APPLIED 3D TEXTURE FEATURES IN ALS-BASED TREE SPECIES SEGMENTATION

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ABSTRACT:

Airborne laser scanning (ALS) data are usually considered not to be very informative with respect to tree species, and the information needed regarding these is often obtained by combining the ALS data with spectral image material. This study employed tree species segmentation based on variables derived solely from ALS point clouds to test the ability of height, density, and applied 3D texture variables to describe species-specific characteristics of crown shape and structure. Linear discriminant analysis was used to find optimal combinations of variables within different predictors and segmentation techniques. Segmentation procedures based on different feature sets were compared. Alpha shape metrics, developed for describing tree crowns in ALS data, proved able to discriminate spatially between all three species evaluated and improved final segmentation result.

1. INTRODUCTION

The forest stand is the basic unit for management planning and data collection. Stands are delineated on the basis of forest management needs, and thus they are mostly also ecologically homogeneous units. Using image segmentation techniques, remote sensing data can be divided into spatially disjoint and homogeneous regions that correspond reasonably well with actual forest stands (Hagner, 1990; Makela & Pekkarinen, 2001). Image vision research has focused on developing segmentation algorithms based on either colour or texture features, and some attempts have been made to combine these to build a unified segmentation concept (Allili and Ziou, 2007).

It has been determined two basic strategies for achieving the integration of dual sets of information, on boundaries and regions (Munoz et al. 2003). The first strategy is described as the use of edge information to control or refine a regional segmentation process, while the alternative is to integrate edge detection and region extraction within the same process. Region growing algorithms are based on the growth of a region whenever its interior is homogeneous according to certain features, such as intensity, colour or texture. The different variants include the traditional implementation based on adding similar neighbours (Narendra & Goldberg 1980), a watershed algorithm (Pitkänen 2001) and an active region model (Munoz et al. 2003). Embedded integration is based on an algorithm which uses region and edge information to avoid errors in segmentation and a post-processing module that tries to refine the results (Munoz et al. 2003).

The object-based analysis of multispectral imagery has been a topic of great research interest within forestry application ever since digital satellite imagery was introduced (eg. Tomppo 1986a), although the object-based approach has largely been ignored recently in favour of pixel-based methods, which are easier to implement, and it has been noted that some forests typically have a heterogeneous vegetation structure inside their management units. Several object-based image analysis techniques have been used successfully for forest information extraction purposes (Hay et al., 1996, 2005; Pekkarinen, 2002; Pitkänen 2001, St-Onge and Cavayas, 1997, Chubey et al. 2006). The use of ALS-based data has improved growing stock estimates, while stand density and stand-level tree size can easily be estimated in this way (Naesset 1997, Packalen & Maltamo 2007). Species detection in Scandinavian forests typically relies on aerial photographs, and the recent development of integrating ALS data with digital colour and infra-red features can improve the results significantly (Packalen & Maltamo 2007).

The idea of region-specific hierarchical representations is based on the hierarchical composition of the classes to be mapped. This approach has been used in eCognition software, which allows polygonal type-specific segmentation (Tiede et al. 2006). Especially in heterogeneous mixed forests, it is difficult to segment regions representing more or less evenly scaled objects (Tiede et al. 2006). Region-specific segmentation can be controlled by means of a combination of rule-sets (Tiede et al. 2006) for single tree crown delineation from laser scanning data while taking account the characteristics of the respective forest types (i.e. deciduous vs. coniferous or spacious vs. non-spacious). Maier et al. (2006) developed a generic automated approach for assessing and quantifying forest structure using landscape metrics on height class patches within a normalized crown model (nCM). Two separate multi-resolution segmentations were carried out, one for tree crowns, and one for forest stands

A forest inventory system in which aerial photographs were not needed for estimating tree species attributes would have many advantages, as varying weather conditions and imaging parameters bring about difficulties in obtaining stable radiometric optical data (Mäkinen et al. 2006). Vauhkonen et al.

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(2008a) have recently employed the alpha shape concept, a computational geometry technique introduced by Edelsbrunner and Mücke (1994), to construct tree crown approximations from ALS point clouds. Different volume and complexity metrics derived from the approximations were found to be capable of discriminating between the economically most important Scandinavian species groups, i.e. pine, spruce and deciduous trees. When this approach was combined with ALS height and intensity distribution variables, an overall accuracy of approximately 95% and a Kappa coefficient of 0.90 were achieved. Furthermore, Vauhkonen et al. (2008b) simulated thinning using original ALS data which had a markedy high initial density of approximately 40 returns m-2, and produced species and diameter at breast height estimates with the thinned data sets. The alpha shape metrics were found to suffer from a lower pulse density, but in general they performed well at pulse densities that were only moderate for the individual tree delineation approach.

Growing stock segmentation is normally carried out using several phases to meet a number of objectives. The delineation of homogeneous forest stand components should be based on a different scale from the characterization of within-stand structure. Also, heterogenous stands are typically delineated to form an independent management unit.The spatial arrangement of trees within a stand is especially likely to vary in terms of species distribution and according to soil conditions. When the permanent sample plots in Finland were analysed, 57% had a regular tree pattern, while 25% were random and 18% clustered (Tomppo 1986b). When the basic pattern of trees has been identified (Uuttera et al. 2003), this can be used directly to determine the sampling unit and design, and it will also be reflected in field estimates. Kangas and Maltamo (2002) showed that calculations of saw wood and pulpwood volumes are especially biased due to inaccurate estimates of median tree diameters (RMSE of 20%). The accuracy of the basal area measurements in the same study was 32%. The variation between field technicians is normally very high and has different effects depending on the variable investigated and the stand structure (Kangas et al. 2004).

We will study here the performance of new 3D metrics for extracting forest inventory information from high spatial resolution ALS data using the Arbonaut image object analysis software. In particular, we will evaluate the success of certain segmentation techniques in terms of typical forest inventory attributes (species proportion, stand tree density and mean height).

2. MATERIAL

The research area is a 67 ha commercial forest property owned by United Paper Mills and located in Juuka, Eastern-Finland. It has been managed in a manner typical of Scandinavian conditions. LiDAR data were acquired on July 13, 2005 with an Optech ALTM 3100C sensor. The nominal average point density was 0.6 pulses/ m2, varying in the range 0.5-1 pulses/m2. The flight altitude was 2000m above ground level and the field of view 30 degrees, with a 60 cm beam footprint. Four returns were recorded by the sensor, and the first and last pulses were attributed. The returns were classified into two classes: “ground” and “default”. A 2.5 m DTM was created using the mean of the ground returns as the z-value and bilinear interpolation for the cells with no ground returns. A vegetation height model was made from the LiDAR return point cloud by replacing the z-values with the difference between the point and the DTM altitudes.

For validation, a systematic grid sample of 729 plot centres with 30-metre spacing was laid over the area. Some of the plots landed on non-forested land, leaving 683 plots to be measured, which was done in July 2006. The plot density was 9.6 plots/ha. The site class was estimated and timber characteristics were measured by species and by canopy layer if several canopy layers existed within one species. A relascope with a multiplier of 2 was used for measuring basal area and selecting the sample trees for dbh and height measurements on timbered plots. The dbh of the basal area median tree was measured with callipers and the height of the same tree using a Vertex height measurement device. In seedling areas a circular 50-m2 fixed area plot was used. A Pathfinder ProXRS GPS device with real-time differential corrections was used for measuring the locations of the plot centres. The timber characteristics of the plots were calculated by generating a beta-function to estimate the stand diameter distribution for each species and canopy layer. The volume characteristics of the trees on each plot (Pukkala 2004) were calculated using the height model of Siipilehto (1999) and standard volume taper curves (Laasasenaho 1982).

Table 1. Statistics for control data variables, their means, and population variances.

Variable	Unit	Maan	Variance
Basal area	m^2/ha	17.6	145
Diameter	cm	19.0	74
Height	m	15.6	45
Volume	m^3/ha	132.0	9373
Number of stems	count	425.5	510546

3. METHODS

The segmentation tasks were accomplished using a multi-step strategy. The imagery was initially segmented at a resolution that was coarse enough to aggregate groups of pixels representing homogeneous areas into recognizable forest stand objects while preserving appropriate within-stand variability. This initial image object level served as a means of calibrating the input parameters in such a way as to avoid arbitrary delineations as much as possible.

The ultimate segmentation criteria were based on forest density, tree size and tree species. The first image object level was based on growing stock density and size. The forest density indicator was estimated using the proportion of ground hits within a 4 x 4 m cell:

$$\mathrm{FDI} \propto \sum_{i=1}^{n} i/n \quad (1)$$

Tree size was a function of the canopy height model (CHM) derived from the laser point data and was estimated for each 4 x 4 m cell separately:

$$TSI \propto 0.85 * CHM \quad (2)$$

A second image object level was created for the purpose of object-based species detection using 3D texture. The premise behind the texture analysis was that 3D tree texture may be described according to the size, shape and spatial arrangement of real species-specific features as captured in ALS. The alpha shape technique (Edelsbrunner and Mücke 1994) was used here to generate tree crown approximations and to derive given 3D texture features from the approximations. Vauhkonen et al. (2008a) have observed that interior and exterior volume and a number of solid component metrics were able to discriminate between tree species when calculated using the correct combinations of relative height and alpha value, while Vauhkonen et al. (2008b) tested the sensitivity of these combinations to pulse density by simulating thinnings in the initial data, and formulated new discriminant functions for each thinning level. In the present case we used the variables that Vauhkonen et al. (2008b) considered best, with a density of 0.5 returns m-2, being closest to the density of the material. The variables are listed in Table 2. Different tree species indicators were tested to find a suitable strategy for refining the species-specific result. The first principal component of the variables and the first canonical variable calculated by means of correlations between the species proportions and the variables of cells intersecting the field plots were tested with this in mind.

$$SPI \propto f(LC3D) \tag{3}$$

where

LC3D = linear combination of 3D variables, determined as either the first principal component, PC1, or the canonical variable CC1.

Table 2. 3D texture features used and their coefficients of linear transformations

Feature	Canonical coefficient
Exterior volume surrounding the 95% height (α=4)	0.0019
Interior no. of solid components surrounding the 95% height (α=4)	0.0504
Exterior volume surrounding the 55% height (α=4)	-0.0069
Interior volume surrounding the 65% height (α=4)	-0.0055
Interior no. of solid components surrounding the 65% height (α=4)	0.1892
Exterior volume surrounding the 65% height (α=0.5)	0.0025
Exterior volume surrounding the 55% height (α=0.5)	0.0102
Exterior volume above the 70% height (α=2)	0.0049
Exterior no. of solid components above the 80% height (α=2)	0.0811

The segmentation was based on the region growing and watershed techniques. The 3D based segmentation was compared with regular segmentation based on forest density and tree size parameters, while the variation within and between stands can be compared with the total variation. The following statistics were calculated to estimate the differences between the segmentation products:

$$SS_{within} = \sum_{i}^{k} \sum_{j}^{n_i} (x_{ij} - \bar{x}_i)^2 \tag{4}$$

$$SS_{between} = \sum_{i}^{k} n_i (\bar{x}_i - \bar{x})^2 \tag{5}$$

where k = number of stands

n_i = number of plots in stand *i*

x_{ij} = plot *j* in stand *i*

$\bar{x}$ = mean of plots

$\bar{x}_i$ = mean of plots in stand *i*

The significance of a difference is based on the F-value:

$$F = \frac{MS_{within}}{MS_{between}} \tag{6}$$

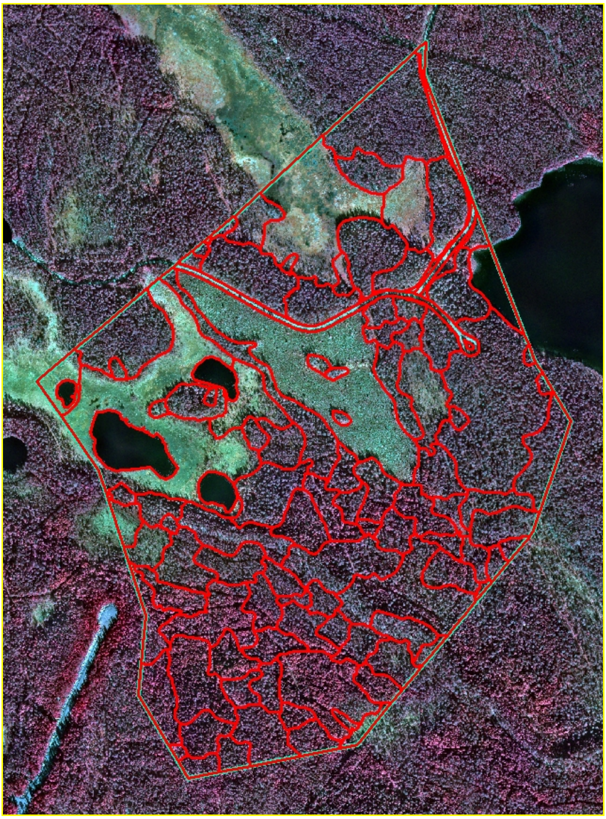

Figure 1. The sample segmentation based on FDI and TSI variables without 3D texture variable.

4. RESULTS

Four segmentations were completed. The growing stock oriented version is mainly focused on raw biomass only (Table 3) and the species-specific information is relatively random. The alpha shape-based principal components solution combines the variation in the tree shape-based variables. The species volume has slightly smaller within-stand variation than segmentation based on density and height features. The results calculated with canonical correlation-based transformation produced the best separation, but the improvement was still quite small. The differences between these results are statistically significant.

Table 3. F-values of different segmentation feature set alternatives (cc=Density+Height+Alpha-based canonical variable, pc=Density+Height+ Alpha-based PC, dh=Density+Height,).

Stand variable	Mean	F-value		
		cc	pc	dh
Total				
Basal area, m2	17.5	**0.92**	**0.92**	0.90
Diameter, cm	18.9	0.94	**0.95**	**0.95**
Height, m	15.5	**0.96**	**0.96**	**0.96**
Volume, m3/ha	132.0	**0.91**	**0.91**	0.90
Number of Stems, N	425.5	**0.80**	0.79	**0.80**
Pine				
Basal area, m2	11.6	**0.88**	**0.88**	0.85
Diameter, cm	21.3	**0.91**	**0.91**	0.89
Height, m	16.8	**0.93**	**0.93**	0.92
Volume, m3/ha	95.1	**0.88**	**0.88**	0.85
Number of Stems, N	321.1	**0.78**	**0.78**	**0.81**
Spruce				
Basal area, m2	4.1	0.79	**0.83**	0.69
Diameter, cm	15.0	**0.78**	0.77	0.72
Height, m	13.0	**0.80**	0.79	0.74
Volume, m3/ha	26.2	0.77	**0.81**	0.70
Number of Stems, N	42.2	**0.15**	**0.15**	0.14
Deciduous trees				
Basal area, , m2	1.7	0.71	**0.72**	0.54
Diameter, cm	12.1	0.64	**0.67**	0.56
Height, m	12.7	0.67	**0.70**	0.58
Volume, m3/ha	10.6	0.71	**0.73**	0.53
Number of Stems, N	62.1	**0.47**	0.46	0.42
mean		**0.77**	**0.78**	**0.72**

The segmentation results do not differ in visual appearance very much between many of the regions, and a large proportion of the stands contain several species. The deciduous-dominant areas in the south were distinguished differently from the biomass-based delineation, and the northern conifer-dominated areas also had some differences in delineation (Figures 1, 2 and 3).

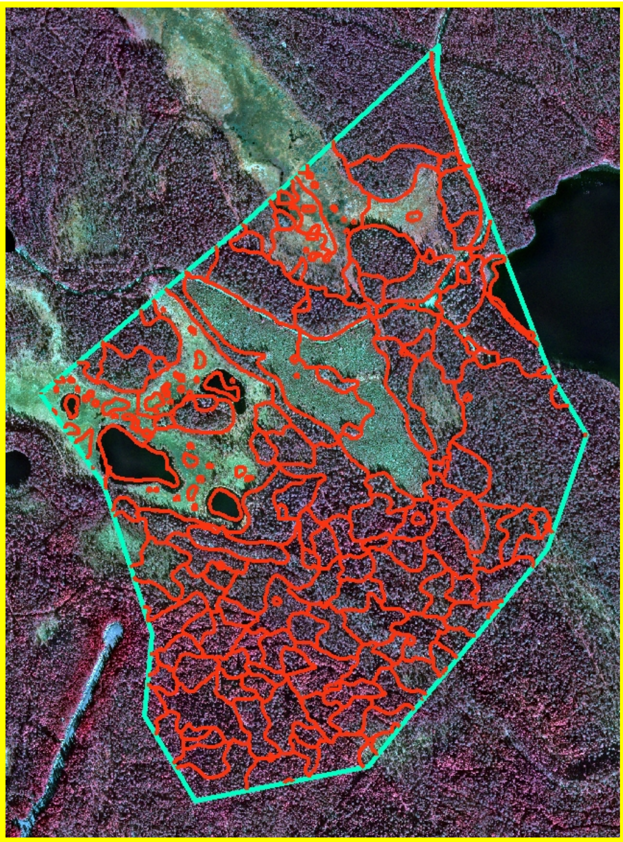

Figure 2. The sample segmentation based on FDI and TSI as well as 1st canonical variable of 3D texture variables.

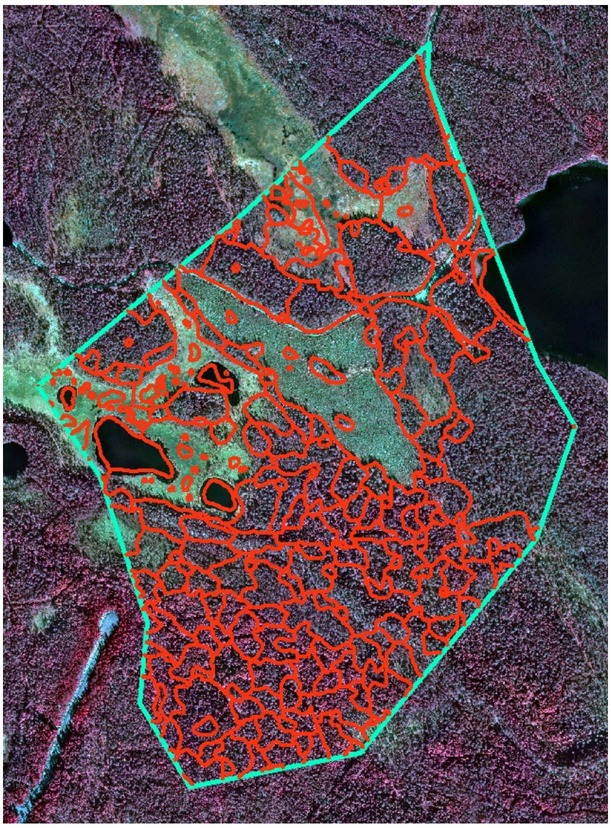

Figure 3. The sample segmentation based on FDI and TSI as well as the 1st principal component of 3D texture variables.

5. DISCUSSION

The 2D type of scheme is applied to some extent nowadays in some forest inventory software tools (Anttila & Lehikoinen 2002) and there is considerable interest in replacing field measurements with remote sensing data interpretation. 3D information-based schemes (e.g. Naesset & Økland. 2002, Korpela 2004, Maltamo et al. 2006) are becoming more practicable and need a good starting point. In this study we tested new 3D metrics based on ALS data to support the segmentation of forest stands. Special attention was given to extracting information on species proportions in order to map distinct species-specific areas in forests.

Segmentation results at the stand level are mainly focused on management, and the requirements for attribute accuracy are not as high for stand delineation. Species recognition accuracy at the subcompartment level should be > 85% (or preferably 90%), otherwise the averaging effect will produce a considerable amount of bias in mixed stands (Korpela & Tokola 2006). The species recognition accuracy in studies with digital aerial photography has been around 75% (e.g. Brandtberg 1999, 2002, Haara & Haarala 2002), while results calculated with canonical correlation-based transformation produced the best separation, with a reduction in species volume variation of 17%.

The segmentation results do not differ very much in visual appearance in many regions, because there are not too many large areas with only single species. Mixed stands with random spatial arrangement cause extra difficulty for this type of analysis, however, and the central part of the area was typically mixed forest. Principal component analysis and canonical correlation analysis were used to combine the information related to species as derived from the ALS metrics, and the new variables slightly improved the delineation and reduced the variation within stands. This was the first attempt to use the alpha shape metrics approach on a scale larger than the individual tree. Although the approach has been found earlier to be very promising (Vauhkonen et al. 2008a, 2008b), it has been evaluated up to now only using accurately delineated individual trees. Thus a lot of development work needs to be carried out on the individual tree level alone. Also, further development is needed to locate ideal tree groups in bodies of sparse ALS data. According to the present results, however, it should be possible to develop a corresponding methodology for proceeding towards an area-based approach that will supplement the stand-level ALS height and density information. The experiments carried out here suggest that more research is needed to detect the full potential of the alpha shape metrics approach. Many practical difficulties will be avoided if tree species can be deduced using only ALS data. The use of spectral images, such as aerial photos, requires all the images used in the analysis to be comparable, i.e. some sort of radiometric calibration is essential. This would complicate the inventory system further and would be difficult for all practical purposes. This present work indicates that species-specific volume estimates can be obtained at a tolerable accuracy level using ALS-derived variables.

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