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## Towards automated and operational forest inventories with T-Lidar

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### Abstract

Forest inventory automation has become a major issue in forestry. The complexity of the segmentation of 3D point cloud is due to mutual occlusion between trees, other vegetation, or branches. That is why, the applications done until now are limited to the estimation of the DBH (Diameter at Breast Height), the tree height and density estimation. Furthermore other parameters could also be detected, such as volume or species of trees (Reulke and Haala) . . . This paper presents an effective approach for automatic detection, isolation of trees and DBH estimation. Tree isolation is achieved using an innovative approach based on a clustering methodology followed by a skeletonization step. The DBH of trees is then determined automatically. The efficiency of our algorithm is evaluated with comparison with ground data, measured by classical methods.

### 1. Introduction

Terrestrial laser scanner has become, in recent years, an important focus in forestry area. This technology allows to completely digitalizing a forest as a dense 3D point cloud. This gives a faithful and very accurate picture of a stand at a given time. The visual exploration of 3D point cloud gives lots of possibilities concerning the description of stem and branch structure of a tree. However, the challenge is to extract pertinent and correctly estimated forest inventory parameters from these raw data.

The absolutely needed parameters are the detection of trees and the estimation of the DBH. This has been already achieved in different works (Dassot et al 2010), with different degrees of success and robustness, but the real benefit in using the T-Lidar for forest inventory is due to determining others parameters which are very difficult or long to identify using traditional field methods, as stem volume, total tree volume, tree height, flexuosity, branchiness . . .

The “Computree” software presented in this paper, is developed by Office National des Forêts (French institute of forest management of public forests), with the goal of an operational approach, identifying all the parameters which can be detected by the T-Lidar. This approach has to put into consideration the important needs of an applied method:

- Robustness regardless different stand types and compositions.
- The approach must be the most computerized as possible, minimizing the ratio between time-consuming (ground and treatment) and quality of the data extracted.
- Try to be the most exhaustive as possible in tree detection and measurement, which requires us to correctly take into account the inter-trees occlusions.

This paper is organized as follows: section 2 presents a short review of recent methods to isolate tree and estimate the DBH. Section 3 details the methods used in Computree followed by a result analysis, a discussion and a conclusion. In the present paper the analysis of Computree's results will focus on DBH and localization. Indeed, the estimation methods of the other parameters are currently a work in progress.

## 2. State of the Art

The algorithms developed for forest inventory applications and reported in the literature usually require an estimation of the Digital Terrain Model (DTM) (extraction of ground profile), the detection of the position of the trees, the estimation of the height and the DBH, and sometimes other parameters like volume. In the subsequent sections, we will give a brief description of the common methods used to obtain these parameters.

### 2.1 Summary of the different methods used in forest inventory applications

#### 2.1.1 Digital Terrain Model

All the applications start by the generation of the DTM, which serves as a height reference for the determination of the DBH. Different approaches have been proposed:

1. **Lowest Z-value:** the point cloud is separated into horizontal grid with a regular cell size. In each cell, the lowest Z-value is selected and specified as a ground height reference.
2. **Density allocation along the z-axis:** the ground reference height is determined by an analysis of the vertical density point repartition.
3. **TIN model:** a triangulated irregular network (TIN) model is iteratively created and used to isolate ground points.
4. **TerraScan and TerraModeler software:** the DTM is generated using TerraScan and TerraModeler softwares by company Terrasolid Ltd, which use a low point's routine. This process is not always a simple task because of the ghost points occurring below the ground, which should be reclassified.
5. **Searching for maxima:** It is similar to density allocation along z-axis, followed by a neighborhood consistency check and bilinear interpolation.

#### 2.1.2 Tree detection method

1. **Hough transformation**
2. **Fitting circles :** Segmentation based on point cluster search, followed by a least square circle fitting
3. **Point density raster analysis:** two-step segmentation method based on point density raster analysis. The first segmentation step is a point cluster search in a cross section of the point cloud. In second step all clusters are analyzed to determine their point density inside a raster.
4. **Crescent Moon method:** creating a 'Crescent Moon' template by subtracting two, radially shifted circles. The points situated at the minimum, the mean and the maximum angle of the template are used to fit a circle. When the diameter is inside a certain range, then the position and diameter of the tree is recorded, otherwise not.
5. **Improved Hough transformation:** the trees stems are detected by using a Hough-transformation and measured accurately using a circle fitting and an ellipse fitting algorithm.
6. **Fitting cylinder:** Reconstructing trees from 3D point cloud automatically by fitting consecutive cylinders to the trunks. The reconstruction based on nonlinear least squares estimation is finalized as far as the RSME of the fitting exceeds a pre-defined value.
7. **Circle fitting statistics:** applying a least square circle fitting routine of the circular package of R.

#### 2.1.3 Tree Height method

1. **Difference between lowest and highest point:** The tree height is defined as the difference between the lowest point (soil reference for the DBH) and the highest point inside of a cut cylinder.
2. **Difference between DSM and DTM:** Calculating the height as the difference between the DSM (Digital Surface Model) and DTM.
3. **Simple taper function:** Extrapolation of a simple taper function from DBH to estimate the height.

#### 2.1.4 DBH method

1. **Fit a circle at 1.3m:** The breast height diameter is determined by cutting a slice of thickness  $d$  at a height of 1.30 meter above the representative terrain model point. An adjusting circle is fitted into the 2D projection of the points of the slice.
2. **Manual Mark:** DBH of each tree in the forest was determined and durably marked with reflecting tape before any measurements were carried out. As a fourth method of DBH derivation the intensity images of the sample plot were used to measure DBH in the scans manually.

#### 2.1.5 Stem profiles estimation

Because of the difficulty of the segmentation of the 3D point cloud, only two approaches were found: one that uses segmentation in a layer with height close to 1.3 m above terrain while the other calculates a stem profile at different heights. We did not find any approach that isolate and extract the whole tree.

### 2.2 Synthetic view of the combinations of methods

The following table summarizes the state of the art

Table 1: state of the art

<i>Authors</i>	<i>DTM</i>	<i>Trees Detection</i>	<i>Trees Description</i>	<i>DBH</i>	<i>Tree height</i>
<b>Simonse et al. 2003</b>	Lowest Z-value + exclusion cone	Hough transform	Layer between 1.25 and 1.35 m	Fit circle at 1.3m	-
<b>Bienert et al. 2006</b>	Density allocation along the z-axis	Fitting circles	Layers at different heights	Fit circle at 1.3m	Difference between lowest and highest point
<b>Bienert et al. 2007</b>	Density allocation along the z-axis	Point density raster analysis	Layers at different heights	-	-
<b>Maas and al 2008</b>	Searching for maxima	Fitting circles	Cutting a vertical cylinder + Layers at different heights	Fit circle at 1.3m	Difference between lowest and highest point
<b>Aschoff and Spiecker 2004</b>	TIN model	Hough transform + fitting ellipses + fitting circles	Layers at different heights	Fit circle at 1.3m	-

<b>Thies and Spiecker 2004</b>	Lowest Z-value	Hough transform + fitting circle	Layers at different heights	Manual Mark	Taper function
<b>Brolly and Kiraly 2008</b>	TIN model	Fitting circles Crescent moon method	Layers at different heights	Fit circle at 1.3m	Difference between DSM and DTM Taper function
<b>Klemmt et al. 2010</b>	-	Circle fitting statistics	Layers at different heights	Fit circle at 1.3m	-

### 3. Proposed methodology

#### 3.1 Material

The data set presented in this paper was acquired with the terrestrial laser scanner Faro Photon 120 (Figure 1.a). This scanner with an horizontal and vertical fields of view of respectively 360° and 320° has a range up to 153 m with a distance accuracy of +/- 2mm. Seven minutes scans were chosen as a good time /quality trade-off, which give a cloud of 44 million of points (Figure 1.b). The distance between two points is 6.3 mm at 10 m (it can reach 1.6 mm at 10 m at maximum resolution). The acquired data in native Faro files format are filtered and exported in Faro Scene as binary format XYB, where each point is defined by its three Cartesian coordinates (x, y, z) and information on the reflectance.



Figure 1: (a) laser scanner Faro Photon 120, (b) a 44 million points scan quick view

#### 3.2. Computree algorithm

##### 3.2.1 Soil extraction and DTM generation

This step consists in determining if each point belongs to soil or vegetation. This allows a size reduction of the analysed cloud by searching trees only in vegetation points, and the computation of the DTM used to have Z base reference for each stem.

An horizontal grid with a regular cell size of 50 cm x 50 cm is created and for each cell, the lowest Z value of points is stored in the “Zmin grid”.

The density of points between Zmin and (Zmin + 32 cm) of each cell is computed. Each cell with a density below 200 pts/m<sup>2</sup> is affected with a NA value (no soil points in this cell).

Each cell is compared with the 4x4 cells around. If at least one neighbour cell has a Zmin forming an angle with the observed cell upper than 45°, then a NA value is also affected to the observed cell.

The DTM is computed from the Zmin grid, interpolated with a Delaunay triangulation. Each cell with a NA value is estimated as the inverse distance weighted mean of its neighbours in the

triangulation. The soil points – between  $Z_{min}$  and  $(Z_{min} + 32 \text{ cm})$  – are separated from vegetation points which are the only points that will be analyzed in the next step.

### 3.2.2 Clustering

The goal of this step is to obtain clusters of points. All of the points from one cluster have to belong to only one tree stem. The cloud of vegetation points, is sliced in horizontal Z-layer 1 cm thick. In each Z-Layer, points are grouped according to their proximity: two points belong to the same group if their distance is lower than 3 cm. Clusters with three or less points are dropped for next steps. For each points cluster, a circle is fitted by a least square routine (assuming trunks are approximately circular in horizontal plane). If the error of the circle fitting is too higher, the cluster is also dropped. Each fitted circle is compared to fitted circles of the ten Z-layers above and the ten Z-Layers below. If at least one circle in these layers has its centre horizontally included in the observed circle, and has a similar radius (between 0.67 and 1.5 times the radius of observed circle), it is kept else it is dropped. This test assumes that a stem should have a minimum degree of vertical continuity.

At the end of this step only the clusters of points that have some degree of circularity (crescent-shape if only one centre scan has been done) should remain.

### 3.2.3 Creation of virtual sections

In this step, 1 cm thick clusters are aggregated in vertically-oriented virtual sections. Two clusters are affected to the same virtual section if the bounding rectangles are horizontally intersected, and their Z-distance is less than 50 cm. The bounding rectangle of one cluster is the smaller XY oriented rectangle that contains all the points of the cluster. The sections containing less than 20 clusters are dropped. Previously, dropped clusters are tested again with each virtual section by the bounding rectangles intersection routine.

At the end of this stage a real tree could be represented by several virtual sections (figure 2A), due to occlusions.

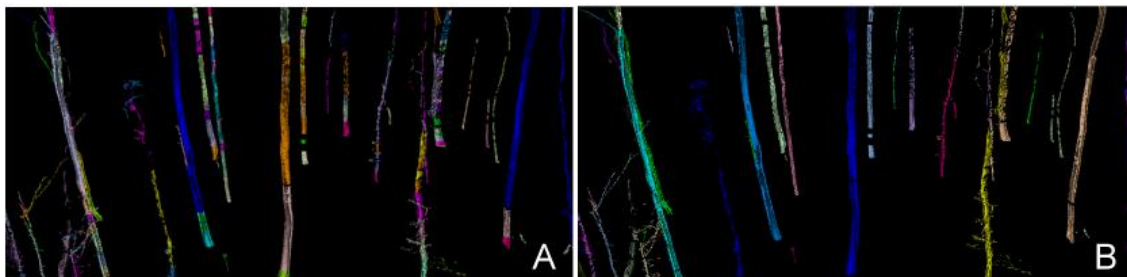


Figure 2 (A) trees represented by a mosaic of virtual sections, (B) trees after sections merging

### 3.2.4 Skeletonization

The goal of this step is to merge virtual sections belonging to the same tree. For each virtual section, a skeleton is created by merging the clusters of the section into skeleton slices, with a thickness of 10 cm. The nodes of the skeleton are defined as the barycenter of the successive skeleton slices. Two sections are merged together if they have approximately the same vertical extend (or one having its vertical extend included in the other ones), and having a maximum horizontal distance lower than 50 cm (figure 3A). The sections vertical continuity is tested. If the skeletons of two sections have their extremity in a reciprocal alignment, then the sections are merged in the same stem (figure 3B). Two sections are considered aligned if the directional extrapolation of the skeleton of each one is intersecting the other one's extremity, close to its node. The proximity criterion from node is defined by the horizontal extends of the extremity slice of the section. After merging the sections together the final skeleton is computed again and

smoothed (with a mobile-mean routine).

At the end of this step, it should be one virtual stem for each real tree stem or branch. The figure 2A shows the virtual sections, and the figure 2B shows the resulting virtual stems.

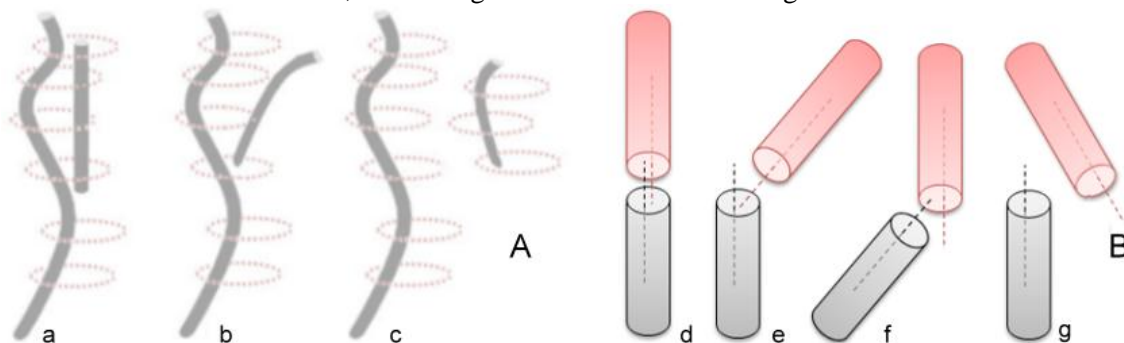


Figure 3: (A) virtual sections, (a) fusion, (b, c) no fusion, (B) segments, (d) fusion, (e, f, g) no fusion

### 3.2.4 Position and DBH calculation

This step fits a circle to each virtual stem at 1.30 m from the DTM. The centre of the circle gives the position of trees, and its diameter is given as an estimation of the DBH. For each skeleton node of a virtual stem, between 0 and 3.30 m from the DTM, a circle is fitted for the node's points, perpendicularly to the skeleton direction in this node. A linear regression is computed for the diameter of these circles against the height value. The outliers circles (from the Cook's distance criteria) are iteratively removed and the linear regression fitted again. The DBH is estimated from the fitted model.

## 4. Results and discussion

### 4.1 Tree detection

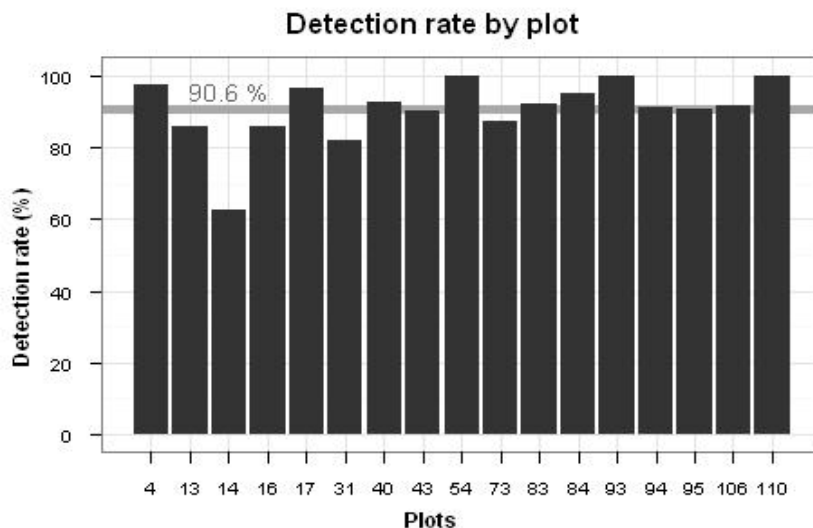


Figure 4 : Detection rate by plot

The test site was composed by 17 plots (of beech, with oak, hornbeam and sycamore maple) of mixed forest in state forest of Montiers-sur-Saulx, (Meuse, France) with a basal areas between 3 and 65 m<sup>2</sup>/ha and a density between 56 and 3600 stems/ha. The plots numbered (13, 14, 16, 17, 43, 84, 93, 95) are coppice with standards while the plots numbered (4, 31, 40, 54, 94, 106, 110)

are even-aged stands. The rest (73, 83) are pole stands. The plots were recorded from one laser scanner position. The figure 4 presents the detection rate by plot. Our algorithm has an average of detection rate of 90, 6% which shows excellent results especially considering the complexity of segmentation of 3D cloud point. Just one plot (14) presents a bad detection rate of 62,5%. Plot 14, has not many trees, far from the centre (between 13 and 15 m) with, between the centre and the trees, a lot of seedlings (3 to 6 m), which completely mask the background: there is a regeneration gap. The results of the detection and the isolation of trees done with Computree software are showed on figure 5.B.

Detection rate could probably be increased with a multi scans approach. It will be tested in the future, considering that our algorithm is low time-consuming, so testing a larger point cloud is not a matter. At the moment, the processing time for a 44 million point cloud is about 3 min on a computer with Intel © i5 processor. The time factor is extremely important for operational efficiency, it was taken into consideration throughout our development.

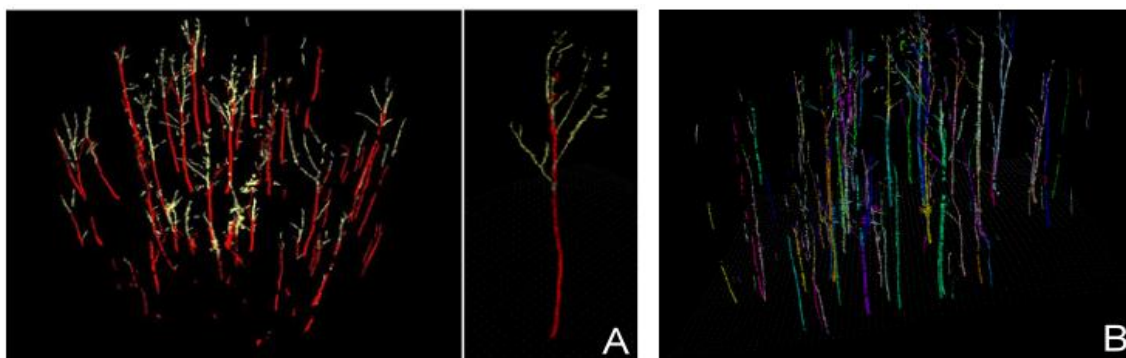


Figure 5: (A) isolated trunk (red color), branches (yellow color), (B) complete isolation of trees with Computree (a different color for each isolated tree)

#### 4.2 DBH estimation

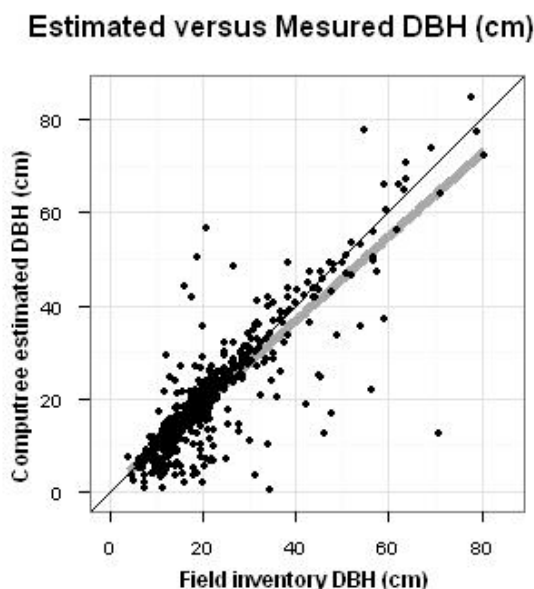


Figure 6 : Diameters computed from Computree Software in comparison with the diameters obtained manually. The identity line is figured as a black line, and the linear adjustment as a thick gray one

The dispersion between Computree estimation DBH and the DBH from the field inventory is presented in figure 6. The objective is to quantify the rate of data variability around the central value that is measured on the field. The algorithm is more powerful as the measures of



difference between the two data sets is optimal and our values are closer to the identity line. There is some little bias related to diameter. The estimation is globally good, 80 % of point having an absolute error below 5 cm. But it remains a little but significant proportion of very bad estimations. They are essentially due to some residuals problems in tree isolation, or to counter-productive effect of the Cook's Distance criteria (then it is more bad circle than good ones). One way of resolution would probably to improve clusters filtering before virtual section creation.

To well analyze the error estimation we study the error estimation by plot (figure 7).

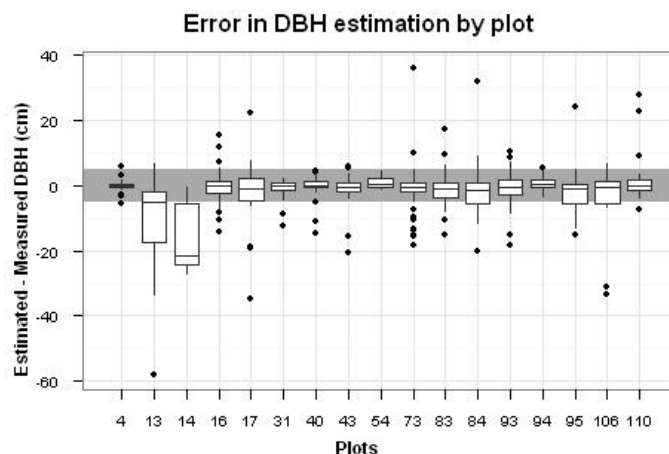


Figure 7: Error in DBH estimation

The figure 7 show the same results but splitted by plots. It gives for each plot the distribution of estimation error on the diameter. The gray area (median) represents an error of  $\pm 5$  cm. We can observe that the distribution is good and in the middle range for most of the plots, except for rare extreme outliers cited previously.

Two plots present a lower distribution: plot 13 and 14. For the plot 14 the result is a consequence of the structure of the plot which is a regeneration gap, containing a very important quantity of seedling, generating a lot of occlusions. The phenomenon is accentuated by the fact that the majority of tree in this plot are far away from the centre. The plot 13 is in a similar situation of occlusion by seedlings, but with a best spatial distribution of trees.

#### 4. Conclusion and perspectives

The approach described provides an automatic method of detecting trees in terrestrial laser scans of forest sites and estimating their DBH. Our approach is very relevant and solves several problems of segmentation of 3D point cloud such as shadow effects and mutual occlusions. Our algorithm is very fast: a 3D point cloud of about 44 million points is processed in few minutes. The process of detection of trees gives a mean rate of 90% what is very accurate. In the future, it is planned compare simple scan versus multiple scans efficiency of Computree estimations, particularly for the case of plots with lots of seedlings. For the estimation of DBH, the results are very encouraging, but some problems have to be solved to avoid the small remaining proportion of outliers. The skeletonization approach seems to be a very interesting way of tree isolation. Several improvements are planned with a more comprehensive study of the ramification of the branches. We also have to implement and test other parameters calculations, like volume or branchiness. Finally a Ph. D. Work has been initiated for automatic species identification.

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