OBJECT-BASED SEMI-AUTOMATIC MAPPING OF FOREST STANDS WITH LASER SCANNER AND MULTI-SPECTRAL DATA

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ABSTRACT:

This paper details the development and testing of an object-based mapping of forest stands using an object-oriented image analysis methodology. The object-based mapping of forest structures using high-resolution airborne data is demonstrated for the Bavarian Forest National Park, which is located in south-eastern Germany along the border with the Czech Republic. Within the project "Evaluation of remote sensing based methods for the identification of forest structures" small-footprint time-of-flight LiDAR and multi-spectral line-scanner data were acquired. The main objective of this paper is to evaluate the suitability of an object-based approach for the mapping of forest-development phases. The goal was to translate the manual mapping guidelines for forest-development phases used by the Bavarian forest service into a rule-base. Following initial image segmentation steps, object relationship modelling allowed to distinguish the main forest development phases. A preliminary accuracy assessment compared a field-based survey of the developmental phases with the semi-automatic mapping. The results are promising although significant confusion between similar classes did occur. It turned out that misclassifications are mainly related to semantic problems of class definitions which are intrinsically linked to the underlying manual mapping guidelines.

1. INTRODUCTION

The forest stand is the most important planning unit for forest management. For decades, in Western and Central Europe the stands were mapped using aerial photographs in combination with field surveys. In Bavaria, a majority of forests belong to the Bavarian Forest administration. These stands are mapped according to the natural life cycle in a forest. This approach partly follows the concepts of silvatic mosaics (Oldemann, 1990) and forest-development phases (Leibundgut, 1959). Their basic components are eco-units (Oldemann, 1983), defined as the units of vegetation which began to develop "at one moment in time..., of which the architecture, ecophysical functioning, and species composition are ordained by one set of trees until the end" (Oldemann, 1990, Bobiec et al., 2000).

The resulting map classes are called forest-development phases. The method to map these stands is very time consuming and highly subjective. Therefore new cost effective forest inventory techniques are needed to supplement and eventually replace the traditional methods.

New sensor technologies (Laser-, digital line scanners and digital camera systems) allow to acquiring data which support a continuous high-resolution reconstruction of the forest surface including the three-dimensional structure. Light detection and ranging (LiDAR) technology provides horizontal and vertical information at high spatial resolutions and vertical accuracies (Zimple et al., 2003, Morsdorf et al., in press). Forest attributes such as canopy height can be directly retrieved from LiDAR data. Direct retrieval of canopy height provides opportunities to model above-ground biomass and canopy volume. Access to the vertical nature of forest ecosystems also offers new

opportunities for enhanced forest monitoring, management and planning.

These sensor developments are imperative for a detailed mapping of forest structure and forest development phases. They produce enormous amounts of data. For instance, in the following case study 10 LiDAR pulses per m² resulted in point data sets with approximately 10 Mb per Hectare. In addition to the data quantity issue, the ever increasing spatial resolution requires different analysis methodologies. Blaschke and Strobl (2001) argue for classification of homogeneous groups of pixels reflecting our objects of interest in reality. They suggest to use algorithms to delineate objects based on contextual information in an image on the basis of texture or fractal dimension. Burnett and Blaschke (2003) developed a multiscale segmentation / object relationship modelling (MSS/ORM) methodology translating the objective of homogeneous objects into the multiple scale reality of real world objects.

In the following study we apply the MSS/ORM methodology to the semi-automatic mapping of forest structure and forestdevelopment phases. The methodological achievements and the outcomes of this study should support future forest planning tasks in the National Park. Furthermore, they will also be used for ecological research and conservation planning. Recent literature (e.g. Bergen et al. 2002) justifies the potential that a detailed mapping of forest structures based on high resolution multi-spectral and LiDAR data serves for a better habitat modelling. This can again be used as a foundation to predict the distribution of species.

2. STUDY AREA AND DATA SETS

2.1 Study area

The research was conducted in the Bavarian Forest National Park (NPBW) which is located in south-eastern Germany along the border with the Czech Republic (49° 3' 19" N, 13° 12' 9"E). Within the park three major forest types exist: above 1100 m there are sub alpine spruce forests with Norway spruce (Picea abies) and partly Mountain ash (Sorbus aucuparia); on the slopes between 600 m and 1100 m altitude, mixed mountain forests with Norway spruce, White fir (Abies alba), European beech (Fagus sylvatica) and Sycamore maple (Acer pseudoplatanus) can be found; in wet depressions often evidencing cold air ponds in the valley bottoms spruce forests with Norway spruce, Mountain ash and birches (Betula pendula, Betula pubescens) occur. For the image analysis described in this paper a test area of 270 ha was chosen. It stretches from the mixed mountain forest zone to the spruce forests of the valleys zone.



Figure 1: Study area (approx. 270 ha) within the Bavarian Forest National Park

2.2 Remote Sensing Data

The Toposys (Topografische Systemdaten GmbH) airborne LiDAR system ("Falcon") was used to survey the test areas on three dates: leaf-off (March and May, 2002) and leaf-on (September 2002). The TopoSys System is based on two separate glass fibre arrays of 127 fibres each. Its specific design produces a push-broom measurement pattern on ground. For further details see Wehr and Lohr (1999). The average point density for these flights was 10pts/m². First and last pulse data were collected during the flights. The datasets were processed and classified using TopPit (TopoSys Processing and Imaging Tool) software. The resulting Digital Surface Model (DSM) and Digital Terrain Model (DTM) were substracted to create a Digital Crown Model (DCM) with 0.5 m resolution.

Simultaneous to the LiDAR range measurements, image data were recorded with the line scanner camera of Toposys. The camera provides 4 channels: B (440-490 nm), G (500-580 nm), R (580-660 nm) and NIR (770-890 nm). Ground resolution was also 0.5 meters.

Sensor type	Pulsed fibre scanner		
Wave length	1560 nm		
Pulse length	5 nsec		
Scan rate	653 Hz		
Pulse repetition rate	83.000 Hz		
Scan with	14.3°		
Data recording	first and last pulse		
Flight height	800 m		

Table 1: System parameters for the Laser Scanner flight

2.3 Forest Inventory Data

In Bavaria, forest-development phases are regularly mapped through terrestrial surveys. For the NPBW, these surveys were conducted by using aerial photography, existing information of older stand mappings and auxiliary data sets. The field work was performed in 2003. Eight major developmental phases were mapped:

-	disturbance phase
-	unstocked
-	terminal phase
-	young phase
-	optimal phase
-	regeneration phase
-	pole phase
-	late pole phase

In addition, these major phases are subdivided depending on the dominance of coniferous or deciduous species. Figure 2 translates the manual mapping guidelines for forestdevelopment phases used by the Bavarian Forest Administration. The guidelines represent a decision tree with a mixture of unequivocal and vague decisive criteria for the classification of different phases, which also depends on the experience of the field personal



Figure 2: Mapping guide for forest-development phases in the NPBW (Heurich, 2001; modified)

3. METHODOLOGY

A multiscale segmentation / object relationship modelling methodology (MSS/ORM, Burnett & Blaschke, 2003) was applied. In the segmentation step, a fractal-based multi-scale segmentation algorithm developed by Baatz and Schäpe (2000) was implemented. The fractal net evolution algorithm (FNEA) has already successfully been applied in many studies (see Blaschke and Strobl, 2001; Flanders et al., 2003; Benz et al., 2004 for an overview) and is based on assessments of homogeneity and heterogeneity. In it, an iterative heuristic optimization procedure is programmed to get the lowest possible overall heterogeneity across an image. The basis for this is the degree of difference between two regions. As this difference decreases, the fit of the two regions is said to be closer. In the FNEA, these differences are optimized in a heuristic process by comparing the attributes of the regions (Baatz and Schäpe, 2000). That is, given a certain feature space, two image-objects are considered similar when they are near to each other in this feature space.

The outcome of the first step was several image segmentation levels on different scales. A suite of segmentation levels was created and the levels to be used for the creation of the rulebase had to be identified according to the target scale. Burnett and Blaschke (2003) in their MSS/ORM methodology call this target level the "focal level" or "level 0" following the nomenclature from ecological theory. They refer to the finest level used as *level* -1 and call it a mechanistic level. Indeed, in this study the objects at the finest level are not of interest as such. Rather, they deliver information to be used at the target level of the mapping application. To avoid a confusion among the remote sensing readership we refer to levels 1, 2 and 3, respectively, as outlined in figure 3. This nomenclature corresponds to image segmentation programmes where usually the finest level is called *level 1* (although in some programmes the finest level can be the pixel level).

One more reason for not directly using the finest level – roughly corresponding to single trees – is that a preceding project (Tiede et al., 2004) demonstrated that the segmentation algorithm used in the software is not ideal for the delineation of single trees. However, for the derivation of forest stands (or forest-development phases) the problems reported by Tiede et al. are not relevant. The underlying FNEA is evaluated to be very efficient if the targeted objects are significantly larger than the object primitives they are built on (Flanders et al., 2003; Blaschke et al., 2004).



Figure 3: Multiscale segmentation / object relationship modelling for forest-development phases

Three target levels were identified for the study area (see fig. 3):

Level 1 is dedicated to represent small objects ("single-tree scale" but not necessarily single trees) at an initial segmentation level to differentiate sub-classes by spectral and structure characteristics (deciduous and coniferous areas, height classes, dead trees, non-tree areas, regeneration etc.).

Level 2 is the main target of the classification rules. A rulebase was developed to summarize forest-development phases by referencing to small scale sub-objects at level 1. The rulebase mimics the manual mapping guide for forest-development phases in the NPBW as outlined in fig. 2.

Level 3 was generated through a "*classification based segmentation*" procedure aiming to unite objects of the same classified forest-development phases into larger spatial units. Additionally, small units below a certain threshold surrounded by bigger units classified as similar developmental phases were reassigned to the respective classes of the majority of neighbour objects. It is achieved through a "*relation to neighbour objects*" parameter in the rule-base.



Figure 4: Classification rule-base (level 1 and level 2)

In a subsequent step, a model of the relationships between the segmented image objects was built. Some object relationships are automatically derived. For instance, the characteristics of level 2 objects (such as mean spectral values, spectral value, heterogeneity, and sub-object density, shape and distribution) can be automatically calculated and stored in the description of each level 1 object.

Best results were achieved when all segmentations were carried out on the basis of the multi-spectral data only. In addition, a thematic layer was used to avoid bridging segmentation objects across forest roads, compartments etc. The laser scanner data were used in the classification step and for the development of the rule-base (see fig. 4).

During the development of the rule-base two major problems occurred:

- (1) transcription of the vague class descriptions of the manual mapping guidelines into semantic rules
- (2) detection of regeneration in closed forest stands

The first problem was encountered by using fuzzy rules in eCognition (cf. Flanders et al, 2003; Benz et al., 2004), with good results after various calibration cycles. For the detection of regeneration in closed forest stands the indicator "*roughness of the surface*" delivered the best results. It turned out that this indicator reflects well the fact that in forest stands with rough surface (more gaps, large and small trees close together) generally more regeneration exists than in forest stands with a smoother (more closed) canopy.

4. RESULTS AND DISCUSSION

Originally, two accuracy assessment techniques were envisaged. The first accuracy assessment test used existing regularly distributed inventory points (lattice of 200 by 200m). This data set was unsuitable. There were too few points and too large gaps in between, relative to the mapping scale and the resulting number of final objects at level 3. The second accuracy assessment is simply a comparison with the manually mapped forest-development phases.



Figure 5: Geometric differences for object delineations of forest-development phases (left: Manually mapped by a human interpreter; right: Semi-automatically constructed through image segmentation)

The accuracy assessment method described above bears some problems which are partially addressed in chapter 2.3.: the manual maps don't represent the "truth". They are afflicted with some unknowns (subjectivity, abstraction, different semantics). Generally, there is increasing evidence that traditional accuracy assessment tools based on cross-tabulation spreadsheets referring to points or pixels are not suitable for object-based classification (de Kok, 2001; Blaschke 2003). Because objects include information about shape, area, area-shape relationships, topology etc., this additional information has to be evaluated in another manner.

A first qualitative visual accuracy assessment shows promising results. Figures 5 and 6 demonstrate the obviously more "precise" delineations compared to manual mapping. While human interpretation intrinsically includes generalisation – which is important and necessary for many applications – image segmentation may also result in very complex outlines following shapes of single trees, bushes or dead trunks. But geometrical fitting is very difficult to evaluate and currently no standardised methods exist. At scales of 1:2500 and finer (Fig. 5) high accuracy terrestrial measurements are needed to validate the geometric accuracy of the objects from the segmentation.



Figure 6: Screenshots of the resulting maps of forestdevelopment phases. Manually mapped by an interpreter (above) and semi-automatically constructed (below). White lines are showing forest roads and compartment borderlines.

The quantitative comparison for the four major forestdevelopment phases within the area results in an overall accuracy of 62% (Kappa Index: 43%, see table 2). A closer look at the single classes shows partly very good (for classes RS, JS), but also bad results (User accuracy for VS). One reason is the inexact and/or subjective reference data set; another reason originates in the resemblances of the classes. Confusion occurred most often between the classes RS – VS and WS – PS – RS, while the most stable subdivision occurred between the classes RS and JS. If only the three stable classes (RS, WS, JS) are taken into account overall accuracy rises up to 77% (Kappa Index: 57%). Differentiation of coniferous forest and deciduous forest, as well as the identification of dead wood were also very good. This corresponds with the results from Ochs et al. (2002) who got an overall accuracy of more than 90% for dead trees.

Developmental phases	RS	WS	JS	VS	
User accuracy in %	90	38	69	12	
Producer accuracy in %	54	48	98	85	
Overall accuracy: 62 % Kappa Index: 43 %					

 Table 2: Accuracy assessment for the four major forestdevelopment phases in the study area

However, the field data are also highly subjective. Their class descriptions are very fuzzy and it is difficult do distinguish forest development phases in the field, if they are proximate in time like pole phase (WS) and optimal phase (RS). Therefore the best way to perform the accuracy assessment is to check the resulting maps in the field which will be done during summer 2004.

5. CONCLUSIONS

In this paper, an object oriented analysis technique has been used for semi-automatic mapping of forest-development phases based on LiDAR and multi-spectral data. The results are satisfying and generally encourage further investments in data acquisition and methodological development. However, some critical points remain. In particular the following tasks need to be solved for supporting or partially replacing traditional ground surveys:

- quantifying to what extent the results simplify a manual mapping using aerial photographs together with stand ground surveys (time, exactness, costs),
- supporting the ground survey with interim analysis results (e.g. stand height maps, differentiation coniferous/deciduous, gap distribution etc.) to get more objective and faster results in case of unclear classifications,
- integrating statistical results in the classification which allow statements about how certain a forestdevelopment phase classification is, how uncertain the distinction from a particular other class is or how stable decision rules are against parameters such as elevation, exposition, or illumination.

For the foreseeable future terrestrial surveys will be necessary (in particular in the production forest) especially for planning purposes. But the proposed method is believed to potentially reduce the efforts necessary for terrestrial surveys. Fieldwork can then focus on uncertain situations and on the most important forest stands concerning forest planning and ecological questions.

6. REFERENCES

Baatz, M. and Schäpe, A., 2000. Multiresolution Segmentation – an optimization approach for high quality multi-scale image segmentation. In: Strobl, J., Blaschke, T., Griesebner, G. (eds.): *Angewandte Geographische Informationsverarbeitung XII*, Wichmann-Verlag, Heidelberg, pp. 12-23.

Benz, U.C., Hofmann, P., Willhauck, G., Lingenfelder, I., Heynen, M., 2004. Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. *ISPRS Journal of Photogrammetry & Remote Sensing*, 58 (2004), pp. 239-258.

Bergen, K.M., D.G. Brown, M.C. Dobson, E. Gustafson, 2002. Integrating Radar Remote Sensing of Forested Habitat Structure: A Pilot Project for Biodiversity Informatics. Proceedings, National Science Foundation Conf. on Digital Government Research, Los Angeles, pp. 149-154.

Blaschke, T., 2003. Object-based contextual image classification built on image segmentation. IEEE Workshop on Advances in Techniques for Analysis of Remotely Sensed Data, NASA Goddard Flight Center, CD-ROM, Washington DC.

Blaschke, T. and Strobl, J., 2001. What's wrong with pixels? Some recent developments interfacing remote sensing and GIS. *GIS Zeitschrift für Geoinformationssysteme* 6/2001, pp. 12-17.

Blaschke, T., Burnett, C., Pekkarinen, A., 2004. New contextual approaches using image segmentation for object-based classification. In: De Meer, F. and de Jong, S. (eds.): *Remote Sensing Image Analysis: Including the Spatial Domain*, Kluver Academic Publishers, Dordrecht.

Bobiec, A., van der Burgt, H., Meijer, K., Zuyderduyn, C., Haga, J., and Vlaanderen, B., 2000. Rich deciduous forests in Bialowieza as a dynamic mosaic of developmental phases: premises for nature conservation and restoration management. *Forest Ecology and Management* 130, pp. 159-175.

Burnett, C. and Blaschke, T., 2003. A multi-scale segmentation / object relationship modelling methodology for landscape analysis. *Ecological Modelling* 168(3), pp. 233-249.

De Kok, R., 2001. Objektorientierte Bildanalyse. Ein Lösungsansatz für den automatisierten Einsatz sehr hoch auflösender Satellitendaten für forstliche Fragestellungen. PhD Dissertation, Forest Faculty Technical University Munich.

Flanders, D., Hall-Beyer, M., Pereverzoff, J., 2003. Preliminary evaluation of eCognition object-based software for cut block delineation and feature extraction. *Can. J. Remote Sensing* 29 (4), pp. 441-452.

Heurich, M., 2001. Waldentwicklung im montanen Fichtenwald nach großflächigem Buchdruckerbefall im Nationalpark Bayerischer Wald. In: *Waldentwicklung im Bergwald nach Windwurf und Borkenkäferbefall*, pp. 99-176.

Leibundgut, H., 1959. Über Zweck und Methodik der Struktur und Zuwachsanalyse von Urwäldern. *Schweiz. Z. Forstwesen*. 110(3), pp. 111-124.

Ochs, T., Schneider, T., Heurich, M., Kennel, E., 2003. Entwicklung von Methoden zur semiautomatisierten Totholzinventur nach Borkenkäferbefall im Nationalpark Bayerischer Wald. In: Strobl, Blaschke & Griesebner (eds.). Beiträge zum 15. Symposium für Angewandte Geographische Informationsverarbeitung. Wichmann Verlag Heidelberg, pp. 336-341.

Oldeman, R.A., 1983. Tropical rain forest, architecture, silvigenesis, diversity. In: Sutton, S.L., Whitmore, T.C., Chadwicks A.C. (eds.), *Tropical Rain Forest Ecology and Management*. Blackwell Scientific Publ., Oxford, pp. 139-150.

Oldeman, R.A., 1990. *Forests: Elements of Silvology*. Springer-Verlag, Berlin, Barcelona.

Tiede, D., Burnett, C., Heurich, M., 2004. Objekt-basierte Analyse von Laserscanner- und Multispektraldaten zur Einzelbaumdelinierung im Nationalpark Bayerischer Wald. In: Strobl, J., Blaschke T., Griesebner, G. (eds.): *Angewandte Geoinformatik 2004*, Wichmann Verlag, Heidelberg, pp. 690-695.

Toposys, 2004. Falcon Lidar Sensor System. Technical outline. 6p. http://www.toposys.de/pdfext/Engl/falcon Folder Mar 2004.pdf (accessed 10 July 2004)

Wehr, A. and Lohr, U., 1999. Airborne laser scanning - an introduction and overview. *ISPRS Journal of Photogrammtry & Remote Sensing* 54, pp. 68-82.