A NEW METHOD FOR INDIVIDUAL TREE DELINEATION AND UNDERGROWTH REMOVAL FROM HIGH RESOLUTION AIRBORNE LIDAR

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ABSTRACT:

High density airborne LiDAR, for example FLI-MAP 400 data, has opened an opportunity for individual tree measurement. This paper presents a method for individual tree delineation and undergrowth vegetation removal in forest area. The delineation of individual trees involves two steps namely 1) tree crown delineation based on density of high points (DHP) and 2) separation of dominant trees and undergrowth vegetation. The DHP method relies on the fact that the density of received laser pulses above a certain height is high at the centre of a tree crown and decreases towards the edge of the crown. In the second step, a special tree filtering algorithm is introduced to remove undergrowth vegetation, which is necessary to ease for instance the measurement of tree diameter at breast height (DBH). Two study sites are selected and the tree delineation method is tested under different tree conditions. It is shown that the method has successfully delineated more than 60% trees. However it failed to delineate the trees in two cases 1) undergrowth vegetation is very near to the dominant trees and it is even hard to separate it manually, or 2) the LiDAR data failed to reflect the complete structure of a dominant tree due to forest interception.

1. INTRODUCTION

Airborne LiDAR data has been used quite extensively in forest mensuration. Studies in utilizing LiDAR data to assess forest conditions have moved from an average forest stand scale to individual tree level (Roberts et al. 2005). This is clearly encouraged by the fact that improvements in LiDAR technology have led to higher pulse rates and increased LiDAR posting densities. Therefore, the semiautomatic mapping of single tree crowns (delineation and estimation of tree parameters), has become a key approach in forest inventory research (Heurich 2008). Measuring forest attributes at fine scales is necessary to manage terrestrial resources, in which natural ecological condition could be replicated much closer (Zimble et al. 2003). Moreover, forest information derived at a fine scale can be easily translated into coarser scales depending on the requirement of certain applications. For example, if the tree measurement is too detailed, then it can be aggregated to mean values per stand of hectare (Brandtberg et al. 2003). However, only few studies have focused on individual tree level (Popescu 2007).

In previous studies, most of individual tree variable measurements, for example DBH measurement were based on low density LiDAR data (Heurich 2008; Hyyppä et al. 2001; Maltamo et al. 2004; Persson et al. 2002; Popescu 2007; Tomoaki et al. 2005). In this case, it requires a relationship between crown dimension, tree height and DBH to be established. The problem is this relationship might be dependent on tree species and site. In consequence, regression model with low regression coefficient value will introduce error in tree variable estimations. It was shown that direct measurement of tree variables on point clouds seems dominated by the ground based scanning LiDAR (Hopkinson et al. 2004; Thies et al. 2004; Watt and Donoghue 2005). Though the ground based LiDAR capable of delivering detailed measurement of tree variable but this method becomes less effective for large area.

The laser beam of airborne LiDAR with specific settings (i.e. FLI-MAP 400 data that has a capability of scanning in three directions (forward, downward and backward) can deliver massive amount of point clouds over forest area) could penetrate deep inside the forest especially during leaf-off condition (Brandtberg et al. 2003). The high density LiDAR data clearly reveals the structure of individual trees, thus giving better opportunity for more accurate forest variable measurements. It was shown by previous studies (Rahman and Gorte 2008b; Reitberger et al. 2007) that high density LiDAR can be used to delineate the whole structure of individual tree which opens to an opportunity of direct measurement of tree variables on the point clouds.

However, direct measurement of tree variables on point clouds is not a straightforward process. Laser pulses reflected by neighbouring trees and undergrowth vegetation are considered as noise and should be removed prior to the measurement. These points might be reflected by vegetation near to tree trunks, thus making measurement of tree variables such as DBH directly on the point cloud more difficult. In this study we introduce a method for individual tree delineation that involves two processing steps; 1) individual tree crown delineation based on density of high points (DHP), and 2) tree filtering. There are several challenges to delineate the whole structure of trees for direct tree measurements on the point clouds.

a. Individual tree crown delineation is not perfect. It still contains errors, in which a single tree segment might contain points from neighbouring trees
b. The lower part of the tree is often covered by undergrowth vegetation, which should be removed

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prior to tree variable measurement, for instance tree DBH.

The main objective of this paper is to introduce a method for individual tree delineation that aims at separating dominant trees and undergrowth vegetation.

2. STUDY AREA AND METHODOLOGY

2.1 Study area

The study site is in forested area of the Duursche Waarden floodplain, the Netherlands (see Figure 1). This floodplain is located along the IJssel River, the smallest tributary of the Rhine River in the Netherlands. The area is partly covered by meadow and arable land and a large part of the areas has become nature.

Figure 1. Study area at the Duursche Waarden floodplain, the Netherlands

2.2 LiDAR data

The LiDAR data were captured using a FLI-MAP 400 system. The FLI-MAP 400 is a helicopter mounted LiDAR system designed to capture highly detailed terrain features with high accuracy. It is claimed that the absolute accuracy of FLI-MAP 400 data measured over hard and level surfaces is 2.5 to 3.0 cm. The system is capable of scanning in three directions (forward, downward and backward) and this increases the amount of reflected pulses from the ground even in a quite densely vegetated area. The FLI-MAP 400 data records a maximum of four partial reflections from a single pulse if the distance difference between the reflections is at least 0.9 m. This enables optimal interpretation of a detailed terrain model even in vegetated areas. The Airborne LiDAR of FLIMAP-400 data with a density of 70 points per meter square were acquired in 2007 (see Table 1). The leaf-off LiDAR data allows better penetration through canopy and thus the vertical structure of tree could be more easily revealed. In this study, two different areas are selected. In these areas, the tree delineation method is tested with different tree conditions.

Date of acquisition	28-03-2007
Observation altitude	100 m above ground level
Observation speed	35 knots per hour
Point density	70 points / m^2
Swath width	404 meter
Number of returns	4 returns
Scanning angle	Swath angle 60 degrees, forward 7 degrees and back 7 degrees

Table 1. Specification of FLI-MAP 400 data

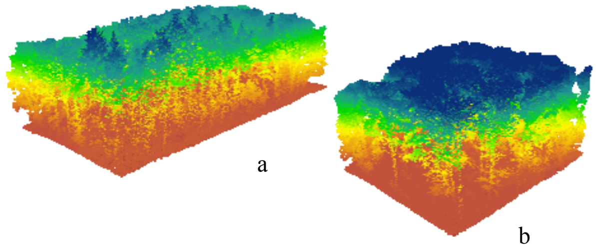

Figure 2. Dataset 1 (a) and dataset 2 (b)

2.3 Extraction of Digital Terrain Model (DTM) and point clouds normalization

In order to reduce the effect of undulating terrain, the datasets are normalized based on DTM (see Figure 3). In this study, the ground points are collected using an adaptive triangulated irregular network (TIN) model (Axelsson 2000). The ground points are interpolated using the TIN approach. The normalization step is important since the tree filtering algorithm needs to define a reference height for further processing (see Figure 4).

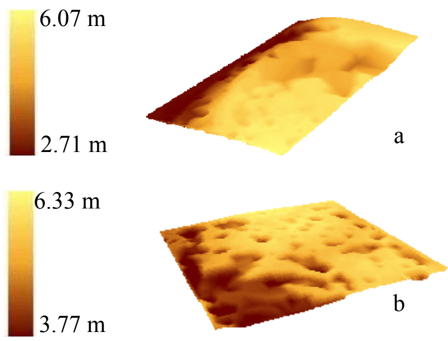

Figure 3. DTM for dataset 1 (a) and dataset 2 (b)

2.4 Individual tree crown delineation

Individual tree crown delineation is based on the DHP method introduced by Rahman and Gorte (2009). The input parameters required by the delineation algorithm are point buffer, cell size of raster data, minimum and maximum crown radius. A similar method had been also used by Rahman and Gorte (2008) for tree detection. The tree crown delineation based on DHP lies on the fact that the laser pulses from tree branches above a certain reference height is highest at the centre of a tree crown and decreases towards the edge of crown. This is because the total volume of tree branches is higher in the centre part of the tree crown and becomes less towards the edge of the crown. The tree crown delineation based on DHP surface is done by using Inverse Watershed segmentation algorithm.

The individual tree crown segmentation based on DHP method produces two outputs, 1) individual tree locations, and 2) individual tree crown segments. The tree location is placed at the centre of the tree with the highest DHP value in each tree segment. The tree crown segments are used to assign the point clouds to their corresponding tree segments and from here on the segmented point clouds are referred as tree segments. The segmented point clouds and the tree locations are then used as input for tree filtering step.

2.5 Tree filtering

In this study, filtering aims at separating dominant trees and undergrowth vegetation. The filtering algorithm requires three input parameters, namely, 1) maximum growing distance for tree crown, 2) maximum growing distance for tree trunk, and 3) average tree trunk diameter. This algorithm is inspired by the fact that a tree would have distinct parts in the histogram that represents tree crown, tree trunk, ground surface and the undergrowth vegetation. It was shown by Straatsma and Middelkoop (2006) that the histogram of the frequency of laser pulses at different heights for a tree during winter season has high frequencies at the tree crown and at the ground surface. However, in case the lower part of the tree is covered by undergrowth vegetation, most of the reflected pulses are coming from the undergrowth vegetation. Then the reflected laser pulses from the trunk show a lower frequency.

The filtering algorithm can be divided into two main phases; 1) region growing (RG) segmentation of an individual tree crown, and 2) RG segmentation of tree trunk. In the tree filtering phase, the tree segments are processed separately. For each tree segment the histogram of point frequency at certain height is created and further filtered using a 1D Gaussian filter. Filtering is required to produce a smoother histogram. The upper part of the filtered histogram is then fitted with a Gaussian function. As the upper part of the histogram represents a tree crown, the reference height is then defined as a 3σ value of the upper Gaussian function (see Figure 4).

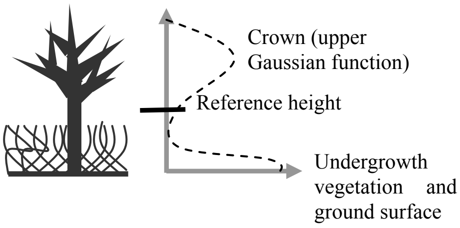

Figure 4. Reference height of a tree

2.5.1 Region growing segmentation of an individual tree crown: The point cloud above the reference height is used for the RG segmentation of tree crown. The segmentation starts from a seed point located on the crown of each tree segments and it continues until it reaches the reference height (see Figure 7). The seed point is obtained during the individual tree crown delineation discussed in 2.4. It should be noted that the point cloud above the reference height still contains points of the neighbouring tree canopy and a constraint for RG segmentation is required to avoid these points. The DHP approach has a good potential to remedy this problem. RG segmentation either for tree crown or tree trunk is based on an approach as depicted in Figure 5.

However, instead of using constant value, the RG segmentation of tree crown assigns a unique growing distance to each point based on its density (see Figure 6). Places with higher point densities are mainly located at the centre of the crown and they are assigned a larger growing distance than points with lower densities at the edge of the crown (see Figure 7). The normalized point density (the value ranges from 0.0 to 1.0) is transformed to a growing distance based on a linear conversion. The minimum growing distance for RG segmentation of tree crown is fixed at 0.1 meter and user is required to specify the maximum growing distance. The seed points for RG segmentation of tree trunk are then selected from the points of tree crown located near to the reference height.

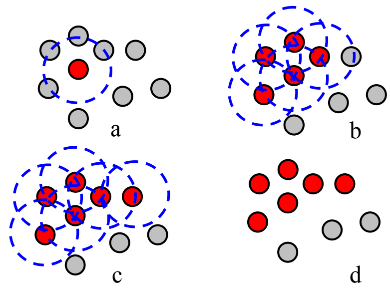

Figure 5. RG segmentation with a constant growing distance. The growing process starts with a seed point (a), and points within a specified growing distance are used as seed points for the next growing process (b). The growing stops when there is no other point within the growing distance of all seed points (c)

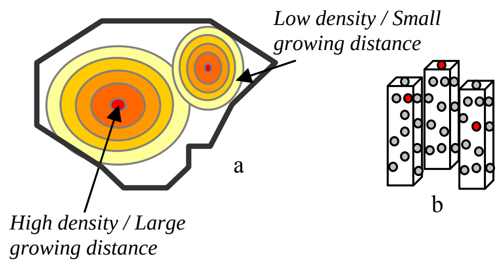

Figure 6. Illustration of DHP and its growing distance in a single tree segment (a), and method to calculate number of point in column (point density) for a particular point (red point) (b).

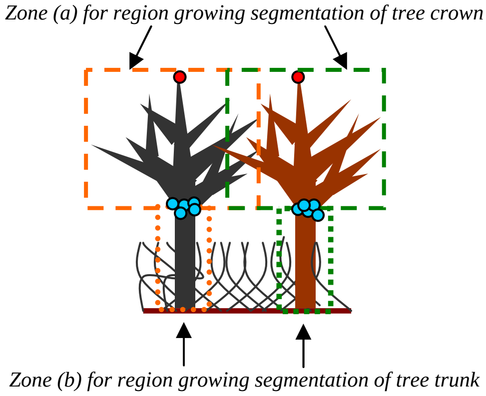

Figure 7. Seed point located at the top of tree crown (red points). The RG segmentation of tree crown with growing distance based on DHP (see Figure 6) is done in zone (a). Meanwhile the RG segmentation of tree trunk based on fixed growing distance starts from the seed points (blue points) (see Figure 5) and the RG segmentation is done in zone (b).

2.5.2 RG segmentation of the tree trunk: RG segmentation of the tree trunk starts from the reference level until the ground surface. The segmentation is done based on a constant value of the growing distance and it is repeated from 0.1 meter to the maximum growing distance from the tree trunk. The purpose of this strategy is to collect as many points as possible candidate points for the tree trunk. As more points are selected as candidate points a histogram is created to represent their vertical distribution and the 1D Gaussian filter is used to smoothen the histogram. The candidate points are assigned to tree trunk only if they meet two conditions; 1) they frequency of the candidate points should be at least similar to the average frequency of tree trunk and, 2) average distance of each candidate points should be at least similar to the pre-specified average tree trunk diameter. At each height the number of points added to the tree trunk is evaluated. In case no more points are added the RG segmentation of the trunk will stop and the RG segmentation of the crown is repeated with different growing distance values (minimum and maximum growing distances). This continues until the segmentation of the tree trunk reaches the ground surface. The overall process of tree filtering is explained in detailed in Appendix A.

3. RESULTS AND DISCUSSION

3.1 Tree crown delineation

The individual tree crown delineation has successfully identified 76 trees and 38 trees in dataset 1 and dataset 2 respectively (see Figures 8(a), (b), (c) and (d)). Table 2 shows the parameters used in the individual tree crown delineation process. The corresponding tree segments are shown in Figures 5(c) and 5(d). However, it is observed that for a single tree segment it still contains points especially from the neighbouring trees.

Dataset	Point buffer (m)	Cel l size (m)	Minimum crown radius (m)	Maximum crown radius (m)
1	2.0	0.3	1.2	5.5
2	2.0	0.3	1.5	4.5

Table 2. Parameters used in individual tree crown delineation based on DHP

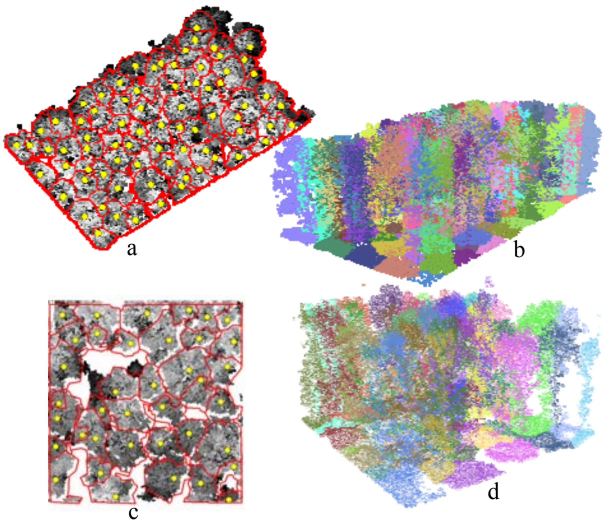

Figure 8. Tree crown segments and tree locations (a and c), and tree segments (a and b) for dataset 1 and dataset 2

3.2 Tree filtering

The maximum growing distances for tree crown and tree trunk are set to 2.0 meter. The tree filtering algorithm has successfully filtered about 63% and 71% from the total trees found in dataset 1 and dataset 2 (see examples of successfully filtered tree in Figure 9 and Figure 12). It is observed that the filtering algorithm needs at least small space of tree trunk, especially in the area just below the tree crown. This allows precise points for tree trunk to be collected starting from the reference height until the filtering routine reaches the ground surface. On the other hand, the crown of dominant tree should be distinguishable from the undergrowth vegetation. Otherwise the RG for tree crown would not be able to separate the points from the undergrowth vegetation (see Figure 10).

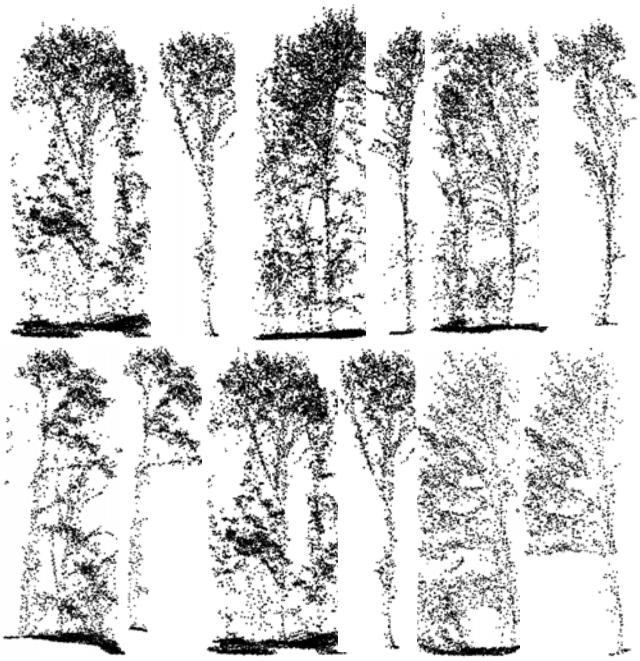

Figure 9. Several examples where the tree filtering algorithm has successfully filtered the trees

There are several cases where the undergrowth vegetation is very near to tree trunk and it is even quite difficult to manually filter out the undergrowth vegetation from the dominant tree (see Figure 10). On the other hand, due to forest interception on LiDAR signal, there are several situations where the LiDAR data failed to reflect a complete structure of a dominant tree and undergrowth vegetation (see Figure 11). This further complicates tree filtering.

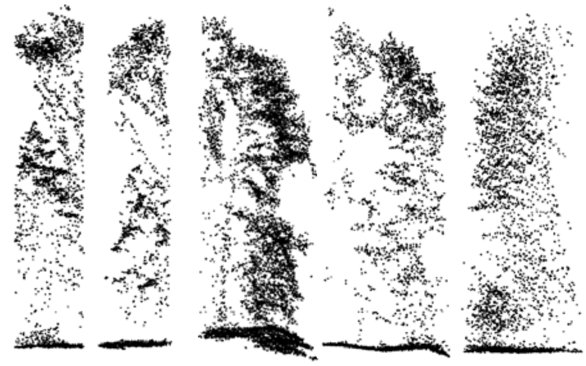

Figure 10. Several examples where the tree filtering algorithm fails to filter the trees where the undergrowth vegetation is very near to dominant tree

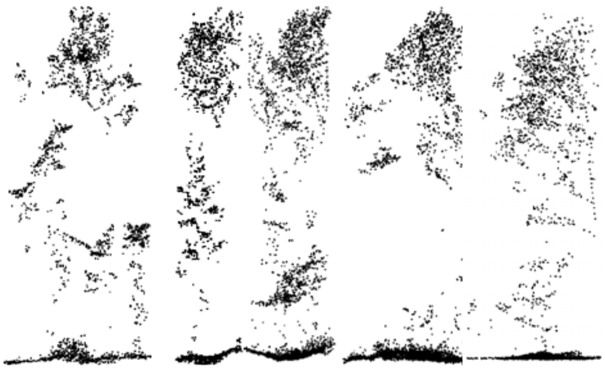

Figure 11. Several examples where the tree filtering algorithm fails to filter the trees where the LiDAR data were unable to reflect a complete structure of dominant tree

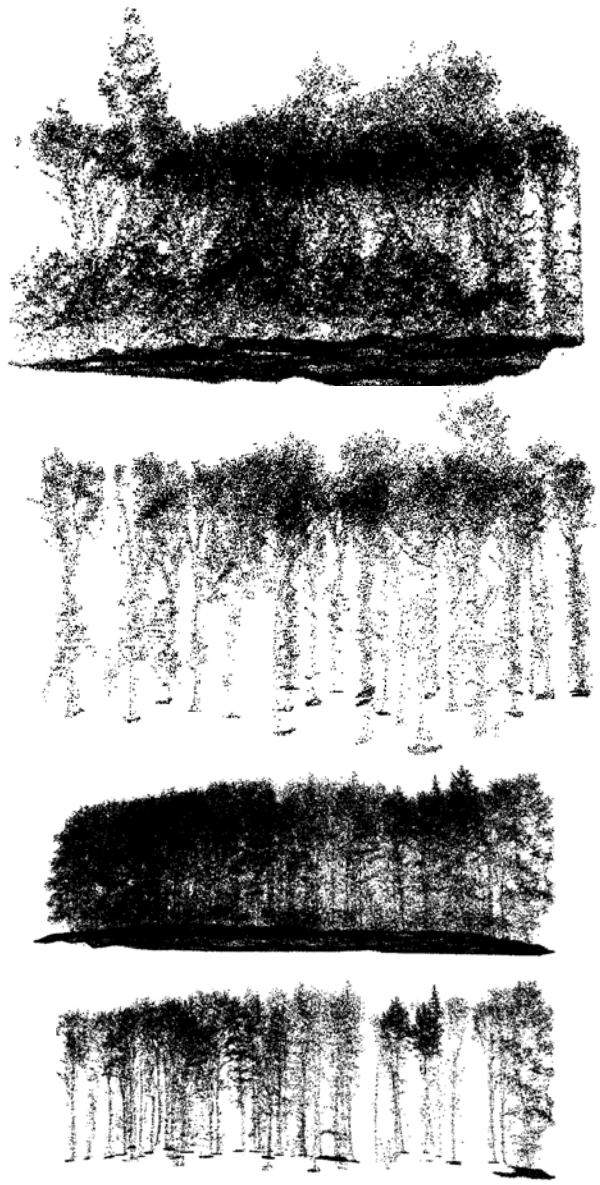

Figure 12. The original datasets and the filtered trees of dataset 1 and dataset 2

4. CONCLUSIONS AND OUTLOOK

It is shown that high density Airborne LiDAR acquired during leaf-off season is capable of delivering individual structure of dominant and undergrowth vegetation. Therefore it opens an opportunity to measure tree properties, for instance tree DBH, on the point clouds directly, instead of being dependent on regression models. However, direct forest measurement on point clouds is not a straightforward process and it requires several pre-processing steps. It is also shown that the algorithm only works in a condition where there tree trunk is still visible especially in the area just below the reference height. For heavily vegetated undergrowth vegetation located very near to the dominant trees, better method still required to separate the points. This method will be combined with the ongoing research of estimating tree DBH directly from point cloud. However, for the cases where the filtering algorithm fails, allometric transfer function in estimating tree DBH is still required. Nevertheless, the tree delineation approach introduced in this study still needs to be optimized in order to minimize the processing time.

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APPENDIX A: ALGORITHM FOR TREE FILTERING

1 Generate Digital Terrain Model (DTM) and normalize the datasets
2 Individual tree crown delineation based on DHP which results individual tree crown segments and tree location based on the highest weight value in each segment
3 Assign point clouds to the corresponding tree crown segments
4 Generate a seed point for each tree segment based on tree location as produced in step 2.
5 Calculate a histogram for each tree segment, filter the histogram using one-dimensional (1D) Gaussian filter and define the appropriate reference height
6 Calculate frequency value at the reference height
7 Calculate density for points above the reference level
8 Segmentation for tree crown and trunk
- 8.1 Set a minimum and maximum growing distance for tree crown
- 8.2 Assign point to growing distance value based on its density with linear conversion. Basically, higher density points are assigned with higher growing distance and vice versa.
- 8.3 RG Segmentation of tree crown - This basically starts from the seed point until the reference level.
- 8.4 Select seed points for tree trunk from points belong to tree crown
- 8.5 Tree trunk segmentation
  - 8.5.1 Set a maximum growing distance for tree trunk and move under the reference height by 0.5 meter interval
  - 8.5.2 Grow and select as many as possible points for tree trunk (candidate points)
  - 8.5.3 Combine points belong to tree crown, trunk and the candidate points and calculate a histogram
  - 8.5.4 Accept the candidate points if 1) the frequency of the candidate points less than the average frequency of tree trunk AND 2) average distance between candidate points less than the pre-set trunk diameter ELSE go to step 8.1 with different growing value
- 8.6 If the tree trunk segmentation reach the ground THEN terminate the RG segmentation ELSE repeat step 8.1 with different value of minimum and maximum growing distance
- 8.7 If the filtering process fails to reach ground level fit a vertical 2d line on the points belong to tree trunk
  - 8.7.1 Set a maximum growing distance for tree trunk and move under the reference height by 0.5 meter interval
  - 8.7.2 Grow and select as many as possible points for tree trunk (candidate points)
  - 8.7.3 Combine points belong to tree crown, trunk and the candidate points and calculate a histogram
  - 8.7.4 Accept the candidate points if 1) the frequency of the candidate points less than the average frequency of tree trunk AND 2) average distance between candidate points less than the pre-set trunk diameter ELSE go to step 8.7.1 with different growing value
- 8.8 Terminate the filtering routine