DETECTION AND MODELLING OF 3D TREES FROM MOBILE LASER SCANNING DATA

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ABSTRACT:

Mobile laser scanning acquires massive point clouds in urban areas to provide high resolution data for 3D city modelling. A workflow for detecting and modelling trees from point clouds is presented. Emphasis lies on data reduction using an alpha shape approach. From the reduced point cloud the parameters are extracted to model the 3D trees using the Weber and Penn (1995) approach. The workflow is applied on two different sample data sets which were acquired with different mobile mapping systems and thus vary in quality and point density. The applied data reduction approach reduces the amount of data to process by about 95%. The tree models generated are consisting of a realistic trunk and branch structure of the tree crown. However, the inner branch structure of the tree crown is parameterised. Only the outer shape of the tree matches with the reality, which is sufficient for the requirements of visualization applications. For the tested areas the tree detection reaches a quality rate of 85% and 78% respectively. The comparison of the generated tree models against photographs and the original point cloud shows that the level of abstraction is sufficient for the integration of the tree models into 3D city models.

1. INTRODUCTION

Recently Mobile Laser Scanning (MLS) data sets are collected for many urban areas and road tracks for 3D data acquisition and mapping i.e. to derive 3D information for cadastre, inventories and 3D city models. In contrast to terrestrial laser scanning (TLS) larger areas are scanned while the resulting point cloud consists of an approximately similar density. The completeness of the tree representation might be less in MLS compared to TLS campaigns, if a tree was scanned from multiple positions.
The appearance of objects such as trees in MLS data depends on the echo distribution, which is determined by vehicle speed, platform configuration (e.g. one or two sensors), relative position between sensor and object, capability of recording multiple echoes, and season of acquisition (leaf-on or leaf-off season). Operational 3D information extraction and modelling from such massive point clouds is still a matter of research.

The objective of this paper is to model single trees for visualisation purposes in 3D city models. The here proposed approach shows a highly automated workflow from tree detection in MLS point clouds to single tree modelling. The workflow consists of a sequence of methods efficiently reducing the amount of data to process without loosing important shape information needed for the visualisation of the final tree model.
The paper is structured as follows. Related work on vegetation detection and tree modelling from laser scanning data is presented in Section 2. Section 3 introduces the test sites and data sets. Then the workflow is presented in Section 4. The results are assessed and discussed in Section 5. Section 6 gives concluding remarks and an outlook on future work.

2. RELATED WORK

Laser scanning is widely used in forestry applications i.e. for the derivation of vegetation properties on forest stand or individual tree level. Current methods for single tree delineation are developed for airborne laser scanning (ALS) data (e.g. Rahman et al. 2009, Reitberger et al. 2009, and Hyyppä et al. 2009). Tree reconstruction and modelling from ALS for simulation or visualization purpose is done by voxel approaches (Wang et al. 2008), simple geometrical models such as rotational parapoloids or spheres (Morsdorf et al. 2004, Vosselman 2003), and wrapped surfaces derived by radial basis functions and isosurfaces (Kato et al. 2009). Little work has been done on vegetation detection from ALS in urban areas (Hecht et al. 2008, Rutzinger et al. 2008).

Some attempts for tree modelling from highly dense point clouds were made for TLS data such as fitting free forms to tree stems (Pfeifer and Winterhalder 2004) or modelling the branch structures by fitting cylinders (Pfeifer et al. 2004). Bucksch and Lindenbergh (2008) developed a skeletonisation approach to derive the branch topology of a tree from TLS point clouds using an octree structure. Cote et al. (2009) model tree structures from TLS for simulation of reflectance signatures and directional transmission properties. Stem and branches are extracted and modelled for coniferous trees. Echoes from leafs and branches are separated by an intensity criteria. The skeleton of the tree is derived from the point cloud by constructing a graph which is directed by the detected foliage points.
Skeletonisation approaches provide high reliable and realistic topologies of the branching structure of a tree. However, their application is restricted by occlusion by branches itself or dense foliage i.e. of deciduous trees in leaf-on season.

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So far little attention has been paid on realistic tree modelling from MLS in urban areas. The difference between tree delineation for forestry and urban applications lies in the needed pre-classification in order to separate tree objects from other urban objects, which might have similar characteristics (e.g. poles, traffic signs, and electric masts). The advantage of MLS to ALS is that the tree trunks are clearly visible in most cases, which is an important parameter for tree detection and modelling.

3. TEST SITE AND DATA SETS

The MLS data used in this study was acquired with the Optech LYNX system, which has two 360 degree rotating laser sensors mounted at the back side of the vehicle scanning in tilted planes orientated diagonal to each other. Each scanner rotates with 150 Hz and has a measurement rate of 100 kHz (Optech Inc. 2007). This sensor setup keeps shadow effects, which might be caused by other objects minimal. All in all a track of about 8 km was surveyed in 2008 in Enschede, The Netherlands. The driving speed was between 30 to 40 km/h, which results in a point density of approx. 1000 pts/m^2 on a solid surface on a distance of approx. 10 m. Up to four echoes and intensity values were recorded from both sensors.

Further tree examples are modelled from the EuroSDR data set, which was acquired in Espoonlahti, Finland using the FGI ROAMER system with a FARO LS 880HE80 on board. The scanner rotates at a frequency of 48 Hz and has a measurement rate of 120 kHz (Kukko et al. 2007).

4. METHOD

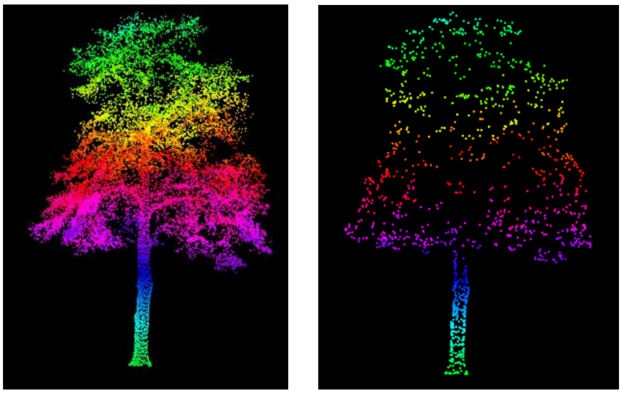
The proposed workflow consists of three processing steps, which are the tree detection from the MLS point cloud (Section 4.1), the simplification of the tree shape for data reduction (Section 4.2) and the final tree modelling, which comprises the extraction of the model parameters from the simplified point cloud and model generation (Section 4.3). Further details on the proposed workflow can be found in Pratihast (2010).

4.1 Tree detection

The applied workflow is hierarchically structured and follows modular processing steps. The aim is to reduce the amount of points to process as soon as possible. First the point cloud is segmented into homogeneous planar regions (Vosselman et al. 2004). Non vegetation segments, which are large and planar, are removed. The remaining laser echoes are re-labelled by grouping nearby points to connected components. For these components the roughness (standard deviation of elevation) and a point density ratio (modified after Rutzinger et al. 2007, Höfle et al. 2009) to a given height interval are calculated. The point density ratio is calculated between the total number of points and the number of points counted in the lower part (e.g. 0.5 m above ground) of the component. The point density ratio is significantly low for trees because the tree crown intercepts much more echoes than the tree trunk. Trees are then extracted by selecting connected components with high roughness and low point density ratio.

4.2 Tree simplification

After separating vegetation echoes the structure of the point cloud is simplified and thinned by applying a 3D alpha shape algorithm (Fig. 1). Alpha shapes represent the outer shape of an unorganised point cloud. The detail of the outer shape is determined by the size of a sphere, which is passed from outside to the point cloud. If the sphere sticks between points these points are used to construct the alpha shape. The alpha value is the radius of the sphere. A large alpha value ($\alpha \rightarrow \infty$) results in a convex hull while a small alpha value ($\alpha \rightarrow 0$) returns the original point cloud (Edelsbrunner and Mücke 1992, Da and Yvinec 2010).



(a) (b)

Fig. 1 Original (a) and simplified point cloud (b) by alpha shape

4.3 Tree modelling

After labelling laser echoes belonging to a single tree the tree model parameters are derived. Depending on the data quality and point density provided by the MLS system the complexity of the tree model can be adjusted. The minimum required model parameters, which are derived from the separated alpha shape point clouds, are tree height, crown width, stem height, stem width, and crown shape (Fig. 2).

The tree models are created using OpenAlea (Pradal et al. 2008), which is an open source framework for 3D plant design. It gives access to different plant model approaches and provides a graphical user interface, 3D visualisation tools and a python scripting interface. The modelling method used in this study is the one of Weber and Penn (1995). This method allows a very detailed reconstruction of the branching structure and texturing with selective types of 3D leafs, which is important for the overall impression of the model. Rules for dimension, rotation, curving and splitting of branches and leafs can be defined. Relations between parental branches and subsequent ones and the number of levels for recursive inheritance of attributes can be defined. For a complete functional overview of the used model the reader is referred to Weber and Penn (1995).

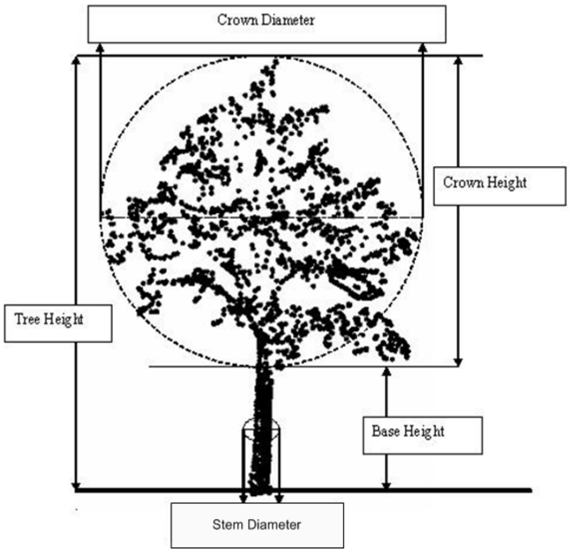


Fig. 2 Derived input model parameters from the simplified MLS point cloud

Four crown shapes are distinguished by comparing the diameters of an enclosing circle at the top (a), middle (b) and bottom (c) of the tree crown (Fig. 3), where the relation between the diameters is a<b<c for conical, a>b>c for inverse conical, a=b=c for cylindrical and a<b ∧ b>c for spherical tree crowns. The branching structure within the tree crown determined by the number of branches and the angle between subsequent branches is not estimated for the individual tree but set to predefined values for each crown shape type.

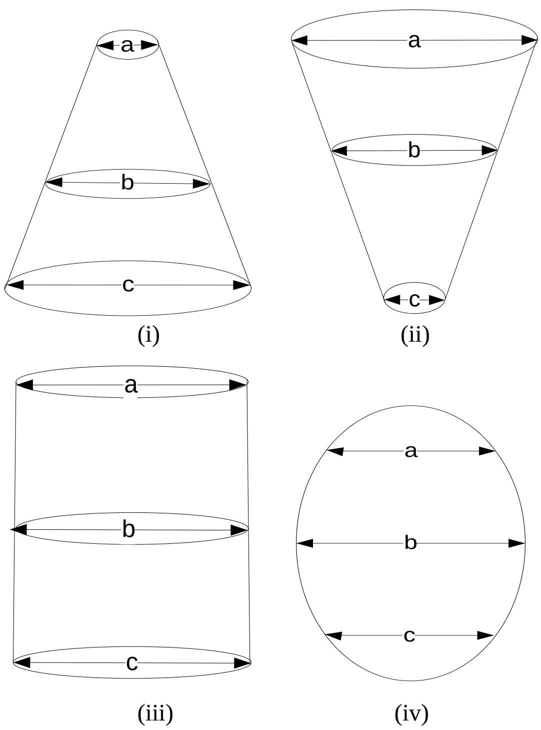


Fig. 3 Distinguished crown shape types: (i) conical, (ii) inverse conical, (iii) cylindrical, (iv) spherical

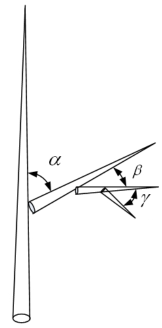


Fig. 4 Angle between subsequent branches

In order to give the trees a more typical appearance the angles between subsequent branches (α, β, γ) are set to 45° for conical, 135° for inverse conical, 70° for cylindrical and 80° for spherical crown types (Fig. 4). The branch length of a subsequent branch has 45% of the primary branch length and the number of subsequent branches is 75% of the primary level. The number of branches is estimated by the ratio between the crown diameter, tree height and the defined distance between branches along the trunk. Finally the tree is textured with oval shaped leafs.

5. RESULTS

5.1 Tree detection

For selected areas in the Enschede and the Espoonlahti data set the detection and modelling algorithm was tested. For these areas completeness, correctness and quality were calculated. In the Enschede data set 40 trees (38 in reference) were detected (89% completeness, 93% correctness, 85% quality). For the Espoonlahti area 66 trees (63 in reference) could be detected (86% completeness, 90% correctness, 78% quality). The difference in the detection rate is related to the scene complexity. In Espoonlahti a large variety of tree sizes and trees connected to each other on slightly undulating terrain makes the detection more difficult.

5.2 Tree simplification

The data reduction and simplification (Section 4.2) was tested for the tree model in Figure 7(c) by applying different alpha values. It can be seen that an alpha value of 1 m can already reduce the point cloud about 95% (Fig. 5).

The robustness and quality of the tree model is tested as a function of data reduction and shape simplification by applying different alpha values. Figure 6 shows that the model parameters do only vary slightly even if a very large alpha value was chosen. Care has to be taken that significant tree parts such as the tree trunk are not lost during data thinning. This would lead to unreliable model parameters.

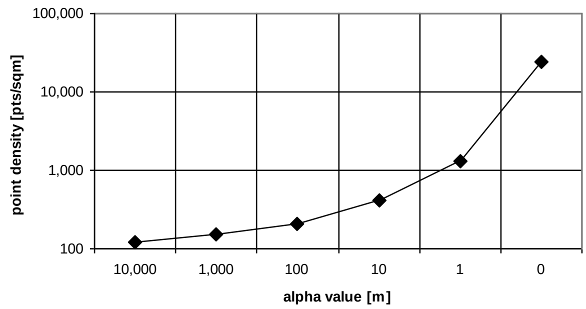


Fig. 5 Data reduction expressed as relation between alpha value and point density

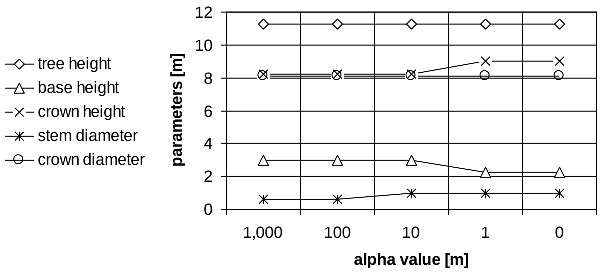


Fig. 6 Robustness of the model parameter to changing alpha value

5.3 Tree modelling

The realistic appearance of the models is checked against photographs and the original point cloud. The comparison shows that the general crown shape types (Fig. 7) match the original tree shape very well. Deviations occur due to the branch angles which are fixed values for each crown shape type (e.g. Fig. 7b). These differences do appear less in the final textured models. One might also expect that the tree crown type is directly related to the tree species such that deciduous trees are more likely to have a sphere shaped crown and coniferous trees are rather conical shaped. The conical shape of the point cloud in Figure 7a is changed into a spherical crown model. Since the current workflow allows only symmetrical tree crowns the lower part of the tree has a smaller diameter caused by the lowest branch pointing to the right side. However the overall representation of the individual characteristics of the trees is sufficient to recognise them in the model.

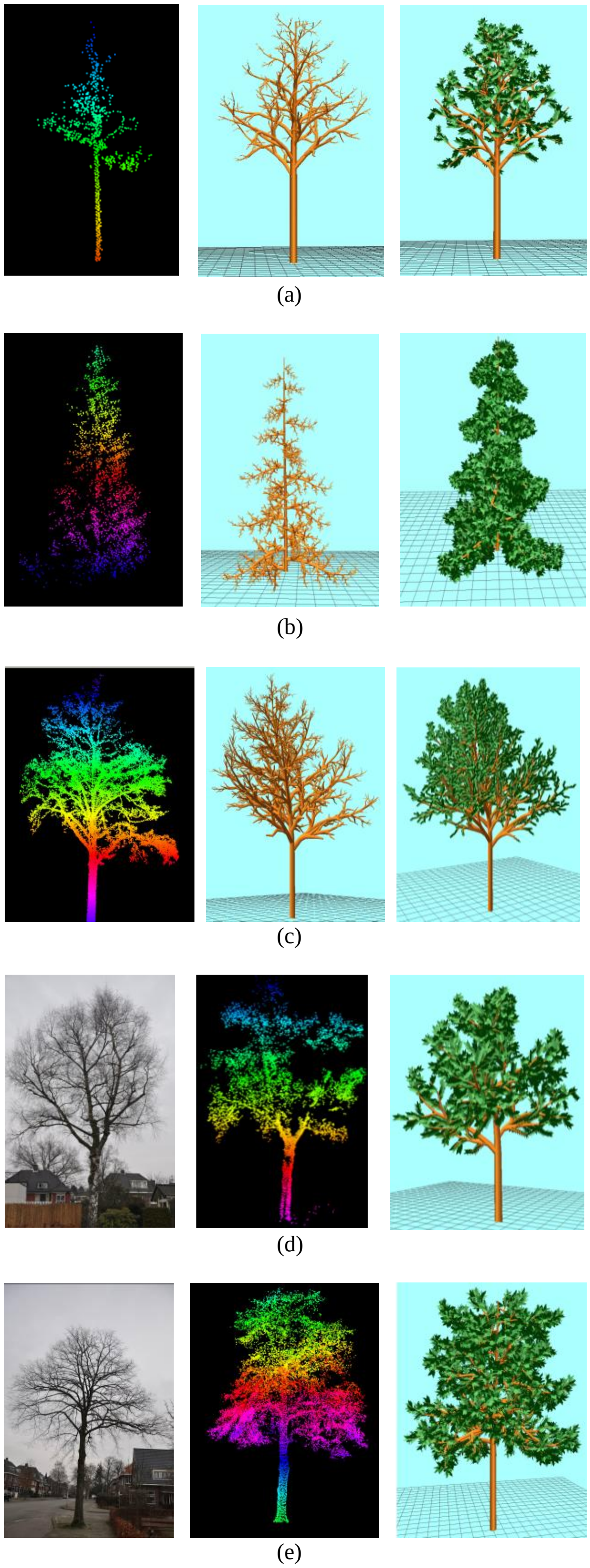


Fig. 7 Comparison of selected model results. The first two models (a, b) are derived from the Espoonlahti data set (left: original mobile laser scanning point cloud, middle: modelled tree skeleton, left: textured tree model). The model (c, d, e) are from the Enschede

test site. For (d, e) left: reference image, middle: MLS point cloud, left: textured tree model

6. CONCLUSION AND OUTLOOK

It could be shown that MLS data sets are well suited to detect single trees and to model 3D trees in a highly automated manner. While other approaches derive the inner tree structure and reconstruct branches directly (e.g. Bucksch and Lindenbergh 2008), the here applied method only preserves the outer shape of high vegetation objects, which still represents the characteristic canopy shape and tree structure. This simplification is sufficient for visualisation applications in 3D city models. On the one hand this method can be also applied if the inner tree structure is not apparent in the data, which can be the case for dense coniferous trees and deciduous trees in leaf-on season.

The workflow presented can be flexibly applied to data sets of different quality. The hierarchical structure reduces the amount of data step by step, which makes the methods also efficiently applicable to large area data sets. Modular appearance of the workflow allows a flexible adjustment if data is already pre-processed (e.g. classified into terrain and object points).

On the other hand the proposed method reduces the amount of data about 95% per tree, which aids for a fast and efficient processing.

Further development will extend the approach to derive parameters in order to be able to classify and model trees according to their type and species using shape information.

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