types (conifers, broadleaved, mixed) in the Krušné Hory Mts., Czech Republic. In order to enlarge class feature space, additional channels were produced by low-pass filtering, IHS transformation and influence of various Haralick texture measures on classification was also examined. The principal component calculated from original Ikonos bands was applied in the pre-processing phase. The segmentation and classification were conducted on three levels to be incorporated into the hierarchical image object network. The higher level separated image into smaller parts regarding the stand maturity and structure, the lower (detailed) level assigned individual tree clusters into classes for the main forest species. The third level was created to distinguish forest/non-forest boundaries. Classification accuracy was assessed by comparing the automated technique with the field inventory data using Kappa coefficient. Apart from transferable rule base creation, the study aimed at determining appropriate scale for species composition estimation using common image data. Therefore the methodology will be tested on colour aerial photos in the further research.

**Keywords:** Object-oriented image analysis, median filters, texture, tree species composition, forestry management

## 1 INTRODUCTION

Remote sensing and image interpretation have been utilized in forestry management for many years. These methods can be applied in various tasks ranging from forest thematic mapping to the detailed tree or stand characteristics survey. Besides the advancement in digital aerial methods, high-resolution satellite sensors (e.g. Ikonos, QuickBird) are now available for operational use. However, the automated classification of such data is still problematic due to greater spectral variation within one class (Halounová, 2003).

Previous studies on high-resolution data (Gougeon, 1995b) proved that traditional spectral-based methods result in rather poor or incorrect classification. Much information is contained in spatial relations of pixels and a few studies already showed the object oriented approach promising when classifying VHR data (Baatz & Schäpe, 1999, Leckie et al., 2003). The contribution of textural and structural information was also examined (Haralick & Shapiro 1992, Brantberg, 1999) and various algorithms, such as co-occurrence matrix were applied to extract texture characteristics of trees (Zhang, 2003). Neural networks (Gopal & Woodcock, 1996) and fuzzy classification improved modeling of real-world dependencies (Benz et al., 2004). Furthermore, increased use of a priori knowledge and information extraction become important with the rapid development of GIS.

This paper explores and demonstrates capability of object oriented image analysis software eCognition (Definiens Imaging, Germany) for the tree species classification from Ikonos imagery. Combination of complex object description, hierarchical image object network and fuzzy system makes eCognition a challenge to knowledge-based image interpretation in a range of forestry management applications. Next project objective is to determine appropriate scale and accuracy of species composition estimation using common image data. The prospect of knowledge base creation for the high level automation in operational forestry is also discussed.

## 2 SITE AND FIELD DATA COLLECTION

The research was conducted in man-planted forests nearby the town Hrob (50$^{o}$40'N, 13$^{o}$43'E) in the Krušné Hory Mts., Czech Republic. This submontane area consists of patches of mature Spruce (Picea Abies L.) and Beech (Fagus Silvatica L.) forest, with the substantial proportion of Larch (Larix deciduas Mill.) and also young plantations of Beech, Birch (Betula pendula L.) and Picea pungens often mixed with Larix and Betula Pubescens. The planted mature stands are mostly of the same age, but very heterogeneous in species composition, stocking density and canopy structure. The natural regeneration in addition to the planted trees sometimes occurs. Silviculture practices range from clear cutting to seed felling with heavy thinning on some spots.

Based on the previous information from LHPO forest inventory, twenty 400m$^2$ plots covering areas with 100% species composition were located as a reference data. Sample plot selection put emphasis on size and class purity to provide representative basis for accuracy assessment. The boundaries of each plot were determined with differential GPS SX Blue™ and PDA with ESRI ArcPad™ mobile GIS.

## 3 IMAGERY PREPROCESSING

The Ikonos (Space Imaging, USA) image was acquired on 17th September 2003. Except for some hardwood species, most vegetation was still green and fully foliaged. Data were delivered in a geo-registered UTM projection (zone N33) with 11-bit radiometric resolution. The image contained significant amount of clouds and atmospheric haze, so a 3x3 km subset of forested area with clear sky conditions was chosen for the analysis. There is also important amount of shadow fraction throughout the scene associated with solar and observation angles (Table 1)

**Table 1.** Ikonos viewing and illumination geometry

| View Azimuth | View Elevation | Sun Angle Azimuth | Sun Angle Elevation |
|---|---|---|---|
| 330.30 degrees | 71.78 degrees | 170.58 degrees | 41.51 degrees |

In the next step, class feature space was enlarged by the calculation of additional channels. Foremost the single principal component from original bands was derived and then Median filter (kernel sizes 3x3 and 5x5) was applied in order to suppress spatial frequency. Several Haralick (GLCM) texture measures were calculated and the contribution to class separability was tested. Measures Mean, Variance and Homogeneity with window sizes of 3x3 and 5x5 were chosen. Further, layers calculated by IHS transformation and edge detection (Sobel operator) were also applied in the classification.

## 4 OBJECT ORIENTED ANALYSIS

After the feature space enlargement, image segmentation was performed to further handle high spectral variation and overlapping values of classes. In this phase, image was split into smaller regions (object primitives) to simplify thematically complex data content. The classification was then performed using segments instead of single pixels.

### 4.1 Multiresolution segmentation

In the segmentation process, size and shape of desired objects are defined by the calculation of heterogeneity between adjacent pixels, where Scale is the main input parameter. Shape factor (colour/shape ratio) and spatial properties (smoothness/compactness ratio) are other variables to define homogeneity of object primitives.

Segmentation was conducted stepwise on several levels using different scales to construct the hierarchical image object network. The primary level was created using Scale parameter of 15. After preliminary classification, objects were merged by classification-based segmentation and the result (basic landuse classification) was re-imported into eCognition as a thematic layer. The sublevel was then segmented only within the area of interest (class Forest) using Scale parameter equal to 5. The finest objects with the Scale value of 3 were calculated at the third level applying the same approach.

The Shape factor was set to higher value for the coarse segmentation and lower value at finer scale (higher influence of spatial properties). The two lower levels were processed using four Ikonos bands and median filtered channel of kernel size 3x3, the coarse landuse segments were made based only on thematic layer. Layer weights were set in relation to their standard deviations.

### 4.2 Class definition

The three level hierarchical image object network was used to delimit classes. Level 3 comprised basic "Landuse" types - Urban, Fields and Forest. This served to mask all non-forest areas. The lower level 2 "Forest" aimed to separate forest regions into Dense (young and mature stands with more less closed canopies), Sparse areas and Clearcuts. Sparse forests mostly consisted of low stocking mature beech trees with presence of visible ground. The detailed level 1 "Stand" was set to distinguish four main forest species in the area - Fagus, Picea, Larix and Betula. Further, structures of shadows and bare ground were classified on this level.

All classes of "Forest" level were also recognised at the lower "Stand" level for purpose of post classification improvement.

### 4.3 Classification

In order to create distinct and fully transferable rule base, fuzzy logic membership functions were used to define object features. Fuzzy description enables classes to be assigned according to membership degree rather than crisp threshold values. Following features were applied:

a) Object features: mean layer values (blue, red, NIR, brightness, GLCM mean 3x3, IHS, Sobel NIR), ratio layer values (blue, red), area generic shape feature,

b) Class-related features: relative border to neighbour objects, relative area of sub-objects, existence of sub-objects (super-objects)

c) Customised features: NDVI, (red-green) vegetation index, IHS/ brightness index,

Besides MF classification, preliminary nearest neighbour classification was done on the lowest level and features suitable to separate tree species were evaluated using sample editor (histogram comparison). The masking technique of determining foremost the easy classes (ground, beech trees) and moving on to more difficult ones was often applied. Then the class boundaries were improved using class-related features and finally corrected by means of classification-based segmentation.

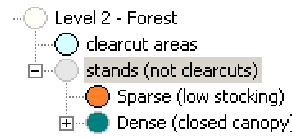
## 5 RESULTS

The classification accuracy was evaluated using field reference data. Sample areas were imported into project by means of TTA mask (Definiens Inc. 2003) and the corresponding classes were linked to form confusion matrix (Table 2). Several measurements such as Producer's, User's, Overall accuracy and Kappa index of agreement were derived for each class. Besides, classification reliability (Best classification result) and stability within fuzzy concept were assessed.

**Table 2.** Error matrix of classification accuracy assessment. The Overall Accuracy is 0.945 with the Kappa index of agreement equal to 0.914

| User \ Referer. Class | Larix | Betula | Fagus | Picea | sparse | ground | shadows | fields | urban | Sum |
|---|---|---|---|---|---|---|---|---|---|---|
| **Larix** | 211 | 104 | 2 | 5 | 0 | 0 | 0 | 0 | 0 | 322 |
| **Betula** | 25 | 322 | 5 | 0 | 35 | 0 | 0 | 0 | 0 | 387 |
| **Fagus** | 93 | 14 | 685 | 0 | 2 | 0 | 0 | 0 | 0 | 794 |
| **Picea** | 34 | 0 | 0 | 444 | 0 | 0 | 107 | 0 | 0 | 585 |
| **sparse** | 10 | 0 | 0 | 0 | 317 | 0 | 0 | 0 | 0 | 327 |
| **ground** | 0 | 0 | 0 | 2 | 17 | 207 | 0 | 0 | 0 | 226 |
| **shadows** | 0 | 0 | 0 | 37 | 0 | 0 | 216 | 0 | 0 | 253 |
| **fields** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 5849 | 0 | 5849 |
| **urban** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1334 | 1334 |
| **unclassified** | 17 | 17 | 5 | 3 | 1 | 0 | 17 | 0 | 0 | 60 |
| **Sum** | 390 | 457 | 697 | 491 | 372 | 207 | 340 | 5849 | 1334 | |
| **Producer's** | 1 | 0.541 | 0.705 | 0.983 | 0.904 | 0.852 | 0.635 | 1 | 1 | |
| **User's** | 0.916 | 0.655 | 0.832 | 0.863 | 0.759 | 0.969 | 0.854 | 1 | 1 | |
| **KIA Per Class** | 1 | 0.526 | 0.693 | 0.981 | 0.898 | 0.847 | 0.626 | 1 | 1 | |

**Figure 1.** Ikonos image (false colour mix)



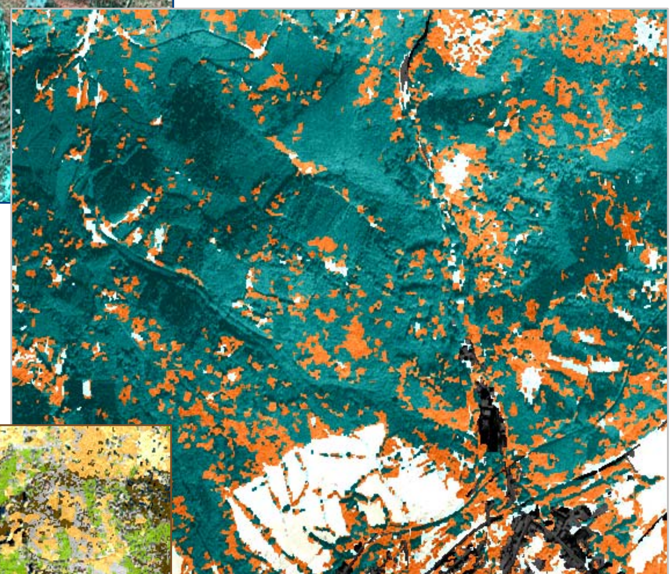
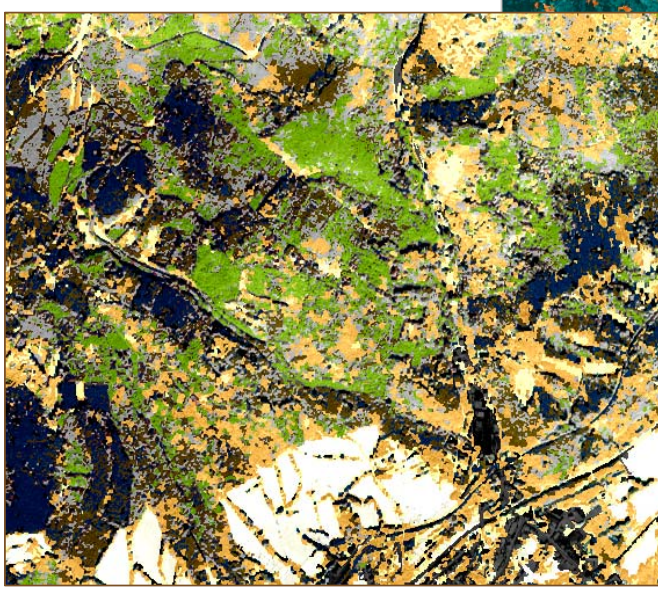



**Figure 2.** Higher level classification



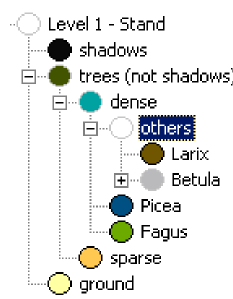



**Figure 3.** Classification at the lower level

Fig. 1 shows the original image, Fig. 2 shows classification on higher “Forest” level. The result of classification at lower “Stand” level is on Fig. 3.

As indicated in the confusion matrix, proposed method offered very good overall results. Both Picea and Larix conifer species were classified with accuracy over 90%. Fagus achieved accuracy about 70%, which was caused by confusion with class Sparse (high proportion of beech trees). The most problematic tree class was Betula, not only by means of error matrix, but also classification reliability and stability. This tool estimating differences in membership degrees between the best and second best class assignment shows that class Betula and Larix often act as ambiguous. The two species have similar spectral and textural characteristics, especially at young age. Besides, shadows are frequently being confused or mixed with Picea pixels. Best results were obtained for all non-forest classes.

## 6 DISCUSSION

The results showed that classification of 4-m Ikonos data can be performed with relatively high accuracy. The image allows to estimate tree species composition at the sufficient scale. To get satisfying outcome, additional channels must be calculated in the pre-processing phase and then included in segmentation and subsequent object-oriented classification. The object shape attributes are influenced by the kernel size and layer weight in the process of segmentation, the contribution of additional layers to classification was high for Sobel Edge detector, IHS transformation and low-pass filters. Other textures measures had lower impact using on such spatial resolution data. The classification rules based on fuzzy membership functions are highly convertible, eCognition protocols developed in this project can be transferred and applied (with some threshold modification) to other datasets. To normalize imagery band ratios can be employed, yet data acquired under fixed viewing and solar geometry are recommended to use for the automated analysis.

Previous studies indicated that variations in image acquisition (different projection centres) become more problematic when analysing multitemporal aerial photos. Lower spectral, radiometric and temporal resolutions are also a drawback comparing to VHR satellite data. However, the current lower price at higher spatial resolution still account for aerial photography when developing knowledge base for the method utilization in forestry management. The necessary conditions to obtain good results are standardised screening plan and introduction of photography on IR material. The object-oriented analysis of aerial photos will be examined in the further research.

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