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Automatic dendrometry: Tree detection, tree height and diameter estimation using terrestrial laser scanning

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ABSTRACT

This study presents an automatic method to identify tree stems, and estimate tree heights and diameters from terrestrial laser scanning (TLS) data. The method is based on the isolation and vertical continuity of the stems. First, a height-normalized version of the point cloud is created. From this, stems are individualized, an iterative process is applied to the points at breast height for estimating diameters, and tree heights are calculated after denoising and clustering the points of each tree. The method was tested in three different sites. All the elements detected as trees were actual trees, and more than 99% of the trees in the plots were detected. Root mean square error (RMSE) of the estimated diameters at breast height (DBH) ranged from 0.8 to 1.3 cm in the test plots, and total tree height (TH) RMSE ranged from 0.3 to 0.7 m. In the cases studied, the algorithm showed robustness to the presence of steep or irregular terrain, the presence of low vegetation and artifacts at breast height, the indistinct use of individual or multiple scans, and tree density in the plot.

1. Introduction

Forests provide a wide range of resources, ecological services, and contribute to diversification of rural economies. They are essential to preserve biodiversity, hydrological assets and soils, and to mitigate the effects of climate change (Trumbore et al., 2015; Tubiello et al., 2015). In this frame, forest management systems play a significant role. The detailed knowledge of forest resources and their monitoring, as well as the effect of treatments that are applied to them should be the base to support any decision-making at different levels and goals such as further silviculture treatments, forest harvesting, climate change impact evaluation, fire modelling, carbon stock estimation, etc (Keenan et al., 2015; MacDicken, 2015). The main objective of any forest inventory is to measure the wood volume, biomass or species diversity, and the monitoring of any of these parameters. Most forest inventories are based on the analysis of sampling plots, and the results are used to infer the global parameters of the forest cover under study. The precision of the derived global parameters is dependent on the representativeness, distribution and quantity of the considered samples (Barrett et al., 2016, Kangas and Maltamo, 2006).

Forest sampling plots are typically small circular areas with a radius of between 4 and 15 m (Liang et al., 2016). The most commonly recorded attributes are: species, diameter at breast height (DBH) and total tree height (TH), although several other parameters are also usually measured in the field or derived from such data (e.g. leaf area index, stem curve, crown diameter, or physiognomy of the lowest branches). Once all the trees of the plots have been characterized, the population values are interpolated or extrapolated into the whole area under study. The conventional instruments for the measurement of forest plots are calipers for trunk diameters and hypsometers for total tree heights. In recent decades, the evolution of these devices has consisted basically in the integration of digital displays, internal memories, and data transfer systems. However, they are still time-consuming, limited for the evaluation of large areas, and operator-skill-dependent. Laser scanning technologies are becoming an alternative to conventional devices, allowing a qualitative step forward in the improvement of the forest inventory processes (Liang et al., 2016, Kangas and Maltamo, 2006).

The Light Detection and Ranging (LiDAR) systems became widespread in the last two decades (Toth and Jóźków, 2016). First LiDAR

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devices were introduced on airborne platforms (Bufton, 1989; Flood and Gutelius, 1997; Hyyppä et al., 2008). Then, they were adapted to provide terrestrial static solutions, and, recently, mobile vehicles in outdoor and indoor spaces are evolving rapidly (e.g. Hyyppä et al., 2013). The application of aerial LiDAR systems (aerial laser scanners, ALS) to forest measurements has been shown to be operative for the evaluation of forest vegetation cover and its characterization. Specifically, the combined use of ALS and plot-level information has effectively increased in the last few years, and proven to be effective for the extraction of forest inventory parameters (Næsset, 2002, Næsset, 2007; Vastaranta et al., 2013; Wulder et al., 2013; McRoberts et al., 2013). However, ALS data is not yet extensively used for strategic forest inventory assessments at a national level. Instead, they are used operationally for stand-level forest management inventories in Finland, Norway and Sweden (Barrett et al., 2016). Several studies provide different approaches to individual tree or plot-level characterization of the vegetation cover from ALS data (e.g. Popescu et al., 2003, or Mundt et al., 2007).

The use of ground-based remote sensing techniques, like terrestrial laser scanning (TLS), often allows the observation of structures and elements that are not visible from an aerial perspective (e.g. stems in layered forests). Some approaches have been described to apply terrestrial laser scanning in dendrometric characterization (Bienert et al., 2006; Liang et al., 2016; Wilkes et al., 2017). TLS systems provide millimeter-level accuracy and a terrestrial point of view; consequently, diameters at breast height and accurate stem models can be obtained. Nevertheless, the proportional instrumental costs per area if compared with aerial LiDAR reveal a potential for calibrating and evaluating data obtained from airborne LiDAR systems, rather than being an affordable and competitive technology for large scale forest inventory. In this context, with the current state-of-the-art-technology, TLS data and approaches have their greatest potential at being used as a substitute for traditional dendrometric methods at plot or individual tree level, and further integration within extensive 3D forest models (e.g. point clouds derived from aerial data). Liang et al. (2016).

Numerous recent studies provide solutions and algorithms for single tree modelling from TLS data (Lefsky and McHale, 2008; Côté et al., 2011; Moorthy et al., 2011; Dassot et al., 2012; Schilling et al., 2012; Vonderach et al., 2012; Delagrange et al., 2014). These studies are mainly applicable when trees stand separately, or, at least, with certain isolation, and can provide a very high level of detail, including small branches and leaves in some cases.

Plot-level algorithms based on TLS data are often focused on detecting trees in sampling plots. Most of them provide information about the location of the trees in a plot, basic dendrometric data, like DBH and TH, and, frequently, individualized 3D models of each tree in the plot. Information derived from the application of these algorithms is currently used for stand-level inventories and for the development and update of allometric models. Moreover, some parameters that now are estimated indirectly through allometric models (i.e. frequently related to accurate wood or timber volume calculations) are becoming directly measurable from TLS data. Comprehensive reviews in this field are provided in Dassot et al. (2012) and Liang et al. (2016).

Individual tree detection in sampling plots is addressed in Maas et al. (2008), Strahler et al. (2008), Liang et al. (2012a,b), Liang and Hyyppä (2013), Yao et al. (2011), Lindberg et al. (2012), Astrup et al. (2014), Olofsson et al. (2014), Kankare et al. (2015), Liu et al. (2017) or Heinzel and Huber (2017) among others. Tree detection rates range between 40 and 100%, and are clearly affected by (i) tree density (i.e. in general, lower detection rates with higher tree densities), (ii) forest structure (e.g. lower detection rates with dense low forest vegetation and branches), and (iii) point density or distance to the sensor (i.e. lower detection with occlusions, low point density and/or large distances to the TLS).

DBH is assessed in Maas et al. (2008), Yao et al. (2011), Liang et al. (2012a), Lindberg et al. (2012), Liang and Hyyppä (2013), Olofsson et al. (2014), Kankare et al. (2015), Koreň et al. (2017), Liu et al. (2017) and Heinzel and Huber (2017). In these studies, DBH is calculated from single scans, from multiple scans joined prior to DBH analysis, or analyzed separately for further diameter comparison at each detected tree location. Most of them use cylindrical or circular least squares fitting methods (e.g. Hopkinson et al., 2004, or Henning and Radtke, 2006), although other strategies/approaches are also used. For example, Mizoguchi et al., 2017 uses bicubic spline fitting, and Olofsson et al. (2014) uses Hough transform and RANSAC (RANdom SAmple Consensus) for circle fitting and DBH estimations. Miscalculations are mainly due to the presence of artifacts at breast height (like branches, leaves or low vegetation), or to the distance to the scanner for the singlescan methods (Liang et al., 2016).

Tree height estimation (TH) from TLS data has been addressed in Moskal and Zheng, (2011), Huang et al. (2011), Maas et al. (2008), Fleck et al. (2011), Liang and Hyyppä (2013), and Olofsson et al. (2014). In these previous studies, the existence or lack of points on the top part of the trees is the main constraint of the process. In this way, dense canopies (and the consequent lack of points on the treetops) lead frequently to tree height underestimation. Tree height overestimation is also frequent in dense plots, where small trees are often closely surrounded by larger ones, and the treetops of the higher trees are assigned to the former.

The main objective of this work is to develop an algorithm able to detect trees in TLS datasets and obtain their position, height, and DBH. The method must be fully automatic, improve the performance of previous studies and traditional methods, and overcome some of their limitations and drawbacks.

2. Methodology

The method consists in the identification and individualization of the stems contained in the dataset (i.e. point cloud), and the subsequent estimation of their position, diameter at breast height and total tree height. In order to achieve this, a terrain model is automatically generated, and based on it, a height-normalized version of the point cloud is created. Then, tree trunks are individualized based on their isolation and vertical continuity. Finally, DBH and TH are estimated from the height-normalized point cloud.

2.1. Terrain model and height-normalized point cloud

The horizontal extent of the point cloud is divided into square cells following a regular grid. All the points within the limits of each cell are identified and labeled, and the lowest elevations are extracted. The elevation of the lowest point of each cell (excluding outliers) is compared to the elevation of its eight closest neighbors. If the difference is larger than a threshold that limits the vertical variation between neighboring cells, the elevation of the cell is reduced to its lowest neighbor. This process is repeated iteratively and traverses all the cells until there is no cell whose elevation difference is larger than the pre-set value (Pseudocode 1).

Fig. 1 shows an example of terrain modelling. The peaks in Fig. 1.A (both over and beneath the terrain) are eliminated after applying the iterative process, while the blank cells remain unchanged in Fig. 1.B. The elevation difference threshold has to allow the presence of some expected features on the terrain, such as the edge across the terrain model.

An alternative version of the point cloud is created from the elevation of the points and the terrain model. In this version, the original point cloud is transformed as if the terrain were flat and horizontal. The elevation of each cell in the terrain model is subtracted from the elevation of the points inside the cell. The result is stored as an only one-dimension vector, and the original XYZ coordinates remain invariant. See Fig. 2 and Pseudocode 2 .