FUSION OF HIGH AND VERY HIGH DENSITY LIDAR DATA FOR 3D FOREST CHANGE DETECTION

Daniele Marinelli, Claudia Paris, Lorenzo Bruzzone

Dept. of Information Engineering and Computer Science, University of Trento
Via Sommarive, 5, I-38213, Povo, Trento, Italy

ABSTRACT

Light Detection And Ranging (LiDAR) data have proven to be very effective in the estimation of parameters for forestry applications. However, little research has been done regarding the multitemporal analysis of these data. In this paper we propose a novel hierarchical change detection approach that first performs the detection of major changes (e.g., harvested trees) and then focuses on the detection of minor changes (e.g., single tree growth), using multitemporal LiDAR data having different point densities. Splitting the change detection problem allows us to analyze the different types of changes with different techniques. In particular, the detection of minor changes is carried out directly on the point clouds in order to exploit all the informative content of the LiDAR data. The approach has been tested on a dataset acquired in 2010 and 2014 on a complex forest area located in the Southern Italian Alps. The experimental results confirm the effectiveness of the proposed approach.

Index Terms— 3D change detection, multitemporal analysis, Light detection and Ranging (LiDAR), remote sensing, forestry.

1. INTRODUCTION

Nowadays, it is necessary to perform a regular forest monitoring for the preservation of the environment. In this framework, LiDAR sensors allow an accurate estimation of the forest parameters due to their capability of measuring the 3D structure of the crowns. However, while a lot of effort has been devoted to the analysis of the LiDAR point cloud for single acquisitions, little work has been done regarding the multitemporal analysis of these data. Indeed, the comparison of pairs of LiDAR point clouds introduces several challenges that have to be carefully addressed: i) the LiDAR point density may be significantly different between the considered acquisitions, ii) the laser may penetrate different parts of the canopy in the two acquisitions, iii) the tree canopies are natural structures with highly irregular properties. Hence, it is not possible to perform a point to point comparison. For these reasons, most of the papers present in the literature work only on the 2D rasterized version of the LiDAR data (i.e., the Canopy Height Model (CHM)). Typically the existing works focus the attention on the detection of major changes such as canopy gaps or harvested trees [1, 2] and on the vertical growth of the forest [1, 2, 3]. Few papers address the lateral growth of the trees by working on the CHM [2, 4]; however, these methods do not allow for the use of the full information content of the LiDAR data. In contrast, by working directly in the point cloud domain it is possible to perform a more detailed analysis.

In this paper, we propose a hierarchical change detection approach that first detects the major changes in the CHMs and then performs the analysis of the minor changes directly in the point cloud space. In particular, an object-based change detection is performed to analyze the growth of the crown (i.e., vertical growth and volume growth of the canopy). The method is divided into four main steps: i) pre-processing of the LiDAR point clouds; ii) detection of major changes; iii) identification and characterization of the canopy structure after matching the trees in the two point clouds having different point densities; iv) detection of minor changes. While the hierarchical approach allows us to decompose the change detection problem and thus to facilitate the multitemporal analysis, the object-based approach allows us to compare the LiDAR point clouds without using the CHM. The rest of the paper is organized as follows. Section 2 describes the proposed method. Section 3 presents the dataset and the experimental results. Finally, Section 4 draws the conclusion.

2. PROPOSED METHOD

The block scheme of the proposed method is shown in figure 1.

2.1. Pre-processing

The first step of the proposed method aims at preparing the data for the netxt steps. First, the two point clouds are registered by means of the Iterative Closest Point Algorithm (ICP)[5]. Then, the same digital terrain model (DTM) is subtracted from the two point clouds to obtain the relative height of the trees with respect to the ground. Finally, a regularization and interpolation process is applied to convert the

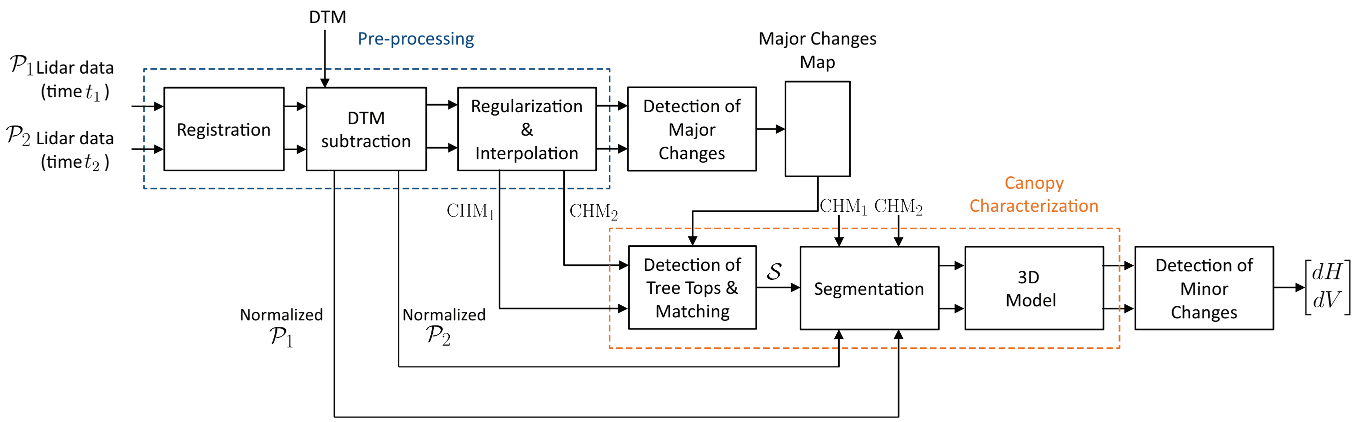


Fig. 1: Architecture of the proposed method.

LiDAR point clouds into the two CHMs (CHM_1 at time t_1 and CHM_2 at time t_2).

2.2. Detection of major changes

At the first level of the hierarchy we aim to detect the major changes, which are defined as significant variations between the two acquisitions. To this end, the most efficient approach is the analysis of the main height differences of the CHMs. First, the difference image between the two CHMs is computed. Second, a threshold is applied to the resulting image to obtain a binary map. Then, a morphological erosion filter is applied to remove the noise and the area of the remaining regions is evaluated to remove small object. Finally, a dilation filter (using the same structuring element of the erosion filter) is applied. By analyzing separately positive and negative values of the difference image it is possible to discriminate between positive changes (e.g., new trees) and negative changes (e.g., harvested trees). Moreover, we use the computed binary map in the detection of minor changes phase to focus only on the areas which are not affected by the major changes.

2.3. Canopy characterization

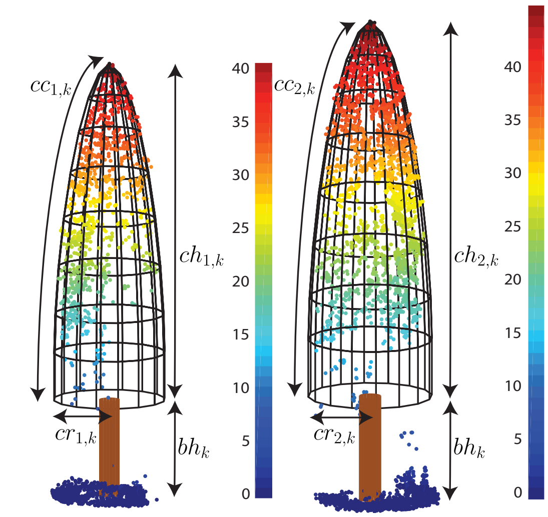
The object-based change detection aims to compare the same canopy between the two considered dates in order to monitor the growth of each individual tree. To this end, the canopy structure has to be accurately characterized. First, the tree tops are identified separately in the two CHMs by using a level set method, thus obtaining the tree tops positions at the two times. Let us define the resulting sets as $\mathcal{S}_1 = \{\mathbf{s}_{1,k_1}\}_{k_1=1}^{N_1}$ at time t_1 and $\mathcal{S}_2 = \{\mathbf{s}_{2,k_2}\}_{k_2=1}^{N_2}$ at time t_2, where $\mathbf{s}_{1,k_1} = (x_{k_1}, y_{k_1})$ and $\mathbf{s}_{2,k_2} = (x_{k_2}, y_{k_2})$ represent the 2D position of the tree tops at the two dates. For each point $\mathbf{s}_{1,k_1} \in \mathcal{S}_1$ the nearest tree top in $\mathcal{S}_2$ is selected according to:

$$\mathbf{s}_{2,\text{nearest}} = \min_{k_2 \in [1\,,..,\,N_2]} \| \, \mathbf{s}_{1,k_1} - \mathbf{s}_{2,k_2} \, \| \, . \tag{1}$$

If the distance between $\mathbf{s}_{2,\text{nearest}}$ and $\mathbf{s}_{1,k_1}$ is smaller than a given threshold the two tree peaks are matched. At the end of this step we obtain a single set of N seeds, defined as $\mathcal{S} = \{\mathbf{s}_k\}_{k=1}^{N}$, representing the trees present at both dates.
For each detected tree $s_k \in \mathcal{S}$ we need to delineate the crown in the two LiDAR data. To this end, we apply to CHM_1 and CHM_2 the segmentation method presented in [6]. For each seed, the crown boundaries are delineated by searching for the local minima along the eight main directions $(0°, 45°, \ldots, 270°, 315°)$. The resulting segmentation regions obtained are used to identify the individual crowns in the two data. Thus, for each tree s_k we obtain two point clouds $C_{1,k}$ and $C_{2,k}$ representing the canopy of the considered tree at time t_1 and t_2, respectively. As anticipated in Section 1, it is highly unlikely that the laser hits the same parts of the canopy at the two acquisition dates. In order to overcome this problem, we reconstruct the canopy structure by fitting a 3D ellipsoid [7] on the two segmented point clouds $C_{1,k}$ and $C_{2,k}$. Let us focus the attention on the general tree k_{th}. For the sake of simplicity, in the following we consider the same x_k, y_k coordinates of the tree top at the two dates while the tree top heights are defined as $H_{1,k}$ and $H_{2,k}$. The ellipsoid model is defined by the tree top positions $(x_k,\, y_k,\, H_{t,k})$, the crown radius $cr_{t,k}$, the crown height $ch_{t,k}$ and the crown curvature $cc_{t,k}$ with $t = 1,\, 2$. It is described as follows:

$$\frac{(z + ch_{t,k} - H_{t,k})^{cc_{t,k}}}{{ch_{t,k}}^{cc_{t,k}}} + \frac{\left[(x - x_k)^2 + (y - y_k)^2\right]^{cc_{t,k}}}{{cr_{t,k}}^{cc_{t,k}}} = 1$$
$$H_{t,k} - ch_{t,k}^{t} < z < H_{t,k}, \;\; t = 1,\, 2 \tag{2}$$

First, the base heights $bh_{1,k}$ and $bh_{2,k}$ of the canopy at the two dates are detected by analyzing the vertical profile of the two point clouds. It is reasonable to assume that there are no significant changes in the base height between the two dates. Hence, we select the minimum of the two quantities in order to obtain $bh_k = min\{bh_{1,k},\, bh_{2,k}\}$, thus reduc-



(a) $C_{1,k}$ and $E_{1,k}$ (b) $C_{2,k}$ and $E_{2,k}$

Fig. 2: 3D models fitted on the segmented point clouds.

ing the probability of overestimating the base height due to missing LiDAR points in the lower part of the canopy. Finally, the crown heights at the two dates can be estimates as $ch_{t,k} = H_{t,k} - bh_k,\ t = 1,\, 2$. The crown radius and crown curvature are estimated by means of a least square method which fits the 3D model to the points of the segmented LiDAR data. It is worth noting that due to the fact that the 3D ellipsoid represents the external surface of the canopy, the fitting has to be performed using only the external points of the point clouds. In order to better exploit the information of the two point clouds, first we carry out the fitting on the point cloud with the highest number of points and subsequently we apply the least square method to the other data adding a constraint based on the previous estimation. The constraint is based on the assumption that $cr_{1,k} \leq cr_{2,k}$. This operation uses the information of the data with higher density to improve the estimation on the point cloud with lower density. The computed parameters are then used to define the 3D ellipsoids $E_{1,k}$ and $E_{2,k}$ that represent the structure of tree s_k at times t_1 and t_2, respectively. Figure 2 shows a real example of the 3D models defined for the segmented point clouds of a given tree.

2.4. Detection of minor changes

The use of a mathematical model to describe the 3D structure of the canopy allows us to compare the characteristics of the same tree between the two dates irrespectively of the point densities. For the generic k_{th} tree we have the tree top heights $H_{1,k}$ and $H_{2,k}$ and the two 3D ellipsoids $E_{1,k}$ and $E_{2,k}$. The vertical growth is computed as $dH_k = H_{2,k} - H_{1,k}$. The volume growth analysis is carried out computing the difference of the volume of $E_{1,k}$ and $E_{2,k}$ defined as:

$$dV_k = \text{volume}(E_{2,k}) - \text{volume}(E_{1,k}) \qquad (3)$$

It is worth noting that dV_k is a metric of the crown volume change and not of the variation of biomass. This is due to the fact that the 3D ellipsoids represent the external surface of the canopy. By applying this operation to each tree $s_k \in \mathcal{S}$ we obtain two sets $d\mathcal{H} = \{dH_k\}_{k=1}^{N}$ and $d\mathcal{V} = \{dV_k\}_{k=1}^{N}$ representing the vertical growth and crown volume growth of all the individual trees of the analysed forest.

3. EXPERIMENTAL RESULTS

The proposed method has been tested on a coniferous forest located in the southern Italian Alps in the Trento Province. The species composition is mainly of *Larix decidua* (European Larch) and *Picea abies* (Norway Spruce). Tests have been conducted on 3 stands. Stands 1 and 3 have similar characteristics of vegetations densities and tree heights, whereas stand 2 is characterized by younger trees and a denser forest structure. The used airborne LiDAR data were acquired in 2010 and 2014 by the same ALTM 3100EA sensor with an average point density of $10pts/m^2$ and $15pts/m^2$, respectively. No multitemporal ground truth was available, thus we validated the results with the help of a team of experts by photo interpretation.

Table 1 shows the numerical results related to the detection of major changes. We manually defined a binary map by visually identifying the areas affected by major changes and compared it with the automatically generated one. The accuracy of the change detection is very high, with only a small percentage of pixel wrongly classified.

Subsequently, according to the proposed hierarchical approach, we moved to the characterization of the canopies. First we evaluated the accuracy of the tree identification by visually identifying the trees present in both data and comparing the resulting set with the one computed by the proposed method. Table 2 shows the obtained numerical results. While the tree detection applied to a single LiDAR acquisition identifies much more trees than the existing ones (i.e., high number of false alarms), the results of the matching between the sets $\mathcal{S}_1$ and $\mathcal{S}_2$ show that the number of false alarms is strongly reduced. Indeed, the matching exploits the information of both the acquisitions thus improving the detection accuracy. Some false and missed alarms are still presents but the number of them is relatively small.

After having identified and characterized the single trees in the two LiDAR data acquisitions, it is possible to perform the detection of minor changes by identifying the vertical growth and crown volume growth. Table 3 shows the statistics of the vertical growth. As expected, the second stand shows a higher vertical growth (both in absolute and relative terms) since it is characterized by the youngest trees. This is consistent with the fact that the youngest trees are also the ones that grow the most. Figure 3 and Table 4 show the results regarding the crown volume growth. We discarded the negative volume variations that were due to small shrubs. Moreover,

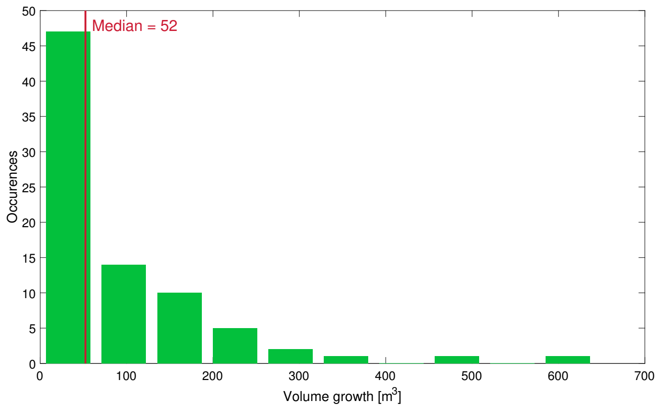


Fig. 3: Occurencies of volume variation for stand 1.

		Estimated	
		Change	No change
True	Change	531	34
	No change	19	54172

Table 1: Error matrix related to the major change detection in terms of classified pixels in the CHM.

the trees with volume variation greater than the the original crown volume were not considered. These cases are due to segmentation errors and thus they do not represent consistent results. It is worth noting that for each stand there are maximum 3 of such errors. Figure 3 shows the occurrences of volume changes for stand 1. As one can see, most of the trees are characterized by a crown volume variation smaller than 200 m^3. Table 4 shows the statistic regarding the crown volume growth of stands 1 and 3. Stand 2 was discarded for this analysis because it is characterized by a very dense forest that limits the penetration of the LiDAR sensor. This strongly affects the base height estimation making the crown volume estimation less reliable.

4. CONCLUSIONS

In this paper we have presented a hierarchical approach to the detection of major and minor changes in bitemporal LiDAR acquisitions having different point densities. The obtained results show that the proposed method detected major and minor changes with high accuracy. In greater detail, the major changes are detected correctly with small false and missed alarms rates. The tree detection is accurate thanks to the use of the information of both LiDAR acquisitions. Moreover, the single tree analysis is capable of characterizing both the vertical and crown volume growth of the canopy. As future developments we plan to convert the measures of overall volume change in a measure of biomass variation.

Stand	Tree peaks $\mathcal{S}_1$ (2010)	Tree peaks $\mathcal{S}_2$ (2014)	Matched trees			Manual detection
			Correct	False alarms	Missed alarms	
1	150	148	124	3	2	126
2	218	234	193	4	4	197
3	143	149	131	2	4	133

Table 2: Numerical results of the tree top identification and matching.

Stand	Median tree height 2010 $[m]$	$d\mathcal{H}$ $[m]$	
		Median	$[\%]$
1	34.9	1	2.8
2	24.1	2	8.1
3	34	0.9	2.9

Table 3: Statistics of the tree vertical growth.

Stand	Median tree volume 2010 $[m^3]$	$d\mathcal{V}$ $[m^3]$	
		Median	$[\%]$
1	850	52	8.4
3	600	46	9.2

Table 4: Statistics of the tree crown volume growth.

5. REFERENCES

[1] Benoît St-Onge and Udayalakshmi Vepakomma, "Assessing forest gap dynamics and growth using multi-temporal laser-scanner data," *Power*, vol. 140, pp. 173–178, 2004.

[2] Xiaowei Yu, Juha Hyyppä, Harri Kaartinen, and Matti Maltamo, "Automatic detection of harvested trees and determination of forest growth using airborne laser scanning," *Remote Sensing of Environment*, vol. 90, no. 4, pp. 451–462, 2004.

[3] Xiaowei Yu, Juha Hyyppä, Harri Kaartinen, Hannu Hyyppä, Matti Maltamo, and Petri Rönnholm, "Measuring the growth of individual trees using multi-temporal airborne laser scanning point clouds," in *Proceedings of ISPRS Workshop Laser Scanning*, 2005, vol. 2005, pp. 204–208.

[4] Daniel Kneeshaw Udayalakshmi Vepakomma, Benoit St-Onge, "Response of a boreal forest to canopy opening: assessing vertical and lateral tree growth with multi-temporal lidar data," *Ecological Applications*, vol. 21, no. 1, pp. 99–121, 2011.

[5] Paul J Besl and Neil D McKay, "Method for registration of 3-d shapes," in *Robotics-DL tentative*. International Society for Optics and Photonics, 1992, pp. 586–606.

[6] C. Paris, D. Valduga, and L. Bruzzone, "A hierarchical approach to the segmentation of single dominant and dominated trees in forest areas by using high-density lidar data," in *Geoscience and Remote Sensing Symposium (IGARSS), 2015 IEEE International*, July 2015, pp. 65–68.

[7] Felix Morsdorf, Erich Meier, Benjamin Kötz, Klaus I Itten, Matthias Dobbertin, and Britta Allgöwer, "Lidar-based geometric reconstruction of boreal type forest stands at single tree level for forest and wildland fire management," *Remote Sensing of Environment*, vol. 92, no. 3, pp. 353–362, 2004.