Automated detection of branch dimensions in woody skeletons of leafless fruit tree canopies

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Abstract

Light driven physiological processes of tree canopies need to be modelled based on detailed 3D-canopy structure – we explore the possibilities offered by terrestrial LIDAR to automatically represent woody skeletons of leafless trees as a basis for adequate models of canopy structure. The automatic evaluation method for LIDAR data of fruit trees is based on a previously developed skeletonization algorithm. Branch length was chosen as example parameter to test the performance of the algorithm with manually measured data. The extraction of the brach length utilizes a graph splitting procedure to extract the individual branches from the skeleton. The algorithm is validated against six leafless apple trees and one cherry tree with small blossoms. The validation against a manually measured ground truth resulted in a good correlation up to 0.81.

Keywords: skeletonization, branch system, Malus x domestica Borkh.'Honeycrisp', SkelTre

1. Introduction

Branch systems of trees are the result of ramification and branch elongation processes that occur outside the tropics in an annual rhythm. They can tell the growth history of trees as good as growth ring chronologies of the stem (Roloff 1986) and their dimensions are closely correlated to other structural quantities of tree canopies like appending leaf or woody biomass (Niklas 1994). Allometric equations were established on this basis for many tree species in order to derive the amount of woody biomass (Bartelink1997), leaf biomass (Burger 1945) or its distribution in space (Fleck 2002) from easier measurable quantities like the diameter of the stem or branches. 3D-canopy light modeling depends on such spatial information on the distribution of biomass and is the key to a number of physiological processes in the canopy that express the vitality and performance of trees (Fleck et al. 2004).

From a remote sensing viewpoint, the automated assessment of branch dimensions in the canopy is unprecedented, except for diameter and tapering of the stem, which is first of all due to insufficient resolution to detect single branches. 3D-laserscanners measure thousands of distances per second between the instrument and its surrounding at regular horizontal and vertical angles (Shan and Thoth 2008), which increased the resolution of the resulting 3D-point clouds dramatically. Thus, terrestrial LIDAR principally allows for the first time in history to measure the complete 3D-structure of the branch system. This information can be made available to modelers in biology and forestry, if an automated evaluation procedure is found, while it is impossible to sort all branch informations out by eye, just due to quantity.

In one sense, laser scanning produces a discrete surface sampling of a real world object and represents it as a point cloud. Therefore single scans are made from different scanning positions to cover the whole object; several scans have to be aligned into one common coordinate system. The process of aligning scans into a common coordinate system is called registration. The drawback of the registration procedure is that regularity in the scan data vanishes and the point cloud is therefore unorganized. The study of unorganized point clouds as an object representation and the possible information extraction from them is still under active research. Meanwhile the majority of research is focusing on the extraction of surface parameters from the point cloud; this paper is using an approach to reveal the underlying structure of the represented object. The investigated object in this paper are leafless fruit trees that are part of a 3D-light modelling approach (Fleck et al. 2009).

Obtaining object topology from unorganized point clouds (compare Fig. 1) can help in various point cloud applications. The target application of this paper is the extraction of the branch length from laser scanned orchard trees. A skeleton is a one-dimensional description of the tree structure, which is ideally representing the tree topology and geometrically centered within the tree. Skeletons are represented as curves, collections of ordered points or graphs. Their extraction from a point cloud faces several algorithmic challenges, such as centeredness, topological correctness and robustness to noise.

Literature on skeletonization of trees from real data like laser scans is limited, although skeletonization is a heavily studied topic in theory. For general information about skeletal structures the reader is refereed to Biasotti et al. (2007), while the review given here is related to tree skeletonization as a special case .

Gorte et al. (2004) presented a first approach on tree skeletonization using mathematical morphology. Their algorithm was based on the sequential data thinning method of Palágyi et al. (2001) and applied to terrestrial laser scan data. The morphological operations opening and erosion used to produce a skeleton (Serra 1982) are applied to a rasterized point cloud, where every raster cell contains several measuring points. Drawback of this algorithm is the large number of parameters that need to be controlled, like resolution of the raster, and type and size of the structuring element. From a theoretical perspective centering within the point cloud is hard and connectivity can not be guaranteed. This approach was later extended to the so-called Dijkstra Skeletonization (Gorte 2006). The connectivity of the skeleton was improved comparing different raster resolution. The major common drawback is that the extraction of a centerline from an object like a tree requires completely represented object hull in order to fill the inner volume with raster cells. Due to occlusion effects by branches this is hardly achieved on trees.

Fig. 1: Registered 3D-point clouds of three investigated apple trees with stem diameters of 3.9cm, 7.3cm, and 7.4cm. While the human eye recognizes parts of it as branches, their automated recognition still needs to be solved.

Bucksch et al. (2008) used an adaptive octree to subdivide the point cloud. Their octree subdivision relies on the directions by which the point cloud is passing through the octree cell sides, which is the key to operate on only a few data points if necessary. This algorithm requires only two input

parameters, a threshold to determine when a cell side is considered to be crossed and a minimum allowed cell size to terminate the subdivision process. From this octree an initial graph, the so-called octree graph, is extracted. This octree graph is reduced to a skeleton. The reduction follows a set of rules, which are applied to redundant structures in the graph.
Recently a semi-automatic approach using tree allometries to produce a model of a tree only for visualization purposes was introduced by Xu et al. (2007). The described procedure computes a rough skeleton of the main branches, until approximately 66% of the tree height. The remaining tree is generated based on pre-knowledge. Their aim is to create a plausible model for visualization, and not to quantify tree geometry.

2. Methods

2.1 Study area

The study was mainly conducted in apple orchards of the Annapolis Valley, Nova Scotia, Canada close to the city of Kentville (45°4'39'' N, 64°29'45''W). The six investigated apple trees (Malus x domestica Borkh. 'Honeycrisp') are located in two orchards that belong to the test sites of the Atlantic Food and Horticulture Research Centre. Three apple trees of them grow on a trellis system and the other 3 trees stand as single trees in rows. The orientation of the rows is from North to South with a spacing of 3m by 5m and trees of comparable height are located next to the investigated trees. The stem diameters ranged from 3.9cm to 8.1cm. The single standing cherry tree (*Prunus* avium, 'Heldelfinger') is located at the Kirschenversuchsanlage Witzenhausen, Germany.

2.2 Field measurements

Each tree was scanned in March 2006 with the 3D-laserscanner Imager 5003 (Zoller+Fröhlich, Germany) from 4 sides with a distance of about 4m to the stem. The laserscanner was placed in different heights above the floor between 1m and 2.3m in order to avoid occlusions. The Scanner resolution was set to 'High', which is equal to a horizontal and vertical angular step width of 0.036 degrees and results in a 10.000 pixel resolution for 360 degrees.
The branch segments of each tree were named in order to be able to reconstruct branch system topology and their length was measured from node to node. Diameter of each internode was measured at its base and tip, about 1cm before the node or end bud. The diameters were taken in two directions and averaged.

2.3 Data processing

Registration of the scans was done with the NEPTAN based registration algorithm in Z+F Laser Control based on 14-18 artificial targets that were placed on the ground and fixed to ladders in a height of about 2m in order to reach a homogeneous distribution of fix points common to multiple scans. The 3D-point cloud was transferred to CYCLONE and subsamples representing one tree were cut. Skeletonization of the tree's 3D-point cloud was performed with the SkelTre method (Bucksch et al. 2009), which is an algorithm to extract a skeleton from imperfect data (e.g. laser scanning data) of trees. For this purpose the space occupied by the tree point cloud is subdivided by an octree. An octree subdivides the space into cubic cells. From these octree cells a graph is extracted. The graph extraction is based on an estimate how the actual surface, that is represented by the point cloud, is crossing the octree cell sides. A graph consists of edges and vertices, where edges connect the vertices and indicate in our case the crossing direction through the octree cells. Every edge belongs to two vertices and is associated with a directional edge label. Based on these edge labels the algorithm guarantees that the initially extracted graph is reduced to a one-dimensional skeleton, by merging suitable neighboring vertices. The benefits of this skeleton are that the centeredness and topology is provable good. Topology correctness is a perquisite to enable proper navigation through the tree structure and centeredness enables us e.g. to measure diameters and length of tree parts. A resulting skeleton graph of the skeletonization algorithm is shown in Fig. 2 (right) next to the point cloud it is originated from.

Fig. 2: 3D-point cloud (left) of an apple tree and the according sceleton (right). Though some parts of the point cloud contain gaps, the skeletonization algorithm is able to detect the general pattern.

Fig. 2 also shows one of the major mathematical problems on laser scanned trees. The youngest branches are strongly undersampled. Furthermore with increasing crown density the amount of occlusions is increased, leading to gaps in the point cloud. A bad incidence angle between the laser beam and the tree surface leads to increased noise, because of the round surface geometry of the branches (Soudarissanane et al. 2008). The increased noise leads to the fact that some – especially smaller – branches may not be skeletonized. For details on this particular skeletonization algorithm the reader is referred to (Bucksch et al. 2009).

The output of the skeletonization is a graph as shown in Fig. 2 (right), consisting of vertices connected by edges centered within the tree. Estimation of branch length requires a graph splitting procedure (Fig. 3) to segment the skeleton graph into subgraphs representing a single branch. Three steps are involved to derive single branches from the skeleton graph:

1. Determination of the stem base vertex. We have chosen the vertex with the smallest z-coordinate a stem base.
2. A traceing along the graph to follow the branch.
3. A criterion that decides which branch which edge belongs to the currently followed branch at branching vertices. Note that vertices with more than two incident edges represent the begin of a new branch.

The skeleton graph allows navigation through the tree point cloud. At every vertex with more than two incident edges (marked red in Fig. 3) the graph has to be splitted into the currently followed branch and newly starting branches. By tracing the graph from the stem base, we can identify the edge *a* (compare Fig. 3) reaching a branching point. The incident edge *b* forming the angle closest to 180 degree between *a* and *b* is selected to continue tracing (purple subgraph in Fig. 3). All other incident edges are marked as branch bases from where a new trace can be started, like starting from the root. This procedure also provides the branch hierarchy as an output. Therefore, the skeleton graph is geometrically embedded into the tree point cloud, the Euclidean length of all edges in one trace is taken as result for the branch length.

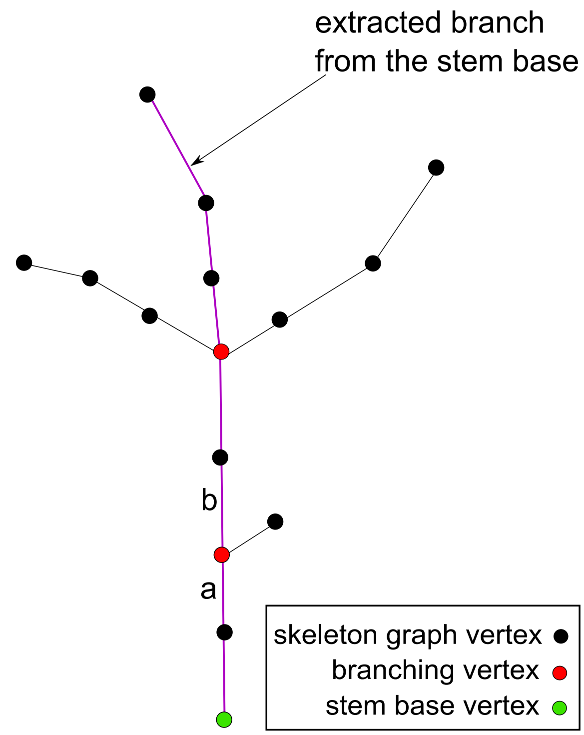

Fig. 3: Principle of the branch splitting procedure. The purple subgraph is the extracted branch from the stem base. Skeleton graph vertices are marked in black, the stem base vertex in green and branching vertices are shown in red. The edge *a* is an incoming edge and edge *b* is an outgoing edge of a branching vertex in direction from the root point to the branching vertex.

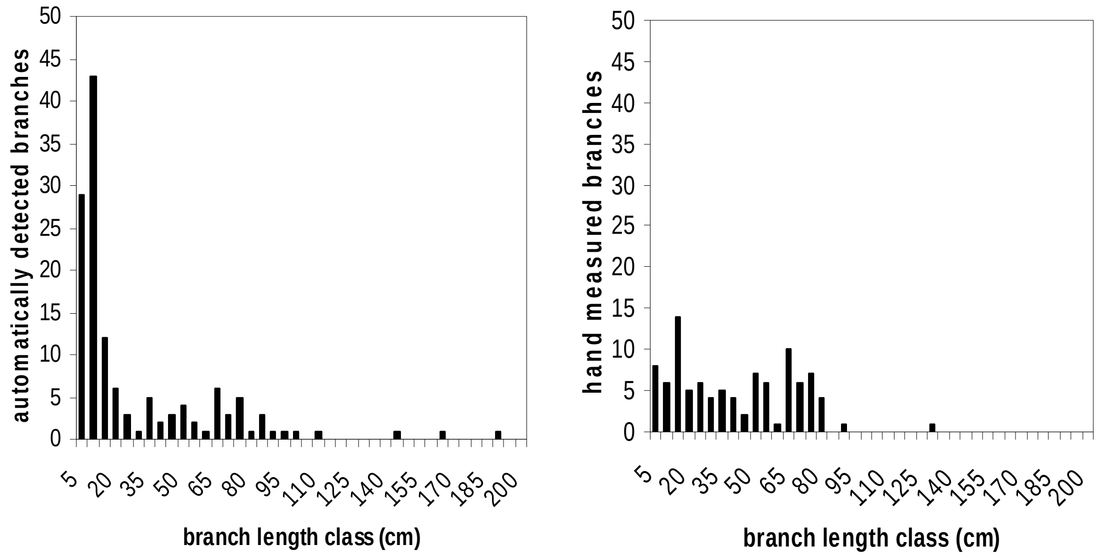

Fig.4: Frequency distributions of detected (left) and hand measured (right) branch lengths in the canopy of apple tree 1_12 (3.9cm stem diameter).

3. Results and Discussion

The algorithm showed good stability to gaps and robustness to noise in the point cloud (compare Fig. 2). Where gaps in the measured data occur, the algorithm still detects the two parts of a branch on both sides of the gap. This leads to a higher number of branch segments than we measured by hand.
Branch length determination was compared to the hand measurements based on frequency distributions of the total amount of branches of a tree. The branch length was categorized in length classes of 5cm from 0 to 210cm. Since the stem below the first ramification point is usually recognized separately from its continuation in the canopy this does not allow conclusions on total tree height. The result for the smallest tree of our study is exemplarily shown in Fig. 4: While the algorithm detected a much higher number of small segments (class up to 5cm and up to 10cm) and did recognize a few longer branches that were measured as separate entities in the hand measurements, the pattern in the middle classes seems to be well related between both methods.

The correlation between all automatically detected branch length classes of this tree except the lowest two classes to their according hand measured branch length class yielded an r^2 of 0.8 (Fig. 5). A regression line forced through the origin shows that the branch number in hand measured branch length classes was on average 69% of the branch number in the according branch length class of the automatically detected branches. Since this percentage did not substantially vary over branch length classes, all branch length classes seem to be affected in the same way by gaps in the 3D-laserscanner data.

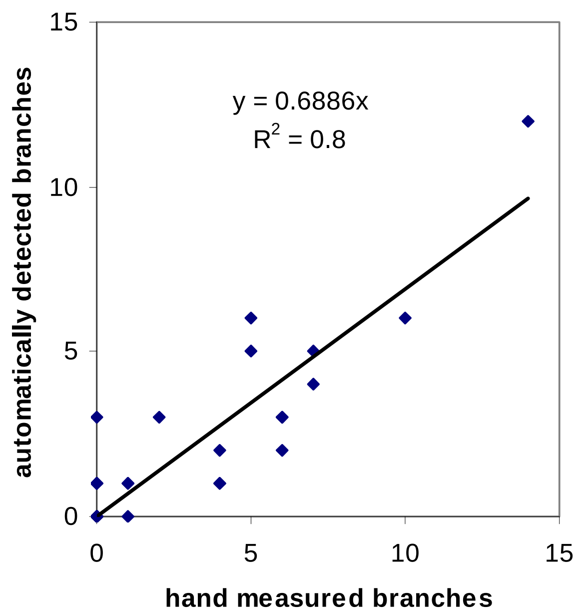

Fig. 5: Comparison of the frequency distributions in Fig. 5 based on the correlation between branch numbers in the same diameter class. The two lowest diameter classes (up to 5cm and up to 10cm) were omitted due to known artefacts in the skeletonization algorithm and the regression line was forced through the origin.

The described analyis procedure was applied to six apple trees and one cherry tree as shown in Table 1. It can be seen that the result is depending the crown complexity. As indicator for the crown complexity the stem diameter is given in Table 1. The tree Apple 2 had a tree pruning between the manual measurement and the laser measurement, which resulted in a correlation factor of only 0.14. The cherry tree was scanned while it had it first blossoms and leafs on. The achieved correlation was 0.44. The average correlation on leafless trees (without Cherry and Apple 2) was 0.69.

Table 1 Results of the canopy analyiy of seven validation trees. Apple 2 had a tree pruning between the manual and the laser measurement.

Tree	Diameter	R^2
Cherry	18,7	0,44
Apple 1	7,3	0,65
Apple 2	6,7	0,14
Apple 3	3,9	0,81
Apple 4	5,9	0,69
Apple 5	8,1	0,63
Apple 6	7,4	0,56

4. Conclusions

This paper presents a new approach to extract the branch length from leafless apple trees. The approach is based on a skeleton extraction from terrestrial laser scan data. On selected examples we could show that high correlation between manual validation measurements and automatically extracted branch length detection is achievable, though problems with gaps in the 3D-laserscanner data were obvious: The more complex the canopy structure of trees is, the more gaps are to expect in the scanned data which remains to be solved on the algorithmic side. Skeletonization algorithms as the proposed SkelTre method may eventually provide the basis for an adequate gap filling strategy in 3D-point clouds with high degree of occlusions. The robustness of the skeletonization algorithm could be indicated by a cherry tree example with small blossoms and young leafs.

Further work will include improvements with the goal to extract a reliable diameter from the data. It is expected to improve the correlation by better approximation of the manual field measurement practice to the algorithmic process. The approximation of the field measurement practice will enable the comparison of individual branches, which is useful on trees with a low amount of branches availible for regression analysis. Furthermore, data of other trees will be included, partly based on improved scanner systems (Imager 5006).

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