A Triangulation-Based Technique for Tree-Top Detection in Heterogeneous Forest Structures Using High Density LiDAR Data

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A Triangulation-based Technique for Tree-top Detection in Heterogeneous Forest Structures Using High Density LiDAR Data

Daniele Marinelli, Claudia Paris, *Member, IEEE,* and Lorenzo Bruzzone, *Fellow, IEEE*

***Abstract*—This letter presents a novel approach to tree-top detection in heterogeneous forest structures characterized by mixed species using high-density Light Detection and Ranging (LiDAR) data. Although literature techniques can achieve accurate results in even-size and even-age homogeneous forests, they detect several false tree-tops in forests characterized by variable crown dimensions. To solve this problem, the proposed method: (1) identifies a preliminary set of candidate tree-tops (CTPs) used to build a triangulated network, (2) performs an edge-based local forest analysis to identify groups of CTPs having the highest probability of belonging to the same crown, and (3) removes false tree-tops according to a local directed graph analysis. To address large-scale forest analysis, the method exploits the Delaunay triangulation that efficiently defines a network topology made up only by relevant edges, thus sharply reducing the edge-based analyses to be performed. Given the triangulated network properties, the computational effort of the local analysis is not affected by the network size. The method has been tested in a mixed multi-layer multi-age forest located in the southern Italian Alps. The results obtained demonstrate that this computationally scalable algorithm outperforms standard tree-top detection methods increasing the overall detection accuracy up to 15.3%.**

***Index Terms*—Tree-top detection, Canopy Height Models (CHM), Forestry, Light Detection and Ranging (LiDAR), Delaunay Triangulation, Remote Sensing (RS).**

I. Introduction

HIGH-density Light Detection and Ranging (LiDAR) data have demonstrated their effectiveness to perform detailed forest mapping [1]. At single tree level, the prerequisite for an accurate estimation of forest parameters is a reliable tree-top detection. This analysis is typically conducted in the Canopy Height Model (CHM), the raster image interpolated from the LiDAR point cloud. A filtering operation is usually applied to smooth the CHM and the peaks are identified according to the use of different possible approaches such as for example maxima filtering. The accuracy and applicability of existing tree-top detection methods is hampered by the need of parameters tuning (e.g., filtering parameters or local maxima window size), which should be adaptive for heterogeneous forest structures. While conifers present a conical crown shape usually dominated by a local maximum, broad-leaves are characterized by almost flat round canopies, where multiple prominent local maxima are present [2]. Moreover, the shape and the size of the broad-leaves canopies are totally different from those of the conifers. Thus parameters tuning one forest type, often reduces the detection accuracy on the other. This is true also for uneven-age forest study areas, where old-growth conifers have larger crown sizes compared to younger trees of the same species. In [3], eight tree-top detection methods are compared over different forest types and structures. As expected, all the methods achieve the best accuracy on single-layered coniferous forests, whereas the multi-layered mixed forests show the lowest detection rates regardless of the method. Besides the peculiar properties of the considered forest structure, also the topography plays an important role in the tree-top detection as demonstrated in [4], [5]. Both the terrain slope and the topographic normalization approach (used to generate the CHM) introduce a tree-top displacement which may affect the detection. Regardless of the specific forest conditions, one of the main limitations of existing tree-top detection methods is that they do not take advantage of the crown structure information [6]. Although this is a valuable information source that can improve the tree-top detection, the complex information is typically discarded to reduce the computation lead on large scale tests,

This letter proposes a novel automatic triangulation-based technique which aims to accurately detect tree-tops in heterogeneous forests in a fast and efficient way. Differently from the literature, the technique refines the preliminary set of tree-tops identified by standard tree-top detection methods by using the local forest environmental information which is modeled using a triangulated local network topology. The method has been tested in a study area located in the southern Italian Alps, where high resolution LiDAR data (i.e., up to 50 pulses per m^2) are available. Due to the peculiar topography, the presence of multi-age and multi-layered trees belonging to both broad-leaves and conifer species, the considered study area represents a complex test case. The results obtained demonstrate the effectiveness of the proposed method, which sharply reduces the false tree-tops detected by standard state-of-the-art approaches.

II. Proposed Method

Figure 1 shows the architecture of the proposed method, which is based on three main phases: (i) tree-tops triangulated network generation, (ii) edge-based local forest area analysis and, (iii) local directed graph analysis. The input data is the filtered CHM, obtained by rasterizing the normalized LiDAR point cloud (i.e., after terrain subtraction) and by applying an

Daniele Marinelli, Claudia Paris and Lorenzo Bruzzone are with the Department of Information Engineering and Computer Science, University of Trento, 38122 Trento, Italy (e-mail: lorenzo.bruzzone@unitn.it)

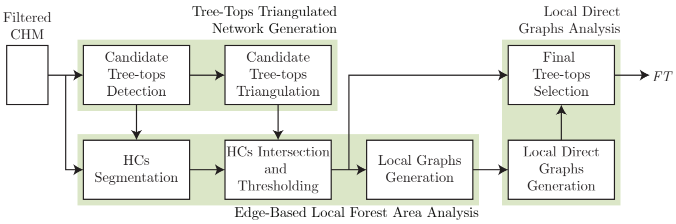


Fig. 1: Flow scheme of the proposed method. The green blocks represent the 3 phases.

average filtering with kernel size of $K \times K$ pixels. Note that, differently from existing literature methods, in the proposed technique the filtering is only a pre-processing step to discard the most obvious false tree-tops. Thus the choice of the K value is not critical for the final results of the method. First, a preliminary set of candidate tree-top (CTP) is identified by using a standard tree-top detection method. Then, the goal of the proposed technique is to automatically identify groups of CTPs having the highest probability of belonging to the same crown. To this end, we determine the relationship between each CTP and its surrounding ones. Indeed, while the CHM features of a false tree-top may be very similar to the ones of a true tree-top (i.e, they are both local maxima), by enlarging the analysis in the local forest environment more discriminant features can be identified. To avoid high computational effort, such an analysis is performed considering small groups of locally connected tree-tops.

A. Tree-Tops Triangulated Network Generation

The first phase of the method identifies a preliminary set of candidate tree-tops in the scene. We exploit a Level Set Method (LSM) technique, which is more robust to noise in the CHM with respect to standard local maxima approaches [7]. However, any other technique can be used. The LSM generates a set $CT = \{ct_i\}_{i=1}^{N}$ of N candidate tree-tops, where each $ct_i = \{x_i, y_i, z_i\}$ represents the CTP location (x_i, y_i) and height (z_i). The preliminary tree-top detection is expected to include several false trees, especially in forest characterized by heterogeneous environmental condition. We aim to identify the false tree-tops by performing a local contextual analysis around each CTP.

For each ct_i, its neighbouring CTPs are identified to generate a network (i.e., define a set of edges locally connected to ct_i). To achieve this goal in a fast and efficient way, it is necessary to minimize the number of edges that have to be analyzed without discarding none of the relevant ones. Since we are dealing with points located in a 2-D space, i.e., $\{x_i, y_i\}_{i=1}^{N}$, the set of defined edges must satisfy two requirements: (i) the edges do not overlap and, (ii) the edges connect only spatially close CTPs. Nearest neighbors strategies are usually considered [8]. However, the results are strongly affected by the distance threshold. Moreover, such methods do not guarantee for an efficient and consistent definition of the edges and may not be compliant with the listed requirements. Therefore, we use a point-set triangulation to connect the CTPs with non-overlapping edges defined in their local neighbourhood, without the need of tuning any parameters. To this end, we consider the Delaunay triangulation that has the peculiar property of generating a network where no vertex (i.e., set CT) is inside of any circumcircle of the triangulation's triangles. This makes the triangulation unique and maximizes the minimum angle of all the obtained triangles, thus minimizing the number of sliver triangles. Such sliver triangles are typically composed by edges connecting CTPs far from each other or edges that almost overlap. Therefore, they are not informative for the problem in analysis. Note that the Delaunay Triangulation has been used for LiDAR data processing to generate Triangulated Irregular Network (TIN) [9] and to delineate individual tree crown [10]. However, to the best of the author's knowledge, such triangulation approach has never been used to improve the tree-top detection.

Let the planar graph $G = (V, E)$ represent the triangulated network obtained on the whole study area, where $V \equiv CT$, and E is the set of connecting edges. Let us focus the attention on the edge e_{ij} that connects the neighbouring tree-tops ct_i and ct_j. By analyzing the geometrical features associated to the edge (see next section), it is possible to characterized the local forest environmental properties. Indeed, even though the triangulation covers the entire area of interest, the edges connect only spatially close CTPs while minimizing the number of connections thus improving efficiency. Figure 2 depicts an example of the resulting local triangulated network showing the local properties of the latter.

B. Edge-Based Local Forest Area Analysis

Using the triangulated network computed in the previous phase, the method works at the edge level to perform a local analysis of the forest structure. Let us focus the attention on edge e_{ij}. We study the spatial interaction of ct_i and ct_j by analyzing the intersection area between their hypothetical crown (HC) areas. We define as HC the two dimensional polygon representing the boundaries of the hypothetical crown. It is reasonable to assume that if two CTPs belong to the same tree, their HCs areas may intersect significantly more than for candidates belonging to different trees. Indeed, in the case where a tree is correctly associated with only one tree-top, its HC boundaries will likely match the actual boundaries of the real crown thus showing little (or no) intersection with HC belonging to different trees. In contrast, in the case that two or more CTPs are detected for one tree, their HCs areas are expected to intersect significantly more. Accordingly, we aim to exploit such a property to automatically identify edges connecting CTPs having the highest probability of belonging to the same tree crown.

To identify the HC polygons, we apply a segmentation algorithm to each CTP in CT. We used an algorithm based on a standard directional analysis in the CHM that searches for local minima in multiple directions starting from the CTP [11]. Note that the objective of this step is not to obtain an accurate tree crown segmentation, since multiple CTPs may belong to the same crown, but a rough estimate of the HC boundaries. Accordingly, the obtained regions (i.e., the HC polygons) are discarded after this step. This step generates

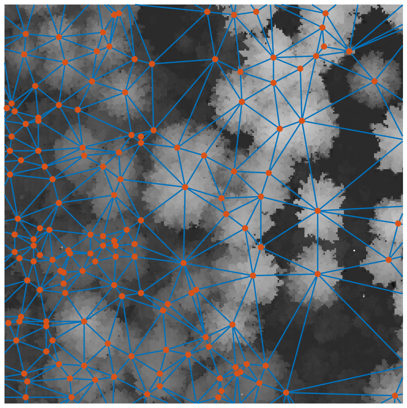
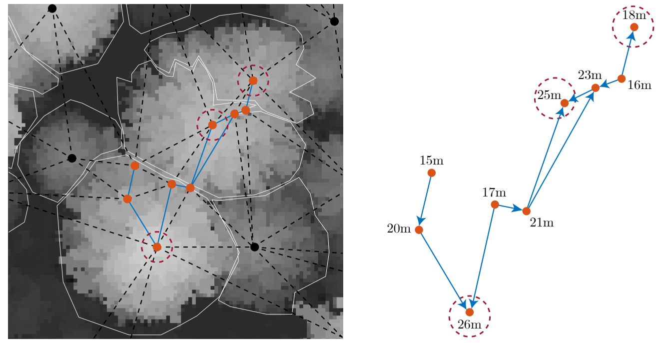


Fig. 2: Example of CTP triangulated network represented on the CHM. The orange dots are the CTPs of CT while the blue lines represent the edges in E.



(a) (b)

Fig. 3: Example of local graph analysis where the selected CTPs are highlighted by red dashed circles: (a) the blue edges denote the local planar graph, while the black ones represent the edges for which $\eta \leq T_\eta$ (white lines indicates the crown boundaries manually delineated), (b) corresponding local directed graph with the values of z_i reported per CTPs.

a set $SP = \{sp_i\}_{i=1}^{N}$ of N segmentation polygons where sp_i represents the polygon associated to ct_i. Focusing on a generic edge e_{ij}, we can now compute the area of intersection $area(sp_i \cap sp_j)$ between the two polygons sp_i and sp_j. To obtain a comparable metric between different CTPs (i.e., the areas of the polygons may vary significantly across the forest) we define a normalized intersection metric η_{ij} as follows:

$$\eta_{ij} = \frac{area(sp_i \cap sp_j)}{\min\{area(sp_i), area(sp_j)\}}. \quad (1)$$

The normalized intersection η ranges from zero (i.e., no intersection) to one (when the smallest polygon is completely embedded in the larger one). The edges having the highest probability to connect CTPs belonging to the same tree crown (i.e., critical CTPs) are identified by applying a threshold T_η to the normalized intersection metric of each edge. The results is a new set of edges $E' = \{e_{ij} | \eta_{ij} > T_\eta\}$.

In the last step of this second phase, we explore the triangulated network to search for groups of CTPs that are connected by the edges belonging to E'. This operation generates a set of M small local planar graphs $\mathcal{G} = \{G_m\}_{m=1}^{M}$ where each graph connects only CTPs having high probability of belonging to the same tree crown. Figure 3a shows an example of a local graph plotted over the CHM where the edges with $\eta > T_\eta$ are depicted in blue. The CTPs that are not connected to edges in E' (black dashed edges) are considered as true tree-tops and added to the final set of tree-tops FT (represented as black dots). Note that moving from the edge-based analysis to the local forest analysis only for the critical CTPs allows us to limit the computational load of the method.

C. Local Directed Graph Analysis

The last phase of the proposed method individually analyzes the local graphs, connecting critical CTPs, in $\mathcal{G}$ to identify only the true tree-tops. Let us focus on the generic planar graph $G_m = (V_m, E_m)$, where V_m is a subset of CT and E_m is a subset of set E'. To determine which CTPs V_m belonging to G_m are true tree-tops, we transform G_m into a directed graph. For each edge $e_{ij} \in E_m$, we consider the height of the two connected CTPs (i.e., z_i and z_j) to define the edge direction as:

$$\text{direction of } e_{ij} = \begin{cases} ct_i \rightarrow ct_j & \text{if } z_i \leq z_j \\ ct_i \leftarrow ct_j & \text{if } z_i > z_j \end{cases} \quad (2)$$

We then compute for all the $ct_i \in V_m$ the outdegree (i.e., $\deg^+(ct_i)$) which represents the number of outbound edges from the corresponding CTP (i.e., the number of edges for which ct_i is the starting point). Finally, we select as tree-tops to be added to set FT the vertices having an outdegree index equal to zero (i.e., only inbound edges connected to the considered vertex). Note that the use of the height information to select only CTPs that are surrounded by lower points in the graph, sharply increases the probability of defining as tree-top the highest point of the crown. Moreover, if the graph spans multiple tree crowns, this strategy decreases the risk of increasing the number of omission errors. Figure 3b shows a real example of local directed graph, where the CTPs with outdegree equal to zero are highlighted with red dashed circles.

III. Dataset and Experiments Description

To test the effectiveness of the proposed method, we considered a 10 ha forest area in the southern Italian Alps in the Trento province (central coordinates 46° 17' 57", 46° 17' 57"). It is characterized by mixed tree species composition with Norway spruce (*Picea abies*) and European larch (*Larix decidua*) representing the 60% of the tree species, while broadleaves represent the remaining 40% (i.e. Aspen (*Populus tremula*), Common alder (*Alnus Glutinosa*), Common Hazel (*Corylus avellana*) Silver birch (*Betula pendula*) and Willow (*Salix*)). Table I shows the range, average and skewness of dendrometric measurements that characterize the considered area. The LiDAR point cloud was acquired in 2012 by a Riegl LMS-Q680i sensor with a mean pulse density of 60 pulses/m^2. To obtain quantitative results, we manually delineated 998 tree crowns by joint photo-interpretation of the CHM and the point cloud. In the considered area, for a subset of trees (130),

TABLE I: Range, average and skewness of dendrometric measurements that characterize the considered area (DBH = Diameter at Breast Height).

Parameter	Minimum	Maximum	Mean	Skewness
DBH [cm]	5.0	89.0	32.3	0.7
Top Height [m]	2.5	39.8	21.5	0.1
Crown Area [m^2]	0.03	123.7	17.0	1.6

ground reference data on the tree species are available. For those trees, the tree species was considered to present the results divided per conifers and broad-leaves.

The resolution of the CHM has been set equal to 0.25 m given the pulse density of the considered LiDAR data. One of the most important parameters to be tuned is the average filter kernel size K. Such parameter is typically defined according to the CHM spatial resolution and the average crown size of the considered forest area. However, in mixed forest condition a large kernel size introduces many omission errors (small trees) whereas a small kernel size sharply increases the number of false trees (large crowns). To assess the effectiveness of the proposed method and validate its sensitivity to the smoothing factors, we tested three kernel sizes $K = 5, 7, 9$. The threshold value on the normalized area intersection $T_\eta \in [0, 1]$ was set equal to 0.75. We selected such high value to reduce the probability to generate local graphs in $\mathcal{G}$ that span too many crowns. Such conservative value can be considered regardless of the forest structure since T_η is used to select the groups of CTPs to be analyzed in the final phase of the method, but it does not directly decide if a CTP has to be discarded.

The quantitative results are evaluated in terms of omission errors (OE), commission errors (CE) and overall accuracy (OA) which is defined as:

$$\frac{\mathrm{TOT} - \mathrm{OE}}{\mathrm{TOT} + \mathrm{CE}} \tag{3}$$

where TOT is the total number of reference trees. Moreover, we consider an additional metric defined as Correct Crown Detection (CCD) that counts the tree crowns where just one tree-top has been detected. Differently from the standard metrics that evaluate a tree correctly identified if at least one candidate tree-top is present in the crown, the CCD metric considers as correct detection only trees associated with a single tree-top. For example, if the method detects 4 CTPs for one tree, the tree is considered detected with 3 commission errors, but it is not included in the CCD metric. The proposed method has been compared with the widely used LSM technique [3] and the method proposed in [12] that we define Point Cloud Domain Method (PCDM). Note that the latter works directly in the point cloud and thus it is not influenced by the CHM resolution and the filtering size K.

IV. Experimental Results

Table IIa shows the OE, CE, OA and CCD obtained for the proposed and literature methods, for different values of K. For the considered CHM spatial resolution, the best case is obtained by setting $K = 7$. This case achieves both the highest accuracy and CCD with respect to the two baseline methods, with a good trade-off between CE and OE for the different crown sizes present in the scene. From the table, one can see that the proposed technique achieves the highest OA with respect to the baseline LSM regardless of the smoothing factor proving the method robustness to variations of K with respect to existing literature techniques. As expected, the heavier the smoothing filtering applied to the CHM, the lower the OA gain of the method with respect to the baseline LSM is. Indeed, the application of heavy averaging filters reduces the CE of the LSM, thus decreasing the capability of the proposed method of improving the OA by detecting such errors. However, such filtering sharply increases the OE, thus leading to poor tree-tops detection results. Indeed, when moving from $K = 7$ to $K = 9$, the LSM shows a little increase of OA since the decrease of CE is almost completely balanced by the higher number of OE. Moreover, the proposed method always decreases significantly the CE without increasing too much the OE regardless of the K parameter. In particular, it decreases the CE with respect to the LSM of 34.9%, 10.4%, 5.9% against a slight increase of the OE of the 1.9%, 3.1%, 3%, for $K = 5, 7, 9$ respectively.

Table IIb shows the results obtained per tree type by the three methods (with $K = 7$ for the proposed and LSM techniques). The proposed method achieved the highest OA and CCD with respect to the two methods for both conifers and broad-leaves trees. Focusing first on conifers, the proposed approach removed 9 CE (-10.7%) with an increase of 2 OE (+2.4%) compared to the baseline LSM. The highest increase of OA is obtained for the class of broad-leaves, where the proposed method shows an increase of 13.3% due to the removal of 13 CE (-28.3%) with an addition of 1 OE (+2.2%). Indeed, as expected broad-leaves are strongly affected by many false tree-tops. For the PCDM, the larger improvement of performances is for the conifers class with an increase of OA of 12.9% which is due to a decrease of 15 CE (-17.9%) and one additional OE (+1.2%). The increase of OA is smaller for the broad-leaves class (+1.4%). These results are also confirmed by the CCD obtained by the proposed method which is higher than those of both literature methods regardless of the class type. This metric emphasizes the capability of the method of reducing the CE by properly identifying the tree crowns present in the scene, which is important for the correct forest parameter estimation at individual tree level (e.g., tree biomass, crown size, tree base height).

We also evaluated the method in terms of computational performances to assess its scalability on large forest areas. All the tests have been performed with a MATLAB implementation running on an Intel i5-4590 3.3 GHz with 16 GB of Random Access Memory (RAM). The total runtime of the proposed method (with $K = 7$) is of 17.8 seconds for the analysis of 2551 CTPs and a triangulation composed by 7585 edges. This roughly corresponds to 7 milliseconds for CTP. The highest computational load is the segmentation step (13.7 seconds), which however can be parallelized as each CTP can be analyzed independently. While the computation of the intersection area between two polygons can be quite heavy, the Delaunay triangulation allows us to strongly limit the number of edges to which apply this operation thus reducing

TABLE II: Omission Errors (OE), Commission Errors (CE), Overall Accuracy (OA) and Correct Crown Detection (CCD) obtained by PCDM, the LSM and the proposed methods: (a) results for different kernel window size $K = 5, 7, 9$ for all the 998 trees, (b) results for the different forest species considering the kernel window size $K = 7$ (for 130 trees).

(a)

Kernel Size K	**# Reference Trees**	**PCDM [12]**				**LSM**				**PROPOSED**			
		OE	CE	OA [%]	CCD	OE	CE	OA [%]	CCD	OE	CE	OA [%]	CCD
5	998					11	616	61.2	692	30	268	76.5	812
7	998	103	104	81.2	809	35	157	83.4	848	66	53	**88.7**	**884**
9	998					93	80	84	836	123	21	85.9	857

(b)

Class	**# Reference Trees**	**PCDM [12]**				**LSM**				**PROPOSED**			
		OE	CE	OA [%]	CCD	OE	CE	OA [%]	CCD	OE	CE	OA [%]	CCD
Conifers	84	1	18	81.4	69	**0**	12	87.5	75	2	**3**	**94.3**	**79**
Broad-leaves	46	1	12	77.6	34	**0**	24	65.7	30	1	**11**	**79**	**35**

the impact of this step (2.9 seconds), which can also be parallelized. Another significant advantage of the triangulation is the possibility of working at local level regardless of the forest size. Indeed, the computational load of the analysis carried out per CTP is not affected by the size of graph G. Therefore, the computational complexity of the method increases linearly with the number of CTPs. In terms of RAM usage, the segmentation step requires a maximum of 45 MB, while all the other operations require no more than 8 MB.

V. Conclusion

This paper presented a tree-top detection method that aims to accurately handle mixed forest characterized by heterogeneous structures. The method first identifies a set of candidate tree-tops, the CTPs. Then, the Delaunay triangulation is used to efficiently define a network topology composed by edges that connect neighbouring CTPs. An edge-based local forest analysis is carried out to detect groups or pairs of CTPs having the highest probability of belonging to the same tree crown. Finally, a local direct graph analysis is performed to define the final set of tree-tops. The quantitative results show an improvement of OA with respect to the baseline LSM for all the filter size and with respect to method that works in the point cloud domain (PCDM). This is due to the capability of the method of identifying and removing the CE without increasing significantly the OE. The numerical results obtained considering only conifers or broad-leaves show an increase of OA for both classes. Such results demonstrate the capability of the method of working in mixed forest condition characterized by heterogeneous environmental properties. The method also proved to be computationally efficient due to the local properties of the triangulation.

As future developments, we plan to improve the segmentation step considering different strategies (e.g., hybrid of directional analysis and watershed segmentation) and to test the method on other forest areas characterized by different heterogeneous environmental conditions and tree species distributions. Moreover, we plan to investigate other geometrical contextual features which may further improve the detection results.

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