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A Three-Dimensional Model-Based Approach to the Estimation of the Tree Top Height by fusing Low-Density LiDAR data and Very High Resolution Optical Images

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***Abstract*—Light detection and ranging (LiDAR) technology has been extensively used for estimating forest attributes. Although high-spatial-density LiDAR data can be used to accurately derive attributes at single tree level, low-density LiDAR data are usually acquired for reducing the cost. However, a low density strongly affects the estimation accuracy due to the underestimation of the tree top and the possible loss of crowns that are not hit by any LiDAR point. In this paper, we propose a 3-D model-based approach to the estimation of the tree top height based on the fusion between low-density LiDAR data and high-resolution optical images. In the proposed approach, the integration of the two remotely sensed data sources is first exploited to accurately detect and delineate the single tree crowns. Then, the LiDAR vertical measures are associated to those crowns hit by at least one LiDAR point and used together to the radius of the crown and the tree apex location derived from the optical image for reconstructing the tree top height by a properly defined parametric model. For the remaining crowns detected only in the optical image, we reconstruct the tree top height by proposing a *k-nearest neighbor trees* technique that estimates the height of the missed trees as the average of the k reconstructed height values of the trees having most similar crown properties. The proposed technique has been tested on a coniferous forest located in the Italian Alps. The experimental results confirmed the effectiveness of the proposed method.**

***Index Terms*—Forestry, high-resolution optical images, light detection and ranging (LiDAR), remote sensing, tree top reconstruction model.**

I. Introduction

THE estimation of forest attributes has been effectively improved by the use of the remote sensing technology. The traditional approach to forest inventories is based on ground measurements that are collected for some stand plots usually chosen by randomly sampling the forest area. Then, these measurements are statistically extended to the entire area in order to obtain global estimates of the forest parameters (e.g., average tree volume, average tree height, tree density). For obtaining reliable estimates, the amount of data collected should be representative of the entire forest ecosystem considered. However, field surveys are costly, time consuming, and constrained by lack of access to remote areas (particularly in mountainous scenarios). In this context, remote sensing represents an important tool for monitoring objectively and accurately large forest areas.

Light detection and ranging (LiDAR) is an active remote sensing technology widely employed for estimating forest stem parameters. LiDAR acquires data by hitting the tree crowns with the laser pulses whose reflections can be used to reconstruct the 3-D structure of the forest. In particular, high density sampling LiDAR data (larger than 5 pt/m^2) allow one to accurately measure the tree top height and result in a precise estimation of forest parameters at single tree level [e.g., diameter at breast height (DBH) and tree stem volume] [1]–[8]. However, high-density LiDAR data have high acquisition costs, particularly when large areas are considered. This is due to the fact that for incrementing the density the duration of the flight should be increased (either by decreasing the altitude of the airborne platform or its speed). As an example, by decreasing the interval of the spacing of LiDAR hits from 1.5 m to 0.3 m the acquisition cost per square kilometer may increase of about three times, i.e. [9]. The reduction of the spatial density of the LiDAR pulses brings to the following: i) the underestimation of the height of the trees due to the missed detection of the tree top positions by the LiDAR points and ii) the missed detection of trees that are not hit by any laser pulse. These effects have been studied in the literature [10]–[13]. In [10], the authors showed that, by increasing the aircraft altitude, the underestimation of both dominant tree heights and number of detected trees increases, due to the decrease in the pulse density and to the increase in the footprint size. Moreover, when the platform altitude increases over a certain level (e.g., 1500 m) there is a considerable deterioration of the height estimation results. This underestimation is more evident in mountainous scenario because of the error associated to the generation of the digital terrain model (DTM) [11], [12]. Indeed, as discussed in [11], by increasing the flight altitude, the penetration rate decreases, and the ground laser data collected are no more sufficient for recovery topography information. In particular, the poor penetration rate of the laser pulses may miss crests and ridges, resulting in an underestimation of the DTM. Moreover, due to the slope of the topography, the elevation obtained at the center of the footprint is higher than that obtained at the last pulse [12]. Therefore, when the tree leans towards upper side of slope, the LiDAR height is

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underestimated. In particular, the tree top detection suddenly declines when the laser sampling density is below 3-5 pt/m^2 and thus, the height of the dominant trees is underestimated. In this context, the joint use of different remotely sensed sources could be a possible solution for improving the performances of the low-density LiDAR data.

The fusion of LiDAR data and optical images has been analyzed in several papers. A detailed analysis of the literature (see Section II) points out that data fusion approaches between LiDAR and optical data can lead to more accurate estimation results. However, only few studies investigated the problem of estimating forest stem parameters considering the joint use of low-density LiDAR data instead of using high-density LiDAR and optical images [14]–[18]. These studies do not report accurate estimates since none of them focused the attention on the precise estimation of the tree top height at single tree level. An alternative solution to the use of LiDAR data for describing the 3-D structure of the scene is offered by image matching techniques [19]–[23]. These techniques use aerial images with stereoscopic coverage to derive Digital Surface Models (DSMs). The integration of the points cloud derived from photogrammetric DSM and the LiDAR points cloud can result in a better description of the 3-D structure of the target (i.e., photogrammetric dense matching techniques). However, only few papers addressed the combination of LiDAR data and photogrammetric surface models for increasing the number of points collected by the laser scanner. Moreover, potogrammetric methods usually require the availability of a DTM when dense forest scenario are considered since aerial images are not able to model properly the ground surface, and therefore, to estimate the height of the trees.

In this paper we propose a data fusion approach to integrate low-density LiDAR data and a single optical image for a precise estimation of the tree top heights at single tree level, which extends the work presented in [24]. Unlike the methods described in the literature, the proposed method aims at accurately reconstructing the tree top height employing a 3-D parametric model of the tree. Differently from the photogrammetric dense matching techniques, we aim at exploiting a single optical image only for describing the horizontal structure of the forest. Indeed, instead of increasing the number of LiDAR points collected on the scene by using the DSM generated with stereo images, we aim at exploiting the geometric shape of the trees for reconstructing the tree top height information.

The proposed method first identifies the crowns of the trees present in the scene by applying a segmentation algorithm to the optical image with the integration of the height information provided by the LiDAR data. After the crown detection, it reconstructs the tree top height of each identified crown by using measures derived from the low-density LiDAR data integrated via a properly defined parametric model. In greater detail the proposed method is based on three steps: i) multisensor segmentation of the crowns by using optical and LiDAR data; ii) reconstruction of the tree top height for those crowns hit by laser points employing a 3-D parametric model of the tree based on the LiDAR height and the crown radius information; iii) estimation of the height of those trees missed by any LiDAR points by using a similarity crown area criterion based on a *k-nearest neighbor* (k-NN) trees algorithm.

The main novelties of the proposed technique are: i) the use of a 3-D parametric model for the reconstruction of the tree top height of those crowns hit by LiDAR points and ii) the estimation of the tree top height for those crowns that are missed by any LiDAR pulse with a k-NN trees technique. It is worth noting that, in this study, we concentrate our attention on coniferous forests in the Alpine scenario. In the experiments, we considered four LiDAR datasets of low laser sampling density (i.e., 1, 0.75, 0.5, and 0.25 pt/m^2) and very high-resolution optical images (0.20 m). First, we tested the technique on three circular stand plots of area 400-m^2 where we have ground reference data. Second, we applied the proposed technique to a wide forest area of 1.9 Ha, where we compared the tree top height estimates obtained with the height derived from the high-density LiDAR data (5 pt/m^2). The results obtained confirm the effectiveness of the proposed technique.

The rest of this paper is organized into six sections. The next section presents the analysis of the state of the art. Section III describes the proposed method illustrating in detail each single step of the proposed architecture. Section IV presents the dataset used in the experimental analysis. Section V describes the experimental results. Finally, section VI draws the conclusion.

II. State of the Art

The joint use of LiDAR data and optical images has been widely addressed in the literature. The fusion between high laser sampling density LiDAR data and optical images is very useful for better describing the structure of the target. Indeed, since the laser measurements are not homogeneously distributed, the gaps among the laser pulses do not always allow a precise reconstruction of the 3-D shape of the target (e.g., building corner missing), while optical images can provide a better description of the horizontal structure of the scene [25]. In the framework of forest parameters estimation, this effect has been encountered in the delineation of the single tree crowns. In [26] and [27], the complementary of LiDAR and optical sources for automatic individual tree delineation is demonstrated. In [26], the authors compared the results obtained by applying a segmentation algorithm to high-resolution multispectral image and to high-density LiDAR data. Although both data achieved accurate crown extraction, the joint use of the two sources allowed an improvement of segmentation results. LiDAR data avoid identifying false trees isolated in open stands, whereas the optical image segmentation results are strongly affected from these errors because of the high radiance value of the bare soil in open field. In contrast, the multispectral image better delineates the tree crowns where the forest is dense. In order to face the problem of commission error (false tree isolated) in the multispectral image segmentation, the authors imposed a minimum crown dimension and a height filtering criterion based on the LiDAR information by deleting the crowns with height smaller than 2 m. Due to the synergistic use of the data, the number of the false tree detected on the multispectral image was strongly

Table I
LEGEND OF NOTATION USED IN THIS PAPER

Symbol	Description
I	LiDAR image
$I(x,y)$	Height value of the CHM image at the position x-line and y-column
M_{sk}	LiDAR derived mask image
G	Green band of the optical image
$G(x,y)$	Radiance value of the green band of the optical image at the position x-line and y-column
$\text{th}_{\text{Height}}$	Height threshold chosen for discriminating between forest and non-forest area
G_m	Green band of the optical image masked by the LiDAR derived mask image $Mask$
Q	the structural element chosen for dilating the image I
D_Q	the domain of the structuring element Q
D_I	the image domain
$S = \{s_1, .., s_t, .., s_T\}$	Set of seeds identified on the optical image, which correspond to the tree top location
$C = \{c_1, .., c_t, .., c_T\}$	Set of tree crowns, where c_t is the tree crown delineated around the s_t seed
$P = \{p_1, .., p_t, .., p_T\}$	Number of LiDAR pulses associated to the tree crowns, where p_t is the number of LiDAR pulses associated with the crown c_t
$A = \{a_1, .., a_h, .., a_H\}$	Set of tree crowns hit by 1 LiDAR point, $A = \{c_t \in C \| p_t = 1,\ t \in [1,T]\}$
$W = \{w_1, .., w_d, .., w_D\}$	Set of tree crowns hit by more than 1 LiDAR points, $W = \{c_t \in C \| p_t > 1,\ t \in [1,T]\}$
$M = \{m_1, .., m_l, .., m_L\}$	Set of tree crowns missed by LiDAR points, $M = \{c_t \in C \| p_t = 0,\ t \in [1,T]\}$
$C = W \cup A \cup M$	where $W \subset C$, $A \subset C$, $M \subset C$ and $D + H + L = T$

reduced. In [27], an approach that aims at mapping the single tree location both on LiDAR data and high-resolution aerial photo is presented. The results confirm that optical images are suited for describing dense forest, whereas LiDAR data allow higher accuracy on lower tree density areas.

The importance of integrating the laser scanner information with the optical images is even more evident in the estimation of forest parameters mainly related to the vertical dimension. In [28], the authors compared the volume estimation results obtained by using only aerial images or integrating them with high-density LiDAR data. By associating to each crown detected in the aerial images the height information derived by the LiDAR data, the volume estimation results significantly improved (R^2 from 0.14 to 0.54). Moreover, the analysis pointed out that, for properly estimating forest stem volume at single tree level, the height of individual trees was the most important geometrical parameter. In the framework of forest species classification, the integration between LiDAR and optical images (e.g., multispectral or hyperspectral images) can be effective for better discriminating species having similar spectral signature but different height values [29]–[32].

Despite the interesting results of the data fusion techniques, only few papers considered the possibility of exploiting optical images as ancillary data for improving the forest attributes estimation obtained by using low-density LiDAR data [14]–[18]. In [14], the authors presented a technique that aims at generalizing the vertical information contained in limited acquisitions of LiDAR transects data by using an optical Quickbird image acquired on the entire scene in order to estimate forest stem volume at stand level. The main idea is to exploit the wide area coverage guaranteed by the optical image in order to train a Support Vector Regression (SVR) model being able to estimate the tree height values derived from LiDAR data. The optical image provided the information about the horizontal structure, whereas LiDAR allowed the vertical reconstruction of the forest. Although the use of the SVR increased the accuracy compared to the results obtained with multiple regression models, the errors on the tree top and on volume estimation are still high. The technique proposed in [15] combines optical data acquired by the SPOT5 satellite with tree height information provided by a laser scanner. A multiple linear regression analysis is developed for both each data source and the combination of the two data sources in order to perform volume estimation at stand level. The joint use of the two sources improved the volume estimation of 49% compared to the use of the only optical image, reducing the RMSE on the average volume from 31% to 16%. In [16], the authors demonstrated the importance of having a precise tree height estimation for accurately estimating tree volume. They compared the results obtained by extracting the tree top height from high-density and low-density LiDAR data from the same segmentation map obtained on a high-resolution optical image. After having calculated the volume at single tree level by means of an allometric equation, they computed the error metrics of the entire stand. In the high-density case the root mean square error (RMSE) ranges from 156.0 m^3/ha to 163.6 m^3/ha, whereas in the low-density case the RMSE ranges from 205.4 m^3/ha to 209.0 m^3/ha. In [17] the authors proposed an approach to estimate plot-level tree height by using multispectral images and low-density LiDAR data. First, they classified the multispectral image in order to distinguish among deciduous and coniferous forest. Then, they derived from the field inventories non-linear regression models being able to estimate the crown width from the tree height. These models were calculated either differentiating deciduous and coniferous forest or considering the two species combined. In order to detect the location of the trees inside the plot they applied a local maxima filtering process to the LiDAR data by calibrating the window filter dimension considering the species and the tree height of the pixel. By comparing the results obtained with and without considering the species information, there is an improvement of the average plot height estimates only for the coniferous forest. In [18], the authors exploited the combination of an aerial photo and low-density LiDAR data in order to delineate the tree crowns and estimate the tree height. The optical image corresponding to the studied area was segmented for deriving the canopy shape of the trees (coconuts plantation), whereas LiDAR data were used to derive the tree height of each individual tree identified. In order to delineate the tree crowns a contouring technique was applied to the green band. For each detected polygon the height information was extracted by overlapping the LiDAR data. Although the segmentation algorithm applied to the aerial photo successfully detected the crowns, the LiDAR derived height was underestimated due to the low-density LiDAR data acquisition. In [33], an approach to the estimation of forest structural parameters based on aerial images and low-density LiDAR data is presented. In particular, the authors proposed an algorithm based on the RGB intensity value of the LiDAR data for coregistering the aerial images. The crown delineation was derived from the aerial images, whereas LiDAR data provided the height information. Although the coregistration properly integrates the two data, due to the low laser sampling density, the height is not accurately estimated.

Several papers have investigated the possibility of generating DSM by using optical images as an alternative to the laser scanner [23] or as additional information to combine with LiDAR data [19]–[22]. In [23] the authors proposed a novel image matching technique for the reconstruction of the 3-D structure of the forest using pairs of stereo images. In the first experiment, the DSM derived from high-resolution aerial images allowed a better description of the 3-dimensional structure of the forest with respect to the DSM obtained by using low-density LiDAR data (i.e. 0.5 pt/m^2). In particular, the authors compared the results obtained with manually measured reference points directly derived from the stereo images. In the second experiment, the best DSM is derived from a LiDAR characterized by 1.5 pt/m^2 compared to the result obtained using multitemporal satellite images. Similar results have been presented in [19], where the authors compared the estimation of plot forest variables derived from the DSM generated by using high-density LiDAR data (7 pt/m^2) and high-resolution aerial images. LiDAR data achieved the best accuracy in the estimation of mean height, mean diameter and volume. In [20], a photogrammetric dense matching technique has been proposed for improving the forest structure estimation provided by low-density LiDAR data. The main idea is to improve the density of the laser point clouds by using the DSM derived from the overlapping aerial images. The authors proposed automatic, semi-automatic and manual methods to increase the density of the laser points. In [21] the authors proposed a hybrid technique that combines photogrammetric Canopy Height Model (CHM) obtained by pairs of stereo aerial images and LiDAR data. LiDAR has been employed both for selecting the absolute orientation parameters of the stereo model and for deriving the ground elevation data. Results pointed out that the quality of the CHM was strongly affected by the dissimilarities of stereo images caused by the combination of view and sun angles, as well as by the complexity of the forest canopy surface. Indeed, in order to accurately match the two optical images, reference points (or edges) should be detected, which results to be difficulties due to the different point of views of the images [23]. Moreover, the complex surface of the canopy could create occlusions that increase image matching uncertainty [34]. Results presented in the paper showed an average RMSE between the DSMs generated by using satellite images and that produced by LiDAR data of 2.7 m, which increased to 5.3 m in the forest area. Note that the stereo matching requires the availability of more than one optical image on the same area. Thus, when multitemporal acquisition are considered, different illumination and atmospheric conditions or different image orientations could result to be very critical.

III. Proposed tree top Height Estimation Approach

The aim of the proposed approach is to improve the accuracy of the tree top height estimates at single tree level obtained with low-density LiDAR data, by fusing these data with a single optical image. Fig. 1 shows the architecture of the proposed method. It is divided into two main parts, i.e., the preprocessing phase and the proposed technique.

A. Preprocessing Phase

The preprocessing phase is made up of three steps for the LiDAR data and one step for the optical image. The goals of the LiDAR data preprocessing are as follows: i) the correction of the height measures from the topography of the scene and ii) the use of the derived height information for generating a binary mask image M_{sk} that identifies the forest area. First, the DTM is subtracted to each point of the raw LiDAR data in order to determine the elevation information with respect to the ground. Second, we generate an image having the same spatial resolution of the optical image, where we assign at each pixel the height measured by the LiDAR pulses in the area correspondent to the pixel. In order to propagate the height information to the neighbouring pixels we apply to the LiDAR image a dilation algorithm (e.g., see [35]). The structural element employed is a disk whose size depends on the tree crowns dimension. This procedure allows us to identify the presence of trees by using the LiDAR-derived height information in order to distinguish the forest area from the ground area. The accuracy of the result obtained depends on a tradeoff between the laser sampling density of the LiDAR

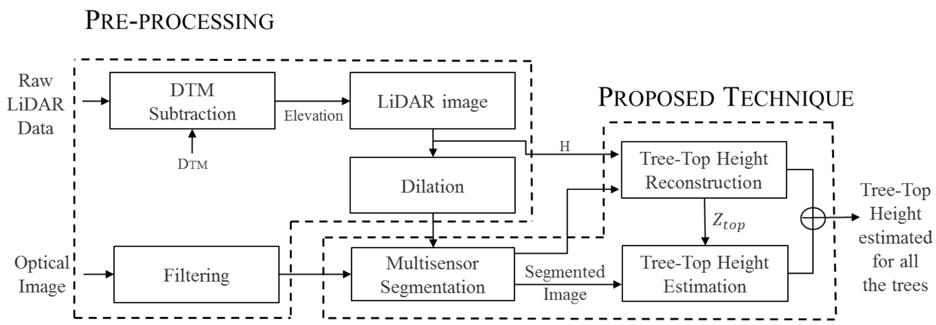


Figure 1. Architecture of the proposed tree top height estimation approach.

data and the density of the forest. However, since we aim at identifying flat ground areas or shrub vegetation, the sparse LiDAR information is sufficient to cope this purpose. Let I be the LiDAR processed image and $I(x, y)$ the height value of the pixel at the position (x, y). For the complete definition of the notation used in this paper see Table I. Let Q be the structural element chosen for dilating the image I, and $Q(x', y')$ the value of the structural element at the position (x', y'). Let D_I and D_Q be the domain of the image I and the domain of the structuring element Q, respectively. The dilation algorithm for the image I by Q is described by the following equation:

$$(I \oplus Q)(x, y) = max\{I(x - x^{'}, y - y^{'}) \mid (x^{'}, y^{'}) \in D_Q, \\ (x - x^{'}, y - y^{'}) \in D_I\}. \tag{1}$$

Let $\text{th}_{\text{Height}}$ be the height threshold value chosen in order to distinguish between forest and flat ground areas. The mask image M_{sk} is obtained by deleting all the pixels of the LiDAR image I having value before the height threshold $\text{th}_{\text{Height}}$, [26]. We can write as follows:

$$M_{sk}(x, y) = \begin{cases} 1 & \text{if } I(x, y) \geq \text{th}_{\text{Height}} \\ 0 & \text{otherwise} \end{cases} \text{ with } (x, y) \in D_I \tag{2}$$

In the optical image preprocessing, the tree apex and the crown boundaries are emphasized in order to allow a better detection and delineation of the single tree crowns during the multisensor segmentation phase. Let G be the green band of the optical image and $G(x, y)$ the radiance value of the pixel at the location (x, y). An $n \times n$ median convolution filter is applied to I for reducing the noise in the image. Then, the image is smoothed by means of a $n \times n$ Gaussian convolution filter in order to emphasize the local maxima and the crown contours. The filters dimension depends on the spatial resolution of the image and the average size of the tree crowns.

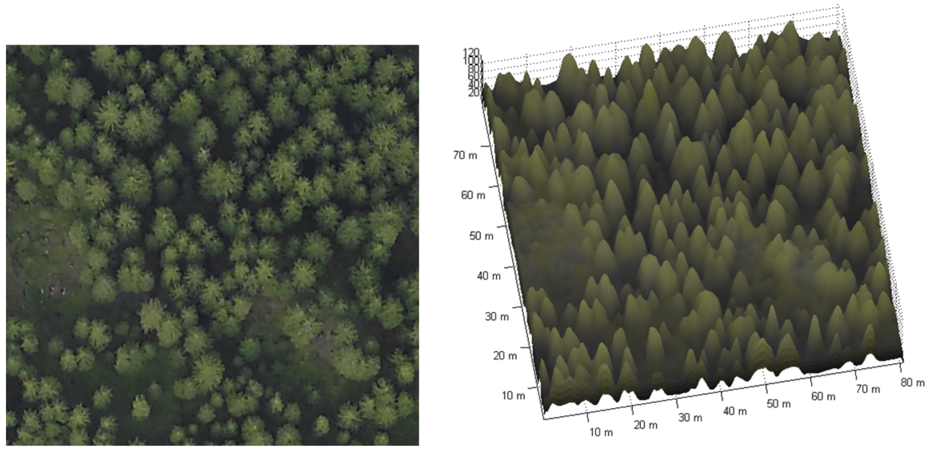
At the end of the preprocessing phase, the proposed tree top height estimation approach can be applied to the remotely sensed data. The proposed technique is made up of three main steps: i) multisensor segmentation that exploits the optical image and the LiDAR data; ii) tree top height reconstruction method for the tree crowns hit by LiDAR pulses; iii) tree top height estimation (k-NN trees) for those crowns that are not hit by any LiDAR pulse. These steps are described in greater detail in the following.

B. *Multisensor Segmentation*

The segmentation phase aims at identifying and delineating the tree crowns present in the scene. Due to the low laser sampling density, the extraction of the tree crowns is not sufficiently accurate when implemented on LiDAR data. For this reason, the segmentation algorithm is applied to the optical image, which represents the entire horizontal structure of the forest. In particular, we consider the green band of the optical image since it is the most correlated band to the radiation intensity of the image [36]. Indeed, the radiance of the optical image, under nadir condition acquisition, can be considered a topographic surface which represents the structure of the forest (see Fig. 2). However, where the forest is less dense, the discrimination between bare soil and trees is a critical issue for the crown recognition in optical images. For this reason, we apply to the optical image the binary mask image M_{sk} generated by using LiDAR data. Let G be the green band of the optical image. Since the G image has the same dimension of the M_{sk} image, the masking procedure is accomplished as follows:

$$G_m(x, y) = M_{sk}(x, y) \cdot G(x, y), \text{ with } (x, y) \in D_I. \tag{3}$$

The obtained masked image G_m is analyzed in order to extract the position of the center of the crown which corresponds to each tree apex. Similarly to the valley following approach [37], we assume that on optical imagery, the highest values of the radiation intensity are concentrated on the uppermost part of the tree, which is surrounded by lower intensity pixels (valleys) (e.g., see [26], [36]). The local peaks of the image are detected by using a set level method (which was used in [38] on very high-density LiDAR data), whereas the crown boundaries are detected by the crown delineation method presented in [39]. By assuming the crown surrounded by shadows, we search the local minima along the four main directions (0°, 45°, 90°, and 135°). Then, the boundaries detected are processed in order to close possible gaps of the border and to remove the pixels that have less than two minimum neighbors. This step provides a minima network, which identifies the regions correspondent to the crown areas. The regions with less than p pixels are deleted from the image, assuming that they are too small for being a tree crown. The value of p depends on the resolution of the image. For each labeled region we analyze the correspondence with the seed image. If the labeled region includes just one seed s_t, then this means that the region



(a) (b)

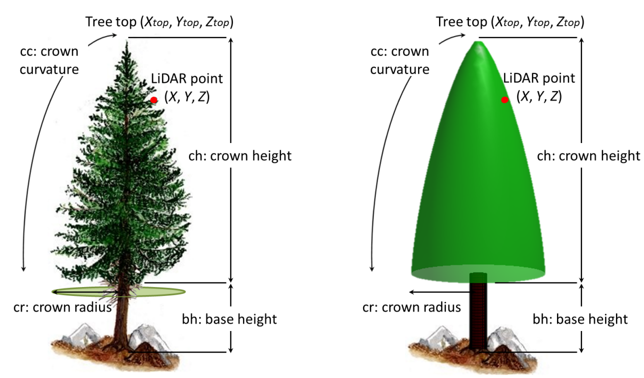
Figure 2. (a) RGB representation of the original ortophoto. (b) Three-dimensional representation of the radiance value of the green band.

describes the tree crown belonging to that specific seed, and thus, it is associated with the tree crown c_t. If the region includes more than one seed, then this means that two or more crowns are fused in a single connected region and should be separated. The remaining connected regions that include more seeds are usually partially separated by the minimum network. For this reason, in order to separate them completely, we just follow the direction of the enclosure and split the remaining crowns. At the end of this process, we obtain the set of T detected crowns $C = \{c_1, .., c_T\}$, where c_t identifies the region delineated around the seed s_t.

C. Tree Top Height Reconstruction Method

The main idea of this step is to define a procedure that can accurately reconstruct the tree top height exploiting the LiDAR elevation information related to the crown. This is done starting from the assumption that: 1) the density of the considered LiDAR data is not sufficient for detecting the top of each tree, and 2) only trees with at least one LiDAR measure are considered. The case in which some crowns are missed by laser pulses is addressed in the next section. Let $P = \{p_1, .., p_T\}$ be the number of LiDAR pulses associated to tree crowns, where p_t is the number of LiDAR pulses associated to the crown c_t. The T detected crowns can be split into three sets: i) the H crowns hit by just one laser point, ii) the D crowns hit by more than one laser point, and iii) the L crowns missed by the laser scanner. Let us define the tree crowns hit by one laser point as $A = \{c_t \in C | p_t = 1, t \in [1, T]\}$, the crowns hit by more than one laser point as $W = \{c_t \in C | p_t > 1, t \in [1, T]\}$ and the missed crowns as $M = \{c_t \in C | p_t = 0, t \in [1, T]\}$, with $C = W \cup A \cup M$ and $T = D + H + L$. In Fig. 4, an example of the classification of the tree crowns is reported. The D crowns hit by more than one laser pulse are represented in white, the H crowns hit by just one laser pulse are represented in blue, whereas the L crowns missed by the laser scanner are represented in red.

It is worth nothing that the low laser sampling density limits the number of pulses acquired inside each crown to few sparse measures (at the limit of one point per crown). Moreover, when low-density LiDAR signals are acquired with a narrow laser beam, there is a systematic underestimation of the height due to the missed tree top location. In order to solve these problems, the proposed technique defines a proper 3-D parametric model of the crown surface for reconstructing the real height of the tree by using the altitude information of the LiDAR points associated with the tree crown and the segmentation results from the optical image. In this paper, we address the issue of reconstructing the tree apex for coniferous forests. Indeed, the broad-leaves forests are usually characterized by a round canopy almost flat on the uppermost part. Thus, due to this umbrella-shaped crown morphology, the tree height is not heavily underestimated when the LiDAR pulses do not center the tree apex. In contrast, the steep morphology of the crown surface of the conifer strongly affects the height estimates depending on the distance of the laser pulse from the tree top. The geometric parametrization of the tree that we use in this paper is derived from the synthetic template presented in [40], which was employed to describe the crown envelope of conifers for delineating the single tree crown on



(a) (b)

Figure 3. (a) Representation of the tree crown parameters of the defined 3-D reconstruction model. (b) Example of 3-D model of the tree.

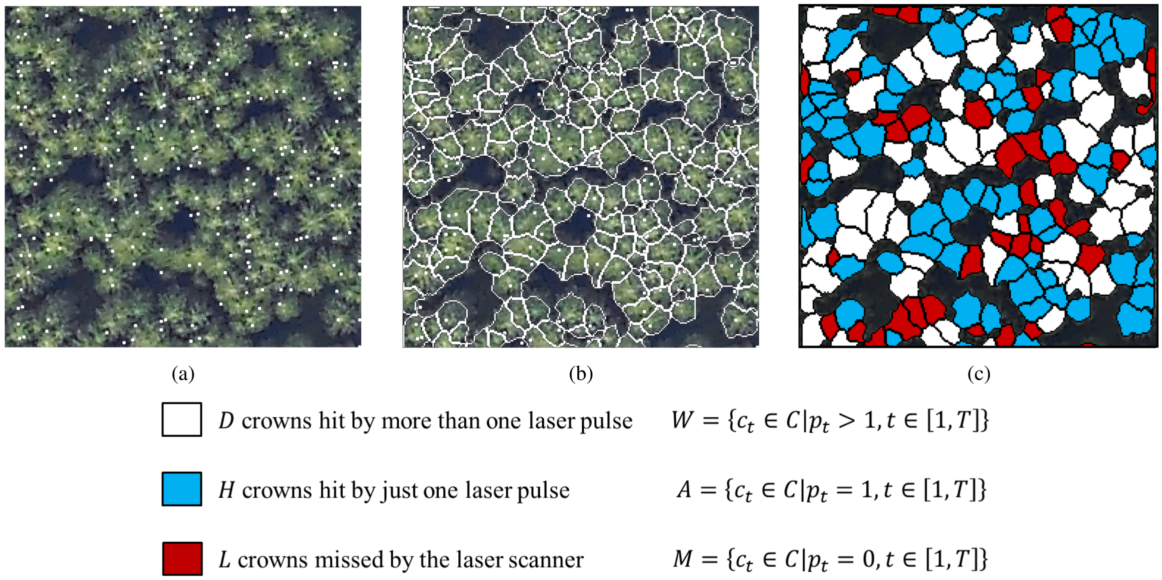


Figure 4. Example of classification of the detected trees based on the number of LiDAR pulses associated to the crown. (a) LiDAR pulses are shown in white and are overlapped on the ortophoto. (b) Both LiDAR pulses (represented in white) and border of the detected trees (represented in white) are overlapped on the ortophoto. (c) Classification of the detected trees in crowns hit by more than one laser pulse (white), the crowns hit by just one laser pulse (blue) and the crowns missed by the laser scanner (red).

high-resolution optical images. In greater detail, the authors proposed a generalized ellipsoid described by the tree top coordinates (X_{top},Y_{top},Z_{top}), the adjusting coefficient of the crown surface curvature cc, the crown depth ch and the crown radius cr (see Fig. 3). The same mathematical representation has been adopted in [4] for delineating the single tree crowns on LiDAR images, and in [41] for reconstructing the structure of the scene after having estimated all the forest attributes by using a high-density LiDAR data (average point density larger than 10 pt/m^2). The mathematical representation of the crown envelope is as follows:

$$\frac{(Z+\text{ch}-Z_{\text{top}})^{\text{cc}}}{\text{ch}^{\text{cc}}}+\frac{[(X-X_{\text{top}})^2+(Y-Y_{\text{top}})^2]^{\text{cc}/2}}{\text{cr}^{\text{cc}}}=1 \tag{4}$$

where

$$Z_{\text{top}}-\text{ch}<Z<Z_{\text{top}} \tag{5}$$

In our technique we use the segmentation results to identify the tree top location (X_{top},Y_{top}) and the crown radius cr. Then, after having associated each tree with the related laser pulses, the coordinates of the LiDAR points (X, Y, Z) are known. Therefore, fixed the parameters cc and ch, Z_{top} represents the only unknown variable to retrieve by employing the height information Z provided by the LiDAR data. Z is constrained among $Z_{\text{top}}-$ch and Z_{top} for ensuring that the considered LiDAR measure is inside the vertical structure of the crown.

If we consider the case of having $p_t > 1$ we have one equation per point and a single unknown variable Z_{top}. Therefore, once the value of the parameters ch and cc are defined in order to find the Z_{top} we should solve the estimation problem with a least square method, i.e.,

$$\begin{aligned} Z_{\text{top}} &= \arg\min_{Z'_{\text{top}}} \left\| Z'_{\text{top}} \right\|_2^2 \\ &= \min_{Z'_{\text{top}}} \left[r_1(Z'_{\text{top}})^2 + .. + r_j(Z'_{\text{top}})^2 + .. + r_{p_t}(Z'_{\text{top}})^2 \right] \end{aligned} \tag{6}$$

where $r_j(Z'_{\text{top}})$ is the residual of the jth LiDAR point described by the ground coordinates (X_j, Y_j, Z_j) and calculated as follows:

$$\begin{aligned} r_j(Z'_{\text{top}}) = &\frac{(Z_j+\text{ch}-Z'_{\text{top}})^{\text{cc}}}{\text{ch}^{\text{cc}}} \\ &+ \frac{[(X_j-X_{\text{top}})^2+(Y_j-Y_{\text{top}})^2]^{\text{cc}/2}}{\text{cr}^{\text{cc}}} - 1 \end{aligned} \tag{7}$$

Under the assumption that $p_t > 1$, instead of imposing a couple of parameters cc and ch for all the trees, we automatically determine the optimal tree model representation for each tree. In particular, we aim to fit as close as possible the 3-D structure of the tree to the LiDAR points acquired inside the crown. The residual metric can be used to identify the combination of parameters that minimizes the distance between the 3-D parametric model and the LiDAR points. The lower is the sum of the residual values the better the crown surface fits the LiDAR points. Examples of the considered 3-D parametric model are represented in Fig. 5. This method cannot be applied to the H crown hit by just one LiDAR point since the residual metric remains zero for all the possible crown surfaces (i.e., combination of parameters). For this reason, for each crown a_h we refine the search of the optimal tree model among n possible models. Afterwards, we select the model that returns the Z_{top} equal to the median value of the n different Z_{top} obtained. Since the single LiDAR point associated to the

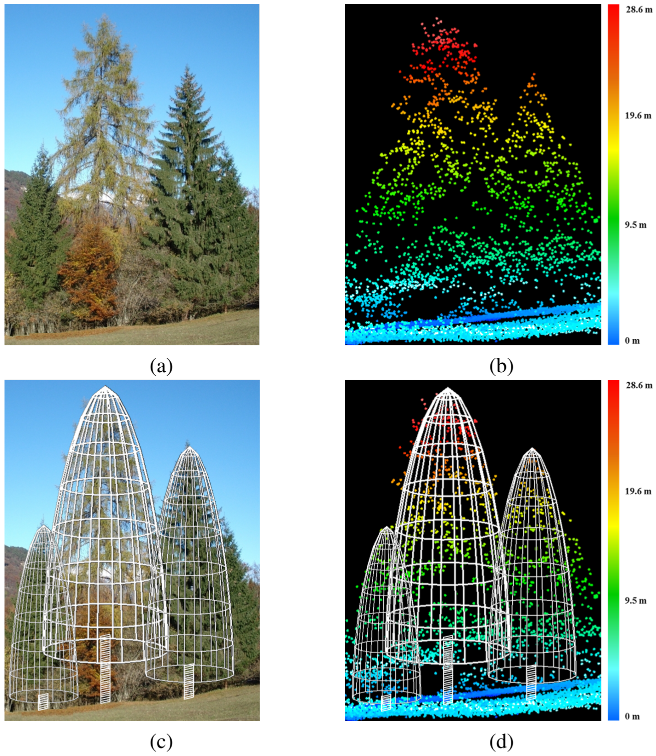


Figure 5. Examples of the considered 3-D parametric model: (a) real scene; (b) LiDAR points cloud of the trees; (c) 3-D parametric models of the trees automatically detected by the proposed method superimposed on the real scene, (d) 3-D parametric models of the trees automatically detected by the proposed method superimposed on the LiDAR points cloud.

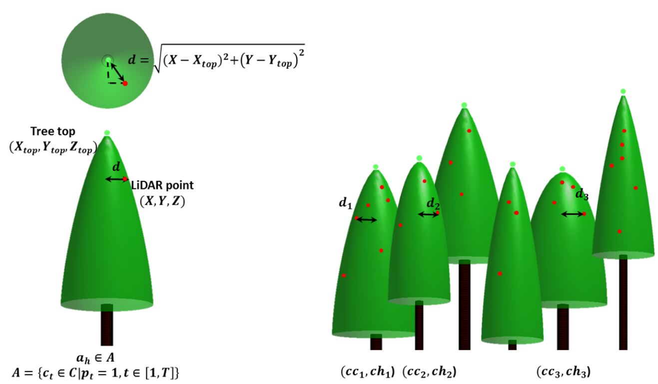


Figure 6. Example of the tree top reconstruction method for those crowns hit by just one LiDAR point, with $n = 3$. For the generic tree a_h, the three trees having similar point distances (d_1,d_2 and d_3) and, thus, the three associated models (i.e., (cc_1,ch_1), (cc_2,ch_2) and (cc_3,ch_3)) are tested. The chosen model is the one that returns the Z_{top} equal to the median value of the three resulting Z_{top}.

crown is described by the height value Z and the distance from the center of the tree given by $\sqrt{(X - X_{\text{top}})^2 + (Y - Y_{\text{top}})^2}$, (later defined as d_{ref}), in order to choose the n combinations of parameters cc and ch to analyze, we consider the distance from the center. We compute the absolute difference between d_{ref} and the distance from the center of the LiDAR points associated to the D crowns hit by more than one laser point. Finally, we select the models of the n crowns having the minimum absolute difference. Fig. 6 shows an example of the described procedure with $n = 3$.

D. Tree Top Height estimation method (k-NN Trees)

Low-density LiDAR measures affect not only the accuracy of the tree top height estimates, but also the capability to detect some of the tree crowns present in the scene. Indeed, although we are dealing with dense forest, by decreasing the laser sampling density the number of crowns hit by laser points decreases as well. As the tree top reconstruction method described in the previous subsection requires at least one LiDAR measure for estimating the tree top height, we need to define a strategy for estimating the tree top heights of the L missed crowns. To this purpose we define a k-NN trees algorithm. Note that due to the segmentation, we are in the condition of detecting crown areas missed by the laser scanner. Assuming that the tree properties can be considered in average homogeneous at local level in the studied area, we define a k-NN trees estimation method based on the correlation among crown area and tree top height. Accordingly, it is reasonable to exploit the crown area information in order to detect trees with similar tree top height by considering the same forest scenario. For this reason, we identify the k trees that: 1) belong to a predefined sparse neighborhood of the forest of the missed tree m_l; 2) are hit by at least 1 LiDAR pulse; and 3) are the most similar in terms of crown area. The similarity measure defined is the absolute difference between the lth missed crown area m_l and the generic crown area c_j hit by the LiDAR pulses, where $J = H + D$. For each m_l, we calculate $d(m_l, c_j)$ as follows,

$$\begin{aligned} d(m_l, c_j) &= |c_j - m_l| \\ l &= 1, .., L \\ j &= 1, .., J \end{aligned} \tag{8}$$

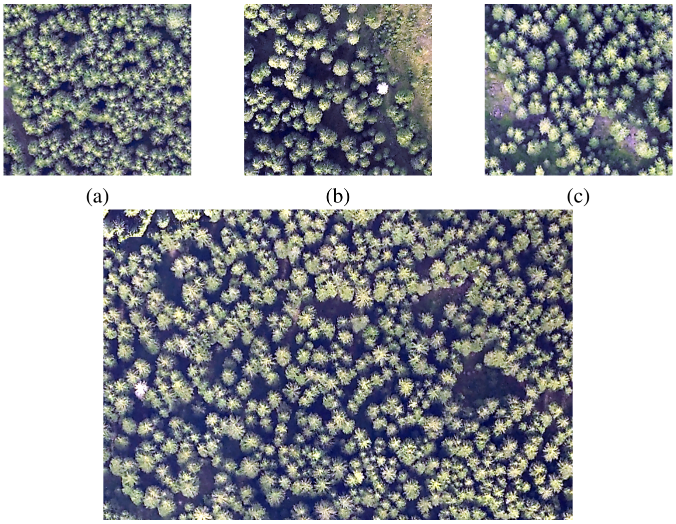
Then, we estimate the tree-height Z_{top} as the average of the tree top reconstructed heights Z_j of the k trees having the minimum distance measure $d(m_l, c_j)$ to the m_l crown. We can write:

$$Z_{\text{top}} = \frac{1}{k} \sum_{j=1}^{k} Z_j \tag{9}$$

It is worth noting that here we considered all the trees belonging to the same coniferous forest to detect the k-NN trees. However, one can define more refined rules restricting the search to trees belonging to areas having similar terrain properties (e.g., same slope and/or same aspect of the terrain).

IV. Dataset description

The study area is a coniferous forest located in the Southern Italian Alps at Parco Naturale Paneveggio-Pale di San Martino in the Trentino region (see Fig. 7). The predominant specie is the Norway Spruce (Picea Abies) with a small presence of Silver Fir (Abies Alba). For the quantitative evaluation we considered three circular stands plot of radius 20 m and area 400 m^2 [see Fig. 7(a)-(c)], where field data were collected during the summer 2007. Within each stand plot, all the



(a) (b) (c) (d)

Figure 7. Ortophoto of the investigated area. (a) Stand plot 1. (b) Stand plot 2. (c) Stand plot 3. (d) Extended test area.

trees having Diameter at Breast Height (DBH) $>$ 3 cm were surveyed. For each tree the parameters measured were the tree position with respect to the center of the sample plot, the tree height, the species, the crown diameter and the DBH. In order to test the method in different conditions we selected sample plots characterized by different topography and different forest densities (see Table II). Moreover, we considered a wide area (for which ground data are not available) located in the same coniferous forest [see Fig. 7d] characterized by an extension of approximately 1.9 ha and an altitude that ranges between 1565 m and 1604 m on the sea level. The coordinates of the central point of this area are $46°18'15{,}24''$ N, $11°44'52{,}04''$ E.

The optical image and the LiDAR data considered in the experiments were simultaneously acquired on September 4, 2007. The optical images employed in this study are ortophotos. The images consist of red, green and blue bands acquired with a geometrical resolution of 20 cm. LiDAR data have been acquired by an Optech ALTM 3100EA sensor. For each laser pulse four returns were recorded, with an average point density $>$ 5 pt/m^2. The laser scanner is characterized by a pulse wavelength of 1064 nm and a pulse repetition frequency of 100 Khz. In order to assess the effectiveness of the proposed technique, we undersampled the original LiDAR data for generating four low-density LiDAR data sets. The undersampling process has been realized by overlapping a uniform grid over the high-density LiDAR data and randomly selecting just one LiDAR point belonging to the first return within each grid cell. In greater details, we generated datasets having 1, 0.75, 0.5, and 0.25 pt/m^2. Although the sensors were mounted on the same airborne platform during the simultaneous acquisition, we coregistered the data by using ground control points. In particular, the warped image has been obtained with a polynomial transformation of first order and a nearest neighbor resampling of the pixels. The RMSE resulting after the coregistration phase was 0.92 for Stand 1, 0.97 for Stand 2, 1.13 for Stand 3 and 1.22 for the wide area.

V. Experimental results

In order to assess the effectiveness of the proposed method, we defined two experiments. In the first experiment, we considered the 3 circular stand plots where we have ground reference data. In particular, we analyze the quantitative results in terms of single-tree height estimates obtained considering: i) the overall method; ii) the 3-D reconstruction model for those crowns hit by more than one LiDAR pulse; and iii) the k-NN trees technique. In the second experiment, we applied the proposed technique to a wide forest area. In this case, since we do not have any ground reference measure, we compared the results obtained with the height derived from the high-density LiDAR data. For both the experiments, the proposed method was tested on the low-density LiDAR data sets generated by undersampling the original high-density LiDAR data. For each data set, the tree crowns are automatically detected by means of the multisensor segmentation algorithm. Then the tree heights are estimated by the proposed approach on the basis of the number of hits associated to the crown.

The Gaussian and the Median convolution filters applied to the ortophoto in the preprocessing phase have window size of 5$\times$5. The Gaussian convolutional filter is characterized by a standard deviation equal to 10. In the segmentation phase the minimum number of pixels of each region has been set to 5. The choice of the parameters is based on the spatial resolution of the optical image and the expected minimum dimension of the tree crowns. Regarding the tree top reconstruction model, the ranges of parameters tested are as follows:

1) The crown curvature $cc \in$ [1.7, 1.9] with a step of 0.1.
2) The crown height $ch \in$ [10, 25] with a step of 1.

We tested a wide set of combinations of parameter values in order to model trees whose height ranges between 15.2 and 35.9 m (see Table II). Indeed, the proposed technique aims at automatically identifying the best model for each tree considering the LiDAR points information.

For those crown hit by one LiDAR point, we set the number of models to test n to 3. Similarly, the value of the k trees selected for reconstructing the tree top height of the missed crowns has been set to 3 in order to evaluate just the most similar crowns. In the following subsections we first present the results obtained on the 3 Stand Plots where we have ground reference data available (first experiment). Then, we report the analysis of the performance of the proposed technique on a wide area of coniferous forest (second experiment).

A. First Experiment: Results on the Stand Plots

Fig. 8 shows the comparison between the segmentation results obtained by using only the optical image and the results obtained integrating the lowest laser sampling density LiDAR data (i.e., 0.25 pt/m^2, which represents the worst case for the considered data sets). While in a dense forest scenario the shadows that surround the trees help in distinguish the forest from the ground, in open field areas, it is difficult to obtain accurate discrimination by using only the optical image. The additional information conveyed by the LiDAR

Table II
NUMBER OF TREES, AVERAGE VALUE OF ALTITUDE, SLOPE AND ASPECT, MEAN AND RANGE OF THE TREE HEIGHTS FOR EACH SAMPLE PLOT

Plot	N.	Central Point		Altitude	Slope	Aspect	Height(m)	
	Trees	Coordinate N	Coordinate E				Mean	Range
Stand 1	71	$46°18'4{,}16''$	$11°45'13{,}80''$	1401 m	6°	264°	23.3	19.3 - 29.2
Stand 2	32	$46°18'26{,}79''$	$11°45'20{,}77''$	1550 m	13°	131°	26.6	15.4 - 35.9
Stand 3	48	$46°18'8{,}95''$	$11°45'34{,}55''$	1554 m	9°	253°	26.9	15.2 - 34.2

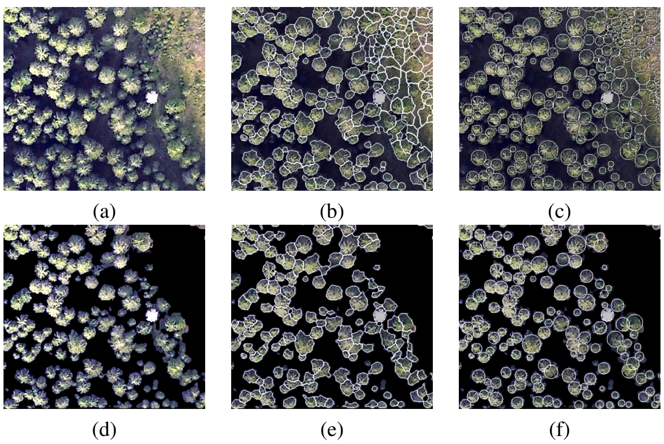


Figure 8. Masking procedure process. (a) Ortophoto of Stand 2. (b) Tree crown delineation result obtained by applying the segmentation algorithm directly to the ortophoto. (c) Circular representation of the detected crowns based on the median crowns radius derived from the segmentation result. (d) Masking process result by using the lowest laser sampling density dataset (i.e., 0.25 pt/m^2); (e) multisensor segmentation result. (f) Circular representation of the detected crowns based on the median crowns radius derived from the multisensor segmentation result.

Table III
NUMBER OF TREES DETECTED BY THE MULTISENSOR SEGMENTATION ALGORITHM COMPARED TO THE NUMBER OF DOMINANT TREES ASSOCIATED TO GROUND DATA AND ME, MAE AND MSE OF THE ESTIMATED CROWN RADIUS

Plot	N. Dominant	N.Detected	Percentage of	Estimated Crown radius		
	Trees	Trees	Detected Trees	ME	MAE	MSE
Stand 1	72	71	99 %	-0.36	0.57	0.74
Stand 2	33	32	97 %	-1.04	1.10	1.44
Stand 3	50	48	96 %	-0.82	-0.89	1.09
All Stands	155	151	97 %	-0.65	0.78	1.04

data in the masking procedure [see Fig. 8d] allowed a better discrimination between trees and bare soil. Indeed, as one can notice from the segmentation results, the fusion between the LiDAR derived height information and the optical image increased the crown delineation accuracy by avoiding that ground pixels were merged inside the tree crowns. The quality of the crown delineation results affects the accuracy of the height estimation, since the derived crown radius and area are employed in tree top reconstruction step and in the k-

Table IV
ME, MAE AND MSE OF THE ESTIMATED TREE TOP AND THE MEASURED TREE TOP. THE AVERAGE HEIGHT ESTIMATION RESULTS OF ALL THE STAND PLOT IS PRESENTED DIVIDED PER LASER SAMPLING DENSITY

LiDAR	All Stands Plot					
	Measured tree top			Estimated tree top		
	ME	MAE	MSE	ME	MAE	MSE
1 pt/m^2	1.61	1.61	3.70	0.90	1.17	2.45
0.75 pt/m^2	1.74	1.74	4.78	0.75	1.31	3.32
0.50 pt/m^2	2.95	2.95	17.89	0.94	1.57	4.03
0.25 pt/m^2	8.20	8.20	134.23	0.27	2.48	11.77

NN trees criterion, respectively. In order to evaluate the segmentation accuracy of individual tree level, we compared the crown radius derived from the segmentation phase with crown radius measured *in situ* (see Tab. III). The results obtained demonstrate that the multisensor segmentation algorithm is able to detect the dominant trees present in the scene and to properly estimate the crown radius with a Mean Absolute Error (MAE) of 0.78 m.

Let us now consider the tree top height estimation results. Table IV presents the comparison between the measured tree top derived from the LiDAR data and the estimated tree top obtained by applying the entire method. The results confirm the effectiveness of the proposed technique, which always reduced the error with respect to the low-density LiDAR data. Considering all the stand plots, for the LiDAR datasets having 1 pt/m^2 the Mean Error (ME) was reduced of 0.71 m and the MAE of 0.44 m, whereas for dataset having 0.75 pt/m^2 there was an improvement of the ME of 0.99 m and of the MAE of 0.43 m. By decreasing the laser sampling density the difference increases. In the case of 0.5 pt/m^2 the ME decreased of 2.01 m and the MAE of 1.38 m, whereas with 0.25 pt/m^2 the ME decreased of 7.93 m and the MAE of 5.72 m. It is worth noting that we obtained a small MAE as it ranges from 1.17 m (datasets of 1 pt/m^2) to 2.48 m (datasets of 0.25 pt/m^2) on an average height value of 25 m (approximately the 10% of average tree height value). These results contain all the sources of errors (included the segmentation errors).

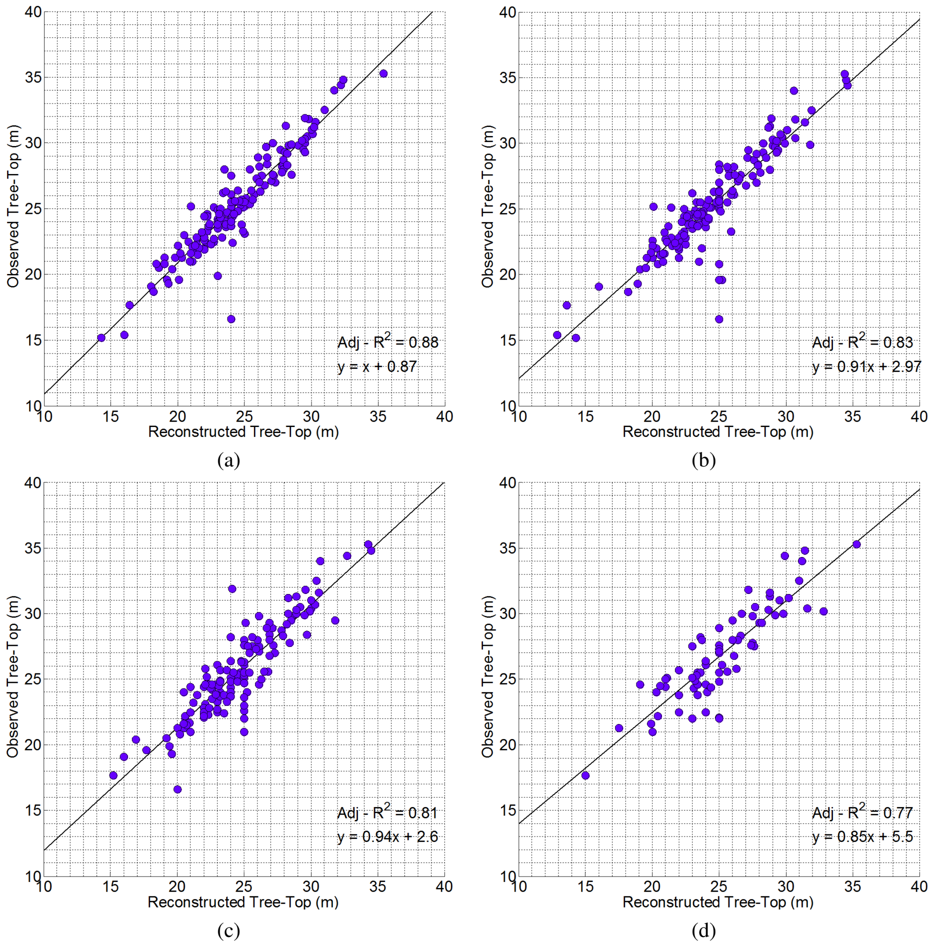


Figure 9. Reconstructed versus observed tree top height for the trees hit by more than 1 LiDAR point. The height estimation results of all the stand plots is presented for (a) the dataset having density of 1 pt/m^2, the (b) dataset having density of 0.75 pt/m^2, the (c) dataset having density of 0.5 pt/m^2, and the (d) dataset having density of 0.25 pt/m^2.

By analyzing the MAE of the measured tree top, one can observe that, as expected, it is equal to the ME since the LiDAR data systematically underestimate the tree top Height. In contrast, the ME obtained with the proposed method was closed to zero (almost unbiased estimate) for all the stands (i.e., 0.90 for the datasets of 1 pt/m^2, 0.75 for the datasets of 0.75 pt/m^2, 0.94 for the datasets of 0.5 pt/m^2 and 0.27 for the datasets of 0.25 pt/m^2). Furthermore, while the Measured tree top estimates were strongly affected by the decreasing of laser sampling density, the proposed method achieved similar accuracies for all the LiDAR density considered. Indeed, by halving the laser sampling density the error metrics of the Measured tree top were almost doubled, whereas the proposed method slightly increased the error metrics.

Fig. 9 depicts the scatterplots of the measured versus the reconstructed tree top height for the trees hit by more than one laser pulse, divided per laser sampling density. The results shows that the geometric representation of the shape of the crown effectively reconstruct the real height of the trees. By decreasing the laser sampling density the number of laser pulses associated to each crown decreases. However, for all the datasets the coefficient of variation (Adj $-R^2$) ranges between 0.77 to 0.88.

Table V

ME, MAE and MSE of the Estimated Tree Top and the Measured Tree Top. The Average Height Estimation Results Are Presented Divided per Number of Hits Associated to the Crowns.

LiDAR points		All Datasets					
		Measured tree top			Estimated tree top		
	N. Trees	ME	MAE	MSE	ME	MAE	MSE
$>$ 1 Point	510	2.15	2.15	7.12	1.02	1.41	3.47
1 Point	59	4.98	4.98	33.53	-0.08	2.25	9.28
k-NN Trees	35	22.83	22.83	532.59	-2.32	3.79	26.86

Table V shows the tree top height estimates versus the number of hits associated to the crowns. As expected the most accurate results are obtained when the tree crowns are hit by more than one LiDAR point. For those crowns, we obtained a MAE error of 1.41 m. By reducing the number of points associated to the crown to one, the error values slightly increased. This is due to the suboptimal choice of the parameters ch and cc, which affected the performance of the tree top height estimation. Indeed, with more than one

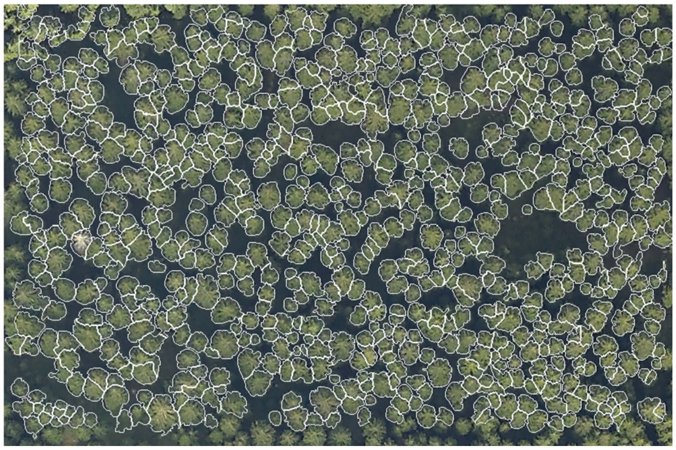


Figure 10. Segmentation result obtained on the wide coniferous forest. The border of the segmented regions are shown in white and are overlapped on the ortophoto.

Table VI
ME, MAE AND MSE OF THE ESTIMATED TREE TOP AND THE MEASURED TREE TOP PRESENTED DIVIDED PER LASER SAMPLING DENSITY

Datasets	Measured tree top			Estimated tree top		
	ME	MAE	MSE	ME	MAE	MSE
1 pt/m^2	1.15	1.15	2.50	0.31	0.97	2.13
0.75 pt/m^2	1.46	1.46	3.92	0.33	1.19	3.13
0.50 pt/m^2	2.79	2.79	16.16	1.20	1.96	7.08
0.25 pt/m^2	4.33	4.33	41.22	1.36	2.39	9.86

LiDAR point per crown it was possible to choose the model parameters more suited to the real shape of the considered tree crown. In contrast, with just one LiDAR point the model was selected only on the basis of the distance of the LiDAR point from the crown center and thus the accuracy of the height estimation decreased. Regarding those crowns that were not hit by any LiDAR point, the MAE is 3.79 m, while the low-density LiDAR could not obtain any measure for these trees.

B. Second Experiment: Results on All the Considered Forest Areas

The purpose of this experiment was to test the proposed technique on all the considered test forest. The considered image extends across an area of 1.9 Ha, where the multisensor segmentation identified 740 trees. Fig. 10 shows in white the border of the obtained segmented regions overlapped on the ortophoto. A qualitative visual analysis of the results confirms that the multisensor segmentation algorithm obtained a reliable delineation of the tree crowns. Similarly to the previous experiment we considered the four low-density LiDAR data. In this experiments since we do not have any ground measure, we used as reference the tree heights measured by the high-density LiDAR data.

Table VI presents the comparisons between the Measured tree top Height and the Estimated tree top height. The height estimates confirmed the results obtained in the first experiment. The proposed technique reduced all the error metrics with respect to the low-density LiDAR measures for all the considered data sets, also in this case. Moreover, we can observe that by decreasing the laser sampling density, the accuracy of the height estimation of the low-density LiDAR data decreases, whereas the accuracy of the proposed technique is not heavily affected. In greater detail, the ME of the Estimated tree top ranged from 0.31 m to 1.36 m and the MAE ranged from 0.97 m to 2.39 m for all the low-density LiDAR datasets, whereas the ME and the MAE of the Measured tree top ranged from 1.15 m to 4.33 m. Furthermore, we can again observe that the proposed method mitigated the systematic underestimation of the tree height.

VI. DISCUSSION AND CONCLUSION

In this paper, we a have presented a novel approach to the estimation of the tree top height at single tree level based on the fusion of low-density LiDAR data and very high-resolution optical images. This approach can be employed in coniferous forest scenarios when the density of the LiDAR data available is not sufficient for an accurate estimation of the height of each single tree.

The proposed technique exploits the synergistic use of the two data sources in order to obtain accurate height estimates at single tree level. In order to identify all tree crowns present in the scene, a multisensor segmentation algorithm is applied to the optical image by integrating the height information provided by the LiDAR data. Starting from the segmentation result, the proposed technique classifies the tree crowns between those hit by at least one LiDAR pulse and those that are not hit by any LiDAR pulse. For those crowns hit by more than one LiDAR pulse, a 3-D parametric model of the tree is applied to reconstruct the real height value starting from the height information provided by the LiDAR measures. The model is adapted to the shape of the tree both in the horizontal and vertical directions. The crown radius and the tree top position in the horizontal plan adopted by the parametric model are derived from the segmentation results, while the vertical structure of the crowns is modelled by fitting the LiDAR points associated to the crown. For those crowns missed by the laser scanner, a k-NN trees technique is defined for estimating the tree height as the average of the k reconstructed height of the trees having similar crown area and belonging to a sparse neighbourhood.

The experimental results obtained on the considered datasets made up of an ortophoto and low-density LiDAR data having laser sampling density of 1, 0.75, 0.5, and 0.25 pt/m^2 demonstrate the effectiveness of the proposed technique. In particular, the quantitative results obtained on the three sample plot confirm that the 3-D parametric model is able to correctly reconstruct the structure of the tree. Indeed, the higher is the number of LiDAR points associated to the tree crowns the better is the choice of the parametric model and thus, the tree top height estimation. This is confirmed by the fact that reducing the number of points associated to the tree crown to one, the accuracy of the height estimation decreases. Regarding the results obtained on those crowns that are not hit by any LiDAR point, the error metrics only slightly increased with respect to those obtained by applying the reconstruction model. However, the k-NN trees technique allows the estimation of the height for those crowns which are not measured by LiDAR. Accordingly, the height estimate of the entire stand plot is strongly improved by the introduction of the proposed method.

The robustness of the proposed technique is confirmed by the results obtained on the dataset characterized by a wide area coverage. The significant reduction of the estimation errors becomes more evident when we deal with very low-density LiDAR data (i.e., 0.5 and 0.25 pt/m^2). Moreover, the height estimation results are almost unbiased and thus do not systematically underestimate or overestimate the tree height. On the contrary the laser sampling density results in strongly underestimated height values due to both the missed tree top by the laser pulses and the missed detection of tree crowns.

As future developments of this work, we will investigate other strategies for selecting the 3-D parametric model for those crowns hit by just one LiDAR point, in order to better adapt the model to the real shape of each considered tree. Moreover, we plan to analyze the performance of the k-NN trees technique by using in the search of similar trees also terrain properties such as slope and aspect.

VII. Acknowledgement

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