IMPROVING THE MORPHOLOGICAL ANALYSIS FOR TREE EXTRACTION: A DYNAMIC APPROACH TO LIDAR DATA

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ABSTRACT

The improvement of laser scanning as a proficient technology to better understand the complexity of the forest has recently allowed the detection of the forestry parameters at tree level. From a forest inventory point of view, however, a common use of such technology is related to the accuracy that can be obtained if vast and differently composed forestry surfaces are considered. In this paper, an improvement in the morphological analysis methods for tree extraction is presented. The method, developed in an open source environment, is based on the automatic determination of the forest structure by means of some LiDAR-extracted vegetation indexes. The study site is located in some mountainous parts of Friuli Venezia Giulia (N-E Italy) characterized by coniferous, mixed and broad-leaved forests with high variability in terms of population densities and composition. The results have been validated using topographic total station data surveyed in situ, in 13 forestry sample plots with a total of about 550 reference trees. Moreover, some further datasets have been studied by mean of photo-interpretation process on high resolution aerial images. The paper highlights the advantages of using this dynamic approach for tree extraction.

1. INTRODUCTION

Monitoring of the forestry ecosystem is a current topic in the context of quantification and sustainable management of wooded resources. To characterize the vegetation from an ecological state and biomass content point of view, an accurate knowledge of the population density is needed. The assessment of such parameters is critical in terms of field operations and time needed. In this context, Airborne Laser Scanning (ALS) is a promising survey technique for forestry inventories because of its capacity to directly assess the three dimensional structure of the forest due to the high point number of sampling per surface.
Computer science plays a major role in the laser surveying field: the data processing and the developing of new algorithms for filtering, classifying and modelling of LiDAR data in the forestry field are research topics constantly being developed. Part of the research activities carried out within the Interreg IIIA Italy-Slovenia 2003-2006 project "Cadastral map updating and regional technical map integration for the Geographical Information Systems of the regional agencies by testing advanced and innovative survey techniques" at the University of Udine concerned the use of LiDAR data in the forestry field. In this context, attention has been focused on the development of informative methodologies and algorithms useful in the automatic extraction of the parameters characterizing the three-dimensional structure of the trees. The experiments were performed using an original software developed in the laboratory. The main components of the software allow the visualization of the laser scanning data, to draw sections, to calculate DTM and DSM and to overlap them with other cartographic maps (Beinat, Sepic, 2005). On this basis a specific tool were implemented in order to extract forestry parameters of interest like the cartographic position of the single trees, the tree height, the crown shape and the crown insertion depth. From a tree-level inventory point of view, the extraction of tree position is the most important parameter to determine. The tree parameters (e.g. crown area, crown depth, volume) can be derived starting from the preliminary detected tree position, as many authors have already done (Hyyppä et al, 2004; Morsdorf et al., 2003; Pitkänen et al, 2004; Weinacker et al., 2004). The results obtained for individual tree extraction have varied significantly from study to study. Many factors contribute to cause this variation: the methods applied and the forest characteristics are the principal ones. Concerning the methods, the first studies were related to the use of rasterized Crown Height Model (CHM) as input data to perform local analysis while, recently, a trend towards using the point cloud data directly has been noticed (Pyysalo and Hyyppä, H., 2002; Tiede et al., 2005; Barilotti and Sepic, 2006). As far as the forest composition is concerned, some authors derive forest information using laser data in synergy with high resolution aerial images. The latter technique provides color information usable for classification (Leckie et al., 2003; Persson et al. 2004). In this paper, a new methodology for tree extraction is presented. The characteristic elements of the implemented procedure are based on the assessment of local forest structure which is carried out by a multivariate analysis on laser-derived vegetation indexes. This allows the application of mathematical morphology in an auto-adaptive way. The method, following an automatic approach, is able to dynamically fit the apex searching parameters on the basis of the dataset characteristics, increasing the efficiency of the tree extraction process.

2. MATERIALS

The study areas are located in some mountainous areas of Friuli Venezia Giulia Region (N-E Italy) essentially characterized by coniferous forests (spruce, spruce-fir), broad-leaved forests

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(beech) and mixed forests (spruce, fir, beech and Alpine Larch). Within these areas some sub-zones of interest have been located and geo-referenced using topographic total station and GPS. This has allowed the precise and accurate determination of the coordinates of 13 circular forestry plots (transects) with radius ranging between 12 and 25 meters. During a field measuring campaign, detailed information on the morphology and the structure of each tree were collected. Using a topographic total station the cartographic position of all trees (diameter at breast height more than 5 cm) and the crown extension (4 sampling points for each one) were measured (e. g. in Figure 1). The total data acquired in situ using topographic instruments covers approximately 550 tree points and 2200 crown points.

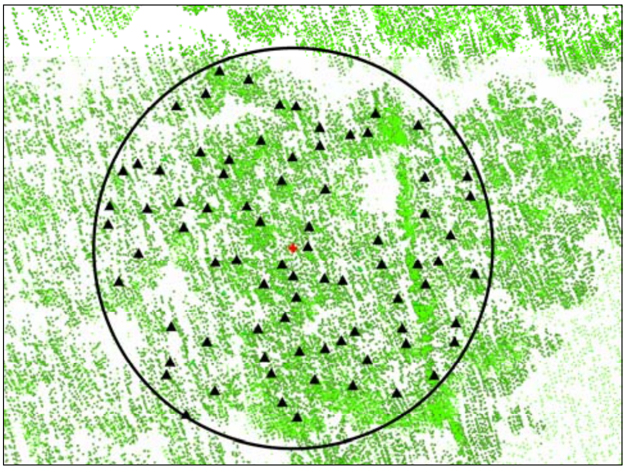

Figure 1 – Example of trees collected on site in MBD plot. The correspondent high vegetation laser points can be seen in the background of the image.

The forestry characteristics of the studied plots with the respective laser point densities are reported in Table 1.

Plot ID	n° of trees/ha	Area (m^2)	Forest characteristics	LiDAR data characteristics
FOA	663	450	Mature - mixed	2 pt/m^2 - F&L
FOB	531	450	Mature - mixed	2 pt/m^2 - F&L
MBA	619	450	Mature - mixed	6 pt/m^2 - Multi
MBB	1525	450	Juvenile - spruce	7 pt/m^2 - Multi
MBC	575	450	Juvenile - spruce	8 pt/m^2 - Multi
MBD	463	2000	Mature - spruce	10 pt/m^2 - Multi
PRB	840	450	Juvenile/adult - spruce	1,5 pt/m^2 - F&L
PRC	752	450	Juvenile/adult - spruce	1,5 pt/m^2 - F&L
SAA	336	2000	Mature - beech	4 pt/m^2 - F&L
TUA	538	700	Juvenile - beech	2 pt/m^2 - F&L
TUB	862	450	Juvenile - beech	2 pt/m^2 - F&L
TUC	553	450	Juvenile - beech	2 pt/m^2 - F&L
VBA	1105	450	Juvenile - spruce	5 pt/m^2 - Multi

Table 1 – Summary of the georeferenced plot characteristics. Considering the different age and composition of the 13 transects compared to the different laser densities, 8 different forestry situations can be found.

The height of crown insertion was measured using portable instruments (length and angle). The diameter at breast height was also measured. These values were used to localize the dominated vegetation. However, the individual trees whose apex did not reach the top of the canopy were objectively surveyed during the field operations. As far as the laser data is concerned, the main characteristics of the datasets are reported in column 5 (Table 1). Some datasets were detected using a multiple pulse laser scanner (Optech ALTM 3100). On one hand, such an instrument increases the capacity to sample the intermediate layers of the vegetation but, on the other, it does not substantially furnish extra information on the higher part of the canopy, when compared to the First and Last (F&L) data. However, in these cases we have plots with higher sampling points (5-10 pts/m^2) than those surveyed with a F&L pulse laser scanner (low density, 1.5 – 2 pts/m^2). The flight altitude was about 1000 m above ground and the laser beam divergence was 0.2 mrad (small footprint), according to the different datasets. It has to be specified that none of this laser data was specifically collected for forestry measurements.
Moreover, 4 further datasets have been studied using high resolution aerial photography (20 cm pixel) which allowed us to single out the position of the trees by a photo-interpretation procedure. The forest characteristics were also photo-interpreted. The corresponding LiDAR dataset was surveyed with a F&L instrument (Optech ALTM 3033) for an average density of about 3 point/m^2, as shown in Table 2.

Plot ID	n° of trees/ ha	Area (m^2)	Forest characteristics	LiDAR data characteristics
PHA	1380	450	Juvenile - spruce	3.5 pts/m^2 - F&L
PHB	410	2000	Adult - spruce	3 pts/m^2 - F&L
PHC	385	2000	Mature - spruce	3 pts/m^2 - F&L
PHD	185	2000	Mature - mixed	2.5 pts/m^2 - F&L

Table 2 – Summary of 4 photo interpreted transect. The PHA transect, in particular, is composed of a very dense population of planted spruces.

Approximately 258 trees were photo-interpreted on the basis of the high resolution aerial photography.

3. METHODS

The methods presented here for tree extraction are related to the morphological mathematical approaches. The procedure is composed of a series of elaborations and transformations that can be schematized as follows:

- Pre-processing of the raw laser data (true DSM);
- Application of mathematical morphology algorithms, following a single tree approach, to extract the canopy apexes;
- Application of a dynamic search radius based on multivariate analysis of LiDAR-extracted indexes.

The last step is an important improvement in the method used for tree extraction because it makes it possible to automatically apply the morphological analysis in a local context. As will be shown later, such a dynamic and auto-adaptive procedure has been implemented in order to eliminate the need for a detailed knowledge of the dataset characteristics and the forest composition as well. A description of the implemented algorithms and the related steps of elaboration are reported below.

3.1 Pre-processing (true DSM)

The implemented step relating to the laser data pre-processing consists of an algorithm that eliminates from the dataset the points corresponding to the laser beam reflection under the canopy. The algorithm executes a first triangulation (Delunay) of all points, then analyzes the height (z) difference between the vertices of each triangle. Those 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 (true DSM) and therefore introduces a higher degree of DSM adhesion to the external forest surface.

3.2 Morphological analysis

3.2.1 Mathematical morphology

The method proposed for the tree extraction is based on the morphologic analysis of the laser point distribution. Accordingly, the Top Hat algorithm, whose formulation is related to the image elaboration theory (Serra, 1982), was implemented. This mathematical function allows the extraction of the highest elements in the scale of the represented values, independently from the image typology (Andersen et al., 2001, Barilotti and Turco, 2006). If we considering *f(x)* as the grey value of a generic pixel *x* of a point localized in *u*; *f(X)* as the corresponding value of the transformation of the matrix *X*; *λ* as the structural geometric element to determine (or as the dimension of the explorative kernel centred in *x*), the Top Hat function is based on the *Opening* transformation (1) defined as follows:

$$O^{\lambda} f(X) = D^{\lambda} [E^{\lambda} f(X)] \qquad (1)$$

Therefore, the following transformations of *Erosion* (2) and *Dilatation* (3) are applied:

$$E^{\lambda} f(X) = \inf \{f(u) : u \in \lambda_x\} \qquad (2)$$

$$D^{\lambda} f(X) = \sup \{f(u) : u \in \lambda_x\} \qquad (3)$$

The Erosion operator (2) associates to the centre of the kernel (λ_x) the inferior (inf) value among the surrounding pixels while the Dilatation operator (3) associates the superior (sup) value.
The extraction of the local maximums in the scale of the image values is carried out by using the function *Top* (4) that subtracts the primitive image (function) from the *Opening-transformed* function:

$$TOP = \{x: f(x) - O^{\lambda} f(X)\} \qquad (4)$$

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. A preliminary set of higher points (seed points) is obtained in this way, the number of which depends on the kernel used (e.g. λ = 3 x 3 and cell value of 1 meter). It is assumed that these points are an over estimation of the real trees, particularly when a kernel smaller then 3 meters is used (e.g λ = 3 x 3 and cell value of 0.5 meters).

3.2.2 Fixed search radius

In order to diminish this kind of error, a checking algorithm that identifies and corrects the erroneously classified apexes (often localized in the crown edges) was introduced. The algorithm compares the height value of each extracted apex to the nearest laser points, using an opportune (user defined) search radius. If a point with a greater height value is found inside the search window, it becomes the new apex. Normally, a search radius slightly bigger than the kernel (λ used in the morphological analysis) maintains the high level of the method efficiency but, on the other hand, the number of false positive trees remains high. Experimentally, it has been observed that the optimal radius ranges between 1.50 and 1.80 meters when a 3 m kernel is used. This average radius can be manually set up and optimized on the basis of the expected forest typology. However, different λ and radius should be used depending on the forestry species present and population density.

3.3 Pre-detection of forestry composition

When the study area is characterized by a very high variability of forest composition and structure, the working procedure should foresee a sub segmentation of the LiDAR dataset, applying different analysis parameters. To avoid this procedure, which is expensive in terms of time, a method to automatically assess the forest structure was introduced, performing a multi-variate analysis on two different LiDAR-extracted indexes:

- Laser Penetration Index (LPI) (Barilotti et al, 2006);
- Crown Height Model (CHM).

3.3.1 Laser Penetration Index (LPI)

The laser beam penetration through the canopy varies depending on to the macro-species composition, the tree density, the height of the forest. Concerning the broad-leaved forests, the season of survey plays an important role for the laser penetration capacity, which is reduced by the presence of the foliage cover. Moreover, geometric LiDAR parameters like the laser beam dimension, the flight altitude and the scan angle should be taken into consideration but, as constant flight setting, are not considered here. This specific capacity of the LiDAR measurements in penetrating the canopy can be studied in terms of ground point number variation through the dataset. On the basis of this assumption, a Laser Penetration Index (LPI) (5) was defined as follows:

$$LPI_{ij} = G_{ij} / (G_{ij} + V_{ij}) \qquad (5)$$

Where G_{ij} = Ground Point Density
V_{ij} = High Vegetation Point Density (h > 1 above the ground)

G_{ij} in the denominator allows the normalization of local sampling density due to LiDAR strips overlapping and variations in the helicopter speed. Because of the non-homogenous distribution of LiDAR sampling points in the studied areas, G_{ij} and V_{ij} are calculated on the basis of a neighbourhood analysis by means of an explorative radius which is determined using the initial point sampling density.
An example of LiDAR data elaboration is given below: Ground Point Density and High Vegetation Point Density are reported in Figure 2-Upper and 2-Center, respectively. In the sequence the values are represented using a yellow-blue coloured scale. As normalized index, LPI ranges between 0 and 1, as expected (yellow to blue respectively in Figure 2-Lower). LPI values close to 0 describe dense vegetation while values close to 1 are characteristic of an open stand or clear ground. Intermediate values of the LPI synthesize local variations of the forest in terms of structure and composition. An analysis of the LPI values leads us to the following conclusions:

- The denser the population the less the penetration (this is

particularly true when the same species is considered);
- The laser penetration is lower in the broad-leaved forests than in the coniferous forests if the dataset is surveyed in summer (the opposite is true in autumn, because of the absence of foliage cover);
- A multi-layered forest tends to reduce the LPI values;
- The penetration is generally lower when tall stand or very dense populations are considered.

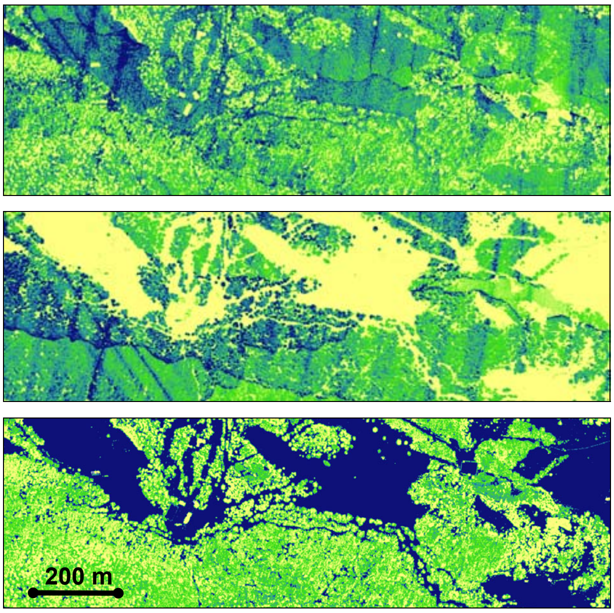

Figure 2 – Penetration index (LPI) elaboration in a mixed forest area. Upper: Ground Point Density map; Center: High Vegetation Point Density map; Lower: Laser Penetration Index.

3.3.2 Crown Height Model (CHM)

The Crown Height Model is a widely used vegetation index allowing the automatic estimation of the forest height, the forest cover and, in the case of multi-temporal surveyed data, the detection of the forestry cover changes. This index can be easily obtained by an algebraic subtraction between the rasterized Digital Surface Model and the Digital Terrain Model (Hyyppä et al., 2001). Even though a tendency to underestimate the real heights has been highlighted (Patenaude, 2004), the information on the CHM can be used to interpret the age of the forest. In a natural ecosystem, if the same species is actually considered, the higher the average stand height, the more mature the population, therefore, the lower the density.

3.3.3 Multivariate analysis

Multivariate statistical analysis allows the exploration of the relationship between many different types of attributes. In an unsupervised classification, the features actually at any specified locations are unknown. The structure of the forest can be however derived in a relative way. Reading the spatial variability of the LPI and CHM values it is possible to aggregate each of the locations into one of a specified number of groups or clusters. The following examples (Figure 3) show 9 classes of variability in 3 different forested areas when multivariate analysis is performed using LPI and CHM. The sequence highlights the capacity of the method to separate differently composed areas. Each clustered area corresponds to a different forestry composition. Thus, the multivariate map can be used for an automatic sub-segmentation of the dataset.

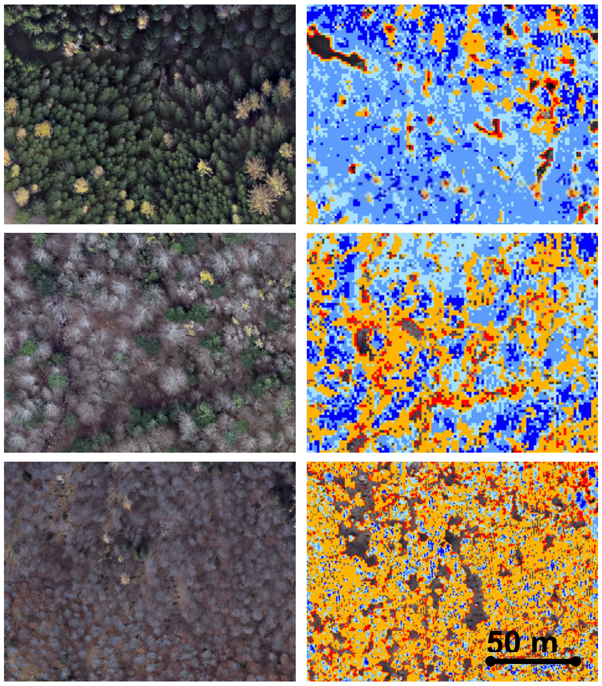

Figure 3 – Examples of multivariate map on three different forested areas. From top to bottom: coniferous forest (spruce with larch.), mixed forest (spruce and beech), broad-leaved forest (beech).

3.4 Dynamic morphological analysis

A dynamic process which considers the multivariate values was implemented allowing the local application of morphological methods previously described. On the basis of the classified index values, a double entrance table was implemented. The search radius is considered as the independent variable which value is empirically determined. Moreover, independently from the stand characteristics, the local density of laser points was taken into consideration for tree extraction processes. This further variable was introduced by performing a triple-entrance table. This means that, for each class of laser density, a double entrance table was implemented. Thus, each location (apex) can be visualized as a point in a multidimensional attribute space whose axes correspond to the represented variables. The method is applied to the preliminary apexes, extracted using the Top Hat algorithm. In this case, a 3 x 3 kernel (λ) with cell dimension of 0,5 m was used in order to guarantee the maximum degree of efficiency. For each seed apex, the average values of LPI, CHM and laser density are calculated within an explorative surrounding window. The combination of these values furnishes the best value to use as a search radius within each preliminary space location. Afterwards, the search radius procedure is iteratively applied, until the false apexes converge to the correct ones. The convergence procedure is performed until no greater height values are found inside the dynamic-defined search window.

4. RESULTS

The result of the comparison between field trees (see Table 1) and laser extracted trees is reported in Table 3 and Table 4. The former table is related to the fixed radius approach shown in paragraph 3.2.2. In this case, the analysis parameters (λ and radius) were manually determined and optimized according to the real tree locations. The latter table reports the results of the correlation between field trees and LiDAR–extracted trees when the dynamic search radius method is performed (3.4 chapter).

Plot ID	LiDAR Extracted	Correct dominant	Correct dominated	False positives
FOA	70	85	0	13
FOB	92	100	0	25
MBA	86	68	0	39
MBB	29	63	0	0
MBC	65	81	0	0
MBD	86	88	0	9
PRB	84	82	0	13
PRC	85	76	0	21
SAA	95	83	0	17
TUA	118	100	33	50
TUB	79	85	0	21
TUC	80	71	0	12
VBA	60	83	0	0
PHA	61	61	0	2
PHB	68	68	0	0
PHC	79	79	0	0
PHD	84	81	0	3

Table 3 – Comparison between field tree number and LiDAR-extracted trees using the fixed search radius method. All values are reported in percentage.

Plot ID	LiDAR Extracted	Correct dominant	Correct dominated	False positives
FOA	60	90	0	0
FOB	88	100	12	17
MBA	89	84	0	32
MBB	29	63	0	0
MBC	81	100	0	0
MBD	95	99	0	8
PRB	71	79	0	3
PRC	68	69	0	9
SAA	97	89	0	12
TUA	116	100	38	45
TUB	79	89	0	18
TUC	120	83	0	40
VBA	60	83	0	0
PHA	82	82	0	2
PHB	86	85	0	1
PHC	85	85	0	0
PHD	111	95	0	16

Table 4 – Comparison between field tree number and LiDAR-extracted trees using the dynamic search radius method. All values are reported in percentage.

In the two tables, trees with a diameter which significantly inferior to the surrounding ones are considered "dominated". Moreover, the apexes which are located 3 meters beyond field surveyed trees are considered "false positives". In Figure 4, an example of the use of these approaches is given. The green triangles represent the position of the trees surveyed on site. The red points identify the trees extracted using a fixed search radius, while the black ones, which are tagged with the corresponding radius used, derive from the application of dynamic radius. As can be seen in the image, three more apexes were detected while a false positive one was extracted in this transect.

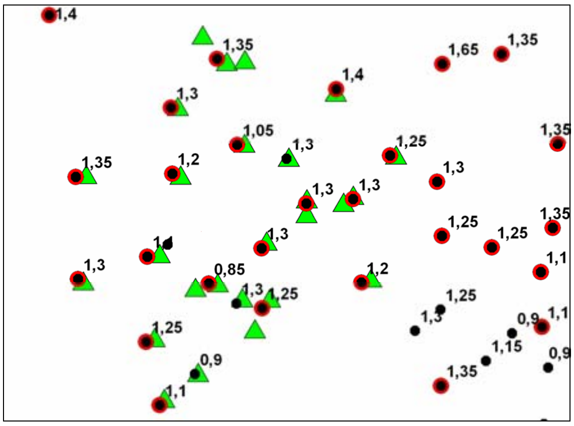

Figure 4 – Example of dynamic search radius application in the MBC transect. The green triangles are the real trees and the black points the extracted trees using a dynamic approach. The apexes, extracted using the fixed-radius method, are shown in red.

A summary of the percentage differences between the two approaches is given in Table 5.

Plot_ID	Diff. correct dominant (%)	Diff. correct dominated (%)	Diff. false positives (%)
FOA	5	0	-13
FOB	0	12	-8
MBA	16	0	-7
MBB	0	0	0
MBC	19	0	0
MBD	11	0	-1
PRB	**-3**	0	-11
PRC	**-7**	0	-12
SAA	6	0	-5
TUA	5	5	-5
TUB	4	0	-3
TUC	13	0	**28**
VBA	0	0	0
PHA	21	0	0
PHB	18	0	**1**
PHC	5	0	0
PHD	14	0	**14**

Table 5 – Comparison between percentage of extracted trees using fixed and dynamic search radius methods. The values reported in red show a decreased quality of the results obtained using the dynamic method.

The first column, showing positive values, implies that the dynamic method generally enhances the performance of the tree extraction process. This improvement reaches significant values especially in the case of juvenile forests, characterized by small diameters, where the population density is very high. The results also seem to improve significantly when the forestry plot is mature and mono-layer structured (even-aged). In this case, the percentage of trees extracted correctly reaches high values, meaning that the most interesting part of the forest (from an above ground biomass content point of view) is extracted in coniferous forests as well in broad-leaved forests. Only two transect (PRB, PRC) show worse results. This is probably due to the insufficient density of the laser survey (< 1.5 pts/m^2). However, the second column in table 5 is related to the differences regarding trees which were extracted but were in fact "false positive". In this case negative values indicate that the dynamic radius approach is able to maintain a lower level of local overestimations, due to the high variability of laser point distribution. However, this overestimation remains high in the case of juvenile converted broadleaved forests. Within these forestry categories, as the LPI tends to assume minimum values, the corresponding search radius become much small. Further experiments should be done, in order to consider whether the use of denser laser surveys could diminish this kind of error.

5. CONCLUSIONS

An innovative method of laser scanning data processing to automatically detect tree positions is proposed. The method, developed in an open source environment, is based on the automatic determination of the forest structure by means of some LiDAR-extracted vegetation indexes. This information is used to improve the quality and the accuracy of the tree extraction process based on mathematical morphology analysis. The main characteristic of the method is its high flexibility due to the multivariate approach implemented that not only considers the local forest composition but also adapts itself to the relative distribution of the laser sampling points. A field survey campaign in some mountainous geo-referenced plots highlighted the optimal performances of the method as far as the positioning and counting of the dominant trees (the main source of forestry biomass), in both coniferous and broad-leaved forests is concerned. The high percentage values of trees extracted prove the LiDAR to be an interesting and efficient technology in improving the knowledge of the forestry ecosystems and may be useful in the better management of natural resources.

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