Tree detection by row recovery on eucalyptus spp. Plantations from TLS data

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Abstract. Precise biomass estimation of trees is of major importance to plantation owners. But the capabilities of conventional inventory methods are limited. In recent years, several studies have proven the value of terrestrial laser scanning (TLS) data for forest inventory and forest management tasks. In order to obtain biomass information from TLS data, tree detection is a necessary first step. In contrast to naturally grown forests, trees on plantations are not randomly positioned; trees are planted in rather straight rows at pre-defined distances. We propose to make use of this row-wise alignment in the process of automatically detecting trees from TLS data. First, the row arrangement is recovered. Second, we examine each row separately in order to actually detect trees. Our approach has been successfully tested with TLS data of 18 plots on *Eucalyptus spp.* plantations, which comprise about 32 to 84 trees within the defined area of interest. The average rate of properly detected trees is 97%. The results show that it is beneficial to include knowledge about the expected positioning pattern of plants on the plantation in the detection process. Further investigation of this approach is necessary to turn the proposed method, which is currently restricted to straight rows, into a flexible tool to be applied to other types of plantations as well.

Keywords. Tree detection, Terrestrial laser scanning, Forest inventory parameters

1. Introduction

Precise biomass estimation is of major importance to plantation owners for exact harvest forecasting. But the parameters that can be manually measured with destructive methods are limited. Conventional methods of forest inventory are labor- and time-intensive and therefore costly. Automatic solutions that can replace and augment conventional methods while reducing costs consequently receive high attention nowadays.

Assessing trees on *Eucalyptus spp.* plantations is often done with Airborne Laser Scanning (ALS) due to the large area. The main objective using ALS is the approximation of tree heights and plot volume as for instance in [1], [2] and [3]. Satellite imagery is also a possibility to assess the local tree density on a plot that can vary due to dead plants as done in [4]. Ground-based laser scanning that provides a higher spatial resolution is employed seldom on plantations. In [5], a tree orchard is scanned with Mobile Laser Scanning where a line scanner is mounted onto a tractor that drives through each row. In this case, row information is directly acquired due to the scan setup. In the *Eucalyptus spp.* plantations that are considered here, rows can be clearly identified. However, due to terrain conditions and spacing, it is not possible to drive through them with a vehicle-mounted laserscanner. For this reason, we concentrate on static Terrestrial Laser Scanning (TLS).

In general, TLS is a valuable tool to capture the geometry of real-world objects as a 3D point cloud in a fast and automatic way. Especially for the scanning of trees that are very diverse and complex in their appearances it is a sensible option to obtain geometry data. In order to assess a sample of trees w.r.t. forest inventory parameters, individual trees need to be identified in the data. Clearly, tree detection is a fundamental task on which all subsequent analysis is based on.

Several publications concentrate on tree detection in natural forests (see e.g. [6], [7], [8], [9],[10],[11], [12]). Although the distribution and growth of trees is governed by factors such as solar radiation, precipitation and spatial conditions, trees in a natural forest appear to be positioned at random. Tree detection in natural forests cannot rely on constraints regarding an expected spatial positioning pattern. However, the situation is different on plantations. Here, saplings are commonly planted in long rows with a predefined inter-row and inner-row spacing between plants. Consequently, a number of assumptions about the expected tree positions can be made. For this reason, we have developed an approach to reconstruct the row arrangement of the trees from TLS data. Afterwards tree detection is performed in a row-wise fashion.

In this paper, we present a novel approach to tree detection on *Eucalyptus spp.* plantations. The key idea is to recover the row arrangement on the plantation first. In a second step, each row is analyzed separately in order to detect trees. Finally, we obtain a set of tree positions with information about their spatial arrangement in rows. The outline of the paper is as follows: First, we briefly describe our data sets and TLS device. Second, we explain our approach in detail. Experiments are outlined in section 3. The proposed method and experiment results are discussed in the following section. Last, we conclude with a short summary.

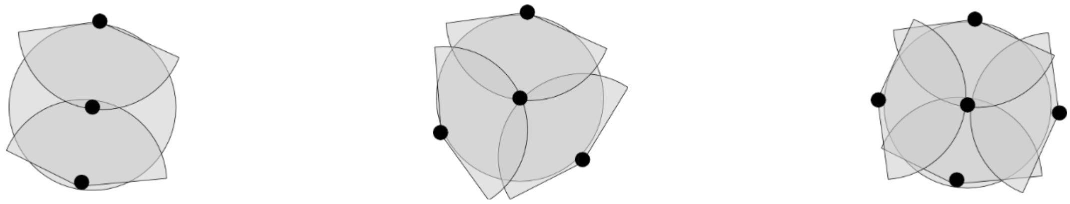
2. Data Set and TLS device

The data sets that were the basis for the presented approach have been acquired in the scope of the PROBRAL-CAPES-DAAD project at Technische Universität Dresden and Federal University of Paraná. In total, 18 plots were scanned on three different Eucalyptus plantations that are located near Três Lagoas in Mato Grosso do Sul, Brazil. The plantations are operated by Eldorado Brasil for the production of pulp for the paper industry. Each of the three considered plantations has a different tree age.

Eucalyptus spp. plants on the plantations grow very straight and have only small crowns. The trunk is mostly smooth, but bark patches may peel off and hang down in shreds that obstruct the trunk surface. Very thin and long branches can fork off from the trunk at any height. Young Eucalyptus trees, which grow on one of the plantations, are about 11 m tall and have more crown structure than older ones. Full grown Eucalyptus plants are harvested when they are about 6 years old and with a height of about 25 m.

The understory vegetation on the plantation consists mostly of higher grasses and has been cleared to some degree for the scans. Beside the planted Eucalyptus trees, there are some other trees present on the plantation that are neglected during processing.

Each of the 18 plots has been scanned using the Trimble TX5 (same device as the Faro Focus 3D 120). A full spherical center scan has been taken on each plot. In addition, two or more scans have been taken in order to sufficiently capture at least a circular area around the center scan position. A radius of 15 m was selected for the circular area to obtain a plot size larger than 400 m², which is the common sample size on the considered plantations. Figure 1 depicts 3 examples of scan setup that was used. The scans of a plot had been co-registered semi-manually with Trimble Scene with 5 spherical markers that were set on the plot for the scanning.



a) b) c)

Figure 1. General scheme of applied scan setup. Black dots indicate TLS viewpoints, gray areas are the corresponding field of view. In all 18 plots, a center scan and 2 to 5 additional scans were taken.

3. Methods

The objective of the method is the enhancement of tree detection, which is commonly uninformed, by exploiting the row-wise arrangement of trees on the plantation. The method can be decomposed into three stages. Each stage consists of a chain of subprocedures that are controlled by a number of parameters.

3.1. Retrieval of a first row

The input data set of a plot consists of three or more co-registered scans. In order to obtain a set of estimates for tree positions, a modified version of the Circle Hough Transform [13] as proposed in [14] is applied. The data set is partitioned along the Z axis into slices of height $t_h = 0.5\ m$. The Circle Hough Transform is applied to each of the slices separately. A disc is used instead of a circle as template in the accumulation process yielding much more distinct peaks for the noisy TLS data. Estimate positions are then determined by fitting circles to selected subsets of 3D points that correspond to peaks in the accumulator array. The result of this first step is a set of 3D points indicating possible tree positions in different heights.

A tree that is well represented by scan points causes position estimates in several slices with only small horizontal displacement. A clustering method similar to an approach presented in [10] is used to merge position estimates of the same tree in a cluster. The estimates from the lowest slice are taken as cluster seeds. For each successive slice, the corresponding position estimates are checked whether they belong to one of the established clusters on the basis of their horizontal distance to the cluster centroid. If they are too far away from any existing cluster, the position estimate is regarded as new cluster itself. Afterwards, only clusters with more than $N_c = 3$ points are considered further. The centroids of clusters are subsequently used as set of approximate tree positions P_t.

The obtained 2D tree positions are input to RANSAC [15] using a 2D line segment as model. RANSAC finds a set of inliers i.e. 2D tree positions that are located on the same line segment. Finally, a 2D line is fitted to the set of inlier points and considered as first row of the plot. The points that belong to the newly retrieved row are labeled with a row number.

3.2. Recovery of rows

The set of inliers and the corresponding line segment L_0 that has been retrieved in the previous step is the basis for the recovery of the row arrangement. In order to get the next row parallel to L_0, the normal vector to L_0 is determined. All points in P_t are projected onto the normal vector. The point projections are sorted w.r.t. their distance from L_0. Starting at the line segment L_0, the projections in direction of the normal vector are inspected. The first projection that is not assigned to a row is selected. All subsequent projections that are within a distance threshold of $s_Y = 1.5\ m$ to it

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are considered to be part of the next row. The corresponding tree positions are used to fit a 2D line. The points that contributed to this line obtain a row number.

The procedure is repeated with the normal vector of the newly obtained line segment. The procedure terminates if there are no tree positions left that project onto the normal vector of the considered line segment. Subsequently, the procedure is repeated along the opposite normal direction starting at L_0 again. The result is a set of line segments L. Each line segment in L is associated with a set of tree positions. Figure 2a illustrates the basic idea.

Next, the set of tree positions that corresponds to a line segment L_i is tested for outliers. The points are sorted along the line beginning at an endpoint. A triangle is formed from each successive three points and inner angles are calculated. If more than one angle is larger than $\Delta = 25{,}8°$, the middle point is removed from the set. After testing all points in order, L_i is updated by a new line segment that is fitted to the remaining tree positions. Afterwards the line segments and the corresponding sets of tree positions are clipped to a 2D bounding polygon. The 2D bounding polygon describes the plot shape i.e. the region of interest of the co-registered data set and was determined manually in advance.

Subsequently, the spacing between line segments is analyzed. The distance between the endpoints of a line segment and their projections onto both of its neighboring lines are calculated, as depicted in Figure 2b. If the line has been generated from less than $N_t = 3$ tree positions and the distances to neighboring lines are smaller than $s_E = 2\ m$ in more than one case, the line L_i is removed from L.

Afterwards the line segments in L are sorted again and distances are updated accordingly. An estimate for the inter-row spacing in the data is computed as

$$s_{avg} = 0.25 \cdot avg(D) - 0.3 \qquad (1)$$

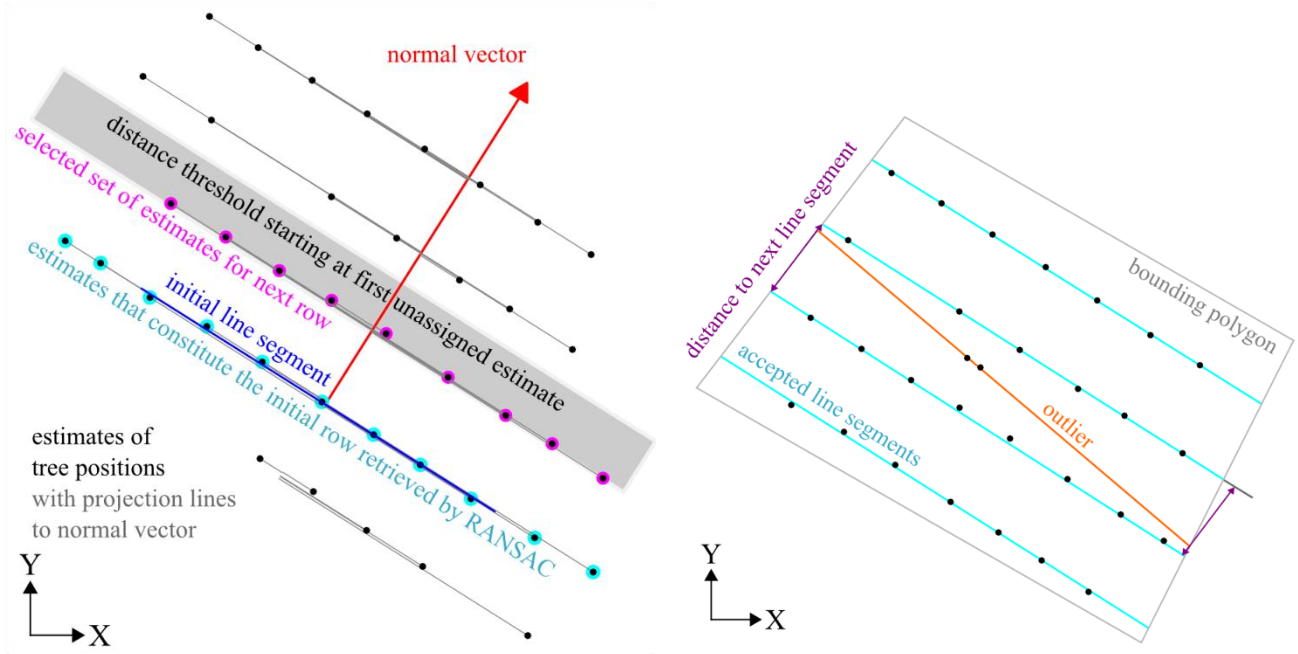
where D represents the distances. Using this parameter, corridors i.e. polygons around each line segment are created.

As final step to recover the row arrangement, missing lines and corridors are estimated on the basis of the set of line segments that has been retrieved. The last line segment L_n in L is selected and a duplicate of the line is translated by $s_C = 0.5 \cdot \big(avg(D)\big)\ m$ along the normal direction of L_n. The normal direction is selected in such a way that the line is translated away from the existing line segments in L and towards the boundary of the bounding polygon. If the new line and its corridor are not entirely located outside the 2D bounding polygon, the newly created line L_{n+1} is added to set L_T that is initially empty. The process is repeated starting at L_{n+1} until the new line and its corridor are located outside the bounding polygon. Again, this step is repeated starting with the first line of set L. Finally, the set L_T is added to the set of line segments L.

3.3. Detection of trees in rows

For each line segment L_i in L, a histogram of point numbers is computed: 3D points of the considered data set that are located within the corridor of the line segment L_i are projected onto L_i. The line segment is partitioned in bins of size $b_s = 0.05\ m$ starting at an endpoint. The number of 3D points that project onto a bin of L_i are counted. Subsequently, the histogram is smoothed using a central moving average with a windows size of 1×3. The 3D data of a row and its histogram are shown in figure 3a and b.

As a next step, the approximate spacing between trees of a row are determined. The set of estimated tree positions that is associated with a line segment is updated: The tree positions are mapped to the histogram as well. A mask of size $h_m = 2 \cdot \lceil b_h / b_s \rceil + 1$ around each of the bins containing tree positions is examined. If the value of the bin with the maximum value is larger than $t_b = 500$,



a) b)

Figure 2. a) Reconstruction of the row arrangement on the basis of the set of obtained estimates of tree positions.
b) Testing of lines for outliers on the basis of the number of estimates and distances to neighboring line segments.

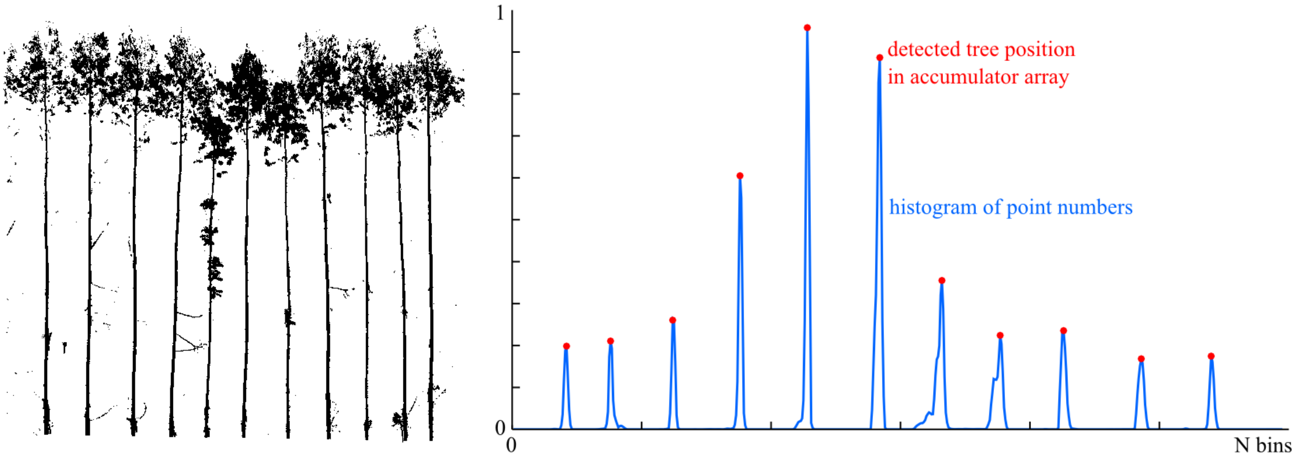
then this bin is used as updated tree position. If the bin value is smaller, the estimate of the tree position is discarded. The set of remaining, updated tree positions is sorted w.r.t. the sequential order in the row. The distances between pairs of successive tree positions are calculated. Eventually, the average tree spacing a_{ts} within a row is computed as the average of distances that are larger than $S_{X1} = 2.0\ m$ but smaller than $s_{X2} = 3.0\ m$. This additional test is necessary because larger gaps between trees may be present due to dead plants or terrain conditions.

Tree detection in a histogram of point numbers is performed as follows: First, an empty accumulator array of same size as the histogram is initialized empty. A sliding window is moved over the histogram bins by one bin per step. At each position, the bin with the maximum value in the window is determined and the corresponding bin of the accumulator array is incremented by one. Afterwards the values of the accumulator array A are normalized by

$$A[j] = A[j] \,/\, (h_w + 1) \tag{3}$$

where h_w is the window size. The window size is set to $h_w = 2 \cdot [(a_{ts}/b_s) \cdot 0.5] + 1$ and therefore depends on the previously calculated average tree spacing a_{ts} in a row. A tree is then identified in the accumulator array as a bin with a value larger than $t_A = 0.3$. Figure 3b shows the tree positions in the histogram that are identified in this way. The procedure is performed for each line segment. The result is a set of tree positions T that are detected in the accumulator array of each line segment in L.

Finally, each found tree position is tested using a histogram of point numbers along the Z axis. Around each tree position, a bounding cylinder of radius $r_c = 1.0\ m$ is created. 3D points of the co-registered data set that are located within the cylinder volume are projected onto the Z axis at the considered tree position. Similar to the previous step, the Z axis is partitioned into bins of size $b_Z = 0.1\ m$ in the interval of $[0\,..\,32]\ m$. Points that do not project into this interval are discarded. If more than half of all bins of a histogram of point numbers for a particular tree position are filled, the tree position is accepted.



a) b)

Figure 3. The set of 3D points that are located in a corridor of a line segment are shown in a). The corresponding histogram of point numbers along the row is shown in b). Red dots indicate the tree positions that have been identified in the accumulator array.

4. Experiments

The method that is described in the previous chapter has been implemented as Mathworks Matlab script. Each of the 18 plots that were described in section 3 was processed separately. The co-registered data set of a plot was the input to the processing. Parameters were used for all conducted experiments with the indicated values.

Computation times are between 4 to 14 minutes. The original co-registered data sets contained between 26 Mio. and 60 Mio. points. A data set of a plot has on average about 40 Mio. 3D points. In order to assess the result of the experiment, ground truth data was determined manually from the TLS data. Table 1 presents a comparison of the results and ground truth data. Figure 4 shows some experiment results.

Table 1. Experiments results of the 18 plots of Eucalyptus spp. plantation. The number of trees on the plot is the ground truth data that has been established manually.

Plot	P01	P02	P03	P04	P05	P06	P07	P08	P09
Trees on plot	32	44	73	43	50	46	47	49	42
Properly detected	32	43	68	38	49	44	47	48	42
False positive	-	1	1	-	-	1	-	-	1
False negative	-	-	5	5	1	2	-	1	-

Plot	P10	P11	P12	P13	P14	P15	P16	P17	P18
Trees on Plot	44	35	47	76	82	77	78	48	82
Properly detected	44	35	47	74	78	73	72	47	82
False positive	4	7	1	6	2	8	21	2	-
False negative	-	-	-	2	4	4	6	1	-

5. Discussion

As the experiments show, nearly all trees in the defined region of interest were properly detected. It works reliably for all 18 plots from the three different plantations. In essence, it shows that considering the particular spatial distribution of trees is beneficial for tree detection on plantations. Though, there are a number of false positive and false negative detections. As table 1 shows, especially in plot 16 an entire row has been detected wrongly. However, the majority of detections are proper. The average rate of properly detected trees is about 97% over the 18 plots.

Since our proposed method is but a first approach to this problem, several issues arise that need to be improved. First, our method presently requires a comparably high number of parameters that need to be set in advance. The indicated parameter values have been determined empirically since the development process was clearly data-driven. The general spacing of rows and trees within rows of the plantations was known and influenced the selection of parameters strongly. Instead of defining parameters in advance, it would be favorable to employ self-adjusting schemes such that suitable parameter values are selected automatically on the basis of the expected average spacing that is commonly known from a plantation.

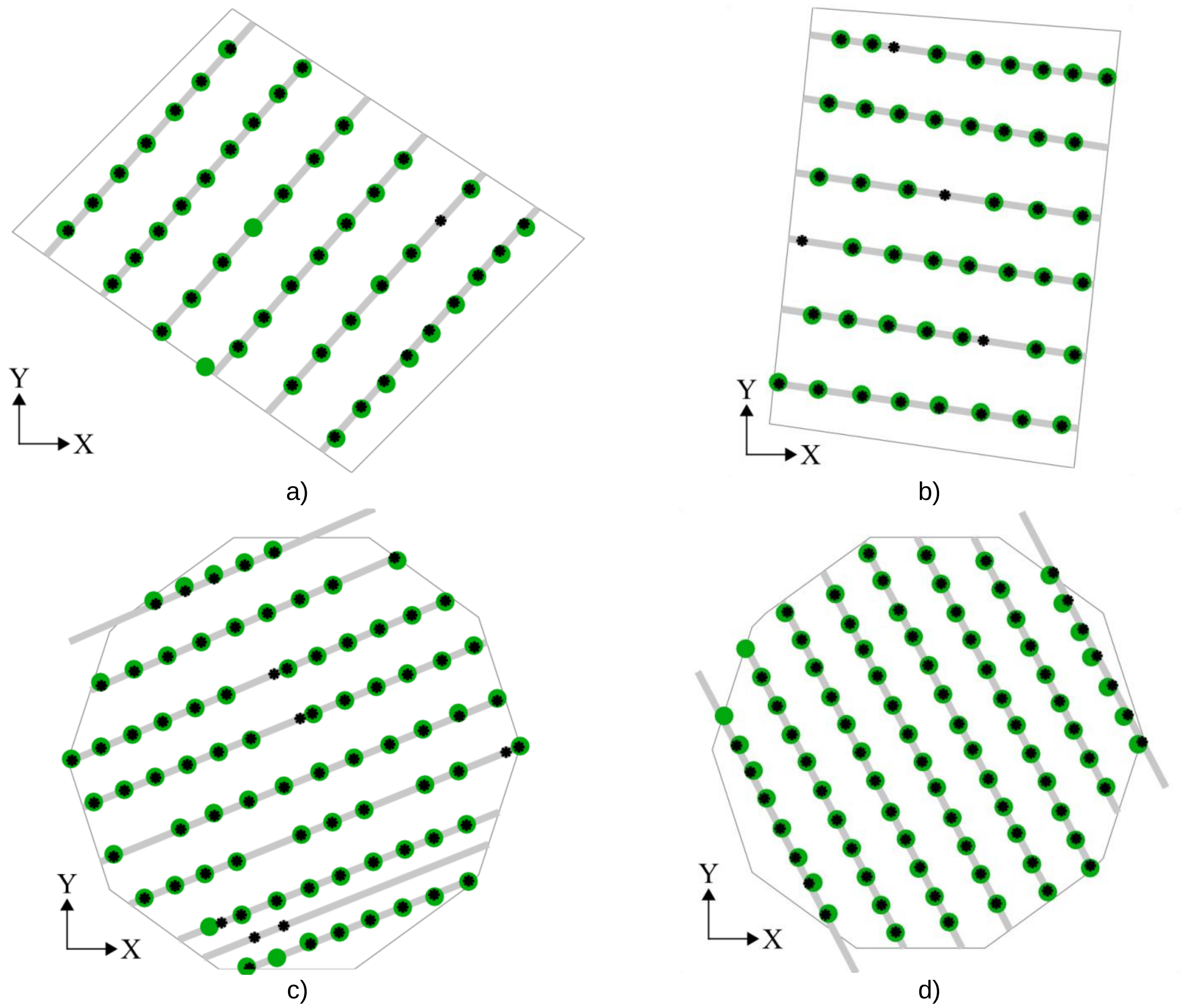


Figure 4. Results of the experiments. Green dots indicate positions of trees according to ground truth. Black dots indicate detected tree positions.

Furthermore, it would be interesting to investigate whether the TLS device has an influence on the data set and consequently the results. In other words, it has to be tested whether the method works reliably for data sets that were taken by another TLS device and which therefore have different noise characteristics. In addition, it is necessary to test the approach on other plantations to assess which kind of plants can be detected successfully.

At present, we assume that a row of trees on the plantation is a straight line. Clearly, this can be ensured prior to scanning manually by selecting a spot on the plantation where the rows confirm

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with this constraint. However, rows are not necessarily straight lines on a plantation. Due to space efficient planting and terrain conditions, rows might have a slight curve. In this case, our method will not be able to produce satisfying results. As a consequence, a strategy that recovers the row arrangement that is more flexible w.r.t. the row shape needs to be found.

Instead of fitting geometrical primitives to subsets of data, we utilized histograms of point numbers to extract information from the data. This approach is a direct consequence of the appearance of the Eucalyptus plants. As mentioned previously, bark shreds peel off and these hanging patches of bark obstruct the trunk surface. Consequently, the trunk surface is not sampled by scan points and circle fitting fails in that region. Instead of attempting to reconstruct the tree trunk exactly to perform tree detection, we decided to interpret point number histograms for detection. This turned out to be a comparably simple but effective tool that is well suited for this task because of the particular properties of plantations: Apart from Eucalyptus trees, no other significant vegetation is present on the plantation. Understory vegetation consists mainly of grasses. Evidently, the tree distribution in a row is therefore well reflected in the corresponding point number histogram because large clusters of scan points can only occur at Eucalyptus trees.

Problems arise only if trees are located very close to the border of the 2D boundary polygon or if the row is very short due to clipping to the region of interest. However, these problems can be neglected because clipping the results could be delayed to be the very last processing step.

Beside the mentioned improvements, investigating plot design and scan setup on plantations is another task of future work. Especially the regular spatial arrangement is problematic w.r.t. scanning a particular region of interest sufficiently with a few number of scan viewpoints.

6. Conclusions

We have proposed a method to detect trees on a plantation that exploits the particular spatial distribution pattern. First, the rows in a selected region of interest are retrieved from the co-registered scan data set. Second, each row is analyzed separately using a histogram of point numbers. The presented method is a prototype to test whether integration of information about the spatial tree arrangement improves tree detection. We have presented experiment results of 18 plots that were scanned on three different plantations with *Eucalyptus spp.* trees. The experiment results show that the number of properly detected trees is 97% on average. The method works reliably for all 18 plots. As a consequence, we arrive at the conclusion that retrieval of the row arrangement prior to actual tree detection is beneficial. The key idea should be investigated further to develop a generic solution that can be applied more broadly.

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