CURVATURE ANALYSIS OF LIDAR DATA FOR SINGLE TREE SPECIES CLASSIFICATION IN ALPINE LATITUDE FORESTS

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Commission III, WG III/2

KEY WORDS: LiDAR, Tree extraction, Curvature analysis, Crown delineation, Forest typology, Species

ABSTRACT:

In this paper we explore the potential of LiDAR to distinguish between principal forest typology of alpine latitudes surveyed in leaf-on conditions. To this aim, a complete processing chain was developed, starting with the point cloud as input data and ending with derived curvature value of single trees useful for species classification. First, the dominant trees are detected by means of a mathematical morphology approach and the laser points are clustered as belonging to the single crowns. To enhance the quality of the calculated clusters, a statistical analysis of the height frequency distribution for each tree is performed which allows the filtering process of the low vegetation under-canopy. Afterwards a Taylor's expansion nonparametric model is applied to study the local differential properties of the surface that approximates single crowns. Classification of single species is based on the study of the surface Gaussian and mean curvatures, computed for each tree from estimated differential parameters of the Taylor's formula extended to second order terms. The extracted data are verified using very high resolution aerial photography as well as forestry typology maps and existing assessment plans. Moreover, a field survey campaign in 5 geo-referenced plots is performed in order to assess the species of single trees in the following three investigated species composition: spruce, beech and mixed forest. The results highlights that, even in leaf-on condition, the LiDAR technology can be used to determine the principal species composition and distribution of a forest at single tree level, which is very important for biodiversity maintenance, stem volume and biomass estimation, habitat mapping and conservation.

1. INTRODUCTION

Laser scanning is one of the most recently introduced active remote sensing technology that shows high potentiality in a wide number of different application fields: from the environmental mapping and protection to the civil engineering, regional and urban planning, archaeology and more. Also the forestry sector seems to have important benefits from this technique. As far as the management of forestry areas is concerned, indeed, a large number of forestry parameters, useful to characterize the vegetation from an ecological state and biomass content point of view, are required and, classically, they are assessed performing field works. As a matter of fact, traditional and most precise forestry inventory are based on the survey of the single tree population, with respect to parameters like tree density, vertical structure, height, volume, age, species distribution, presence/absence of renewal storey. Nowadays, the assessment of such parameters is critical in terms of field operations and time needed, particularly in Alpine latitude because of their complex and irregular ground morphology. So that traditionally, ground surveys are supported by the use of aerial photography in the way that ground survey component provides a sample of quantitative measurements of species and volume whereas aerial photography is used for canopy stratification (Edwards & Christie, 1981) and spatialization of other field data in a Geographical Information System (GIS) environment. In this context, aerial laser scanning (LiDAR) is a promising survey technique for forestry inventories because of, basically, its intrinsic capacity to directly assess the three

dimensional structure of the forest due to the high sample point number per surface. The ISPRS & EuroSDR Tree extraction test (Kaartinen and Hyyppä, 2008) recently confirmed the potential of some methods of laser scanning data processing for the assessment of forestry inventory parameters (e.g. tree density and position, tree height estimation, crown base height). Concerning the composition of a forest, the species classification is particularly important for a number of applicative management fields, for instance, biodiversity maintenance, stem volume and biomass estimation, habitat mapping and conservation. There are many case studies involved in this topic, in which the researchers mainly developed methods based on the analysis of aerial photography or satellite remote sensing. In Brandtberg (2002) for instance, an application of fuzzy set theory for classification of individual tree crowns into species groups using high spatial resolution colour infrared aerial photographs was presented. In this case, the accuracies obtained in distinguishing between coniferous/deciduous, Scots pine/Norway spruce, and Birch/Aspen were 87%, 76%, and 79%, respectively. Other studies pointed out the difficulty to identify the dominant species in mixed forests from aerial photo interpretation alone, because of the very small spectral difference between some species like pine and spruce trees in closed canopy conditions (Donoghue et al. 2007). The airborne laser scanning data has also been analyzed by implementing different methods for the classification of the principal tree species, almost in forests belonging to boreal latitudes. Liang et al. (2007) used the

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difference between first and last pulse in leaf-off conditions to distinguish coniferous from broad-leaves. The authors found 89% of accuracy but also reported some reasons of misclassification (e.g. similar penetration of laser signal in some ecological conditions). Holmgren and Persson (2004) separated Scots pine and Norway spruce by segmenting crowns at individual tree level on the basis of LiDAR rasterized data. Afterward, they studied some statistic variables calculated on the intensity of the returned pulses. The trees portion correctly classified on all plots was 95%. Diedershagen et al. (2004) classified broad-leaved and coniferous trees by the ratio of "light crown height" versus "light crown area". Donoghue et al. (2007) used a mixed approach based on LiDAR height and previously calibrated intensity data to perform classification in mixed conifer plantations. Finally, mixed approach LiDAR-Near Infrared Images for species classification are also investigated in Persson et al. (2007). Resuming, the methods studied for tree species classification are basically based on two different main LiDAR characteristics: penetration rate differences and intensity return in leaf-off conditions. Reliability of former methods seems to be affected by ecological condition of the dataset as well as the LiDAR instrument used (first & last vs multipulse vs fullwaveform) while latter need efficient models of intensity data calibration. The aim of this research is to develop a reliable and robust method based on the single tree top morphology for assessing the outcome of coniferous, broad-leaved and mixed standing species in Alpine latitudes. The method is performed on previously extracted single tree clusters using the approach presented in Barilotti et al. (2007a). A Taylor's expansion local nonparametric algorithm (Crosilla et al., 2007) is applied afterward in order to estimate locally the surface function value and the first and second order partial derivatives for each tree crown. Minimum, maximum, mean and Gaussian curvatures are calculated from the second order partial derivatives of the Taylor's formula (Crosilla et al., 2008). The curvature values are used to perform classification of the single trees. The paper shows the first results obtained with this method in terms of coniferous, broad-leaves, mixed forests discrimination on the basis of laser scanning data surveyed in different composed forestry areas surveyed in leaf-on condition.

2. STUDY SITE AND DATA

The study area is located in a mountain sector of Friuli Venezia Giulia Region (N-E Italy) essentially characterized by coniferous forests (spruce, spruce-fir, larch), broad-leaved forests (beech) and mixed forests (spruce, beech). An overview of the study site is given in Figure 1.

Figure 1 – Winter overview of the study area where part of it is located in the centre of the image. From the right to the left respectively, coniferous, mixed and broad-leaved forests.

The area is almost totally managed and relative assessment plans were used as reference to distinguish between different forestry compositions. Moreover, the cartography of forest typology were at our disposal and used to identify the dominant species and the homogeneous species distribution. This map was photo-interpreted at small scale (1:25.000) and afterward verified in field. The cartographic layers and the boundary of the study site is reported in Figure 2. In the same figure a high resolution digital orthophoto (pixel size of 0.20 m) is included and used in this work to assist the validation of forest species composition together with the cartographic maps. Moreover, a field campaign was performed in order to acquire detailed information on the number of trees and species in 5 geo-referenced plots. All the plots were circular, with a radius of 25 meters (about 0,2 ha).
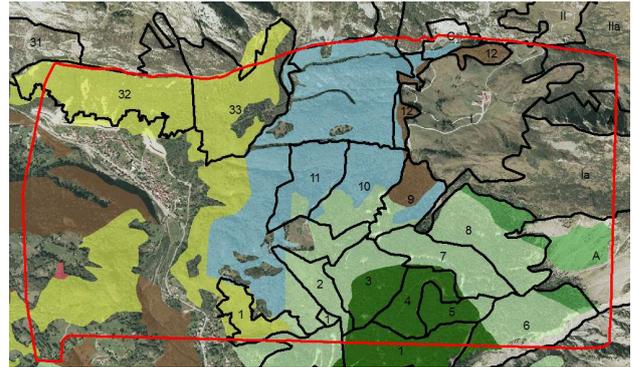

Figure 2 – The study area. The boundary of laser scanning data is reported in red, while the black polygons represent the managed forestry parcels with their respective ID number. The coloured polygons correspond respectively to the: broad-leaved forest (beech) in yellow; mixed forest (spruce, fir, beech) in ciano; spruce forest in light green, larch forest in average green and spruce-fir forest in dark green. The brown polygons represent respectively new regeneration of mixed plantation on the left and larch forest on the right.

In the area, the coniferous parcels are composed by a adult/mature trees with population densities ranging between 300 and 500 trees/hectar, while mixed and broad-leaved stands have more juvenile populations with tree densities ranging between 600 and 1100 trees/hectar. The altitude of the site ranges between 800 and 1.700 m asl. The total surveyed area covered about 600 hectares, 60% of which is covered by the forest.

As far as the LiDAR data is concerned, the datasets were acquired in summer using a multiple pulse Optech 3100 instrument. The system operated at a flight altitude of about 1000 m above ground and was configured to acquire data with an average point density of 4 returns/m^2. The footprint size of the laser beam was set at 0.2 mrad (about 0.20 m at the sensor operating height). The resulting average point density was about 4.2 pts/ m^2 but substantial differences were noted in the same survey. Particularly poor was the point density (1.5 pts/m^2) in the lower part of the area composed principally by juvenile broad-leaved forests. Significant variation in the point density was also noted in the whole dataset.

3. METHOD

A complete processing chain has been developed, starting with raw laser points as input data and ending with derived tree parameters for each single tree. The procedure is composed

of a series of elaborations and transformations that can be schematically related to the following methodological aspects:

- Pre-processing of the raw laser data;
- Application of mathematical morphology algorithms, to extract the canopy apexes (Barilotti et al. 2007b);
- Identification of the laser points belonging to the single crowns by means of a cluster analysis algorithm;
- Low vegetation sub-clustering using a local filtering method;
- Curvature analysis of clustered points belonging to single crowns for species discrimination.

The experiments have been carried out using original software in which the algorithms were developed and the experiments were performed.

3.1 Pre-processing of LiDAR points

The implemented step relating to the laser data pre-processing consists of an algorithm that eliminates the points corresponding to the laser beam reflections under canopy from the dataset. The algorithm executes a first triangulation (Delaunay) of all points, then analyzes the height (z) difference between the vertices of each triangle. The vertices whose height difference is greater than a threshold value (according to the minimal height of the forest) are eliminated. This allows the creation of a Digital Surface Model (DSM) without any triangulation inside canopy and therefore introduces a higher degree of DSM adhesion to the external forest surface.

3.2 Tree extraction

The method proposed for the tree extraction is based on the morphologic analysis of the laser point distribution. To this aim the Top Hat algorithm, whose formulation is relative to the image elaboration theory (Serra, 1982), was implemented. Extending the Top Hat concept directly to the pre-filtered point cloud, the method allows the detection of the set of points belonging to the top of the crown, avoiding the interpolation on raster images. The direct space position (x, y, z coordinates) of the laser data apexes is obtained. It is assumed that the x, y coordinates of such apexes correspond to the cartographic position of the single trees.

3.3 Single tree crown delineation

In order to identify the single crowns a region growing algorithm was implemented. Starting from the apexes previously extracted, the algorithm classifies the vegetation points according to the criteria defined below:

- If the points located in the proximity of the starting apex are lower (height difference) than a fixed threshold, these are marked as belonging to the same cluster;
- When the same laser point is marked as belonging to different apexes (this is particularly true when the forest is characterized by close vegetation), the algorithm associates the point to the nearest apex.

3.4 Crown filtering

An example of clustered data is given in Figure 3. The image highlights the auto-adaptive nature of the method for crown delineation. Basically, the shape of the tree crowns tends to be regular and circular but, because of the presence of low vegetation in the dominated layer of the forest, a non optimal restitution of the crown geometry (area, insertion depth) can be observed. As a matter of fact, if points reflected by low

vegetation are recorded by the instrument, they are clustered within the dominant tree layer. To refine the classification of points belonging to a single crown, a method for crown point filtering was applied (Barilotti et al., 2007b).
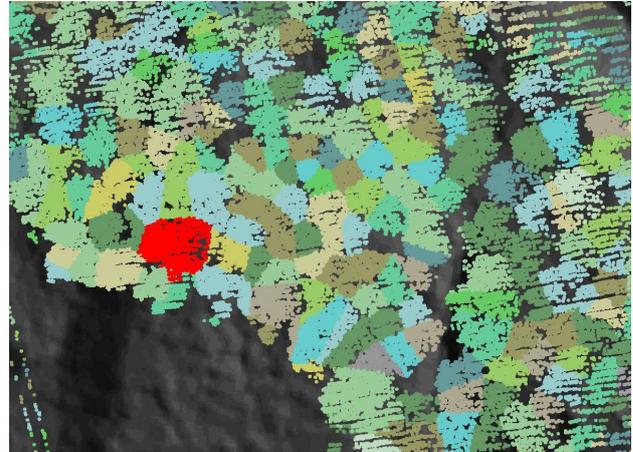

Figure 3 – Example of clustered laser data in a coniferous transect (MBD). The red coloured clusters emphasize the differences in terms of shape of the same species (spruce) in dependence of the ecological state.

The algorithm first calculates the histograms of the point height frequency distribution, cluster by cluster. Afterwards, a polynomial regression function is used to interpolate frequency histograms, obtaining a curve of frequency distribution for each one. Finally, the curves are explored by means of a study function in order to individuate bi-modal distributions. If the function is bi-modal, the height value of the internal minimum of the interpolated function is used as a threshold to perform a local filtering of the cluster. This procedure makes it possible to eliminate those points belonging to the low vegetation from the dominant tree crown (e.g. in Figure 4).
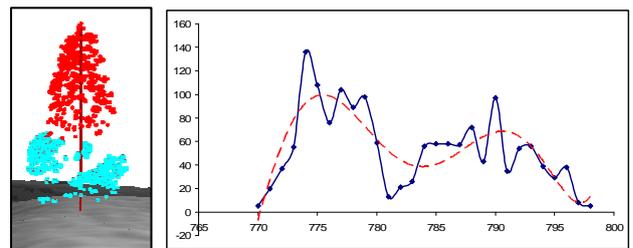

Figure 4 – Case of cluster constituted by a dominant tree (spruce) together with dominated low vegetation. On the right the relative point cluster height frequency distribution is reported (blue line). For each frequency diagram, the polynomial distribution is calculated (red line) and then used to re-filter the sub-clusters (cyan).

3.5 Estimation of local surface parameters by a non parametric regression model

Our proposal to compute the local Gaussian curvature for each tree is based on the application of a non parametric local polynomial regression extended to the second order differential terms. Dealing with parameters estimation by regression models, the main advantage of a non parametric approach consists in its full generality. In our case, to locally estimate the surface passing through the clustered laser points, neither a

priori knowledge of the point geometry nor the fitting analytical function is required. Let us consider the following polynomial model of second order terms (Cazals and Pouget, 2003):

$$Z_j = a_0 + a_1 u + a_2 v + a_3 u^2 + a_4 uv + a_5 v^2 + \varepsilon_j \qquad (1)$$

In the equation (1), the coefficients and the parameters are locally related to a measured value Z_j by a Taylor's expansion of the function $Z = \mu + \varepsilon$ in a neighbour point j of i.
The coefficients are defined as follows:

$$a_0 = Z_{0_i} \ ; \ a_1 = \left(\frac{\partial Z}{\partial X}\right)_{X_i} \ ; \ a_2 = \left(\frac{\partial Z}{\partial Y}\right)_{Y_i} \ ; \ a_3 = \frac{1}{2}\left(\frac{\partial^2 Z}{\partial X^2}\right)_{X_i} \ ;$$

$$a_4 = \left(\frac{\partial^2 Z}{\partial X \partial Y}\right)_{X_i, Y_i} \ ; \ a_5 = \frac{1}{2}\left(\frac{\partial^2 Z}{\partial Y^2}\right)_{Y_i}$$

while the parameter definition is:

$$u = (X_j - X_i) \ ; \ v = (Y_j - Y_i)$$

In this specific experiment, X_i, Y_i represent the coordinates of point i which is the apex of each previously extracted single tree and X_j, Y_j are the coordinates of point j corresponding to the relative clustered crown.
The a_s parameters ($s \neq 0$) are the first and second order partial derivatives along X,Y directions at the i-th point of the best approximating local surface, collected in the [6 x 1] vector $\boldsymbol{\beta}$:

$$\boldsymbol{\beta} = [a_0 \quad a_1 \quad a_2 \quad a_3 \quad a_4 \quad a_5]^T \qquad (2)$$

where $\quad a_0$ = estimated function value at point i

The weighted least squares estimate of the unknown vector $\boldsymbol{\beta}$ from a selected number of p neighbour points (for j = 1, …, p) results as:

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}^T \mathbf{W} \mathbf{X})^{-1} \mathbf{X}^T \mathbf{W} \mathbf{z} \qquad (3)$$

where $\quad \mathbf{X}$ = coefficient matrix
$\quad \mathbf{W}$ = weight diagonal matrix defined by a symmetric kernel function centred at the i-th point

The p rows in the coefficient matrix X are defined as:

$$\mathbf{X}_j = \begin{bmatrix} 1 & u & v & u^2 & uv & v^2 \end{bmatrix} \qquad (4)$$

and the elements of the weight diagonal matrix W are:

$$w_{ij} = \left[1 - (d_{ij}/b)^3\right]^3 \ \text{for} \ d_{ij}/b < 1$$
$$w_{ij} = 0 \ \text{for} \ d_{ij}/b \geq 1 \qquad (5)$$

where $\quad d_{ij}$ = distance between the points i,j
$\quad b$ = window encompassing the p furthest points from i

In the general model (Crosilla et al. 2007), the value of b, rather than the kernel function, is critical for the quality in estimating $\boldsymbol{\beta}$. In fact, the greater the value of b, the smoother the regression function results, while the smaller the value of b, the larger is the variance of the estimated value. The application of the described model in the context of this work does not require a priori definition of any bandwidth (parameter b), because it is dynamically calculated for each clustered crown.

3.6 Single tree computation of local curvatures values

For the local analysis of a surface obtained from a laser point cloud, some fundamental quantities, defined in differential geometry, are considered. In particular, local Gaussian, mean and principal curvatures values are taken into account. All these can be obtained from the so-called "*Weingarten map*" matrix **A** of the surface (e.g. Do Carmo, 1976), that is given by:

$$\mathbf{A} = -\begin{bmatrix} e & f \\ f & g \end{bmatrix} \begin{bmatrix} E & F \\ F & G \end{bmatrix}^{-1} \qquad (6)$$

where $\quad$ E, F, and G = coefficients of the so-called "*first fundamental form*"
$\quad$ e, f, and g = coefficients of the "*second fundamental form*"

These coefficients are computed from a_s ($s \neq 0$) parameters as:

$$E = 1 + a_1^2 \ ; \ F = a_1 a_2 \ ; \ G = 1 + a_3^2 \qquad (7)$$

and:

$$e = 2a_3 \Big/ \sqrt{a_1^2 + 1 + a_2^2} \ ; \ f = a_4 \Big/ \sqrt{a_1^2 + 1 + a_2^2} \ ;$$
$$g = 2a_5 \Big/ \sqrt{a_1^2 + 1 + a_2^2} \qquad (8)$$

The *Gaussian* curvature K corresponds to the determinant of **A**:

$$K = \frac{eg - f^2}{EG - F^2} \qquad (9)$$

The *mean* curvature H can be instead obtained from:

$$H = \frac{eG - 2fF + gE}{2(EG - F^2)} \qquad (10)$$

The *principal* curvatures k_{max} and k_{min}, corresponding to the eigenvalues of **A**, are given instead from the solution of the system $k^2 - 2Hk + K = 0$, i.e. from $k_{min,max} = H \pm \sqrt{H^2 - K}$. Substituting the a_s terms into the formulas (9) and (10) (see e.g. Quek et al., 2003), the following expressions for the *Gaussian* K and the *mean* H curvatures can be obtained:

$$K = \frac{a_3 a_4 - a_5^2}{(a_1^2 + 1 + a_2^2)^2} \qquad (11)$$

$$H = \frac{a_3(1+a_2{}^2) + a_4(1+a_1{}^2) - 2a_1a_2a_5}{2(\sqrt{a_1{}^2 + 1 + a_2{}^2})^3} \qquad (12)$$

Summarizing, for each i-th point, four local curvature values K, H, k_{max} and k_{min} can be automatically obtained as functions of the vector $\hat{\boldsymbol{\beta}}$ terms. Furthermore, such curvatures are invariant to the reference frame, providing a very important property in analyzing the surface shape. The analysis of the sign and of the null values of *K* and *H* makes it possible to discriminate the approximated geometric surface of single crown into the following basic types (Table 5): elliptic (*K*>0), hyperbolic (*K* < 0), parabolic (*K* = 0, *H* ≠ 0), and planar (*K* = *H* = 0).

	K < 0 : hyperbolic	K = 0 : parabolic/planar	K > 0 : elliptic
H < 0			
H = 0			not possible
H > 0			

Table 5: Classification of surfaces according to the values of gaussian K and mean H curvature (Image from Haala et al. 2004).

4 ANALYSIS AND DISCUSSION

For this study 24 millions of laser points were managed and analyzed. From the tree extraction process, a total of 214.000 trees were detected and the respective crown points were clustered. Previous works highlighted the performances of the extraction process in similar forestry composition (Barilotti et al. 2007a). Resuming, a number comprised between 90-95% of correctly extracted trees was calculated in the coniferous areas, while 80-85% of trees elsewhere. For each tree, the tree top curvature was calculated. Considering the scheme in table 5, it is assumed a tree has to be approximated by an elliptic curve (H < 0, K > 0). The experimental results show that, while H is always < 0, K is in some cases < or equal to 0. The percentage of trees corresponding to different K values are given in Table 6.

	K < = 0	K > 0
% of trees	9,32 %	91,68 %

Table 6 – Percentage of trees in the K classes.

It is well known that the percentage of tree extraction plays a main role in determining the morphologic values of single trees (e.g. tree height, crown base height). Concerning the crown top curvature, the value basically depends on the adherence of clustered points to the real crown shape. Some examples of clustered crowns and respective parabolic surfaces approximating the point distributions are given in Figure 7, that shows different tree species within different forestry composition. The figure shows that the curves correctly approximate the crowns in the cases where trees and respective clusters are extracted correctly (cases a, b, c, d in the figure). Otherwise, when co-dominant trees are not detected, the surrounding dominant tree crown tends to include the points belonging to lower vegetation strata (e.g. figure 7e). This implies that, dominant trees can have a wider crown and a flatter top morphology (K tending to 0) than the real one,

especially in coniferous trees. Moreover, some co-dominant trees can be present also in cases in which K < 0. Anyway, almost curves in which K < 0 are generated by a low density of raw laser points (less than 2 pts/m^2) (see figure 7f). This negative values of the Gaussian curvature can be used to individuate those cases where the morphological analysis is not able to ensure a high percentage of extraction of co-dominant tree layer, because of the poor point density.
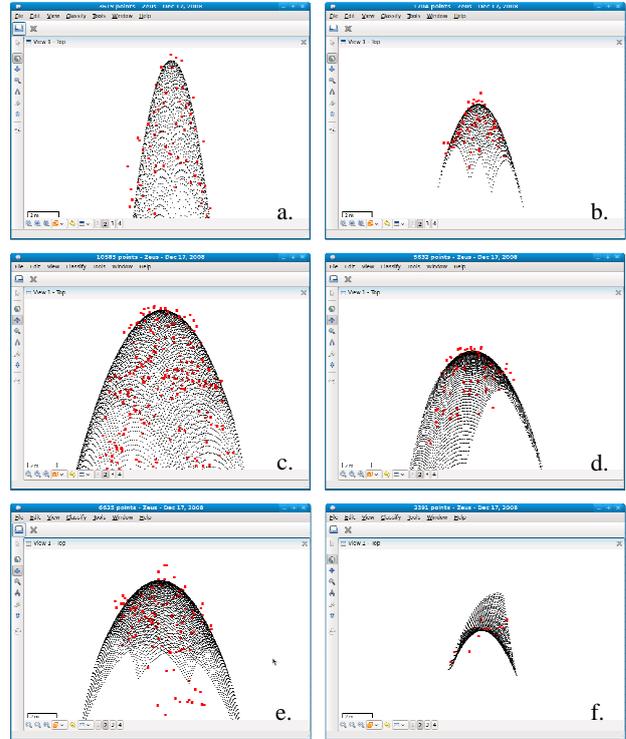

Figure 7: Examples of clustered crowns points and respective parabolic surfaces approximating the distribution for: a) mature spruce; b) mature larch; c) mature beech; d) juvenile beech; e) bad cluster (two spruce in the same cluster); f) sparse clustered point (false tree).

For all trees in which the Gaussian curvature was > 0, a statistical analysis was carried out within homogeneous forestry areas (as reported into the cartographic maps previously described) to calculate the optimal threshold value for the subsequent classification. The density of extracted trees, the real composition in species and the % of correctly classified trees are reported in Table 8.

Area ID	Point density	Trees/ ha	Forestry composition	% of correctly calculated species
4	4,5 pt/m^2	345	Spruce, Fir	88
5	3,6 pt/m^2	384	Spruce	91
8	5,2 pt/m2	386	Spruce, Larch	85
32	1,7 pt/m^2	824	Beech	69
33	2,4 pt/m^2	710	Beech	75

Table 8 – Summary of the laser data characteristics, forestry composition and % of correctly calculated species for each analyzed forestry area.

At this level of the analysis, the classification was performed in terms of distinguishing between coniferous and broad-leaved forests; it follows that Spruce, Fir and Larch are considered as

being the same group of species. The table shows high performances in the classification of coniferous areas while slightly lower accuracy in the cases of broad-leaved areas (particularly in the area 32). This is probably due to the following aspects:

- the higher the tree density, the lower the number of points per crown available for the curve approximation; consequently, the higher is the number of curves with negative K;
- non-homogeneous distribution of points in the datasets which have a poor density in the lower part of the area.

Concerning the geo-referenced plots, the results of correlation between extracted and classified trees and field measurements are reported in Table 9.

Plot ID	Point density	Trees	Forestry composition	% of correctly calculated species
PR1	4,6 pt/m2	75	Spruce, Fir	93
PR2	5,3 pt/m^2	83	Spruce	96
PR3	3,8 pt/m^2	67	Larch	75
PR4	1,4 pt/m^2	139	Beech	65
PR5	6,5 pt/m^2	115	Beech	87

Table 9 – Summary of the laser data characteristics, forestry composition and % of correctly calculated species for each analyzed forestry plot.

The results seem to substantially confirm those obtained in the area-level analysis. In fact, the correlation seems to be high also in the case of beech forest when it is sampled by a sufficient number of laser points (e.g. cfr. PR5 and PR5 plots). Concerning larch, this species tends to have the curvature values comprise between spruce (high K values) and beech (very low K values). This similarity seems to be the reason for the reduced correlation in the PR3 plot and area 8, while the other coniferous parts have higher performances.

5 CONCLUSIONS

In this study, a method of laser scanning data processing to automatically determine the curvature values of single tree is reported. These values are used to perform a classification of coniferous/deciduous tree species surveyed in leaf-on condition. The results, validated using ancillary data for large areas and 439 trees geo-referenced in 5 forestry plots, highlighted a high accuracy (85-95%) in classifying species when the laser point density is more than 4 pts/m^2. Lower laser point density tends to reduce this level of accuracy.

REFERENCES

Barilotti, A., Sepic, F., Abramo, E., Crosilla, F., 2007(a). Assessing the 3D structure of the single crowns in mixed alpine forests. *IAPRS,* Vol. XXXVI, 3/W49A.

Barilotti, A., Sepic, F., Abramo, E., Crosilla, F., 2007(b). Improving the morphological analysis for tree extraction: a dynamic approach to lidar data. *IAPRS,* Vol. XXXVI, Part 3/W52.

Brandtberg, T., 2002. Individual tree-based species classification in high spatial resolution aerial images of forests using fuzzy sets. *Fuzzy Sets and Systems*, 132(3), pp. 371–387.

Cazals, F., Pouget, M., 2003. Estimating differential quantities using polynomial fitting of osculating jets. *Proceedings of the 1st Symposium on Geometry Processing*, pp. 177-187.

Crosilla, F., Visintini, D., Sepic, F., 2007. An automatic classification and robust segmentation procedure of spatial objects. *Statistical Methods and Applications*, 15, pp. 329-341

Crosilla, F., Visintini, D., Sepic, F., 2008. A statistically proven automatic curvature based classification procedure of laser points. *XXI ISPRS Congress*, Beijing, China, Jul. 3-11.

Diedershagen, O., Koch, B., Weinacker, H., 2004. Automatic estimation of forest inventory parameters based on lidar, multispectral and Fogis data. Freiburg, Germany. http://www.natscan.unifreiburg.de/suite/pdf/040212_1809_1.pdf (accessed 10 Mar. 2009).

Do Carmo, M.P.,1976. Differential Geometry of Curves and Surfaces. *Prentice-Hill Int*., London

Donoghue, D., Watt, P.J., Cox N.J., Wilson, J., 2007. Remote sensing of species mixtures in conifer plantations using LiDAR height and intensity data. *Remote Sensing of Environment*, 110, pp. 509–5,22

Haala, N., Reulke, R., Thies, M., Aschoff, T., 2004. Combination of terrestrial laser scanning with high resolution panoramic images for investigations in forest applications and tree species recognition, *IAPRS&SIS,* XXXIV, part 5/W16, Dresden.

Holmgren, J., Persson, A., 2004. Identifying species of individual trees using airborne laser scanner. *Remote Sensing of Environment,* 90(4), pp. 415–423

Kaartinen, H. and Hyyppä, J., 2008. EuroSDR/ISPRS Project, Commission II "Tree Extraction", Final Report. *EuroSDR – European Spatial Data Research*, Official Publication n°53.

Liang, X., Hyyppä, J., Matikainen, L., 2007. Deciduous-coniferous tree classification using difference between first and last pulse laser signatures. *IAPRS*, Vol. XXXVI, Part 3/W52, pp. 253-257.

Persson, A., Holmgren, J., Söderman, U., Olsson, H., 2007. Tree species classification of individual trees in Sweden by combining high resolution laser data with high resolution near infrared digital images. *IAPRS*, Vol. XXXVI – 8/W2, pp. 204-207

Quek, F.K.H., Yarger, R.W.I., Kirbas, C., 2003. Surface parameterisation in volumetric images for curvature-based feature classification. *IEEE Transactions on Systems, Man, and Cybernetics*, part B: Cybernetics, 33, 758-765

Serra, J., 1982. Image analysis and mathematical morphology 2. *Theretical advances,* Academic press, London.

ACKNOWLEDGEMENTS