3D tree modelling using mobile laser scanning data

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by

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Abstract

Vegetation is an important component in an urban environment. In recent years, technological advancement has offered opportunity for virtual city modelling. Incorporation of environmental components in the model enables better planning and decision making. In this context, integration of 3D tree models adds a more complete and realistic view in virtual city modelling. Mobile laser scanning (MLS), is an active technique to capture highly dense 3D point cloud of larger urban areas in a rapid and cost effective way(Norbert et al., 2008). The acquired point cloud is highly suitable for the extraction of 3D cadastre information, urban objects inventory and 3D city modelling.

Urban environments are a mixture of heterogeneous objects like poles, traffic signs, buildings and trees. Thus, the tree delineation technique developed for forestry applications using airborne laser scanning (ALS) is not directly applicable. Attempts made so far using highly dense point cloud to model the tree are however, comparatively unrealistic, labour-intensive and time consuming.

In this research, a fully automated workflow for single tree modelling using MLS point clouds is proposed. The workflow starts with pre-processing detection of tree point cloud from a dense mixture of urban objects. After this, the structure of tree point cloud is simplified by applying a 3D alpha shape algorithm. In the remaining point cloud, connected groups of trees are separated and detected by analysing the structure of the canopy and the appearance of tree stems if they are visible. After labelling laser echoes belonging to a single tree, the tree model parameters are derived. The minimum required model parameters, which are derived from the separated alpha shape point clouds, are tree height, base height, stem diameter, crown length, width and crown shape. The obtained parameters are used to generate the approximate model of the tree. 3D file format of the model is developed and finally exported to appropriate 3D environment. The quality of the tree models is tested as a function of data reduction and shape simplification by applying different alpha values. Furthermore the realistic appearance of the models is checked against acquired photographs.

Performance of the workflow is evaluated in terms of tree detection and data reduction rate. The overall quality of tree detection is achieved more than 80%. The result shows that the developed modular structure of workflow reduces more than 80% points during the pre-processing and more than 90% points during the 3D alpha shape generation without loosing the important information. This result concludes that the presented workflow is applicable for large data set of varying point density.

Keywords: 3D tree model, MLS, point cloud, 3D alpha shape

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1. Introduction

1.1. Motivation and problem statement

Vegetation is an important component in urban environments. The integration of 3D tree model offers a more complete and realistic view in virtual city modelling and city planning (Slob and Hack, 2004). 3D cadastre of tree is needed by planners and environmentalists for planning, modelling and ecological assessments of the city (Ross et al., 2009; Vosselman, 2003).

Traditionally airborne and satellite means of optical images have been extensively used for tree identification, 3D modelling, texturing and visualization (Shlyakhter et al., 2001; Tan et al., 2007; Teng and Chen, 2009). One of the advantages of these methods, the data collection for a large area can be performed in a single attempt. The disadvantages of these methods include comparatively coarse resolutions and some shadow effect on all the optical images. So, it is complicated to identify the single tree pixel for 3D reconstruction. In some studies, the tree outline detection, tree specification, shape analysis and texture assignment has been done manually. The manual method is less accurate due to human errors, expensive and time consuming (Shlyakhter et al., 2001).

Several researches have attempted for the estimation of tree geometry parameters such as canopy height, crown width and foliage for the forest monitoring applications and modelling of 3D tree using airborne laser scanning (ALS) data (Kato et al., 2009; Koch et al., 2006; Kwak et al., 2007) as well as terrestrial laser scanning (TLS) data (Bucksch and Lindenbergh, 2008; Mallet and Bretar, 2009; Rosell et al., 2009; Slob and Hack, 2004; Vauhkonen et al., 2009). As the ALS is done from top of the tree, it is difficult to receive the appropriate amount of laser echoes from lower part of the tree. Acquiring the larger area data is still matter of challenge using conventional means of TLS data.

The multi-sensory data, i.e., the combination of ALS data and optical image has been used for the generation of 3D tree model by Chen et al. (2006). However, in their approach a fully automatic technique for fusion of spectral images and tree parameters from point cloud and optical images is lacking. This requires more manual interaction to increase the accuracy of individual tree model.

Mobile laser scanning (MLS), an advancement of ground-based kinematics means of TLS, is an active technique to capture highly dense 3D point cloud of larger urban areas in a rapid and cost effective way (Norbert et al., 2008). The obtained point cloud is complete geo-referenced, accurate, and suitable for 3D modelling (Ussyshkin, 2009). The acquired point density of the objects such tree depends on the speed of the vehicles, sensor configuration and season of the acquisition (leaf-on and leaf-off season). Since, the MLS is a rather new operational development in the field of LS, no significant contribution has been done to process the larger area data in an efficient manner.

In this context, taking account of the problems and suggestions given by previous researches and taking the advantages of MLS data as mentioned before, this study will focus on how to detect the tree in a dense urban area, simplify tree geometry and furthermore to develop a new method for realistic 3D modelling for integration in 3D city model.

1.2. Research identifications

As discussed in the problem statement, till date limited research has been done in the domain of 3D tree modelling, texturing and visualisation. As an attempt to carryout modelling of tree stems from high dense point clouds, Pfeifer et al. (2004) used TLS data and developed a method where necessary parameters are derived by fitting free form cylinder to the stems. Later, Bucksch and Lindenbergh (2008) developed a skeletonisation approach for deriving branch topology from a tree. Lately, a method has been developed for deriving single tree delineation parameters for forestry application using Airborne Laser Scanning (ALS) data (Rahman et al., 2009; Reitberger et al., 2009). These methods are not suitable for urban application. The main reason is that these methods cannot separate tree objects from other urban objects with similar characteristics such as poles, traffic signs, and electric masts. With the advancement in the sector of virtual city modelling, complete 3D modelling of a tree is highly demanded in recent years, and, therefore, a research in this sector may deserve a high importance. In this context, this research has been proposed. From the research, it is intended to develop a fully automated method applicable for tree detection to single tree modelling using MLS point clouds.

1.2.1. Research objective

The main objective of this research is to develop a new method for 3D tree modelling using MLS data.

The main objective can be achieved by the following sub objectives:

- To extract and simplify the 3D tree geometry parameters from MLS data
- To develop an improved 3D tree model from extracted tree geometry
- To develop a model, that can be exported in several 3D file format standards
- To evaluate performance and quality of the developed algorithm

1.2.2. Research questions

Scope of the research is defined by outlining some research questions. These research questions are formulated based on the objectives outlined in Section 1.2.1. The following research questions corresponding to each objective are presented.

To simplify the 3D tree geometry parameters from MLS data

1. How to extract the tree point from dense mixture of urban objects?
2. How to simplify the tree geometry of point clouds?
3. Which method can be used for separation of the connected tree crown?

To develop an improved 3D tree model from extracted tree geometry

1. How to extract the tree geometry parameters?
2. How to develop a 3D model from extracted tree geometry parameters?

To develop the model, that can be exported in several 3D file format standards

1. What are the different 3D file formats?
2. How to export the model in to widely used open standard?

To evaluate the performance and quality of developed algorithm

1. What is the performance of the algorithm?
2. How to evaluate quality of the model?

1.2.3. Innovation

The innovations intended in this study are:

- New approach for tree geometry simplifications from 3D alpha shape which has not been used thoroughly in previous methods using MLS data.
- Development of automatic algorithm from MLS point clouds to realistic 3D tree model.

1.3. Thesis structure

Chapter 1 Introduction: This Chapter covers motivation and problem statement, objective, research questions and innovation aims to achieve during this research.

Chapter 2 Literature review: This Chapter reviews the literature regarding the previous work related to this research. This Section covers principle of laser scanning, review of segmentation and filtering techniques, data reduction techniques and 3D tree modelling.

Chapter 3 Research methodology: This Chapter is all about the development of algorithm for 3D tree modelling.

Chapter 4 Implementation and results: This Chapter presents the information about the test data set and presents the results.

Chapter 5 Performance evaluation: This Chapter includes three different aspects of performance evaluation namely tree detection rate, data reduction rate in hierarchical structure and visual analysis of developed model.

Chapter 6 Discussion: This Chapter presents the discussion on the result obtained during research.

Chapter 7 Conclusions and recommendations: This Chapter provides final conclusions and recommendations for future works.

2. Literature review

The aim of this Chapter is to provide theoretical foundation on the content of the research. The Chapter begins with the explanation on the principle of laser scanning (Section 2.1). The next Section 2.2 reviews different techniques of segmentation and filtering for identifying tree and non-tree urban objects. The Section 2.3 describes different data reduction methods for efficient processing of data. Then, different techniques of single tree delineation and modelling are described in the Section 2.4. Finally, the Section 2.5 concludes the Chapter.

2.1. Principle of laser scanning

Laser scanning is an active remote sensing technology. It transmits the high energy short wavelength pulse, thus it is used in collecting the accurate coordinate of the object within its range (Fujii, 2005). The main working principal in this scanning is range measurement. There are two basic approaches in measuring distance with lasers range-finding: time-of-flight and triangulation. In time of flight measurement, time elapsed between the emitted laser pulse and reflected pulse back to the photosensitive sensor is measured. If t is the amount of time taken by laser pulse to travel and return back to sensor, c is the speed of light and d is the distance of object which is approximately half the distance travelled by the laser pulse. Following mathematical formula can be used to calculate the d:

$$d = c * t/2 \tag{2-1}$$

Precision in distance measurement is improved by applying phase shift measurement. The following mathematical formula is used for the calculation of phase shift between transmitted and received signal.

$$r=\Delta\Phi /(2\Pi) * \gamma/2 + \gamma/2 *n \tag{2-2}$$

Where $\Delta\Phi$ is the phase difference measured in radian, γ is the wave length measured in meter and n is number of full waveform between the sensor and object surface. To obtain the higher precision with laser scanning, range is determined via angle measurement instead of direct measurement. In triangulation, two laser beams produced by either separate laser or formed by splitting of the single laser beam is used. Based on the source position, the angle of intersection between two laser beams is measured and finally the distance to target object is calculated. Collected data of laser scanning is called point cloud. Each point cloud contains three dimensional information (X, Y, Z) and reflection intensity value.

The first airborne platforms for terrain measurement using laser scanning had been done in the early 1965 (Miller, 1965). Airborne laser scanning combining with GPS and inertial navigation system were started in 1988 (Lindenberger, 1989). As the advancement in the development of sensors in the recent years, collection of multiple echo and full waveform of reflected rays is easier and accurate. The accuracy of ALS increases up to a few centimetres (Mallet and Bretar, 2009). Terrestrial laser scanning (TLS) was started in late 1990's. It is an alternative way of laser scanning which is used to captures the 3D information of complex surfaces in high speed and often in accessible environment.

Based on the sensor movement, there are two types of terrestrial laser scanning techniques namely static and mobile laser scanning.

2.1.1. Static terrestrial laser scanning

These types of laser scanning are usually done for the measurement of buildings, bridges and tunnel facilities and energy infrastructures development. The scanners used in this type of laser scanning are fully integrated with high quality digital cameras. Obtained point clouds are highly dense and accurate. Scanning is independent with weather conditions.

2.1.2. Mobile laser scanning

Mobile laser scanning (MLS) is a dynamic means of terrestrial laser scanning. It is used to acquire the point cloud by means of one or several scanners mounted on a mobile platform. These mobile platforms might be car, train or vessel. Shan and Toth (2008) published a comprehensive study on current devices and specification of mobile platform. During the scanning, the laser beam is deflected by a rotating mirror (scanner) across the driving direction and the swath terrain along the driven direction is recorded. Runtime measurement is conducted for the calculation of distance to the surface. Figure 2-1 shows the field of view of MLS sensors. The recorded point cloud is highly dense and complete geo referenced which has high potential in the corridor mapping (Barber et al., 2008), 3D modelling of urban environment like tree, building and poles (Haala et al., 2008; Ussyshkin, 2009). The vehicle based MLS used for the data acquisition in this research is shown in Figure 2-1. The main elements of mobile laser scanning are Differential GPS, Inertial measurement unit (IMU), Distance measurement instrument (DMI) as Odometer, Software and hardware for registering and processing data, Laser scanner(s) and/or Digital camera(s) and/or Video camera(s).

Figure 2-1. Vehicle based mobile laser scanning (Optech, 2008)

2.2. Review of segmentation and filtering techniques

Extraction of tree points from a dense point cloud in an urban environment is still a challenging task. Efficient segmentation and filtering techniques are essential to extract these features from high amount of data set. In this Chapter different segmentation and filtering methods are reviewed. First, the surface growing segmentation is introduced in Section 2.2.1. Different techniques for filtering the ground points are described in Section 2.2.2 and then after filtering the urban objects for extraction of tree point cloud are reviewed under Section 2.2.3

2.2.1. Surface growing segmentation

A comprehensive review of various segmentation techniques is done by Vosselman et al. (2004). Among them the relevant surface growing segmentation in point cloud data is discussed in this Section. Surface growing segmentation in point clouds works similarly to the region growing segmentation in image. It is mainly the culturing of the surface points having similar properties. The process is carried out in two steps. First step includes the identification of seed surface and second is the growing of seed surface.

Identification of seed surface

Selection of seed surface is performed by fitting the plane to the group of points and analysing the residual values of each of them. The point belonging to a plane having residuals less than some threshold is considered as seed surface. In the presence of outlier, more robust methods like the least square or the Hough transformation methods are used to fit the plane.

Growing of seed surface

Once the seed surface is identified, the growing of the seed surface towards the neighbourhood points is done based on the proximity, global planarity and smooth normal vector field.

***Proximity of points*:** The points which are within a certain distance from the selected seed surface are added to the surface. 2.5 D and TIN data structures are used to identify the points on the surface.

***Locally planar*:** For this, first the equation of enclosed plane through all the surface points within the radius is determined. A candidate point is selected from surface points. The selection criterion is based on the orthogonal distance of a point to the plane. The Point within this distance is selected if all the neighbouring points in a plane are below some threshold value.

Smooth normal vector field: To implement these criteria, local surface normal for each point in the point cloud is calculated. A candidate point is chosen if the angle between the normal of growing surface and local normal of point is below some threshold value.

Rabbani et al. (2006) presents the smoothness constraint to segment the unstructured point cloud of industrials scene. The method is based on two steps, local surface estimation and surface growing. Local surface normal is estimated by fitting the plane to neighbourhood points based on the k-nearest neighbourhood (KNN) or the fixed distance neighbourhood (FDN). KNN uses K-D tree data structure to create adjacency information of points by maintaining a list of indices for each neighbourhood points. FDN considers a given fixed Area of Interest (AOI), and selection is done within the area for each query point. The surface growing of segment is performed based on the calculated norms and its residuals. In this phase, additional points are added to the segment based on the proximity and smoothness criteria of the surface.

2.2.2. Filtering ground points

Different approaches for identification and filtering ground and no ground points in ALS datasets are proposed in different literatures. Vosselman (2000) proposed a slope based filtering method for the identification of ground points by comparing slopes between the laser point and its neighbours. The working principal of this algorithm is closely related to the erosion operator used in mathematical morphology. A point is classified as a ground if the calculated slopes value between a points and its neighbourhood point is less than a predefined threshold. The critical step in this method is setting of slope threshold, by using prior knowledge of the terrain which is somewhat subjective. The improvement is done by using progressive morphological filter (Zhang et al., 2003). The method utilizes different windows size for the identification of ground and no ground surface from laser scanning data. The filtering results are satisfactory in both the urban and mountainous areas however selection of windows size is a difficult task.

Several attempts have been made for the improvement of slope-based filter. Slope adaptive neighbourhood method was proposed as a modification of the slope-based filter to correct the problem regarding the steep sloped terrain (Filin and Pfeifer, 2006). Cluster-based segmentation approach is used for computing the features like normal vector and the classification of surface based on the similar orientation. It has improvement over the feature quality so the segment tends to be greater with respect to triangulation based segmentation. A slope-based planar-fitting filtering algorithm for data filtering and feature extraction in urban area is presented by (Qihong, 2008). Their methods analyse the spatial distribution of laser point cloud. This study uses a plane fitting algorithm. It fits the horizontal planes for filtering the ground points and vertical planes for the building walls in the urban areas. Meng, Wang et al. (2009) explore the Multi-directional ground filtering (MGF) algorithm which is sensitive to detect steep slopes as it integrates the advantages of neighbourhood based and directional scanning approaches. The major limitation of these algorithms is on the assumption of slope difference. Most of these slope based algorithm assume that the slope difference between the ground points to another neighbouring points are gradual. However these are abrupt in reality. The scan line directly produces an elevation or slope profile for each scan line. An adaptive filtering technique for identification of ground points by utilizing the slope threshold of a profiler has been proposed in Sithole and Vosselman (2001). The scan line technique produce a slope profile for each scan line which is useful for the identifications of ground points along the profiles. Elevation differences along scan lines are used by (Sithole and Vosselman, 2005) for the identification of ground and non-ground point along the scan lines. The major drawback of these approaches is that the result is highly influenced by the choice of filtering direction.

2.2.3. Urban tree point cloud detection

An urban area is a heterogeneous composition of objects like tree, building, poles, vehicles etc. Several researches have been done for the detection and filtering of these objects. Haala and Brenner (1999) proposed an integrated classification approach from the multi spectral images and laser altimetry data for the extraction of urban objects like building, tree and grass covered area. The algorithm requires normalised DSM derived from laser data to get the height information of each image pixel. The morphological filtering operation to detect and filter urban objects was used by (Chen et al., 2007). Their method performed well even in many complicated objects such as large buildings, steep slopes, bridges, ramps, and vegetation on steep slopes. However, the main limitation of this method is every data sets, parameters should be specified on trial and error basis which leads to more manual iteration.

Normalized difference vegetation index (NDVI) is a numerical indicator, used by researchers to detect the vegetation in urban environment. Lovan et al. (2007) detect the urban vegetation by combining NDVI and saturation index (SI) from a high resolution aerial image and a DSM with 20 cm resolution in an automatic way. Tao and Yasuoka (2002) used high resolution satellite imagery and ALS data for the detection of urban tree. The methods use digital elevation model (DEM) derived from ALS data. There is a limitation in the calculation of NDVI value due to a number of perturbing factors including spectral effects, atmospheric effects, clouds, soil effects etc.

Derivative approach was used to separate building and tree in (Morgan and Tempfli, 2000). The main concept behind this algorithm was canopy structure of tree was irregular whereas roof surface of buildings were considered as planner. The first and second derivatives of an irregular surface should be variable whereas the first derivatives planar surfaces were either zero in flat roof case or constant in sloped roof case, and the second derivatives of a sloped planar surface were zero. These methods are not free from limitations because of the small features such as chimneys or water tanks introduce the discontinuity in the measurement and finally lead to abnormal derivatives value.

Laser scanning systems have the capability to record the multiple reflections caused by the objects on the earth's surface. Alharthy and Bethel (2002) used the difference between the first and last echo to separate building and tree. Tovari and Vogtle (2004) had implemented a fuzzy logic approach based on first and last echo differences to classify vegetation. The difference is generally larger for tree and close to zero for building measurements. However, their method does not work well for dense trees area where laser pulses cannot penetrate.

Object-based point cloud analysis (OBPA) was used for the detection of urban vegetation in (Rutzinger et al., 2007). The presented algorithm used surface roughness, the ratio between 3D and 2D point density and the statistics on first and last echo occurrence within the segments for the extraction of objects. The main advantage of this method is that it does not require DTM calculation. Their algorithm has limitations over heterogeneous distribution of point cloud.

2.3. Data reduction methods

Operational 3D information extraction and modelling from massive point clouds is still a matter of research. Efficient data reduction techniques are required for processing the data without loosing important information. In this Section, the relevant data reduction techniques such as thinning and 3D alpha shape are reviewed.

2.3.1. Thinning

The idea of thinning based on triangulation is a well established concept, and is more commonly referred in the literature. This process filters insignificant points based on the linear interpolation over the Delaunay triangulation. Heckbert and Garland (1997) reviewed and evaluated the strength and weakness of simplification methods both for terrain models (triangulated scattered data in the plane) and free form models (manifold surfaces represented by 3D triangle meshes). They found that the triangulated meshes had some drawbacks. These methods produced a significant amount of error during removal of points and required high computational cost in the order of O (N2) to O (N logN). Later, adoptive thinning algorithm was proposed in (Dyn et al., 2002). The implementation of the algorithm produced fast and accurate result compared to triangulated mesh. Mesh free thinning algorithm which is solely based upon the geometry of the input 3D point clouds was developed by Dyn et al (2008). The main advantage of the method was that the topological information such as point connectivity was not required during the thinning process. Application of sequential 3D thinning algorithm for medical image analysis was done in (Palágyi et al., 2001). Many improvements have been done in the thinning process. However none of the thinned datasets were free from topological consistency and exact shape perseverance.

2.3.2. 3D alpha shape

Alpha shape is a geometric concept for the shape reconstruction from a dense unorganised set of points. A linear approximation of the original shape from an alpha shape is demarcated in (Bernardini and Bajaj, 1997). An extension to three dimensions simultaneously with an implementation is reported in (Edelsbrunner and Mucke, 1992). Mathematically, the alpha shape is well defined as a generalisation of the convex hull and sub graph of Delaunay triangulation (Cholewo and Love, 1999). The set of finite points S and a real parameter of alpha directly illustrate the alpha shape. The real parameter alpha controls the complexity of the boundary and leads to the family of shapes capturing the intuitive notion of "crude" versus "fine" shapes of a point set. For sufficiently large value of alpha ($\alpha \to \infty$), the alpha shape looks identical to the convex hull. On the other hand, when the alpha value is very small ($\alpha \to 0$), every point might represent as the boundary points in alpha shape. As the value decreases the shape shrinks and gradually forms cavity. For evenly distributed point-set S and an optimal value of alpha, the α-shape can extract the inner and outer outlines of the polygon at the same time, as shown in Figure 2-2.

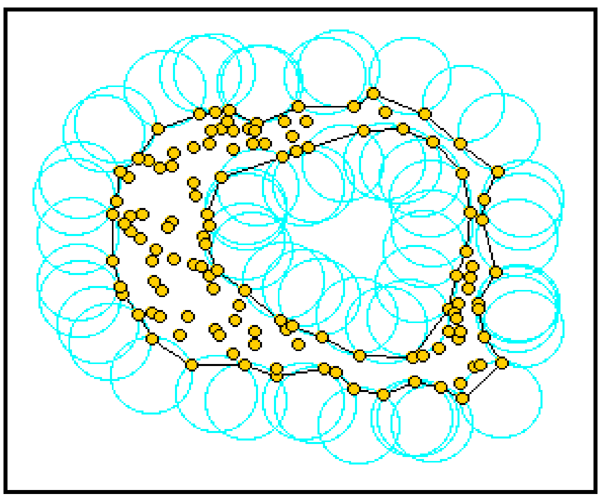


Figure 2-2. Alpha Shapes algorithm extracting principle (CGAL, 2009)

Later on, alpha shape is broadly classified in two categories namely basic alpha shape and weighted alpha shape. Basic alpha shape is derived from Delaunay triangulation whereas weighted alpha shape is derived from regular triangulation (Facello, 1995). In the basic alpha shape, the input points are set of points. For a particular value of alpha, the alpha complex is computed as a sub complex of the Delaunay triangulation from the set of points. For a given particular value of alpha, the alpha complex contains all the surplices in the Delaunay triangulation. The collection of alpha complex domain produces the alpha shape. The alpha shape computation process is analogous to basic alpha shape in the case of weighted alpha shapes. Here, the input points are a set of weighted points. For a particular value of alpha, the weighted alpha complex is derived as a sub complex of the regular triangulation from the set of points.

2.4. 3D tree modelling

The extraction and separation of single tree and delineation algorithm is reviewed in Section 2.4.1, 3D modelling techniques in Section 2.4.2, texturing in Section 2.4.3 and 3D environment data structure formats in Section 2.4.4.

2.4.1. Single tree and crown delineation algorithm

Most commonly, single tree detection and crown delineation are based on the local maxima of the canopy height model (CHM) (Hyyppa et al., 2001; Pitkänen et al., 2004; Pyysalo and Hyyppa, 2002; Solberg et al., 2006). Hyyppa et al. (2001) utilised the highest laser reflections to interpolate a local CHM. Watershed segmentation algorithm was used by (Pyysalo and Hyyppa, 2002) to extract the single tree crown information. Adaptive method for individual tree detection based on CHM derived from airborne laser scanning data was developed in (Pitkänen et al., 2004). In this method, Gaussian filter was used to smooth the CHM and the height of the pixels was assigned as the degree of smoothness. Later, Solberg et al.(2006) improved the CHM with a grid method. However, the CHM method had several drawbacks. CHM is reconstructed from the laser points by an interpolation process that smoothes the data to some extent. The degree of smoothing is directly related to tree detection success rate in terms of false negative and positive. Furthermore, success rate of CHM will be limited by heterogeneous situation where trees are closer to each other and smaller trees below the canopy do not appear in the CHM.

The density of high points (DHP) from the ALS data to detect individual tree locations was used by (Rahman and Gorte, 2008a). The DHP approach was based on the fact that the receiving laser echo above a certain height has high density, which is referred as the tree crown centre and the density gradually decreases toward the edge of the crown. This method was tested in four data sets and result showed that more than 70% of the trees were detected correctly under different tree conditions. A method for individual tree crown delineation and separation of undergrowth vegetation from dominant trees is proposed in (Rahman et al., 2009). Their method applied the DHP concept to identify the individual tree crown. Furthermore, undergrowth vegetation is filtered on the basis of tree diameter at breast height (DBH). However, this algorithm does not work for the invisible tree stem and significant amount of post prospecting is required for the improvement of over all accuracy of tree crown delineation.

The advancement in sensor technology had made possible to record full waveform of reflected laser beams. Calibration issues of full waveform data is discussed in Wagner et al.(2006). Furthermore, they used cross Section calculation of the waveform to detect the different type of vegetation like trees and bushes. Reitberger et al.(2008) classified the tree species by using full waveform property of laser data. Reitberger et al. (2009) has presented new normalised cut segmentation derived from watershed segmentation methods in full waveform data. Figure 2-3 shows the visual representation of CHM with local maxima of each tree. The implementation of the algorithm has significant improvement in tree detection. However, the total amount of full waveform data required for the tree inventory purpose needs to be resolved.

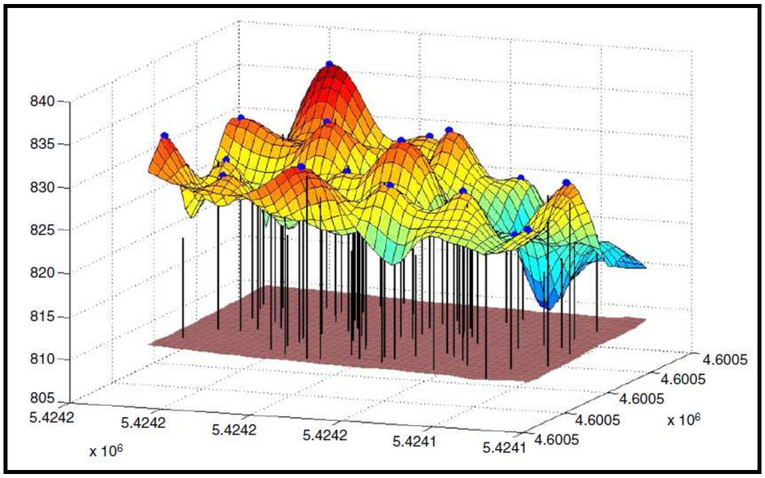


Figure 2-3.CHM with local maxima and reference tree as black lines (Reitberger et al., 2009)

2.4.2. 3D tree modelling techniques

Several research works carried out in the past are mostly inspired by the promising nature of LS data for 3D tree modelling. Weber and Penn (1995) developed a model based on plant structure. This model accounts for two primitives namely stem and leaf. Stem were used for branching. The most powerful aspect of this model is that parameterization of the model is flexible and accounts for the wide variety of the tree structures. These parameters are responsible for almost every possible shape, size, curve, number of splits, split angle, taper, and orientation of each primitive. Figure 2-4 shows the tree parameters of Weber and Penn model. However, the measurement of such parameterisation is mostly dependent on direct physical observations.

The 3D modelling of tree using different instrumental optical image has been carried out by Shlyakhter et al. (2001). The developed model is realistic however the process required more manual interaction. The reconstruction of 3D tree modelling using ALS and optical images has been proposed by Chen et al. (2006). The modelling was completed by the following intermediate steps: prepossessing, vegetation detection and tree modelling. Coarse to fine resolution strategy were used to detect the vegetation and morphological filter was used to find the tree boundary in the digital surface model (DSM) produced from the ALS data. The methods (Chen et al., 2006) have 80% accuracy in tree detection and 1 m accuracy in extracted tree height. However, the fully automatic technique is lacking for the fusion of spectral images and tree parameters from point cloud and optical images. More manual interaction is needed to increase the accuracy of individual tree model.

Prior knowledge and heuristic-based approach was used for reconstruction of realistic looking tree in(Xu et al., 2007). Their method utilised a graph based technique to find the rough branching structure. Furthermore, fake branches are added in the final model of tree to give more realistic look of the tree. Fully automatic modelling of single tree from terrestrial laser scanning data has been implemented by Pfeifer et al.(2004). A cylindrical modelling approach was used for modelling the branch of the tree. The accuracy of result in millimetre was achieved for denser part of the point cloud.

Collapsing and merging procedures in octree-graphs (CAMPINO) method, for point cloud skeletonisation was proposed by Bucksch and Lindenbergh (2008). Tree skeleton was derived by implementing octree based space division method. Their method has linearity in processing of the huge point cloud and sensitive to detect the minute changes in object boundaries. Their method has the limitations over a leafy tree and produces topologically inconsistent result.

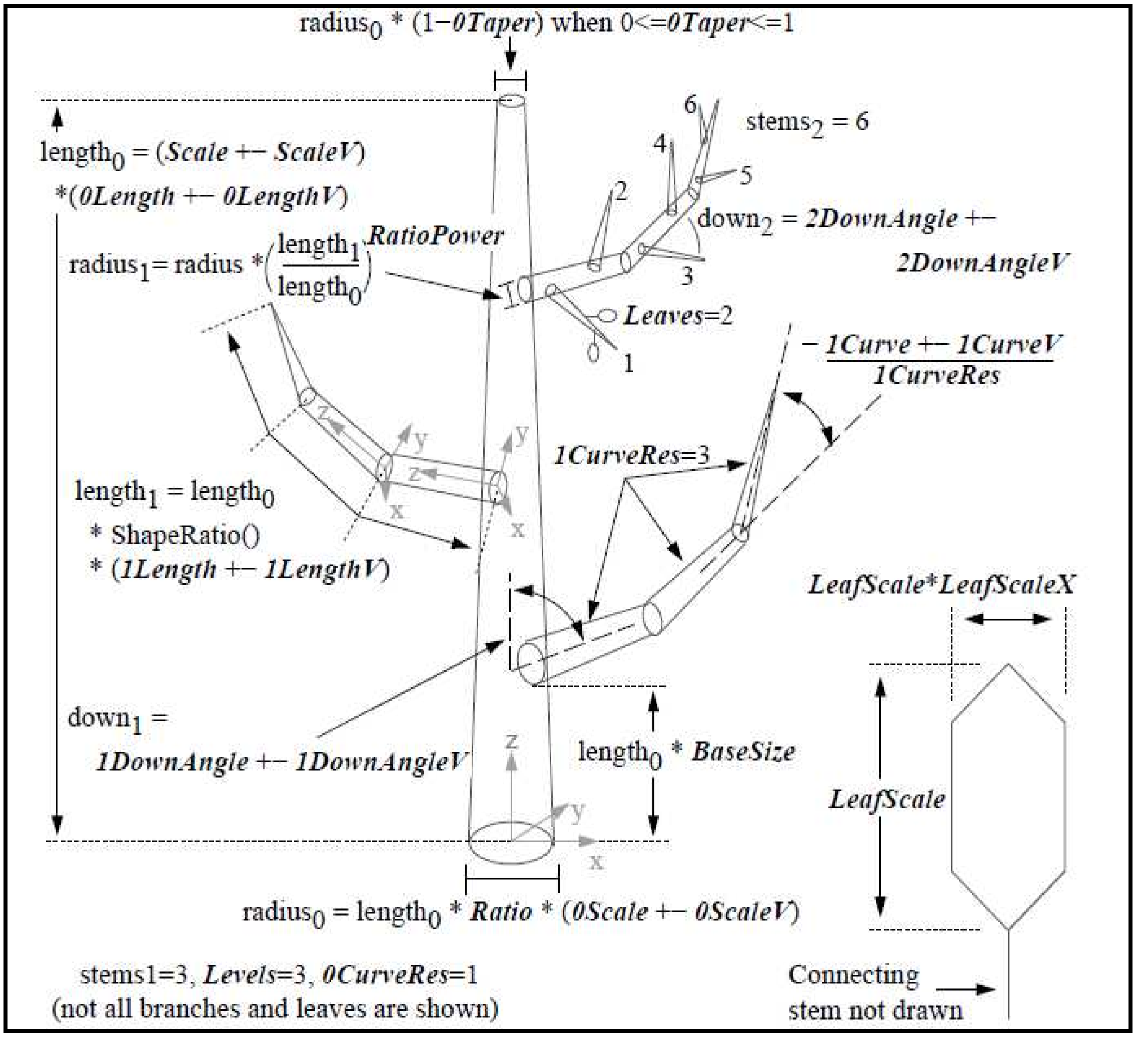


Figure 2-4. Example of multi-label sets of primitives (Weber and Penn, 1995)

Reconstruction of the tree crown using 3D alpha shape was implemented in (Xu and Harada, 2003). Their method was the generalisation of convex hall and sub graph of Delaney triangulation. The Construction of crown surface mesh was done by choosing the boundary triangles based on the alpha value. A graphical approach for modelling and estimation of the tree parameter from aerial laser scanning data was applied by Kato et al. (2009). Their algorithm constructs a wrapped surface around the crown surface of the tree and utilises radial basis functions (RBF) and iso-surfaces generation methods for extraction of tree parameters like tree height and crown width. Though the method is relatively accurate and species independent, the estimation of tree geometry parameter from wrapped surface is computationally expensive.

2.4.3. Texturing

Texturing assigns the appropriate colour and details to the model. Various contributions have been made in the field of proper texture assigning principle. An efficient pyramid based texturing algorithm was proposed by Heeger and Bergen (1995). This algorithm is simple and required target image as input texture. However, the algorithm has some limitations. The produced texture was bulky and far from the realistic look. Volumetric approach of reconstruction and rendering the tree was proposed in (Reche-Martinez et al., 2004). Their method utilises recursive grid techniques for assigning the texture. The entire process was efficient, and satisfactory results were obtained for sparse foliage tree. However, their method needs improvement regarding texture generation techniques and opacity estimation. Multi layered 3D tree texturing technique has been implemented by García et al. (2007). The technique was indirect and implements realistic lightning and global illumination computation, for rendering the realistic tree.

2.4.4. 3D environment data structure formats

There are different 3D environment for the effective visualisation such as Google earth and 3D city models. These different environments have different exportation format. Google earth supports the keyhole mark-up language (KML) exportation format (Google, 2010). This KML is based on extensible mark-up language (XML) schema and is an international standard of open geospatial consortium (OGC). The VRML is a standard file format, are supported by many 3D web browsers. In this research, the model is developed in both KML and VRML exportation file formats.

2.5. Conclussion

This chapter reviews the state-of-the-art principles and processing of laser scanning point cloud. Mobile laser scanning collects larger amount of urban data in an efficient manner. However, efficient processing of these data is still a challenge. This chapter explores different segmentation and filtering techniques available to overcome this issue. One of the most common segmentation techniques is Surface growing segmentation technique. The technique helps to structure the point cloud before processing. It has two steps. First step identifies the seed surface by fitting the plane to the group of points whereas the second step performs growing of seed surface based on the proximity, global planarity and smooth normal vectors. Regarding the filtering techniques, this chapter describes two techniques; Slope based filtering technique and tree detection in urban environment. The first technique is useful for determining ground and no ground points by comparing the slope between the laser points and its neighbours. The second technique detects the trees in urban environment.

The data acquired from segmentation and filtering needs to be reduced in an applicable size. For this purpose two techniques are commonly available, thinning and 3D alpha shapes. Thinning filters insignificant points based on the linear interpolation over the Delaunay triangulation but the obtained results lack topological consistency and shape perseverance. 3D alpha shape also filters insignificant points based on triangulation method with better results than the thinning. Furthermore, it produces varieties of shapes, crude versus fine, by varying the alpha value.

This chapter further describes the 3D tree modelling techniques. Different algorithm of single tree and crown delineation such as CHM height model, DHP height model and web form analysis of reflected laser beams are reviewed. Furthermore, different modelling techniques such as Weber and Penn model, image based model, and combination of image and ALS data, free form cylinder model, CAMPINO method, etc are available for the modelling of 3D tree. However, the Weber and Penn model gives better model among them. This model has been selected for the purpose of this research.

3. Research methodology

This Chapter provides stepwise explanation of the methods applied in this research. The details of each step of the used methodology are described in the following sub-Sections. Section 3.1 deals with the pre-processing steps in which point cloud belonging to trees is extracted. Section 3.2 presents the tree geometry simplification and separation algorithm. Section 3.3 describes the tree geometry parameter extraction. Section 3.4 explains modelling, texturing and visualization process. Section 3.5 describes the performance evaluation of the algorithm. The Chapter ends with a conclusion in Section 3.6. The overall approach is shown in the following Figure 3-1.

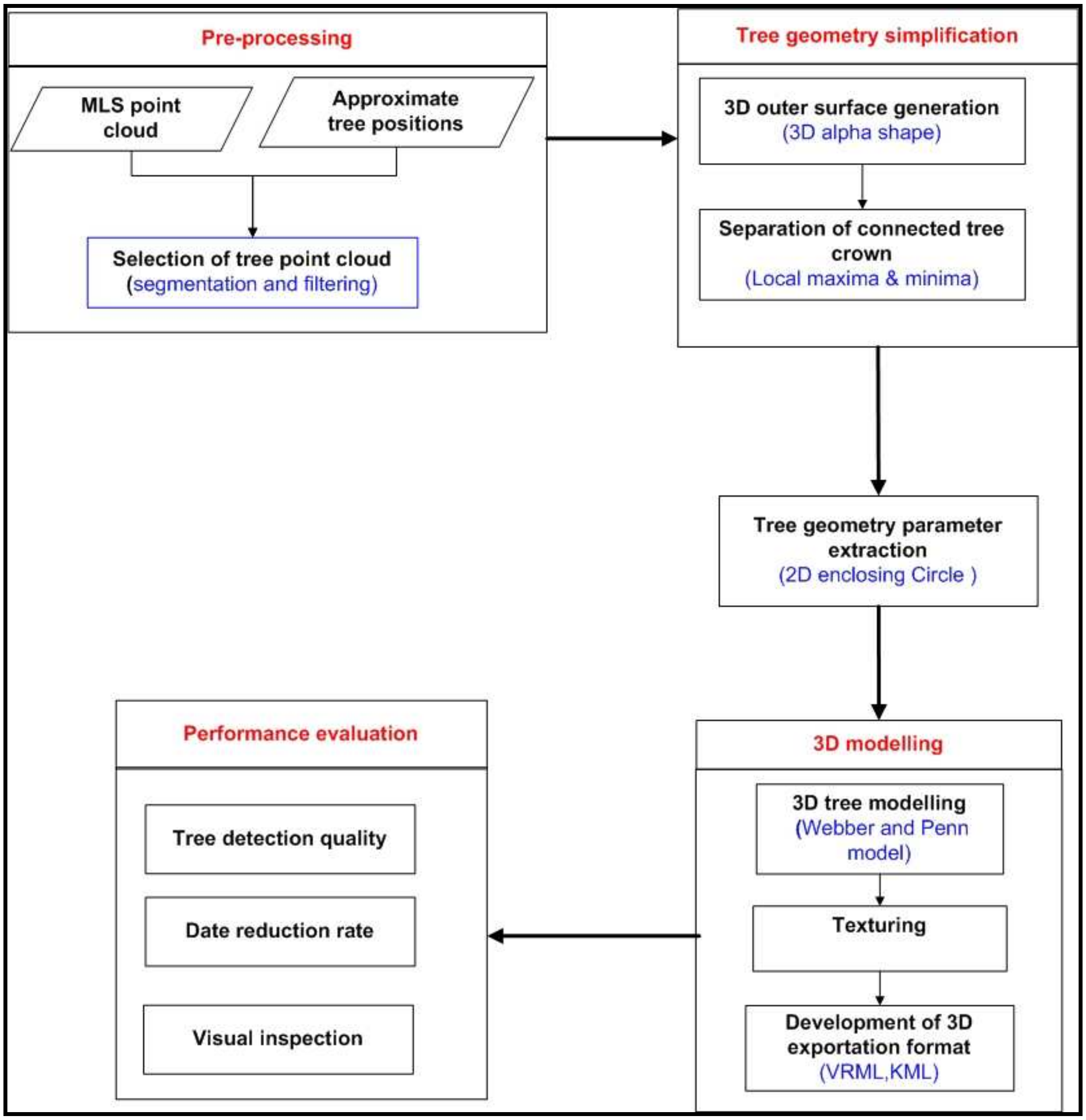


Figure 3-1. Overall methodology

3.1. Pre-processing

Urban environments are a mixture of heterogeneous objects like poles, traffic signs, electric masks, buildings and trees. Pre-processing is necessary to detect the tree point cloud from dense mixture of urban objects. A flow chart describing the pre-processing is shown in Figure 3-2 .

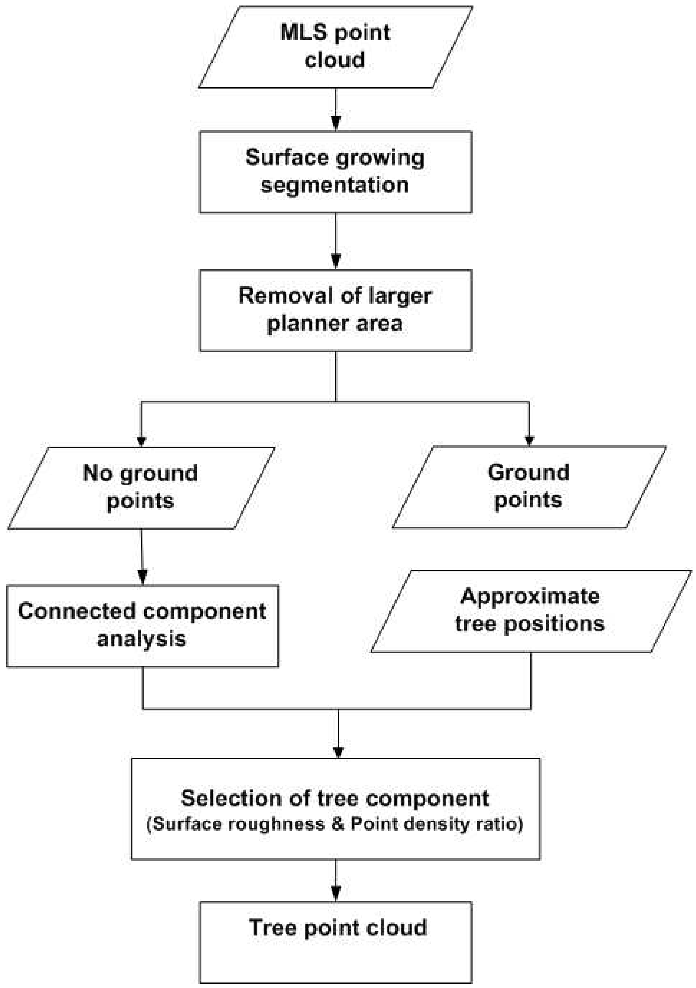


Figure 3-2. Pre-processing steps

3.2. Input

Laser scanning point cloud and approximate tree positions were used as input data set for pre-processing. From the laser data, 3D information i.e. (X, Y, Z) coordinate was utilised for the further processing. Approximate tree positions were obtained by manual digitization. It was utilised for the identification of tree segments.

3.2.1. Surface growing segmentation

Surface growing segmentation was performed on MLS point cloud data. The theoretical concept of surface growing algorithm is reviewed in Chapter 2.2.1. Implementation of this algorithm was done using point cloud mapper (PCM) software. PCM uses kd-tree, Delaunay triangulation and Octree data structure techniques to establish relations to the neighbourhood points. In this research, 3D kd-tree was used as neighbourhood definition. The seed surfaces were generated using 3D Hough transformation.

The extension of the seed to the neighbourhood point was guided by user defined surface growing parameters such as surface growing radius, maximum distance to the surface and the minimum distance to the recomputed local plane. The developed algorithm in PCM utilises smooth and planner surface model to generate the surface. The planner surface model was used for segmentation.

3.2.2. Removal of larger planner area

Identical to the plane fitting algorithm proposed by (Qihong, 2008) , the horizontal plane fitting algorithm was used to remove the larger planner area. The method for removing larger planner area starts after the surface growing segmentation. While removing larger planner area each segment was considered as plane. Surface normal vector of each plane was calculated. The ideal horizontal plane was enclosed to each segment. θ is the angle between normal vector of segment and horizontal surface was calculated as follow:

$$\theta = \cos^{-1}(\overrightarrow{n_1} * \overrightarrow{h_1}) \tag{3-1}$$

Where:

$\overrightarrow{n_1}$ = Normal vector

$\overrightarrow{h_1}$ = Normal vector of ideal horizontal plane

Based on the appropriate threshold angle, ground and no ground segment were separated.

3.2.3. Connected component analysis

The aim of connected component analysis was to connect the near by points and to assign the appropriate segment number. Method starts with the selection of seed point. The point which falls inside the object is selected as seed points. The set of points connected to this seed point with distance smaller than some threshold were labelled as connected one. This analysis comprises better implementation for simple cases where the objects are relatively dense and well-separated from other one. It is implemented as a simplified version of clustering algorithm (Barbakh et al., 2009). However, this algorithm has two major problems. It is rather difficult to establish a global threshold which works well in wide range of objects and in different point densities. Hence, an appropriate choice of distance threshold is crucial otherwise it might produce unreasonable large connected components. PCM was used for the connected component analysis. The threshold distance for connecting the component and a horizontal cut-off radius for the point was used as the input parameters for the analysis.

3.2.4. Removal of near by tree objects

Approximate tree positions were used to select the component which belongs to a tree. Still, there might be some chances of small objects near by tree like poles and pedestrians. These objects were filtered based on surface roughness and point density ratio. In this research, Point density ratio was calculated using the following formula:

$$DR = N_{Totl}/N_{Hth} \tag{3-2}$$

Where:

DR = Point density ratio

N_{Totl} = Total number of points

N_{Hth} = Number of points present in certain height threshold

Point density ratio shows a promising factor of separation between trees and other object. Height threshold of 0.5 m was considered. However, the vertical walls nearby tree have similar point density as trees. This problem was solved by using the roughness features. There are different methods for calculation of surface roughness like standard deviation (SD) of height (Z coordinate) value, curvature value which shows the irregularity of the surfaces. The SD of Z values and SD of plane fitting residuals as a surface roughness was used to remove the vertical walls near to tree (Hofle et al., 2009).

3.3. Tree geometry simplification and seperation

3.3.1. Tree geometry simplification using 3D alpha shape

As mentioned in Section 2.4.2, alpha shape is used to derive a simplified shape from dense points. There are basically two methods for alpha shape generation (CGAL, 2009). One is basic alpha shape generation from Delaunay triangulation and the other is weighted alpha shape generation from regular triangulation. Delaunay triangulations are based on the non weighted point which has an empty sphere property. On the other hand, Regular triangulation is based on the weighted point which is sphere in nature. Thus, regular triangulation is also referred to as weighted Delaunay triangulation. In this research, basic alpha shape was used to simplify the tree geometry parameters. The algorithmic details of the steps taken to simplify tree geometry parameters are depicted in Figure 3-3.

This algorithm begins with tree point cloud as the input data set. The Delaunay triangulation over the set of point was computed (Fischer, 1988). The alpha complexes of these points are identified as the sub complex of Delaunay triangulation. For a particular value of α, all simplices of Delaunay triangulation having an empty circum-sphere with squared radius equal to or smaller than α is included in alpha complex. The word "empty" represents an open sphere. Based on the triangulation, CGAL provides two versions for the alpha shape general mode and regular mode. In general mode, alpha complex contains the singular face of Delaunay triangulation whereas in regular mode alpha shape removes the singular face from regular triangulation. For the range $0 \leq k \leq d-1$, k simplex of the alpha complex is singular only when it is not a facet of a (k+1) simplex of the alpha complex (CGAL, 2009).

In this research, general mode was used for the alpha shape computation because the entire points are non weighted points. The real value of alpha (α) was assumed for the initialization and then the computation of alpha shapes was done among these alpha complexes. The varying of alpha values was used for thinning the faces of Delaunay triangulation. As the alpha varies from large value ($\alpha \rightarrow \infty$) to small value ($\alpha \rightarrow 0$), the alpha shape also varies from coarse to detail. For the geometric information extraction, the detail shape was required. Thus, setting of alpha value was done iteratively until it produces desirable detailed shape of tree. Thus, the final output represents the simplified 3D alpha shape of the tree.

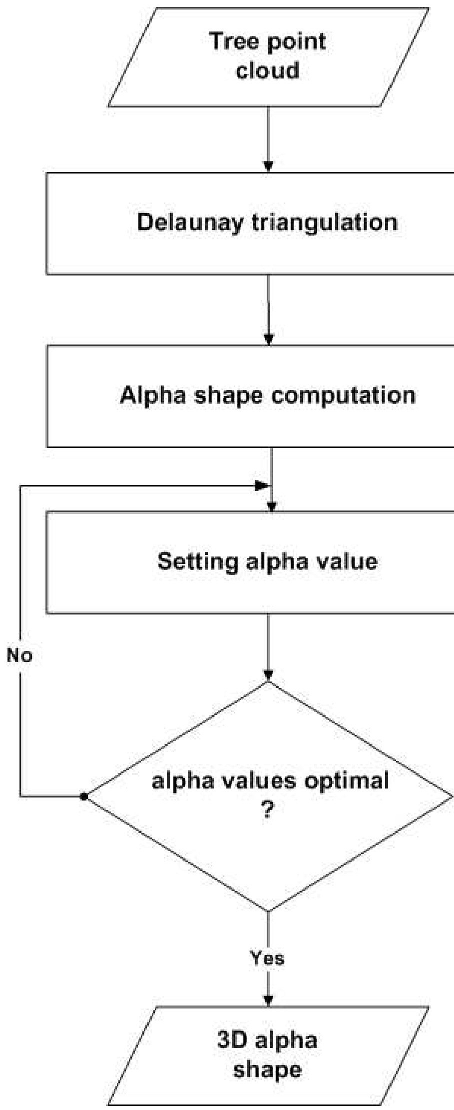


Figure 3-3. 3D alpha shape generation

3.3.2. Separation of connected tree crown

Theoretical concept behind the separation of connected trees was reviewed earlier in Section 2.4.1. A method based on the local maxima and local minima of height value was developed for the separation of connected trees. Most of the related work for tree separation used raster based analysis for finding local maxima and minima. In this research, a pragmatic solution for finding the local maxima and minima directly from the point cloud is proposed. This algorithm starts with the connected tree crown and approximate tree positions as input parameters. A 3D alpha shape of connected tree is used as an input to improve the processing performance. Figure 3-4 represents one example of the connected tree alignment. In Figure 3-4 shows that three trees namely A, B and C are connected to each other.

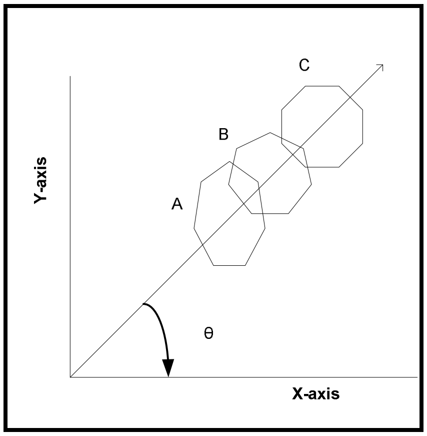


Figure 3-4. Connected tree alignment

The rotation of all the connected tree points along the x axis at certain angle θ was performed using the following formula:

$$R_z(\theta) = \begin{bmatrix} \cos\theta & -\sin\theta & 0 \\ \sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \qquad (3\text{-}3)$$

After the rotation, the Euclidian distance between the tree positions along the axis was calculated. Figure 3-5 illustrates the trees after rotation of trees in x-axis. A, B and C are approximate tree positions having coordinate values (x_1, y_1, z_1), (x_2, y_2, z_2) and (x_3, y_3, z_3). Euclidian distance between the trees positions A, B and B, C is represented as d1 and d2 respectively along the x-axis. The mathematical formula for the calculation Euclidian distance is follows:

$$d_1 = \sqrt{(X_2 - X_1)^2 + (Y_2 - Y_1)^2 + (Z_2 - Z_1)^2} \qquad \textbf{(3-4)}$$

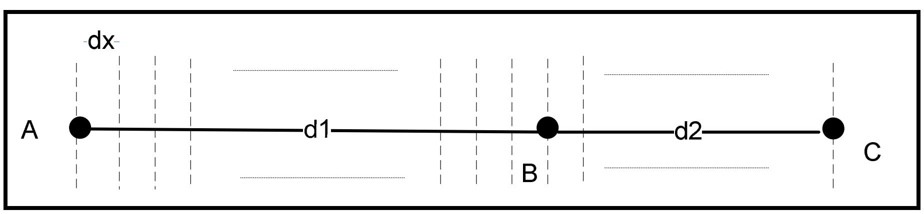


Figure 3-5. Tree separation

"*dx*" be the bin size distance. Then the selection of the laser points was done in a small incremental manner. The height range of each selected Section was calculated and stored in a memory. From the stored height, the highest height value near to the approximate tree positions were considered as the local maxima and the lowest height value between the two tree positions were considered as local minima. The local minima value was used as the separation between the connected trees. After the separation of connected tree, back rotation was performed using $-\theta$ to align the tree in original position.

3.4. Tree geometry parameters extraction

Tree geometric parameters consist of tree height, base-height, stem diameter, crown length and width. Figure 3-6 shows a pictorial representation of these parameters. Several methods for extraction of these parameters are reviewed in Chapter 2.4. Among them, 2D circle fitting approach in a different height is an efficient and is used widely to estimate the tree parameters. Because of its promising nature, we used this approach for finding the tree geometry parameters. The detail of the 2D enclosing circle approach is explained in Section 3.4.1.

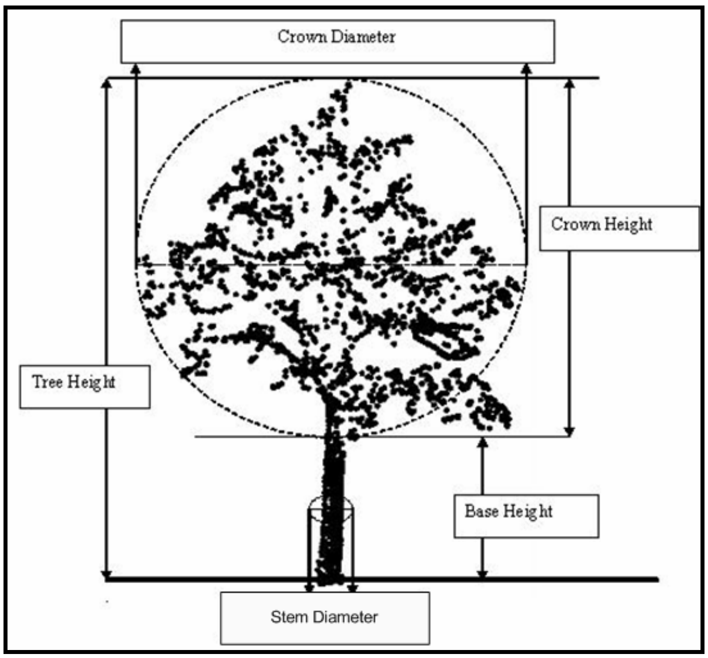


Figure 3-6. Tree geometry parameters

3.4.1. 2D enclosing circle algorithm

The main aim of 2D enclosing circle is to find the best enclosed circle through points. Initially, this algorithm takes all the possible combination of three points to make a circle. After that, it selects the smallest circle that contains all points. If the radius of selected circle is larger than the maximum distance between two points, the algorithm generates a circle with a centre as the midpoint between these two points with the largest distance. Circle is called the best enclosed circle if it has the minimum radius and contains the maximum number of points.

In this research, 2D enclosing circle at regular interval of height was enclosed thought out the tree. Figure 3-7 shows the 2D enclosing circle enclosed at regular height interval of 0.5 m. From Figure 3-7, it is clear that the radius of the enclosed circle at steam is smaller as compared to the radius of the crown.

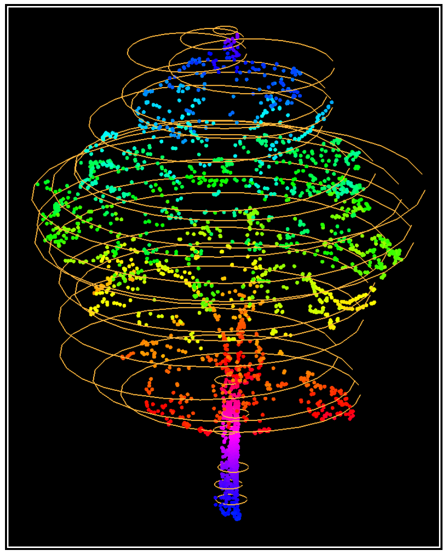


Figure 3-7. 2D enclosing circle enclosed in 3D alpha shape of tree

Thus, analysing the radius of the 2D enclosed circle and enclosed height value from bottom to top, the required tree geometric parameters were calculated. Tree height was calculated by subtracting maximum and minimum height of the tree. Demarcation between stem and crown was done based on the high jump in radius of circle analysing from bottom. Average diameter of enclosed circle at stem was considered as steam diameter. Similarly, an average diameter of the enclosed circle along the crown part was used as crown diameter.

3.4.2. Crown shape determination

Shape of the tree is represented by crown. However, the crown is highly irregular in nature and shape is highly influenced by surrounding obstacles. Thus, a single geometry shape can not be applied for the representation of different type of tree crown. Thus, an appropriate determination of crown shape is crucial for realistic tree modelling. There are different predefined solid geometries which can be used for the representation of (Coder, 2005). Figure 3-8 shows the different solid geometry shape of tree crown.

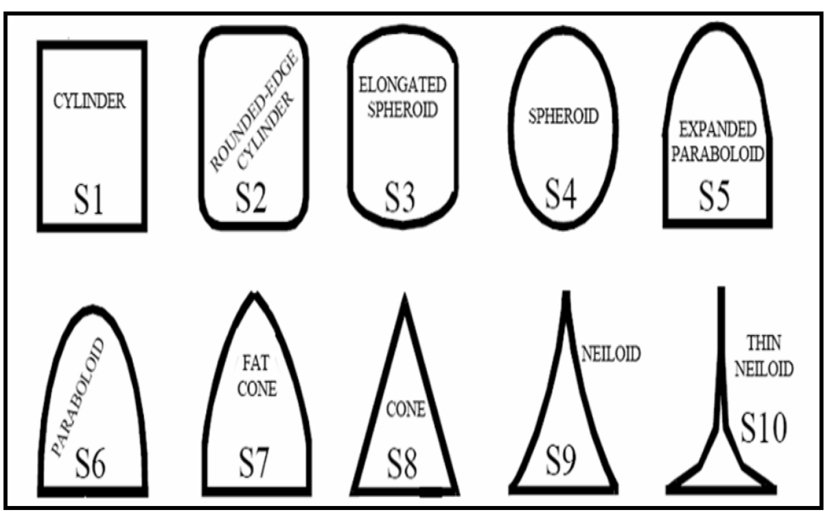


Figure 3-8. Two-dimensional side view of crown shape (Coder, 2005)

For the simplification of the model, four types of crown shapes namely conical, cylindrical, spherical and inverse conical were considered in this research work. Classification to these shapes was done by comparing the diameter of enclosed circle at different label of crown part. Suppose ‘a’, ‘b’ and ‘c’ are the diameter of the crown at different label then, crown type can be determined based on the criteria which are expressed in Table 3-1. Conical shape of the crown has larger diameter towards the bottom part, inverse conical shape has larger diameter toward top part of the crown, cylindrical has nearly constant (±10%) diameters through out the crown and spherical shape has larger diameter at the middle portion of the crown as compared to other portion of the crown.

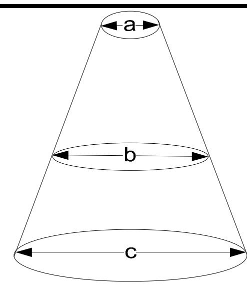
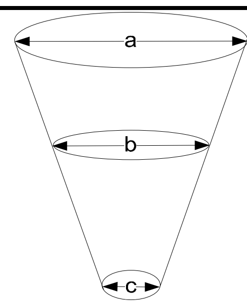
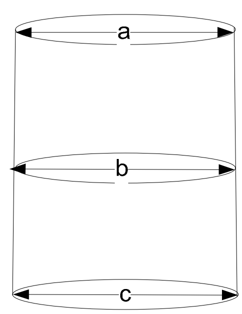
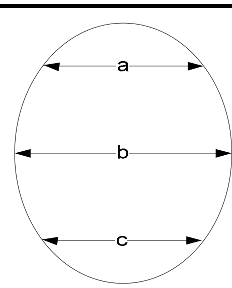
<table>
<tr><th>Criteria</th><th>Visual representation</th><th>Shape name</th></tr>
<tr><td>a <b< c</td><td>
</td><td>Conical</td></tr>
<tr><td>a>b>c</td><td>
</td><td>Inverse conical</td></tr>
<tr><td>a= b = c</td><td>
</td><td>Cylindrical</td></tr>
<tr><td>a<b And b>c</td><td>
</td><td>Spherical</td></tr>
</table>

Table 3-1 Crown type classification

3.5. 3D tree modeling

Different approaches regarding the modelling of tree are reviewed in Chapter 2.5.2. Weber and Penn model (1995) available in plantGL (Pradal et al., 2009) was used for modelling purpose because this model depends on geometric parameters which are consistent and accounts for wide variety of tree structures. Modelling parameters can be divided in to two groups namely tree stems and their branching structures including trunk and leaves. The trunk of the tree is used as the base structure of the tree and all the branches are generated from this base. Figure 3-9 shows the multi-label of primitives and branching angle used for modelling the tree.

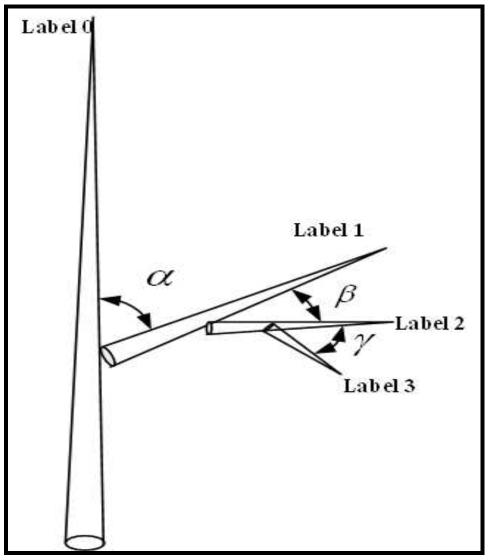


Figure 3-9. Example of multi-label sets of primitives adopted from (Weber and Penn, 1995)

Construction of the trunk and branches are done in a sequential order, i.e. on the label basis. The trunk represents label 0, major branches are labelled 1 and splitting from the branches adds the additional levels and leaves are on the final level. Weber and Penn (1995) claim that most of the real life tree can be shaped using three to four levels at the most, having leaves at the last level. This model uses standard computer graphics techniques of object space rotations. The strength of this model is that it requires relatively less modelling parameters and these parameters are accountable for forming almost all possible shape, size, and number of split, split angle, curve of stem, taper and orientation of the primitives. These parameters are generally obtained from direct physical observation of tree. Thus, using these parameters to model produces the desirable shape of the tree.

In this research, the geometric parameters (tree height, base height, stem diameter, crown length, width and shape) extracted from 3D alpha shape point cloud was used as input values (Section 3.4). As the number of branches, sub branches and branching angle are crucial elements for modelling but these parameters could not be automatically extracted. Several research were conducted in past to calculate these parameters in forestry (Honda, 1971; King and Loucks, 1978). However, none of the relations are generic because these branching structures vary from tree species to tree species and depend highly on the age of the tree as well as the external environment. Thus, field knowledge was used for generation of branch on the model. Total number of branches is one of the major missing information for the realistic look of the tree. This number was calculated using following formula:

$$N_{Branch} = CD/DB \quad \textbf{(3-5)}$$

Where:

N_{Branch} = Total number of branch

$CD =$ Crown diameter

$DB =$ Distance between consecutive branches

Figure 3-9 shows the primary, secondary and tertiary branching angle α, β and γ respectively in a clockwise direction. Table 3-2 shows the assumption of the branching angles with respect to crown shape of the tree. Primary branch length was guided by crown shape. The sub label branch length and its number were derived using the relationship expressed in Table 3-3. Secondary branch was generated on the primary branches whereas tertiary were generated on the secondary one. Length of secondary and tertiary branch was calculated as 45% of its parental branch and number of these branches was calculated as 75%.

Table 3-2. Crown shape and alpha

Crown shape	Value of α, β and γ
Conical	45°
Spherical	80°
Cylindrical	70°
Inverse conical	135°

Table 3-3. Sub label branch parameters calculation methods

Secondary branch length	45% of primary branch length
Number of secondary branch	75% of total number of primary
number of tertiary	75 % of total number secondary branch
Tertiary branch length	45% of secondary branch

3.5.1. Texturing

Texturing of the model is crucial for the realistic representations of 3D scenes. Different methods of texturing and their limitations are reviewed in Section 2.5.3. In this research, data acquisition of trees was carried out in leaf off seasons so acquiring the actual texture from the tree was not possible. To overcome these issues, appropriate number of leaves were generated for texturing the trees from plantGL library (Pradal et al., 2009). While assigning the texture to the model, appropriate light setting and shadow effects were taken under consideration.

3.5.2. Exporting the model in different 3D environment

Integration and exportation of the model to the widely used open standard is essential for proper exploitation of the model. Different 3D environment and their exportation formats are discussed in Section 2.5.4. To meet this requirement, virtual reality modelling language (VRML) and keyhole mark up language (KML) formats was developed. VRML formats was developed using plantGL (Pradal et al., 2009). The model was exported and visualised through 3D web browser. Google earth is another popular means of 3D visualisation. However, this environment supports KML formats of the model. This format was developed with the help of Google sketch up (Google, 2009).

3.6. Conclussion

In this Chapter, an automated workflow for the modelling of tree is presented. The workflow is modular in nature. It starts with pre-processing to detect tree point cloud from the heterogeneous mixture of urban objects. For this purpose, first non vegetation areas, which are large planar regions, are removed. The remaining laser point cloud are further refined by checking significant point features such as surface roughness and density ratio parameters in a certain 3D neighbourhood. After this, tree point clouds are simplified by applying a 3D alpha shape algorithm. Connected group of trees are separated based on local maxima and minima of height value. Separation of connected group of trees is followed by the derivation of tree modelling parameters of single tree. Based on the extracted tree geometric parameters, appropriate model of tree were generated. For the proper integration of the model to other 3D environment, the model was developed in different exportation formats like VRML and KML.

4. Implementaion and results

An algorithm for 3D tree modelling has been proposed in the previous Chapter 3. This Chapter aims at implementing of the algorithm in different cases. Section 4.1 gives a brief description of the data set used for the test of the methods. Section 4.2 describes the methodology applied for the extraction of tree points from the dense mixture of the data set. Then, the methodology adopted for tree geometry simplification and separation of connected tree crown are described in Section 4.3. Section 4.4 presents the tree model developed using the tree geometry parameters extracted from alpha shapes. The Chapter ends with concluding remarks in Section 4.5.

4.1. Datasets and test site

Two data sets, each having different point density, are used for the implementation of the developed algorithm. Most of part in data set contains deciduous species of tree. In some parts, few coniferous species of trees are also present. More than 100 trees were processed. The details of both data sets are as follows:

4.1.1. Data set and test site: I

The first data set was acquired by surveying eight kilometre long track city of Enschede, The Netherlands in 2008. The scanning was done by Optech Inc. LYNX system (Optech, 2008) which has two 360° rotating laser sensors mounted at the back side of the vehicle orientated diagonal to each other. The sensor setup contains minimal shadow effects. Table 4-1 shows the manufactory information of the sensor. Field study was also carried out to acquire the recent photographs of respective trees and to derive the imperial relationship regarding the branch structure of the tree. Furthermore, the acquired photographs were used for the visual analysis of the model. Strip overview of Enschede is shown in Figure 4-1.

Table 4-1. Manufacturer specifications of LYNX system (Optech, 2008)

Maximum range	100 m (at 20% reflectivity target)
Range precision	0.7 cm (1 sigma)
Absolute accuracy (GPS)	5.0 cm (at 100 km/h)
Scan angle	360 degree
Scan rate	150 Hz (9000 rpm)
Measurement rate	100,000 pulses/sec per sensor
Echo per pulse	4 echoes

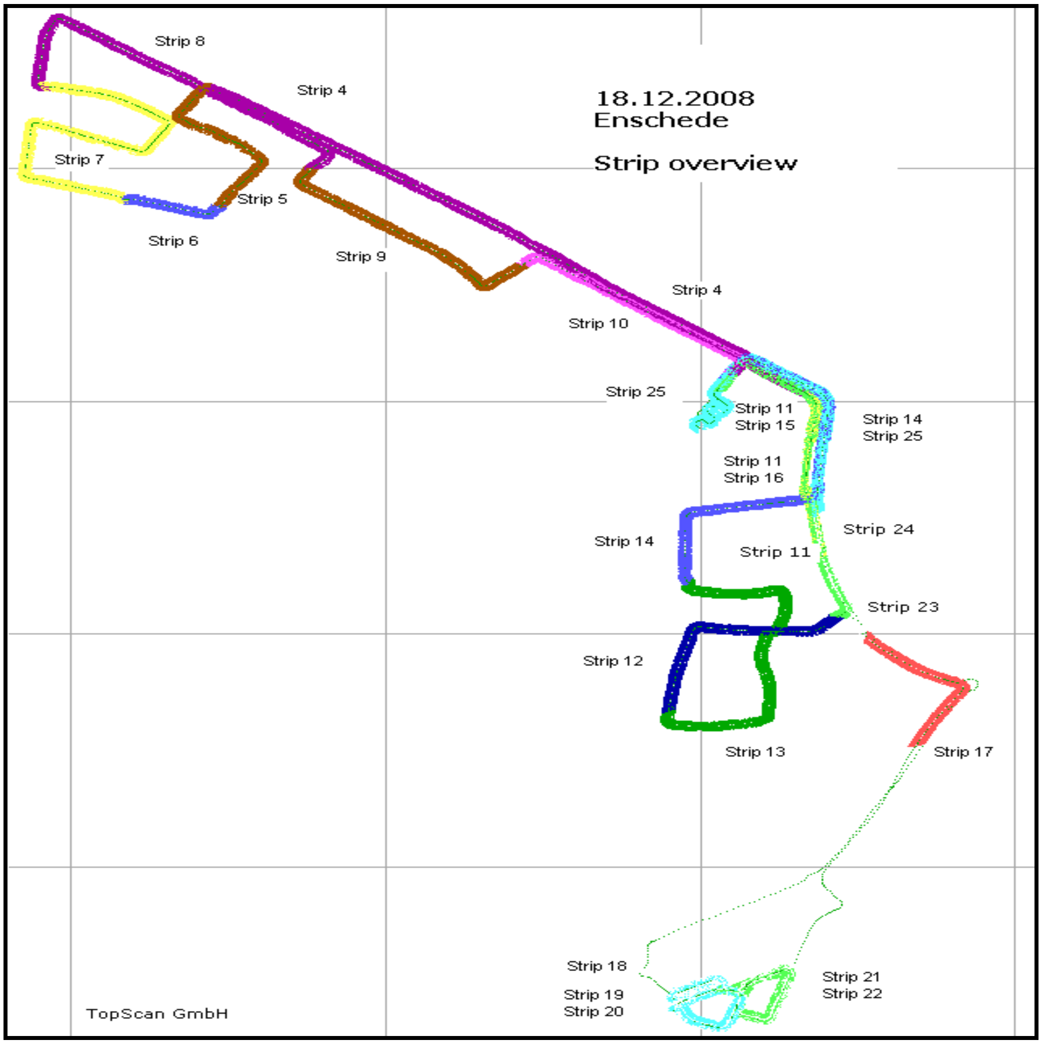


Figure 4-1. Strip overview of Enschede (TopScan, 2007)

4.1.2. Data set and test site: II

The second data set was obtained from EuroSDR (Kukko et al., 2007). The test site Espoonlahti is located in Espoo, about 15 km west of Helsinki, Finland. Mobile laser scanning data was acquired on June 10th using the ROAMER-system along the 1700 m of road environment. The scanner used frequency of 48 Hz on both directions of street (clock wise and counter clockwise) and 30 Hz on counter clock wise for laser profiling. Details about scanning are summarised in

Table 4-2.

Table 4-2.ROAMER data of Espoonlahti (Kukko et al., 2007)

Date	June 10, 2009
Laser scanner	Faro Photon™ 80
Laser point measuring frequency	120 kHz
IMU frequency	100 kHz
GPS frequency	1 Hz
Driving speed	30 km/h

Profile measuring frequency	30 Hz and 48 Hz

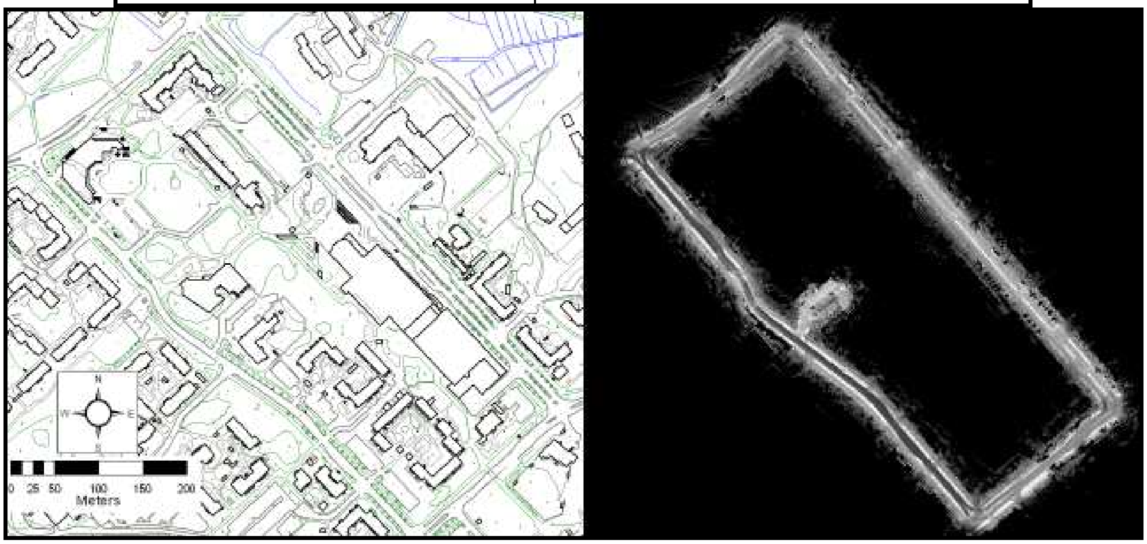


Figure 4-2. Espoonlahti test site. Left: city map of Espoo. Right: Mobile mapping data.(Kukko et al., 2007)

4.2. Pre-processing

Pre-processing algorithm was implemented using PCM and C++ as a programming language. Figure 4-3 shows the set of sequential process implemented during pre-processing. Figure 4-3 (a) is the raw input point cloud from Enschede data set which contains trees along with poles, buildings, peoples and vehicles. First, a surface growing segmentation was performed in this input dataset using PCM. These parameters were obtained by trail and error basis to obtain larger planner ground segment area. Table 4-3 shows the parameters for surface growing segmentation.

Table 4-3. Surface growing segmentation parameters used in point cloud mapper

Surface growing parameters	Value
Surface model	Planner
Surface Growing neighbourhood definition	Direct neighbours
Surface growing radius	0.6 m
Maximum distance to surface	0.3 m
Minimum distance to recomputed the location	0.15 m

Figure 4-3 (b) shows the result after implementation of surface growing segmentation. It can be seen that the larger segmented area is a planner region. After the surface growing segmentation, the ground and no ground points was identified by fitting the horizontal plane to each segment. Angle threshold of 10 ° and area threshold 100 m² was used to fit the plane.

Figure 4-3 (c) represents the dataset after removing the ground points. Connected component analysis was done in no ground points through PCM. The parameters used for this analysis through PCM are presented in Table 4-4.

Table 4-4. Parameters for connected component using in point cloud

Connected component parameters	Value
Maximum distance between the points	1.5 m
Minimum number of points	10

Figure 4.3 (d) shows the result after application of connected component analysis. Each unique connected segment is visualized in a unique colour. The approximate tree position was used as additional input information to select the tree component. Further removal of the tree nearby objects was done using surface roughness and point cloud density ratio value. Surface roughness of greater than 0.85 and point density ratio larger than 2 was used to select the vegetations. Figure 4-3 (e) shows the final output of this pre-processing. From the figures, it is clear that the final out contains the point cloud belonging to tree.

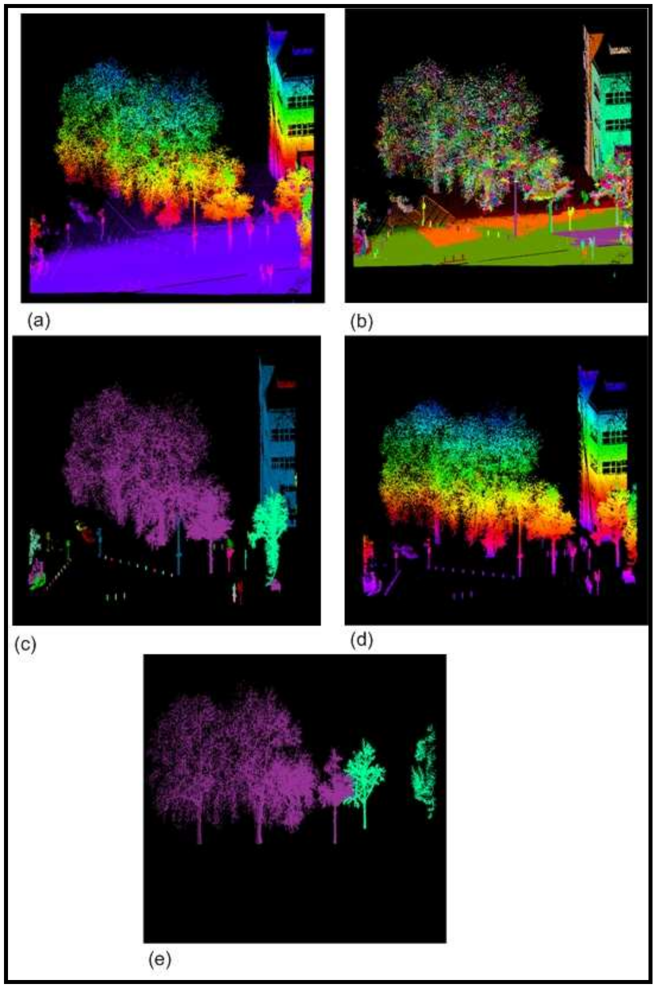


Figure 4-3. Pre processing in data set 1,(a) Input data set, (b) surface growing segmented data set, (c) data set without ground, (d) connected component analysed, (e) final output of pre-processing

4.3. Tree geometry simplifications and seperation

4.3.1. Tree geometry simplifications using 3D alpha shape

Tree geometry simplification was carried out using 3D alpha shape of the tree. The algorithm for development of alpha shape using Delaunay triangulation is explained in Chapter 3.2.1. Implementation of this algorithm was done in C++ using CGAL library (CGAL, 2009). Results obtained after executing the implementation of this algorithm are shown in Figure 4-4 and Figure 4-6 respectively.

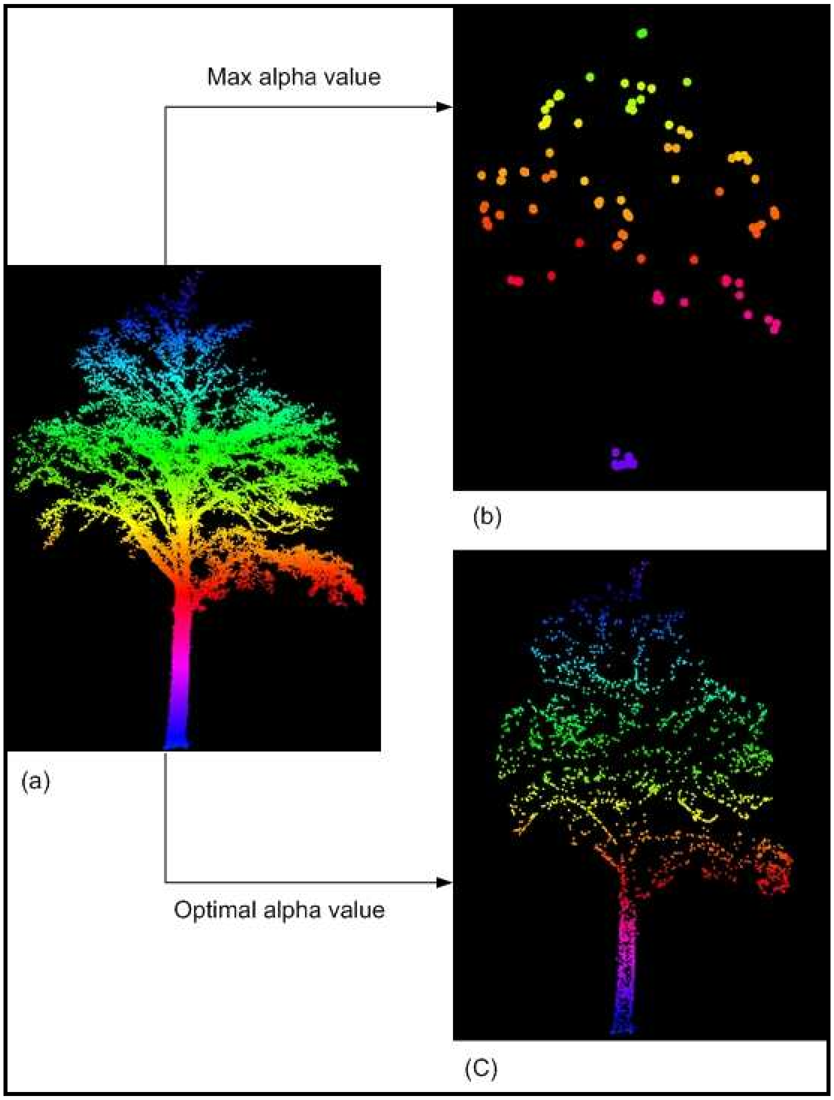


Figure 4-4. 3D alpha shape of tree, (a) Input tree, (b) 3D alpha shape of tree with maximum alpha value, (c) 3D alpha shape of tree with optimal alpha value

Figure 4-4(a) is the input tree point clouds for the 3D alpha shape algorithm. It contains 23,895 points. Graph depicting the number of output point in 3D alpha shape verses alpha value is plotted in Figure 4-5. This graph shows that for the higher value of alpha the number of output points is low. On the other hand for the lower value of alpha the number of output point is high. The maximum alpha value that can represent the basic shape of the input tree is $1.7*10^{10}$. Figure 4-4(b) shows the result of the shape of tree having maximum alpha value. Total number of point in Figure 4-4(b) is 111. As the alpha value decreases, the number of output point increases which leads gradually to the fine shape of the tree. The minimum alpha value that can produce the detail shape of the tree is considered as optimal alpha value. Figure 4-4(c) shows the detail 3D alpha shape of tree, having alpha value 0.4 and number of output points are 2,524. Figure 4-6, (a) and (c) shows input data set of connected trees. While Figure 4-6 (b) and (d) are results after application of optimal alpha value in 3D alpha shape of connected trees. Table 4-5 shows the number of input point, optimal alpha value and the output point of the Figure 4-6.

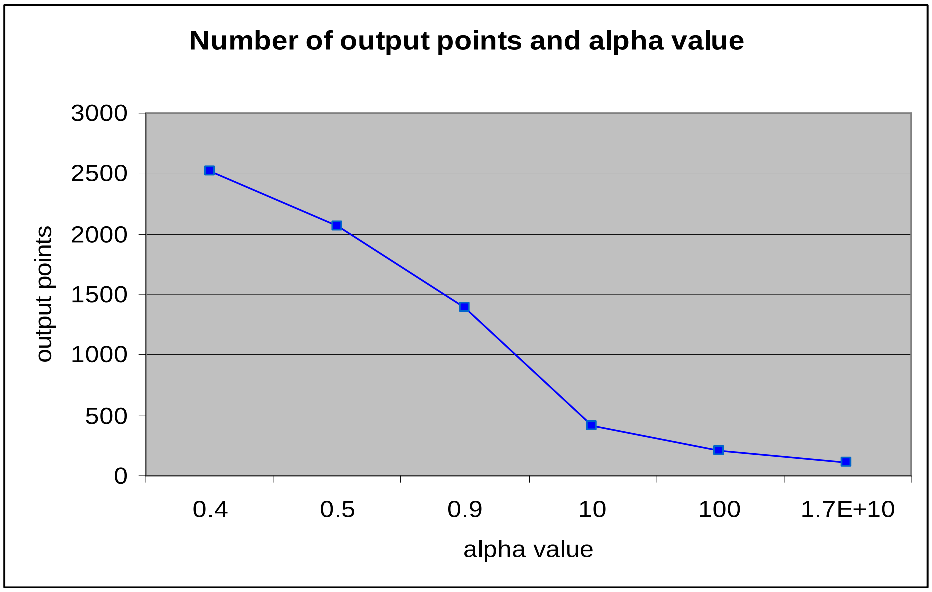


Figure 4-5. Number of output points Vs alpha value

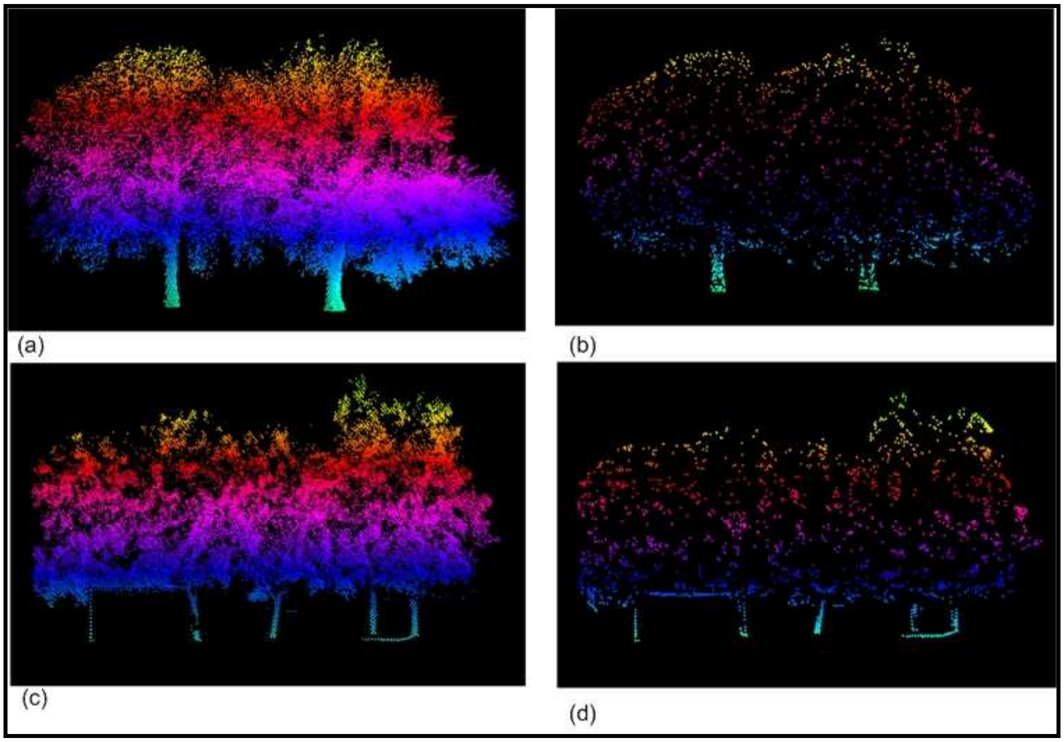


Figure 4-6. 3D alpha shape of connected tree, (a) input connected tree from data set 1, (b) 3D alpha shape of Figure 4-6(a), (c) input connected tree in data set 2, (d) 3D alpha shape of Figure 4-6 (c)

Table 4-5. Alpha shape parameters for connected trees

Number of input point	Optimal alpha value	Number of output point
57687	0.5	1800
39663	0.9	2123

4.3.2. Separation of connected tree

In urban areas there are some trees which are connected in nature. The separation of these connected trees was performed on the basis of local maxima and minima of height value as described in Section 3.3.2. The algorithm was tested in two scenarios. First with the two connected trees as shown in Figure 4-6 (a) and second is the group of connected trees as shown in Figure 4-6(c). 3D alpha shape of Figure 4-6 (a) which is shown in Figure 4-6 (b) was passed as input for the tree separation. Firstly, all the connected points of tree were rotated toward the x axis with an appropriate angle such as 30°. After that, the height range was calculated along the x direction in the interval of 0.5 m. Local maxima of tree was determined by using the approximate tree position. Local minima were determined between the two local maxima. In Figure 4-7, red bar indicates the local maxima and the dark blue bar indicates the local minima.

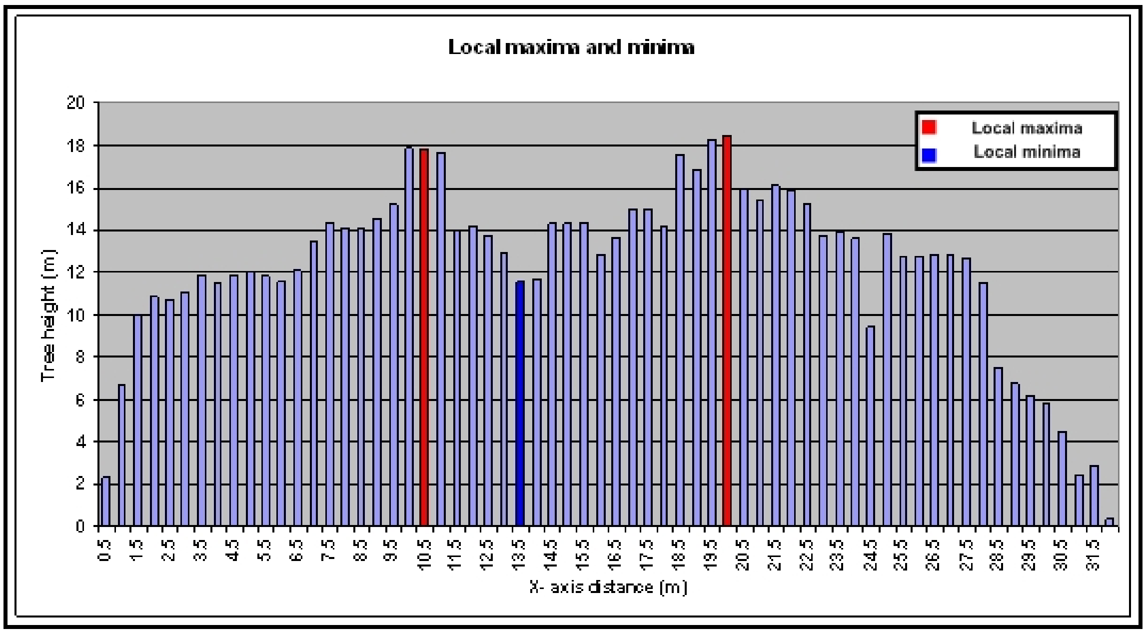
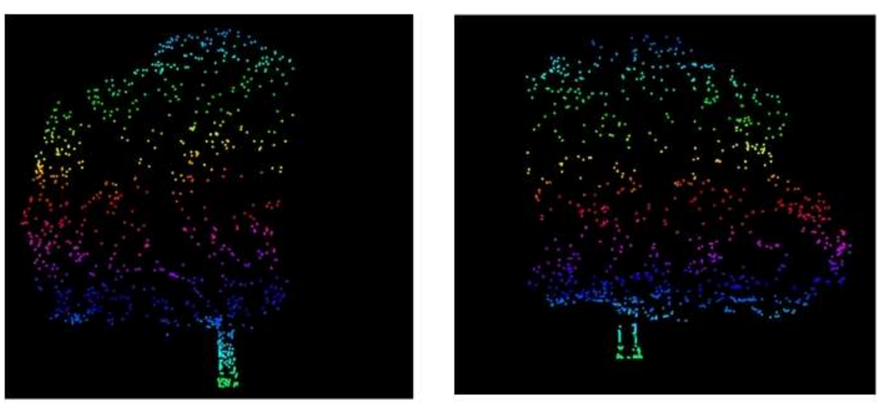


Figure 4-7. Local maxima and minima for height value

The separation was done based on the local minima of height value. The separated points were rotated back with an angle -30° to preserve the co-ordinate value. The result of separated tree is shown in Figure 4-8.



(a) (b)

Figure 4-8. Separated tree (a) right tree of input data (b) left tree input data

In a similar manner, the algorithm was tested for a group of connected tree shown in Figure 4-6 (c). This group of connected tree was simplified using 3D alpha shape algorithm and the output is shown in Figure 4-6 (d). Separation was done based on the local maxima and minima of height value. In Figure 4-9 , red bar indicates local maxima and blue bar indicates minima of the group of connected tree. Result of separated trees is shown in figure 4-10.

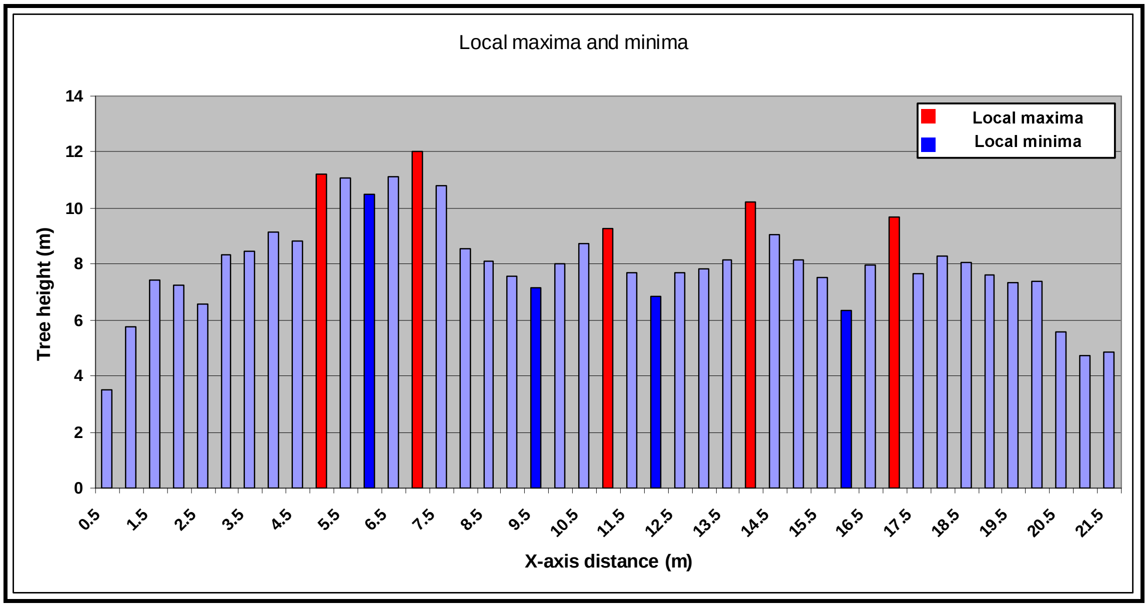


Figure 4-9. Local maxima and minima of group of connected trees

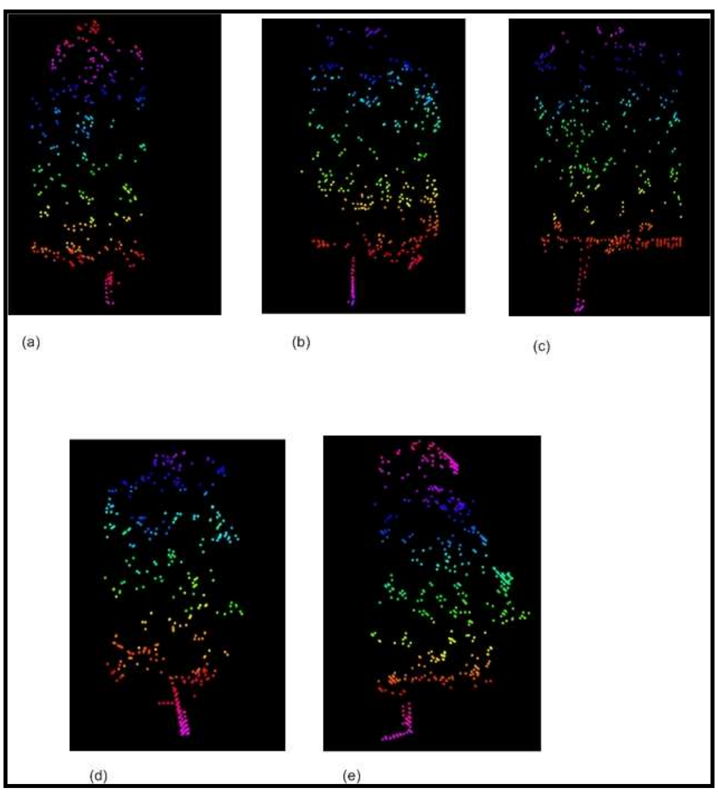


Figure 4-10. Separated trees of input Figure 4-6(d)

4.4. 3D tree modelling

Modelling of tree was performed by using plant simulator based on Weber and Penn method available in plantGL (Pradal et al., 2009). Modelling process starts after labelling each single tree point cloud. More than 30 trees of different age group and species types were modelled. One complete example of 3D tree modelling process is shown in Figure 4-11. Figure 4-11(a) shows the acquired input point cloud of tree. This tree contains 67,696 numbers of points. Geometric simplification of this tree was done by producing 3D alpha shape of the tree. Alpha value 0.8 produces the detail shape of the tree having 1826 number of points. Figure 4-11 (b) is an alpha shape of the input tree. 2D enclosed circle was used to extract tree geometric parameters from 3D alpha shape of the tree. 2D circle was enclosed at a regular sequence of tree height. Figure 4-11 (c) shows a graph of circle radius verses enclosed height. These graphs give the visual impression regarding the shape of the tree.

Table 4-6 shows the extracted parameters such as tree height, base height, stem diameter, crown height, crown diameter and crown type of the input tree. Here the input tree has conical type of crown. Branch information was derived based on the experience and field observations. Table 4-7 shows the extracted branch information of input tree. Third labels of branch were assigned to model. Primary branches were generated from tree stem. Length of the primary branch was controlled by tree crown shape. The obtained parameters were used as input in Weber and Penn model.

Table 4-6. Tree geometric parameters

Tree height	15.75 m
Base height	0.75 m
Crown height	15 m
Stem diameter	1.47 m
Crown diameter	3.47 m
Crown type	Conical

Table 4-7. Tree branch information

Total number of primary branch	20
Primary branching angle	45°
Secondary branch length	45% of primary branch length
Secondary Branch angle	45°
Number of secondary branch	15
Number of tertiary	15
Tertiary branch length	45% of secondary branch

First, stem of the tree was created by using tapering cylinder of base diameter equal to the tree stem diameter. Primary branches were created in the crown area originated from stem. Length of the primary branch was controlled by the crown shape. For example, given input tree has conical shape. Thus, length of primary branch is decreasing toward the top of the crown. Secondary branches were created based on the primary branch and tertiary on the secondary branch. Figure 4-11(d) shows the developed model of the tree. Available texture library in plantGL (Pradal et al., 2009) was used for texturing purpose. Texturing of the model was done by assigning appropriate number of leaves on the tree. Figure 4-11 (e) represents the trees after texturing. Two different 3D file formats of the model VRML and KML were developed. Figure 4-12 depicts the developed 3D model exported in Google earth.

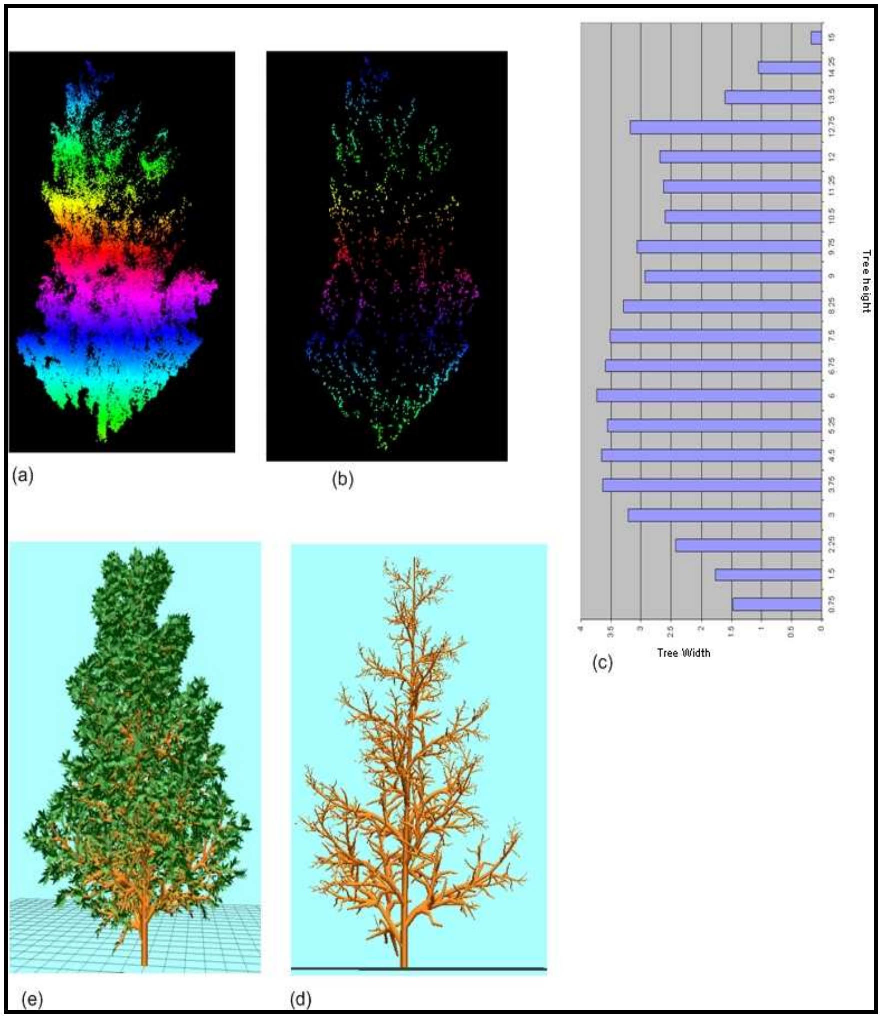


Figure 4-11. 3D tree modelling (a) Input tree (b) 3D alpha shape of input tree (c) Graph of tree width verses tree height (d) Developed model (e) Textured model

Figure 4-12. 3D tree models exported in Google earth

4.5. Conclusion

In this Chapter, the algorithm explained in Chapter 3 was implemented on both data sets acquired from LYNX system And ROAMER-system. First the implementation of processing algorithm was done and the trees were detected from dense urban point cloud. 3D alpha shape algorithm was implemented in detected tree point cloud and geometry of tree was simplified. To preserve the detail shape of the tree, the minimum value of alpha is found to be the best choice. After the simplification of tree, group of connected trees was separated using local maxima and minima of height value. Tree geometric parameters were extracted from single tree alpha shape by fitting the 2D enclosing circle in a sequence of height value. Field knowledge was utilised to derive branch information. Geometric parameters and branch information were further utilised as the input parameters for Weber and Penn model available in plantGL to model the tree. Appropriate texture available in plantGL library was used for texturing the model. The models were developed in different 3D exportation file format such as VRML, KML. The successful implementation of this algorithm in different stages validates the usability of the developed algorithm in real cases.

5. Performance evaluation

After processing the data set with the best set of primitives, it is important to assess the performance of the developed algorithm. This Chapter includes three different aspects of performance evaluation. The evaluation of tree detection rate is presented in Section 5.1. Data reduction rate are described in Section 5.2 and visual inspection of the model is shown in Section 5.3 and finally the chapter concludes in Section 5.4.

5.1. Completeness, Correctness Assesment

To evaluate the tree detection results numerically, completeness and correctness was used. For this purpose, 10 different samples from both data sets were selected and number of tree in each data set was estimated manually. The counted number of tree was used as a reference data set. The developed pre- processing algorithm was applied in sample data set. Based on the result different variable like true positive (TP), true negative (TN), false positive (FP) were identified. TP is the tree which is present in both, the extracted and the reference data set. TN is the tree which was not present in reference data set but was extracted. FP is the tree which is present in the reference data set but not in the extracted data set i.e. the tree which is missed in extracted data set. False Negative (FN) is the tree which is present in the extracted data set but not in the reference data set, i.e. the tree which is wrongly extracted as tree. Completeness (Comp) was referred as detection rate of the tree. Correctness (Corr) was related to how well the detected trees match with the reference data set. Mathematically it can be derived as (Agouris et al., 2004).

$$Corr = TP/(TP + FP) \qquad \textbf{(5-1)}$$

$$Comp = TP/(TP + FN) \qquad \textbf{(5-2)}$$

Quality of the results balances the completeness and correctness and provides a compound performance metric (Agouris et al., 2004):

$$Quality\ \% = TP * 100/(TP + FP + FN) \qquad \textbf{(5-3)}$$

Analysis was performed on both data sets separately and overall summary for both datasets is presented in table.

Table 5-1. Tree detection accuracy

Data set	No. tree detected	Correctness (%)	Completeness (%)	Quality (%)
EuroSDR	66	90	86	78
Enschede	40	93	89	85

The completeness, correctness, quality of tree detection in EuroSDR data set is 90%, 86% and 78 % whereas 93%, 89% and 85% respectively in Enschede data set. The over all quality of the algorithm is 81.5%. These results prove that the developed algorithm have higher potential to detect the trees in varying point density data set.

5.2. Data reduction rate

The goal of the developed algorithm in this research is to follow hierarchical i.e. modular processing steps in order to reduce the amount of points efficiently. The amount of data reduction in pre processing and 3D alpha shape is calculated using the following formula:

$$DRR = (N_{in} - N_{out})/N_{in} \quad \textbf{(5-4)}$$

Where:

$DRR =$ Data reduction rate

$N_{in} =$ Number of input points

$N_{out} =$ Number of out points

Data reduction rate in pre-processing phase and 3D alpha shape was calculated using equation (5-4). The result shows the developed algorithm reduces more than 80% points during the pre pro processing and more than 90% points during the 3D alpha shape generation without loosing the important information. These results speed up the further processing exponentially. Figure 5-1 shows the input and output points of pre-processing. Similarly, the Figure 5-2 shows the input point and output points in 3D alpha shape. Both figure shows that the points are reduced significantly.

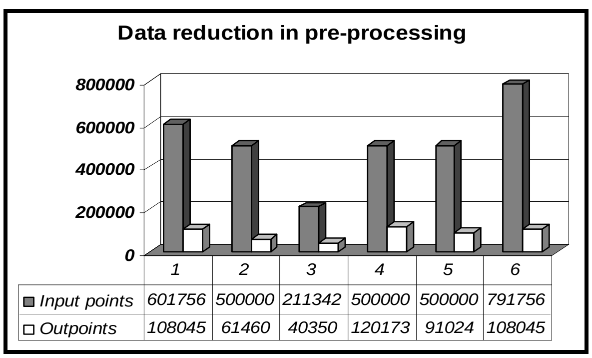


Figure 5-1. (Left) Data reduction in pre processing

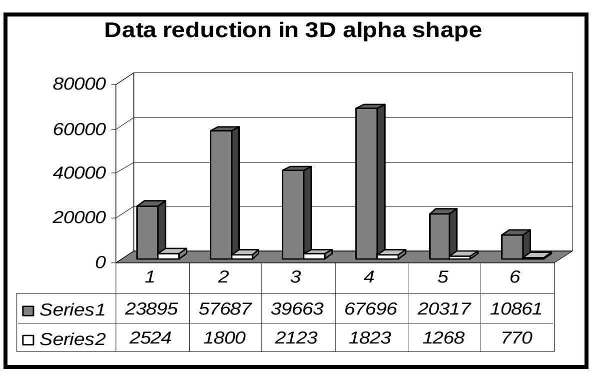


Figure 5-2. (Right) Data reduction rate in 3D alpha shape

5.3. Visual inspection

This research focused on effective visual representations of 3D tree models from a point cloud data set. This analysis considers the perceptual issues behind the visual interpretation of 3D tree models and integration of the model in different 3D environment. The data set contain both young and old trees having deciduous and coniferous species. In this Section, different typical types of modelled trees and their series of intermediate steps were visually compared with each other. For Enschede data set, photographs of the respective trees were acquired and used during compression, whereas, photographs were not available in the case of EuroSDR data set.

Ideal tree has been considered as straight tree stem, crown shape in fixed slid geometric shape and regular branch structure. The developed modelling algorithm shows the potentiality to model such type of trees. The Figure 5-3 shows the different modelling stage of ideal tree for visual analysis.

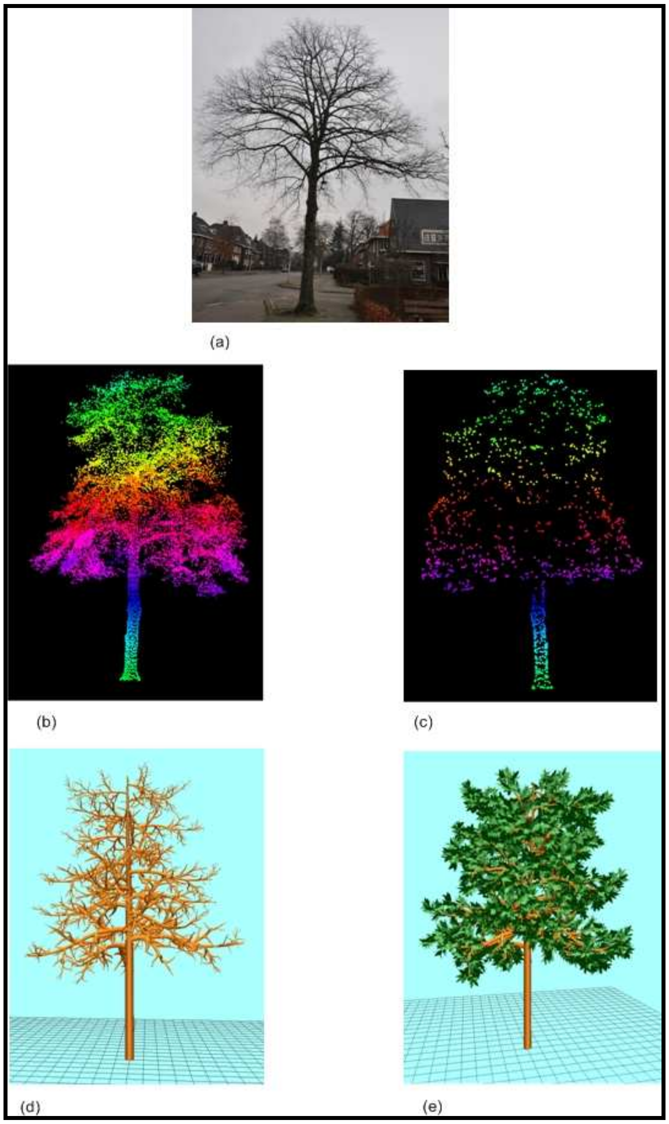


Figure 5-3. 3D tree model (a) Photo graph of tree, (b) mobile laser scan point cloud of tree (c) 3D alpha shape of tree (d) 3D model of the tree (e) Textured 3D tree model

Figure 5-3(a) is the recent photograph of a tree taken in January 2010. Figure 5-3(b) is the MLS point cloud of the tree which was acquired in December 2008. It can be noted that there is more than a year gap between the point clouds data set and photograph. So, the crown shape of photograph Figure 5-3(a) is slightly different than acquired point clouds Figure 5-3(b) and some of the lower branches are missing in photographs whereas it is present in MLS data. Figure 5-3(c) is the 3D alpha shape of the input MLS data of Figure 5-3(a). In alpha shape, isolated points are removed and point density is reduced up to 90%. However, the developed model looks identical to the input point cloud. Modelling parameters were derived from the alpha shape. Based on the derived modelling parameters and crown shape, developed 3D tree model is shown in Figure 5-3(d). An appropriate texture is assigned to the model which is shown in Figure 5-3(e). Developed 3D tree model and textured model looks almost symmetrical in shape and visually impressive with respect to the input point clouds and 3D alpha shape. Comparing with the photographs, the crown shape is almost similar. The developed modelling algorithm performs satisfactory to model these types of trees since the relationship between steam, branches and sub branches are in a proper order and there are no irregular branching structures present.

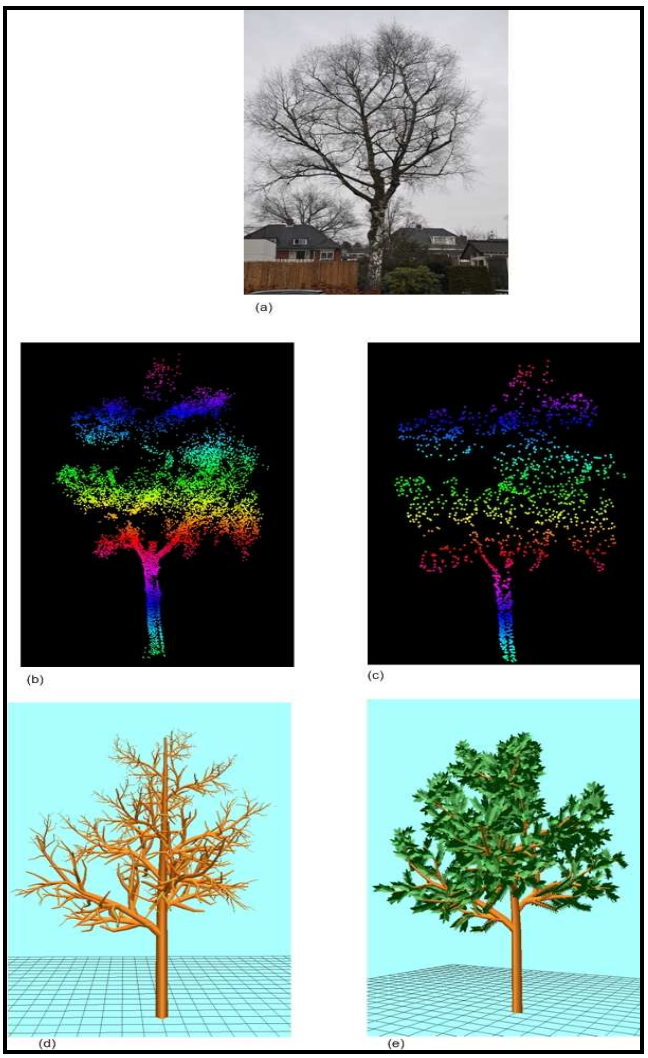


Figure 5-4. 3D tree model (a) Photo graph of tree, (b) mobile laser scan point cloud of tree (c) 3D alpha shape of tree (d) 3D model of the tree (e) Textured 3D tree model

Modelling steps and their step wise visual analysis of another typical tree is shown in Figure 5-4. The photograph of the tree is shown in Figure 5-4 (a). Figure 5-4(b) is the acquired MLS point cloud of the tree. Comparing with the photograph and acquired point cloud, the point cloud represents almost all the major structures however there is some data gap in the acquired point cloud. It might be because of the thinner branches. Figure 5-4(c) is the alpha shape of the tree. 3D alpha shape is the simplification of input tree geometry. Input point cloud and 3D alpha shape look symmetric in shape. Figure 5-4(d) is the developed model of the tree. The developed model is based on the modelling parameters and crown shape extracted from alpha shape of the tree. Shape of crown is derived from alpha shape. Thus, the model looks identical to alpha shape and input data set. Figure 5-4(d) is the developed model and Figure 5-4(e) is the textured model. Compared to the real photographs, developed models preserve the crown shape. However, the developed branch structures partially match with photograph because the model uses the set of general rule for generating the branch based on crown shape. Visually in photograph, there are three dominant primary branches originated from stem and all the secondary and tertiary branches belong to these main branches. However the developed model is a mathematical surface and branch generations were guided by modelling rule and crown shape. Number of branch is derived based on the length of crown shape. Particularly, in this model 15 primary branches are present and all the secondary and tertiary branches belonged to these primary branches.

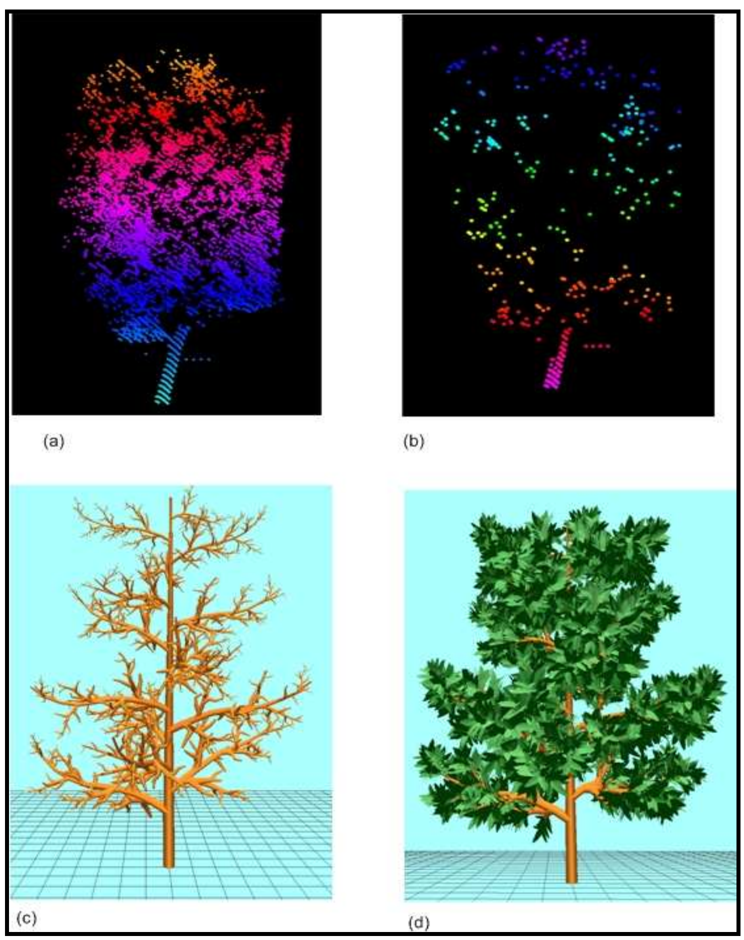


Figure 5-5. 3Dtree model (a) mobile laser scan point cloud of tree (b) 3D alpha shape of tree (c) 3D model of the tree (d) Textured 3D tree model

Figure 5-5 shows the modelling steps of the EuroSDR data set. Figure 5-5(a) is the input MLS point cloud. Figure 5-5(b) is the 3D alpha shape of the input point cloud. In this case also, the developed 3D alpha shape is symmetric with the input data set. Figure 5-5 (c) is the developed model of the tree. Figure 5-5(d) is the visualization of the model after assigning the texture. Comparing the models with the input point cloud and 3D alpha shape, the crown shape is identical whereas there is a difference in tree stem. It is inclined in the input however it is straight in the model. So, in those cases, the developed modelling algorithm partially matches with the reality because the developed modelling algorithm uses the assumption of straight steam generation.

Modelling steps of comparatively old age trees are shown in Figure 5-6. Figure 5-6 (a) is the input point clods of the tree. Figure 5-6 (b) is the 3D alpha shape of the input tree. Similar to previous case, here also the alpha shape preserves outer point boundary shape of the input tree point clouds.

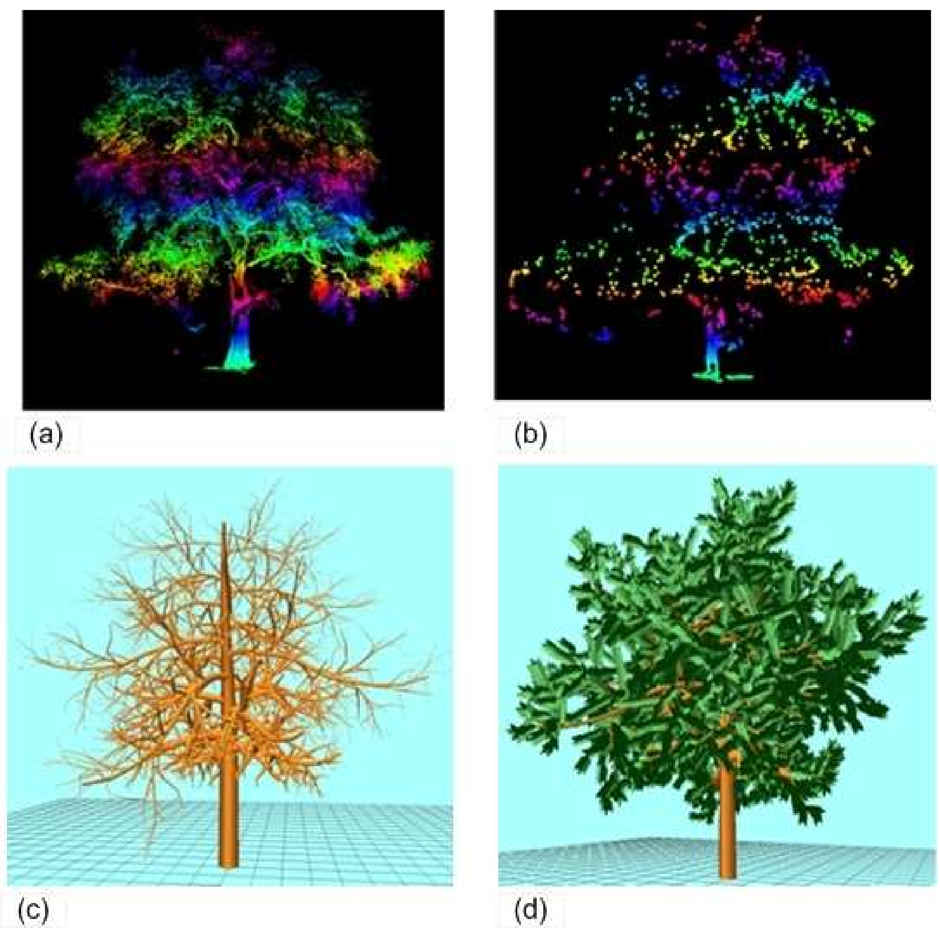


Figure 5-6. 3D tree modelling (a) mobile laser scan point cloud of tree (b) 3D alpha shape of tree (c) 3D model of the tree (d) Textured 3D tree model

Figure 5-6 (c) and Figure 5-6 (d) is the developed model and textured model of the tree. In this case, the crown shape of the developed model matches partially with the input point clouds and 3D alpha shape. The developed modelling algorithm consider four type of crown shape namely conical, cylindrical and inverse conical and spherical however the input tree has the bell shape crown shape. During the modelling, these bell shape considered as spherical so the developed model have the spherical crown shape which looks different than reality. Branch structure of the models and the input trees are different. The model has longer branches in the middle whereas the input tree has the longer branches at the bottom. The reason for that is the spherical crown has larger radius at the centre.

5.4. Conclussion

In this Chapter, tree detection, data reduction rate and visual inspections were carried out to evaluate the performance of the developed algorithm. Accuracy of tree detection was examined by calculating the completeness, correctness and overall quality and was obtained 93%, 89% and 85% for Enschede data set and 90%, 86% and 78 % for EuroSDR data set respectively. The over all quality of the algorithm was 81.5%. These results prove that the developed algorithm have higher potential to detect the trees in varying point density data set. Data reduction rate of the pre-processing and 3D alpha shape was calculated. The result shows the developed algorithm reduces more than 80% points during the pre pro processing and more than 90% points during the 3D alpha shape generation without loosing the important information. The visual analysis of the model shows that the model matches almost perfectly with ideal tree having straight tree stem, crown shape in fixed solid geometric shape and regular branch structure. For the irregular trees, the developed model matches partially.

6. Discussion

This Chapter presents the discussion on the result obtained during research. The discussion is presented in relation to input data set, applied algorithms and obtained results. Discussion of tree detection in an urban environment is presented in Section 6.1, the tree geometric simplification using 3D alpha shape in Section 6.2, separation of connected trees in Section 6.3, tree geometric parameter extraction in Section 6.4 and 3D tree modelling in 6.5.

6.1. Tree detection

A modular pre-processing approach was applied to extract the tree points from the heterogeneous urban objects. The modular approach was able to reduce the points in further analysis. The advantage of modular approach was step wise point reduction which leads in faster processing of points. The angle and area threshold of the fitted horizontal plane segment was identified as ground points. The angle between the normal vector of segment and normal of fitted plane, and segment area was used as the decision parameters to fit the plane. The angle was used due to the sensitivity and importance in differentiating surfaces. The area on the other hand acted as constraint to reduce the number of iteration because the planner segment has larger area. Surface roughness and density ratio of points were used to differentiate between the trees and non tree objects. The trees has highly scattered point orientation thus leading to higher surface roughness as compared to non tree points. As such, the surface roughness in Z direction provided with standard deviation which was used to remove the wall and other objects near the tree. The accuracy of tree detection was satisfactory in an over all urban areas however it dropped down in cases with bushes and small trees because of similar surface roughness and point density ratio.

6.2. Tree geometry simplification

Tree geometry simplification was obtained through the application of 3D alpha shape algorithm described in Chapter 3.2.1. This algorithm is able to preserve the outer shape of high vegetation even in leaf on condition. This is an advantage compared to skeletonising and direct branch reconstructing approaches which need a clear representation of the branch structures (Bucksch and Lindenbergh, 2008). Here, the proposed method is independent of internal tree structure. Data reduction rate of up to 90% is achieved which makes more efficient further processing of 3D models.

6.3. Separation of connected trees

Method based on local maxima and minima of height value from MLS data was developed for separation of the urban connected trees as described in Chapter 3.2.2. The other methods however, use raster based analysis that involves lots of elevation models such as DSM, nDSM , CHM for finding local minima and maxima (Hyyppa et al., 2001; Solberg et al., 2006). Here, proposed method pragmatically finds the local maxima and minima from the point cloud. Where a local minima of height value is the region of separation for connected trees. The method produces satisfactory result in cases with single minimum value, and produces poor result where dense trees with many minimum values are present. The method is robust in urban areas where trees are planted in sequences as compared to forest where trees occurrence is random.

6.4. Tree parameters extraction

The method for tree parameter extraction such as tree height, base height, stem diameter, crown length, width and crown shape was described in Chapter 3.3.1. The extraction of parameter was based 2D enclosed circle algorithm. 3D alpha shape was used for determining the best circle instead of original tree point clouds. 3D alpha shape is a simplified geometry of original tree and have comparatively 90% reduced points representing the boundary, whereby it reduces the number of iteration significantly and improves the accuracy of tree width. Based on the height, radius, and total number of enclosed circle the tree geometry parameters and shape of crown were estimated automatically. This method is simple and helpful to extract tree geometry in an automatic manner. However, Irregular branching structure and curved stem of the tree influenced the estimation of 2D enclosed circle which might as a result affect the accuracy of tree geometry parameters.

6.5. 3D tree modelling

The automated approach in modelling, rendering and development of different 3D compatible file format forms the foundation of the method. This provides the transferability of the model to different 3D environments. The visual analysis of the model shows that the model matches almost perfectly with the tree in reality having straight tree stem, fixed solid geometric crown shape and regular branch structure. However, the model matches partially for irregular trees because of the assumptions such as straight tree stem, dichotomous branching system and crown shape branch generation techniques.

7. Conclusion and recommendation

7.1. Conclusions

The main objective of this research is to develop a realistic 3D tree model from MLS data in an automatic manner. Based on the obtained results and discussions, following conclusions are drawn:

- The study revealed that the proposed workflow is able to detect the tree in a dense urban environment. Surface roughness and point density ratio is a significant feature to separate the tree and non tree objects.

- 3D alpha shape algorithm is useful to simplify the tree geometry. This method is independent to internal tree structure and is able to derive detail outer shape of high vegetation. Furthermore, data reduction rate is significant that makes efficient further processing of 3D modelling.

- Separation of connected tree crown was achieved from local minima of height value. The method is operable in point cloud and there is no need to derive raster models like DSM, nDSM, and CHM. The performance of the separation algorithm works well when there is a single minima height value.

- 2D enclosed circle algorithm is useful to derive the tree parameters such as tree height, base height, stem diameter, crown length, width and crown shape. Input of 3D alpha shape reduces the number of iteration significantly to find the best enclosed circle and improves the accuracy of tree width because points represent the outer boundary of tree.

- Weber and Penn method is useful to model realistic tree through extracted tree geometric parameters. Texturing the model gives the realistic visual impression. Accuracy of the model depends on the input tree geometric parameters.

- Exportation of the model in 3D file format such as VRML and KML is achieved. These file formats add efficient scalability of the model to different 3D environments.

- Performance of the workflow is evaluated in terms of tree detection and data reduction rate. The overall quality of tree detection is more than 80%. The result shows that the developed modular structure of workflow reduces more than 80% points during the pre-processing and more than 90% points during the 3D alpha shape generation without loosing the important information. This study concludes that the presented workflow is applicable for large data set of varying point density.

7.2. Recommendations

The following are the recommendations drawn for further research:

- Separation of bushes and trees in dense urban area is not investigated yet. As the both objects have same point features such as surface roughness and point density ratio. Further advanced separation techniques should be explored to separate these objects.

- Separation of connected trees through local maxima and minima of height value produces poor result when there are tree having same height and no clear minima value present. Further improvement is required for better results.

- In this research four crown types are considered for modelling. However these types are not sufficient to represent all kinds of tree. Further consideration of crown shape is recommended for wide range of coverage.

- Weber and Penn method produces the model of tree having straight tree stem, crown shape in fixed slid geometric shape and regular branch structure. However, this method has limitation over the curved stem and irregular branch structures. Further research is recommended to model irregular shape tree.

- Visually attractive models and portable file size is essential for efficient integration of the model to other 3D environment. To address these issues properly, further exploration towards improved approach of texturing and compression technique are recommended.

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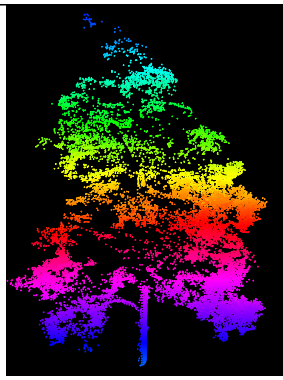
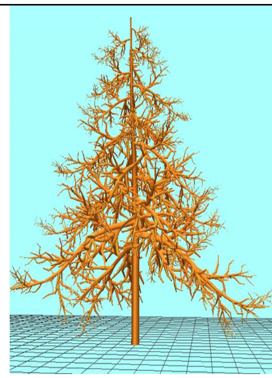
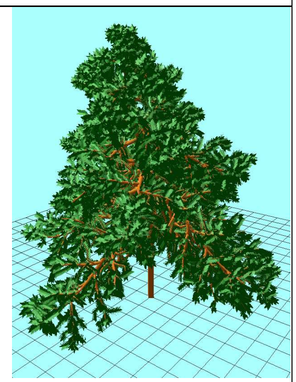
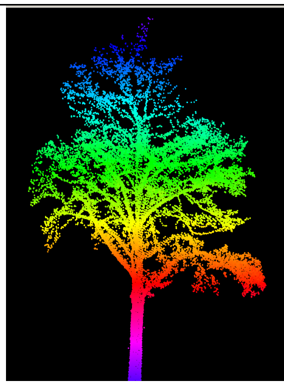
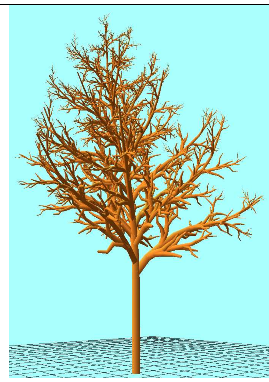
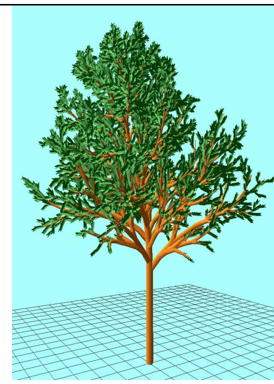
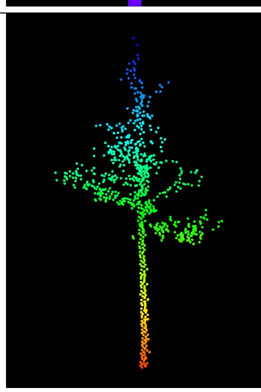
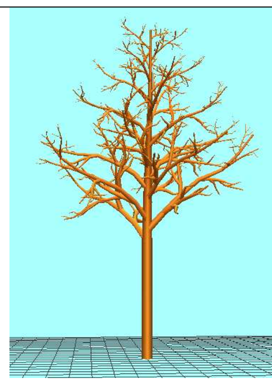
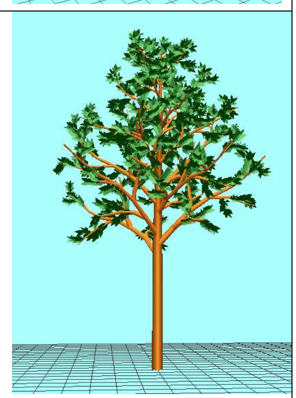
Appendix: Developed models

Id	Input	Model	Texture model
1			
2			
3			
4