Optimising Detection of Road Furniture (Pole-like Objects) in Mobile Laser Scanner Data

DAN LI
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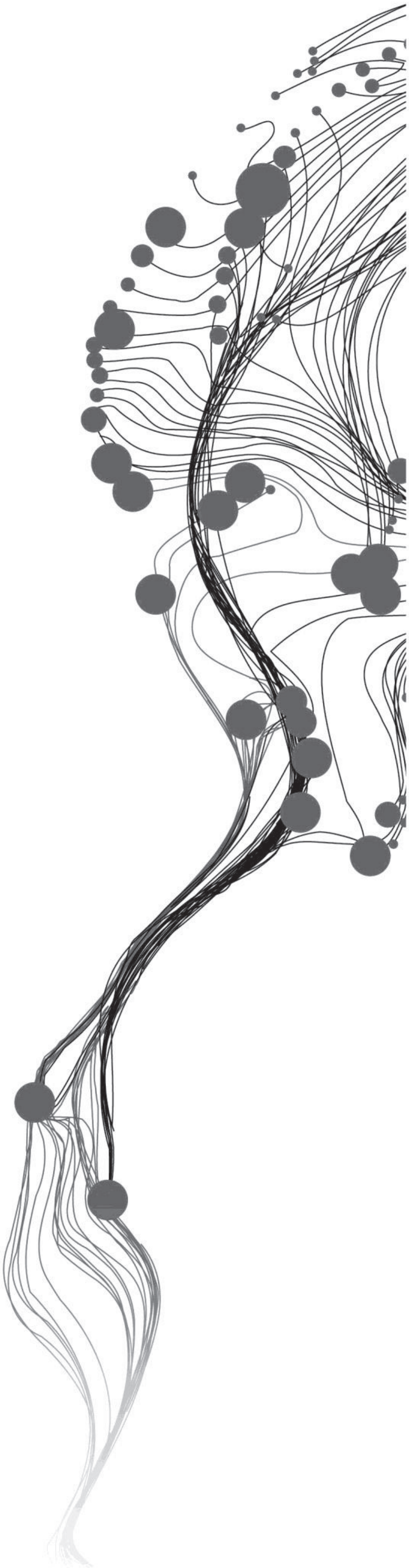
SUPERVISORS:
Dr. Ir. S.J. Oude Elberink
Prof. Dr. Ir. M.G. Vosselman
Supervisor: Prof. Lichun Sui, Chang'an University



Optimising Detection of Road Furniture (Pole-like Objects) in Mobile Laser Scanner Data

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Enschede, The Netherlands, February, 2013

Thesis submitted to the Faculty of Geo-Information Science and Earth Observation of the University of Twente in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation.
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SUPERVISORS:
Dr. Ir. S.J. Oude Elberink
Prof. Dr. Ir. M.G. Vosselman
Supervisor: Prof. Lichun Sui, Chang'an University

THESIS ASSESSMENT BOARD:
Prof. Dr. Ir. A. Stein (Chair)
Dr. R.C. Lindenbergh (External Examiner, Delft University of Technology)

ABSTRACT

Due to the road safety problem is becoming more and more serious recent years, transportation safety problem becomes a research focus in Europe now, in which the road infrastructure safety assessment is crucial to improve the traffic safety. Mobile mapping system is becoming a popular method for collecting high quality 3D information of terrestrial scenes to complete the road safety assessment of existing roads. Meanwhile, since the pole-like objects stand out from the road environment, which include traffic light, traffic sign, lamp post or tree, have large effect on the road safety and are in high demand as facilities to be managed, the automatic pole-like objects extraction is becoming a hot issue.

An automatic pole-like objects detection and classification algorithm in mobile laser scanner data is proposed in this research to develop a robust, quick algorithm and remedy the defects of existing algorithm. This proposed algorithm consists of five phase: rough classification, rule-based tree detection, percentile-based pole detection and knowledge-based classification. After getting the detected result, an automatic evaluation is presented to loop throughout the entire processing to get optimal result. In rough classification phase, segmentation algorithms including the surface growing segmentation and connected component analysis are applied at first to remove the ground surface and group the points in the same object together as a component. Then a rule-based detection algorithm, which uses the component features especially pulse count information, is utilized to detect tree. In the third phase, pole-like objects are determined by using percentile-based algorithm. In the fourth step, knowledge-based algorithm is proposed to further classify the detected pole-like objects into various types of pole. At last, the detected result is evaluated by circularly using automatic evaluation to get optimal result.

Performance of the proposed algorithm is evaluated on selected testing areas, and a detailed analysis is discussed in this research. The overall quality of the pole-like object is over 80% based on point wise. The result shows that more than 90% points of tree are detected correctly and other pole-like objects is 72.4%. Addition to this, an object wise assessment based on the human visual examination is carried out. The achieved result demonstrates that the presented algorithm is feasible in the pole-like objects detection in MLS. Based on the discussion of the result, some recommendations of the current algorithm are given for the further research.

Keyword:
Mobile laser scanner (MLS), 3D point cloud, segmentation, object detection, tree detection, pole-like objects detection, automatic evaluation

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1. INTRODUCTION

1.1. Motivation

Due to the large amount of deaths occurred on the European road during recent years, road safety problem becomes a research focus in Europe now. The road safety is influenced by three main factors such as: vehicle, driver behaviour and road environment or infrastructure(Mc Elhinney et al., 2010). In which, road infrastructure safety assessment is crucial to improve the transportation safety. In order to implement the safety inspection of existing roads, 3D road feature modelling and extraction from laser data or imagery which is rapid and efficient adopted. Since the pole-like objects stand out from the road environment and have large effect on the road safety problem, they play an important role in the road environment. The pole-like objects are common in road environment. These include different kinds of pole, e.g., traffic light, traffic sign, lamp post. Moreover, the tree trunk can be also considered as pole-like objects.

The manual or semi-automatic model reconstruction from terrestrial surveying or photogrammetry was used in traditional modelling method. However the drawback of the methods is quite time-consuming with a lower accuracy, for instance, the incomplete and inconsistent representation due to the difficulty to recover 3D objects from 2D images(Pu, 2008). Mobile mapping systems equipped with the camera and GPS/IMU have been developed since early 1990s and are most important part of growing geographic information system industry (Doubek et al., 2008; Pu et al., 2011). In recent years, process in laser scanning technique led to the integration of laser scanners on mobile mapping platforms to provide mapping capacity(Barber et al., 2008; Kukko et al., 2009). Research by Maas (2001) shows that LIDAR data is a rapid, dense and accurate data resource for automatic objects extraction. Comparing with the photogrammetry, the laser scanning data provide explicit 3D spatial information which could achieve the accurate and detailed geometric features extraction since its high spatial resolution.

The LIDAR data is produced by the laser scanner that combined with different kinds of platforms, such as airborne laser scanning (ALS) or terrestrial laser scanning (TLS). In which, ALS can cost-effectively obtain wide range information and its point cloud is dense enough to roughly detect the roof structure and outlines(Lehtomäki et al., 2010). While owing to the angle and integral street-view objects detection, terrestrial laser scanner can also get high dense point data that is more suitable to detect detailed geometric features of the road infrastructure. Although ALS and TLS have such advantages, there are still some difficulties on road furniture extraction through these two ways. On the one hand, the dense points from ALS are not good enough to recognize the detailed road features because of the view direction or occlusion. Then on the other hand, the range of detection area covered by the static TLS is limited.

To remedy such defects, mobile laser scanning (MLS), for which laser scanner is integrated to ground-based mobile mapping systems, performs better in road furniture extraction(Grejner-Brzezinska et al., 2004). That is not only because the high dense point cloud data and high accuracy, but also the large area detected by the mobile laser scanner, in virtue of the combination of laser scanning technology and mobile mapping platforms.

In terms of the importance of detecting the pole-like objects from the MLS data, several studies on the pole-like objects detection using mobile laser scanner data have been reported. However, still a robust, quick and fully automatic technique to extract pole-like objects in mobile laser scanner data is lacking. Therefore, the influencing factors which reducing the accuracy of detection algorithm have to be analyzed. Additionally, how to improve the accuracy of the detection algorithm comes to be necessary and needs further research.

1.2. Problem statement

Many current algorithms using mobile laser scanner data to detect the pole-like objects have been proposed. However, a robust, quick and fully automatic technique is still lacking. In this MSc research, the main research is based on an existing method proposed in Pu et al. (2011). Due to some types of pole-like objects have similar appearance in laser point cloud and part of tree trunks are occluded by leaves which lead to no pole-like parts are visible in the laser point cloud, it is difficult to distinguish different types of poles accurately and get high detection accuracy with current algorithm.

Furthermore, in this existing algorithm, only the laser point's coordinate information was used. However in fact, for better visualization, most of the traffic signs are painted by special material with high reflectivity, thus the reflectance strength information of laser scanner data would be beneficial for the algorithm improvement. In addition to the laser scanner data, to our expectation, the imagery can provide much richer texture and colour information, which not provided by the laser point clouds, would help to improve the current detection algorithm performance. The problem here is that exact registration between the imagery and laser scanner data have not been solved, thus we will not consider the imagery data in this research.

1.3. Research identification

1.3.1. Research objectives

The overall objective of this research is to optimize detection of road furniture in MLS data, in which focus on the pole-like objects detection in this MSc research. To accomplish that, several sub-objectives should be fulfilled sequentially:

- Analyze the existing algorithm and find the problems occurred in the existing algorithm
- Refine the improvement of the algorithm parameters/steps, which reduce the performance of the detection algorithm, to increase the detection accuracy till fulfilling the satisfied output quality.
- Evaluate the detection algorithm after improvement

1.3.2. Research questions

To achieve the sub-objectives mentioned above, several research questions need to be answered:

- Analyze the existing pole-like objects detection algorithm
  - What are the factors affecting the performance of existing algorithm?
- Improve the existing pole-like objects detection algorithm
  - What is the more suitable classification of the road furniture including further categories?
  - How to optimize the parameter setting, e.g. threshold values, in the extraction algorithm to reduce the influence?
  - How can we detect the tree trunks with dense foliage or branches, as well as the poles occluded by some other objects?
  - How can we distinguish different types of pole-like object from the 3D laser point clouds?
  - Are there any other data resources can be used to improve the detection accuracy?
- Evaluate the detection algorithm after modification
  - What is the completeness of the pole-like detection algorithm after improvement?
  - What is the correctness of the pole-like detection algorithm after improvement?

1.3.3. Anticipated result

This research is expected to get a result like this: The unstructured input laser points can be segmented into components, each component represents one object. After formulating the optimal threshold values or proposing new detection and classification method, pole-like objects detection accuracy would be improved comparing with the existing algorithm and further classification can be carried out to classify the pole-like objects more specifically into different types of pole. The ideal expectation is that all of pole-like objects are supposed can be detected correctly, and no poles are false detected. And then all of the detected pole-like objects can be classified into different classes correctly.

1.4. Thesis structure

To achieve the overall objective and answer all of the questions above, the thesis is divided into 6 chapters. Chapter 2 reviews the theoretic background of the objects extraction as well as objects extraction methods using ALS/ MLS data or imagery proposed in the previous researches. Chapter 3 analyzes the existing pole-like objects algorithm and describes the improved methodology based on the existing algorithm. Chapter 4 describes the implement and result of proposed algorithm. Chapter 5 discusses the improvement and performance of the proposed algorithm in this research. Final conclusion of the research, answers to the research questions and recommendation for further research are presented in chapter 6.

2. LITERATURE REVIEW

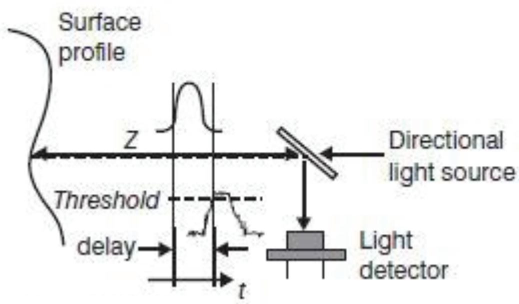
In this chapter, theoretical background required in this research and several previous researches are presented. Section 2.1 starts with describing the principle of laser scanning and mobile laser scanning. The next, pre-processing which is regular the first step on objects extraction in 3D point cloud is proposed in section 2.2. Once again, some previous researches on the pole-like objects extraction are reviewed in section 2.3. Finally, section 2.4 gives a short summary of reviewed researches.

2.1. Principle of laser scanning

2.1.1. Laser scanning

The general principle of laser scanning includes data acquisition, data processing and objects extraction from LIDAR data have been reviewed in various of literatures(Pfeifer & Brises, 2007; Vosselman et al., 2004; Vosselman & Maas, 2010). Different principles can be used to measure the distance between the sensor and target. There are mainly two active methods for optically measuring: light transit time estimation and triangulation. Light transit time estimation is also known as time-of-light or LIDAR (light detection and ranging) system, the distance between sensor and target is calculated through measuring the time difference between the beam sent from the sensor to a reflective target and then return to light detector. At this point, the velocity of light travelling in a given medium is known. Figure 2-1 shows the principle of light transit time measurement. The following formula can be used to calculate the distance Z between sensor and target while c is the velocity of light and t is the time delay between the light is emitted and return to the detector:

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



$$Z = c * \Delta\ t/2$$

Figure 2-1: Principle of light transit time measurement of 3D surface (Vosselman & Maas, 2010)

Higher precision and measurement rates can be obtained using the phase shift measurement. A continuous wave laser is used as the carrier for a signal modulated on it, typically using amplitude modulation. In the phase measurement technique, the phase of the emitted and the received signal are compared. The following formula is used to evaluate the range:

$$r = \Delta\ \varphi\ /(2 * \pi) * \lambda/2 + \lambda/2 * n \tag{2-2}$$

whereλ is the wavelength in meter and n is the unknown number of full wavelengths between the sensor and the target. Shorter distances, e.g. up to 2m, can be measured with even higher precision by triangulation. In a triangulating laser scanner, the laser energy is widened in order to form a plane than a beam. The detail of different principles of laser scanning is reviewed in (Vosselman & Maas, 2010).

2.1.2. Mobile laser scanning

Mobile laser scanning is a kind of ground-based laser scanning which mounted on the mobile platforms such as ground vehicles. A comprehensive review on devices and specification of mobile platform is published by (Shan & Toth, 2009). Similar with airborne laser scanning, the mobile laser scanning consists of differential GPS, Inertial Measurement Unit (IMU), and Distance Measurement Instrument (DMI). The recorded point cloud is geo referenced and the dense is high enough which is beneficial to the 3D modelling of urban environment(Haala et al., 2008). Figure 2-2(a) indicates the field of view of Optech's Lynx Mobile Mapper system which is used in this research, and working diagram illustration of the single laser scanner in Figure 2-2(b) shows the upward facing and down facing laser scanner while Figure 2-2 (c) shows side facing laser scanner (Haala et al., 2008)

(a)

(b) (c)

Figure 2-2: Field of view of the single laser scanners (a) Lynx Mobile Mapper (Optech, 2010) (b) upward facing and down facing laser scanner (c) side facing laser scanner (Haala et al., 2008)

2.2. Pre-processing of point cloud

To identify the objects in laser scanner point cloud, segmentation and filtering are usually the first steps to pre-process the point cloud. In airborne laser scanner data, point cloud captured by ALS involves the data not only ground surface but also the objects on the ground. For the urban application, the first step to pre-process the point cloud is filtering the ground surface from point set. A filtering method named slope based filtering is proposed by (Sithole, 2001; Vosselman, 2000).

Both of the airborne, terrestrial and mobile laser scanners obtain large amount of laser points for the object extraction. In order to avoid extra computational consuming, segmentation is usually applied at start to extract surface in point cloud. Several techniques are used to group nearby points together according to some criterion such as same plane, cylinder or smooth surface (Vosselman & Maas, 2010). (Sithole & Vosselman, 2003; Vosselman et al., 2004) describe a segmentation method called scan line segmentation. Scan line segmentation initially process the scan lines (row of a range image) one by one. Each scan line is split into 3D line segments, and then adjacent scan line segments are merged based on some similarity criterion. Although the split-and-merge method is designed for the image segmentation, it also can be applied in laser point cloud. (Jiang & Bunke, 1994) present selection of seed surfaces for the growing phase form triples of line segments that satisfy three conditions: all line segments should have a minimum length, the segments should overlap with some percentages, and all pairs of neighbouring points in two line segments should be within a specified distance(Hoover et al., 1996). A pole-like objects detection algorithm proposed by Lehtomäki et al. (2010) applies the scan line segmentation at first to pre-process the unstructured point cloud.

3D Hough transform or random sample consensus (RANSAC) can be used to detect a set of points as seed surface; then through calculating norms and residuals, this seed is extended to adjacent points to get larger segments by surface growing or connected component analysis. (Vosselman et al., 2004) review different kinds of segmentation techniques such as surface growing algorithm, scan line segmentation and connected component analysis as well as recognition of specific geometric shapes. (Rabbani et al., 2006) compare several segmentation methods and indicate the limitations of each segmentation method, then a segmentation method using smoothness constraint is presented, which contains two steps: local surface estimation and surface growing. The local surface is estimated by fitting plane to neighbouring points based on k-nearest neighbourhood (KNN) or fixed distance neighbourhood (FDN).

2.3. Pole-like objects extraction

After the segmentation, various methods have been developed on the pole-like objects detection either with laser scanner data or imagery. In this research, trees are also recognized as pole-like objects, thus this section starts with reviewing several tree detection methods, then pole-like objects extraction from imagery and laser scanner data are discussed.

2.3.1. Tree detection

Due to the limitation of existing algorithm by (Pu et al., 2011), some occluded and thick trees trunks in the road environment cannot be detected in MLS data. For improving tree detection accuracy, it is necessary to develop a new tree detection algorithm.

(Haala & Brenner, 1999) propose an integrated classification approach with multi-spectral images and laser point cloud data to extract the trees and buildings, which requires normalised DSM derived from laser data, to get height information of each image pixel. (Rutzinger et al., 2007) detect the high urban vegetation using airborne laser scanner data. At first, the point cloud is segmented and then attributes of segments are obtained to separate vegetation from others. In (Darmawati, 2008), due to the characters of objects surface, the pulse count information is used to separate the trees and buildings. (Rutzinger et al., 2010) present a workflow for detecting and modelling trees from mobile laser point clouds, the workflow consists of three processing steps: tree detection, tree simplification and tree modelling. (Yu et al., 2011) present an approach for predicting individual tree attributes, by using the physical and statistical features such as tree height, the diameter on breast height (DBH) in airborne laser scanner data.

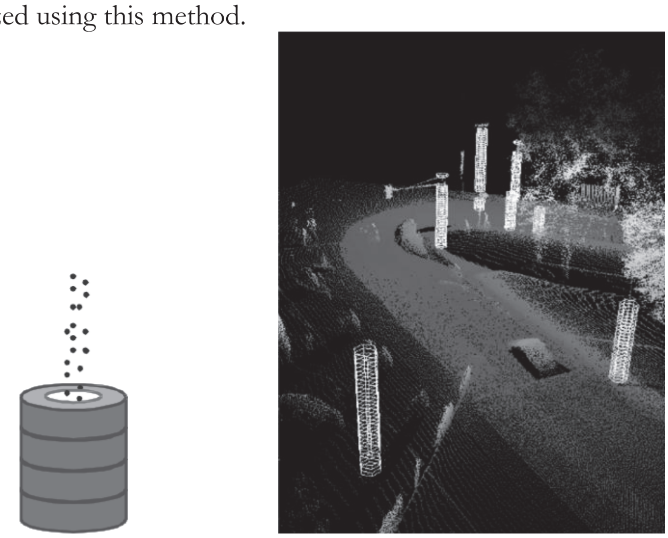
2.3.2. Pole-like objects extraction on imagery

A three steps algorithm is proposed by (Doubek et al., 2008), which detect and localize vertical traffic infrastructures using video sequences recorded by four cameras mounted on a survey vehicle. The three steps method contains: Firstly, an anisotropic Gauss filtration is used to detect 2D vertical poles in each frame of sequence. Secondly, 2D detections are integrated on ground to generate 3D hypotheses of potential positions of the vertical objects. Lastly, the 3D hypotheses are tested. The generation phase was able to detect about 95% of the reasonable visible lamps finally. Problems within this method include the difficulty on detecting vertical poles against non-contrasting background, missing detection of stripe-painted lamps, calibration error between the intersection maps and parameter optimization needs further research.

Another three steps method is proposed by (Arlicot et al., 2009): Firstly, colour properties of signs and a pre-detection are performed to provide several ROIs in image space. Then, detect the circular shape signs within the ROIs using an ellipse detection algorithm, the detected shapes are considered as road signs hypotheses. Finally, comparing the detected circular road signs with reference set after ellipse rectification, the hypotheses are accepted if the maximum of correlation is greater than 60%. As a result, the algorithm detected 67% of total road signs because the problems happened in the radiometric calibration of the camera and test of other colour spaces; however colour detection and recognition steps work well. The limitations of this algorithm are incapable working in real time and on video sequences. And the edge detection is the most time consuming step as well.

2.3.3. Pole-like objects extraction on MLS data

Due to time-consuming and lower accuracy of results, LIDAR data is used frequently to extract objects in recent years. (Brenner, 2009) presented an intuitive approach for the extraction of points with a certain structure in the neighbourhood. If eigenvalues analysis yields one large and two small eigenvalues, it indicates a linear structure. But it would cause false detection when people standing close to the poles although it can extract poles with additional structures mounted on, such as traffic lights and signs. Therefore, a model-based approach was investigated. A pole is assumed when a certain minimum number of stacked cylinders are present, and an additional ray density analysis is performed. After the stack has been identified, the points in the kernel are used for an estimation of the exact position of the pole. Figure 2-3 illustrates the analysis in terms of cylindrical stacks: (a) shows measured laser points in the kernel region (white) and no points in the outside region (gray). (b) indicates identified stacks (white) in the scene (Brenner, 2009). This method is only applied to the poles without additional structures, the traffic signs or trees cannot be recognized using this method.



(a) (b)

Figure 2-3: Analysis in terms of cylindrical stacks, (a) measured laser points in the kernel region (b) identified stacks (white) (Brenner, 2009)

(Golovinskiy et al., 2009) propose a four steps method to recognizing objects in 3D point clouds of urban environments: locating, segmentation, characterizing and classify clusters of 3D points (Figure 2-4). The paper presents several alternative methods for each step. In the locating step, first approach is to generate an image using the maximum height of points in each pixel, run a Gaussian filters to extract the components under a threshold to find small objects; the second one is to find the local maximal of point density through adapting a Mean Shift (Fukunaga & Hostetler, 1975); the third one is to find the location in the centre of connected component; the fourth method creates clustering of points using nearest neighbours graph and then place object locations in cluster centre. Three segmentation methods are reviewed in the segmentation step to group the points from background. In the feature extraction phase, both shape and contextual features are investigated. In the last classification phase, K-Nearest Neighbours (KNN), random forest, support vector machines (SVM), 5^{th} order polynomial kernels are compared. Quantitatively evaluation of the methods' performance showed that 65% of objects in the test area were recognized.

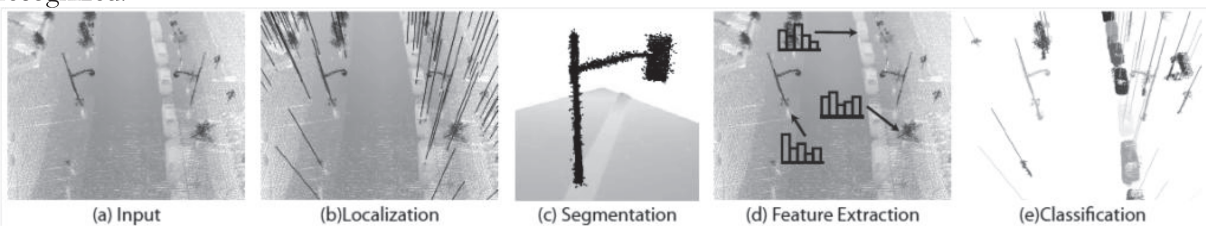


Figure 2-4: Working steps in (Golovinskiy et al., 2009)

Lehtomäki et al. (2010) propose a vertical pole-like objects detection algorithm by using of the profile information of the scanner. It is supposed that at least three sweeps would be gained from a pole. In the first phase, possible sweeps are extracted from the data by segmenting each profile separately into point groups that consist of points are close to each other. After this step, long groups are removed leaving short point segments that are possible sweeps of poles. In the second phase, groups are clustered into a set of candidate pole clusters. In the third phase, the clusters which belong to same poles have to be merged. In the last phase, candidate clusters are classified as poles or non-poles. Figure 2-5 indicates the procedure of clustering the point groups. From left to right, black group shows the added group in the cluster. The already added grouped is compared to the groups in the previous or next profile. If the previous/next group can fulfil constrain, it is added to the cluster.

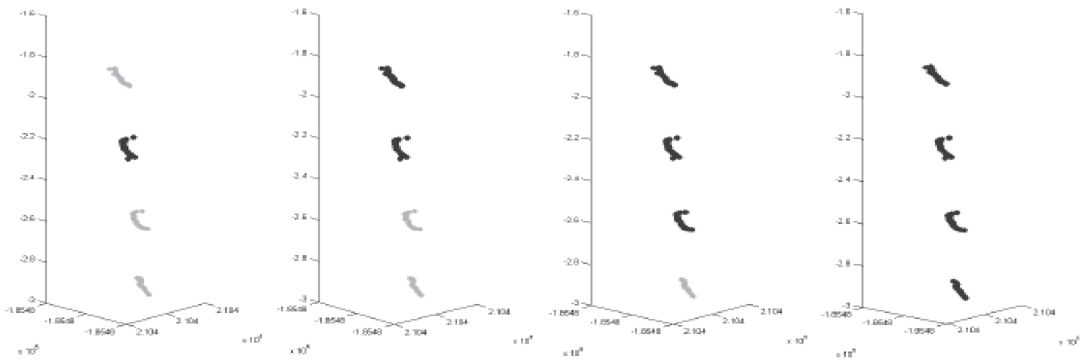


Figure 2-5: Clustering the point groups (Lehtomäki et al., 2010).

Out of 148 data reference poles, the developed algorithm in this literature detected 115 poles and 33 poles were missed. Totally 142 targets were detected thus there were 27 false positives. Poles inside vegetation, tree trunks inside branches and behind parked cars, poles that had some scattered points around them and too oblique poles were the most difficult ones to find with the developed algorithm. The poles had substantially many points around them were not classified as poles by the current algorithm and needed some further research. Cameras which mounted on the Roamer system could be used in the detection of the traffic signs which had the poorest visibility in the laser data. In addition, use of the combined data sets from different scanners in the same area may improve the detection rate of the method.

An algorithm that automatically recognizes pole-like objects with tilt angles and various radii from MLS point clouds is proposed by Yokoyama et al. (2011). In this method, ground points are assumed already removed from given point clouds. The algorithm consists of four phases: Firstly, the input point cloud is segmented using the k-nearest neighbours graph, as the result the points estimated on each object are grouped. Secondly, endpoint preserving Laplacian smoothing is applied to each segment. Thirdly, each point is classified into the points on the pole-like objects, on the planar objects, or on other objects by performing Principal Component Analysis (PCA). Finally, the degree of the pole-like objects of each segment is evaluated, and the segments of the pole-like objects are extracted by threshold values, for which segment is more than 2m and the number of points in segment is over 50. As a result, the average accuracy of the pole-like object recognition was 63.9% for all segments and 97.4% for correctly created segments. This recognition algorithm is designed for correctly segmented point clouds. Therefore recognition will be failed for the incorrect segments. And the algorithm cannot classify pole-like objects into more detailed object classes such as street lights and street signs.

In the paper of El-Halawany and Lichti (2011), a pipeline for point cloud process to detect road poles and find their dimensions from unorganized point clouds captured from a kinematic terrestrial laser scanner is proposed. This method is consists of two phases. In the first phase, eigen-based segmentation technique is applied. In the second phase, linear features like poles are extracted by either intensity-based filtering or utilizing the relation between the radius of the pole and its eigenvalues. The cylinder fitting based on intensity filtering technique can be used with lower radius poles, such as sign poles and flagpoles, while the eigen-radius relation can be used with higher radius poles, such as street light poles. The problem of this algorithm are classifying poles to different classes needs other information and for pole-like objects extraction more than one method are needed.

(Vakautawale, 2010) proposes a pole-like objects detection algorithm based on 2D enclosing circle algorithm, the proposed method consists of four phases: segmentation, multiple filtering criteria, 2D enclosing circle algorithm and supervised classification. At first, segmentation is utilized to remove the planar ground surface and connect points within the same object together. Secondly, apply the multiple filtering criteria to remove the unwanted components such as building or car. The segments which has Euclidean distance over 15 meters are removed at first, and then a section between 1.70 to 2.00 meters on each component is selected to check its 2D Euclidean distance, the components which has the distance over 0.4 meters are also removed. The third step is applying 2D enclosing circle to get the information of the difference between adjacent circle radius, displacement of circles and average circle radius of each partition in the object. At last, a rule-based classification is derived based on several attributes of top three circles. Three pole classes of street light, traffic light and others are classified using the rule-based classification. As a result, the overall accuracy of such three types of pole was 79.2%, 77.8% and 72.2% respectively. The defects of this algorithm are that, firstly the pole attached with additional structure would be removed after multiple filtering criteria and then few pole classes can be classified by this algorithm.

The existing algorithm will be analyzed and improved in this research is proposed by (Pu, 2008). Three phases are included in the algorithm: rough classification, percentile-based detection and further classification. In the first step, segmentation and filtering criteria are applied to remove the unwanted segments (e.g., building, car, bus platform). Secondly, percentile-based algorithm checks feature values based on one section from the component to determine whether the component is pole-like object. At last, knowledge-based shape recognition further classifies the already detected pole-like objects. Quantitatively evaluation of the proposed algorithm indicated that 20% of bare poles, 63.5% of trees, 60.8% of traffic sign and 81.8% of other poles were detected. Since the low detection accuracy of the pole-like object, this existing algorithm will be further studied and improved in this research. This existing algorithm will be described and analyzed in detail in chapter 3.

The limitations of each method mentioned above are listed in Table 2-1:

Table 2-1: Limitations of reviewed pole-like objects detection algorithms

Method	Limitation
(Brenner, 2009)	Only works on the poles without additional structures attached on it
(Golovinskiy et al., 2009)	Cannot work well on detection of different object types
(Lehtomäki et al., 2010)	Require clear scan lines in point cloud
(Yokoyama et al., 2011)	Require correctly segmented points, failed in incorrect segmented point cloud, cannot classify detailed types of pole-like objects
(El-Halawany & Lichti, 2011)	More than one method are needed, require further information to further classify pole-like objects
(Vakautawale, 2010)	Poles with additional structures attached on it and thick poles are very likely removed, and only few classes are classified
(Pu et al., 2011)	Cannot work well on thick pole-like objects like tree, accuracy of further classification is low

2.4. Summary

Based on the review of current researches, we could notice that although the pole-like objects detection algorithm has been studied in many researches, there is still a lack of robust, quick and fully automatic algorithm. Therefore, it is necessary to propose an automatic and robust detection algorithm to improve the existing algorithm. In the next chapter, the existing algorithm in (Pu et al., 2011) will be analyzed in detail and corresponding improvement measures will be described then.

3. ANALYSIS AND METHODOLOGY

This chapter describes the workflow and approach utilized to achieve the objective of this research. As mentioned in section 1.2, there are several shortcomings in the existing algorithm, lead to low detection rate and large amount of false detection. The methodology of this research is described at first in section 3.1. Then in order to clarify the problems, the overall performance of existing algorithm is described in section 3.2 to show the defects. After that, detailed analysis and the corresponding proposed improvement are described in the following sections.

3.1. Framework of methodology

Three phases are included in the existing algorithm. At first, segmentation and filtering criteria are used to remove the ground surface and large building facades, and then connect the points within the same component together; filtering criteria is utilized to remove the unwanted component and keep the on-road segments as the input of next phase. The second phase focuses on pole-like objects detection from the kept on-road segments. A percentile-based algorithm selects one section from each component and divides the section into multiple slices. Several attribute values are calculated based on the multiple slices to determine the pole-like objects. At last, knowledge-based shape recognition is presented to further classify the detected pole-like objects. To assess the algorithm, a visual inspection is used to quantitatively evaluate the algorithm performance.

Based on the existing algorithm, the methodology used in this research is proposed with respect to five phases: rough classification, rule-based tree detection, percentile-based pole extraction, and knowledge-based further classification; at last, quantitative assessment works cyclically to show the performance of proposed algorithm, which includes two parts: an automatic quality assessment based on point wise and a visual examination based on object wise. If the classified result is not accurate enough, the optimization would start again from the beginning and then continue to loop until getting the optimal result. The overall workflow to optimize the existing algorithm is depicted in Figure 3-1. The optimization process consists of two parts: optimize threshold values of the existing algorithm through statistical analysis or modifying certain steps (which labelled with blue colour in Figure 3-1), develop new rule-based tree detection algorithm and knowledge-based algorithm, propose an automatic point wise evaluation (which labelled with green colour in Figure 3-1), in which input and output data are labelled with red colour in Figure 3-1.

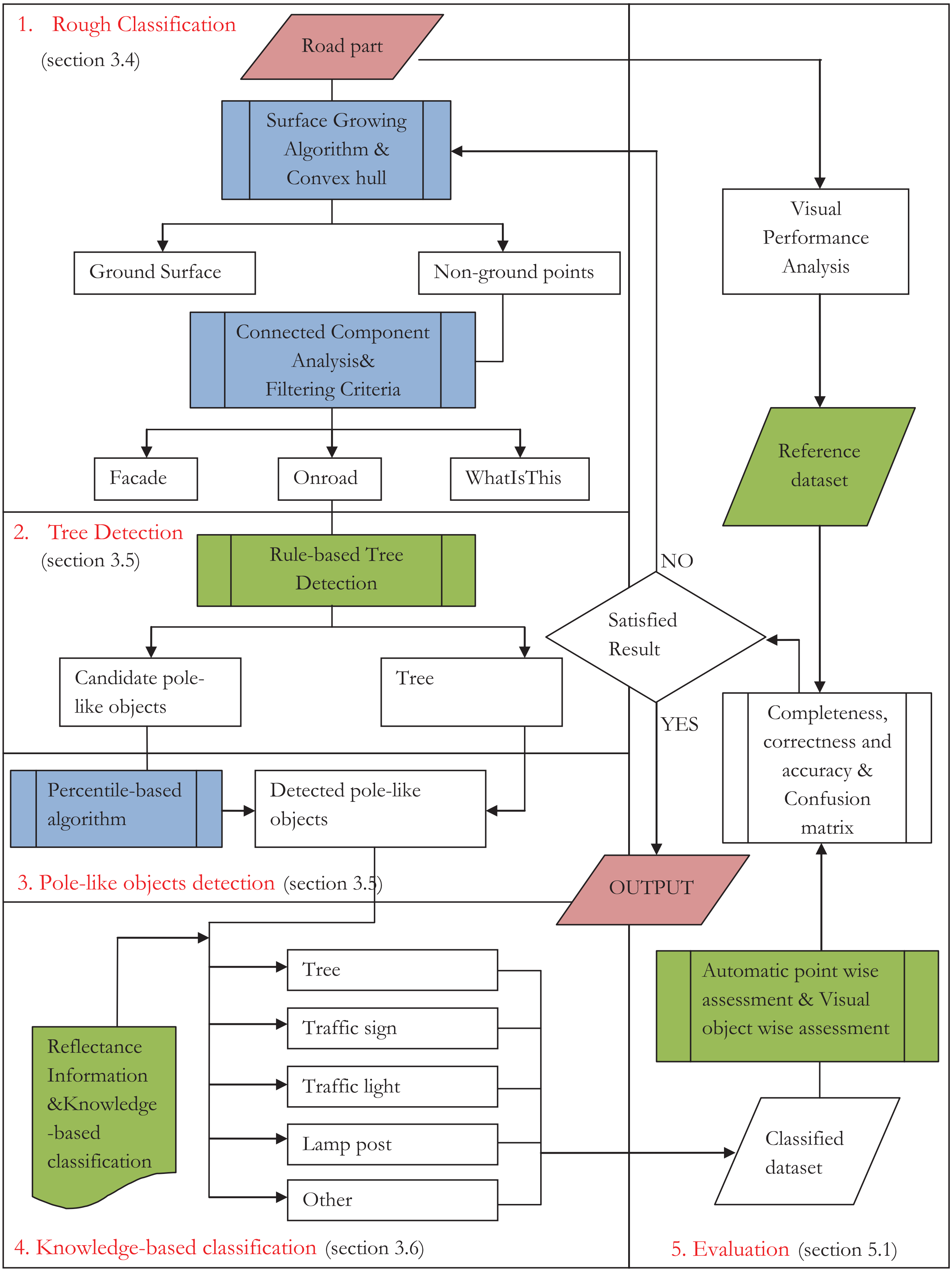


Figure 3-1: Workflow of proposed methodology in this research

3.2. Performance of exsiting algorithm

This section gives a brief description of the problem in the existing algorithm. To assess the performance of algorithm by (Pu et al., 2011), classified points were back overlying with the original unstructured laser point cloud. Figure 3-2(a) shows an example of the assessment. From this figure, it is noticed that some objects are missing detected and false detected. Two traffic signs are classified as others (number 1) and one flagpole is classified as tree (number 2) in the left figure, and one traffic sign was missing while it actually exists in reality (number 3) in the right figure. The evaluation result of the existing algorithm is shown in Table 3-1 using confusion matrix. From Table 3-1, we notice that the problem of the existing algorithm is mainly on two aspects: missing pole-like objects detection and false positive detection. This has resulted in the low detection rate and relative high false positive. 22 poles were missing detected in total 162 pole-like objects by the existing algorithm, and detection rate of different pole types except the others were lower than 80%. In the following sections, the existing algorithm will be analyzed in detail sequentially. After analyzing each step, the defects and corresponding improvement will be proposed successively.

(a) (b)

Figure 3-2: Back projecting classified points to original laser point cloud, (a) point cloud (Pu et al., 2011), (b) image from Google map

Table 3-1: Confusion matrix of the pole-like objects recognition (Pu et al., 2011)

Enschede total		Visual inspection					False positives (%)
		Poles	Trees	Road signs	Others	Total detected	
Algorithm	Poles	5	1	1	1	8	37.5
	Trees	1	33	4	1	39	15.4
	Road signs	0	2	45	0	47	4.3
	Other poles	16	2	19	9	46	**80.4**
	Missed	3	14	5	0	**22**	
	Total visual	25	52	74	11	162	
	Detection rate (%)	**20**	**63.5**	**60.8**	81.8		

3.3. Rough classification

Due to the huge amount of data to process, at first, partition the whole dataset into multiple parts, and then extract the information of interest locally. The partition of the raw dataset is accurate enough because of the overlap between two adjacent road parts.

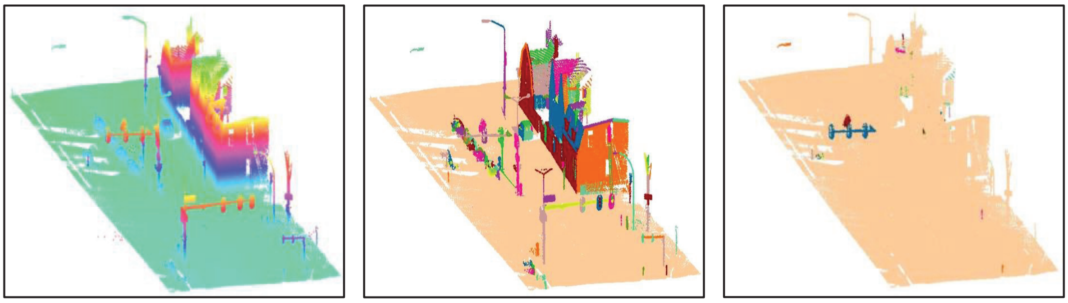
The purpose of rough classification is to remove the points that are not the ones of interest, in order to make the remaining points significantly less than the original data and reduce the unnecessary computational consuming. Segmentation is often the first step with regard to extract objects in laser point cloud, and group points together according to some criterion such as same plane, cylinder or smooth surface (Vosselman & Maas, 2010). After surface growing segmentation, ground surface is removed and deriving the convex hull, then nearby points are connected into component through connected component analysis. Geometric and spectral attributes of component can be utilized in the next stage to detect the poles and further classification.

3.3.1. Surface growing segmentation

Surface growing in point cloud can be regarded as the three dimensions extension of the well-known region growing algorithm in images. Surface growing segmentation is utilized to group nearby points based on the homogeneity criterion such as planar or smooth surface (Vosselman et al., 2004). Seed detection and surface growing are two steps in surface growing segmentation. At first, a set of nearby points are grouped to form a planar surface as the seed surface. Selection of seed surface is analyzed by fitting planar surface to the group of points which use least square or the 3D Hough transformation method and check the residual values for each of them, the ones which have residual less than setting threshold are considered as seed surface. Then, in the growing phase, the points which are within a certain distance from the selected seed surface are added to the surface. The parameters of the plane can be re-estimated to improve the accuracy once a new point added to the plane. However, when there are large amount of points within the plane, it is more efficient to re-estimate the parameters after certain percentage (20-50%) of points added to the surface. The points are added to segment until defined growing criteria is exceeded. In addition to check the distance to the plane, it is useful to compare the local surface normal vector around the neighbouring point with the normal vector of the growing plane.

Another segmentation algorithm is smooth surface segmentation that defines a smooth surface by grouping a seed point and its neighbouring points within specific distance. The main set back of smooth surface segmentation is the difficulty in separating the sharp edge between two objects, such as building facade and the road surface. The performances of two segmentation methods are shown in Figure 3-3. Due to the connection between road surface and on-road objects, surface growing segmentation is more reliable than smooth surface segmentation in this research.

Because the ground and facade surface are easily detected in the laser data, parameters on the surface growing algorithm are not so critical and mild under-segmentation or over-segmentation can be tolerated for on-road objects detection. The parameter threshold values of surface growing segmentation in existing algorithm are not the key point to optimize the algorithm.



(b) (c)

Figure 3-3: The segmentation performance. Segments coloured by (a) height (b) surface growing segmentation (c) smooth surface segmentation

3.3.2. Convex hull

After surface growing segmentation, the laser points are grouped into different segments with variable geometric attribute, such as area, the slope of plane, the range on the Z axis, number of points. Planar segments are usually the basic elements, which compose more complex human made objects. Therefore the derived planar segments are well suited to serve as the basic elements for the recognition of ground surface and facades in the next step. For these reasons, the ground and building facades can be removed using the geometric attribute when it can fulfil constrains like:

(a) The ground surface segments are probably the large planar surface below the 3D trajectory of the laser scanner.
(b) The segments on building facades are assumed as the large vertical planar surface which connected to the ground surface

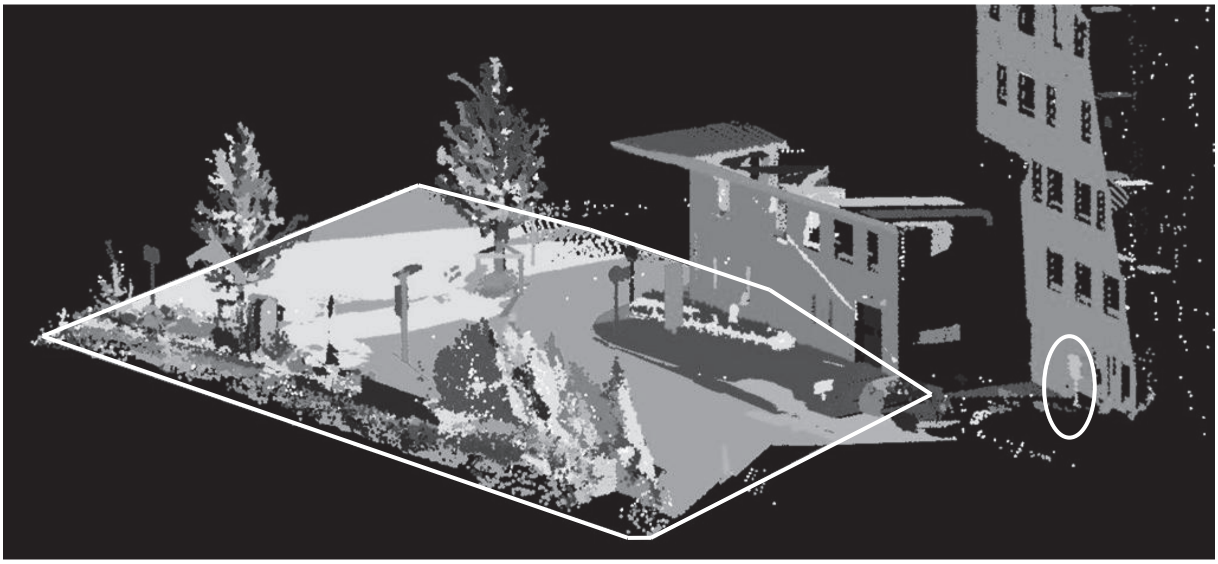


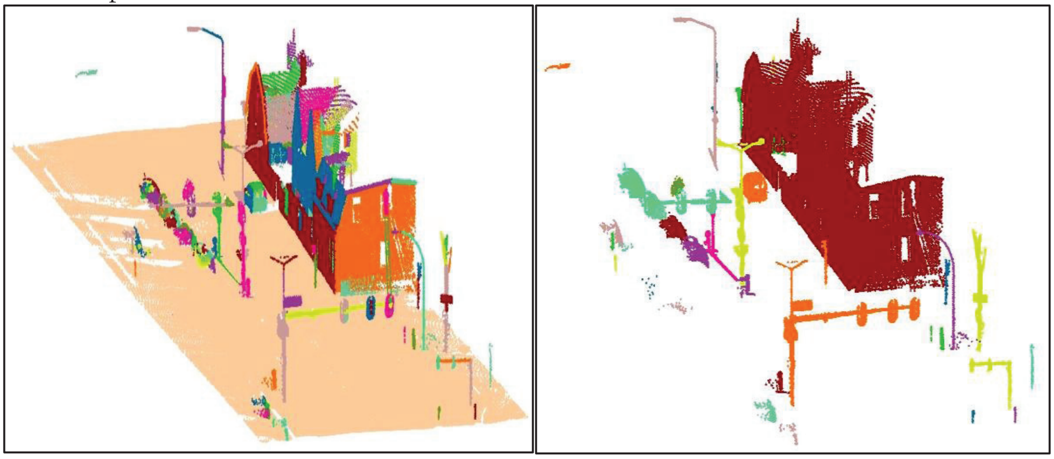
Figure 3-4: Problem of convex hull

- Defect of existing algorithm: After detecting the ground surface, planar segments are combined together as the ground surface. Then a 2D outline is generated according to the ground segments, while on-ground segments are recognized as the ones completely within the 2D outline and connect to the ground surface. The rest segments, including the ones which disconnect to the ground and are not entirely within the outline, are removed. Only the on-ground segments are considered in the next step. There are some problems occurred in the existing algorithm. Firstly, some segments, which are not completely within the 2D outline but actually candidate pole-like objects, are removed incorrectly. For example, Figure 3-4 illustrates such problem: the white polygon indicates the 2D convex hull and white circle shows one incorrect removed on-road object. In additional to this, removing the off-ground points cause some potential pole-like segments have been deleted, also reduces the detection accuracy.

- Improvement: To improve the existing algorithm, on-road segments should be redefined. For ensuring all of the points of interest are included into the on-road segments, not only the segments which are completely within the convex hull, but also the ones not within the convex hull should be recognized as on-road segments. Furthermore, through field observation and statistical analysis on the laser points, objects near but do not connect to the ground should be considered to better define the on-road segments.

3.3.3. Connected component analysis

Connected component segmentation also starts with a seed surface mentioned in section 2.3.1. However, connected component analyzes the points assumed in object space and merges similar considering components feature, and then object space is performed (Figure 3-5(b)). When segmenting point clouds (in PCM), two parameters need to set, the maximum distance between points and the minimum number of points in component.



(a) (b)

Figure 3-5: Comparison of segmentation algorithms, (a) segments by surface growing algorithm (b) segments by connected component analysis

- Defect of existing algorithm: In the existing algorithm, several trees and lamp posts, some traffic signs were connected together because of the high threshold value setting. An example is shown in Figure 3-6. For this reason, the detection rate of trees and lamp posts reduced.

- Improvement: To improve the algorithm, the selection of segmentation threshold valuesshould be careful. If the threshold value of the distance between two points is large, two different segments would be merged together, called under-segmentation. Conversely, if the threshold value is too small, points within one segment would be separated into different segments, the situation is so-called over-segmentation. Therefore, various trials are carried out to get the optimal threshold values and a trade-off between the under-segmentation and over-segmentation is proposed.

Figure 3-6: Defect of threshold value

3.3.4. Filtering criteria

After the segmentation, the point clouds are grouped into different components. Before detecting the pole-like objects, it is necessary to remove the points that are not the ones of interest, i.e., cars, small building structures, bus shelters, to reduce extra computational consuming. Thus, filtering criteria is applied next.

To filter the points from the laser point cloud, a section of each segment is automatically selected from component to check the diameter value (Figure 3-7). One segment can be labelled if the diameter is less than a given threshold value. At last, an assumption is proposed to label the entire component: if part of the component labelled, the whole component can be recognized as a candidate pole-like object.

- Defect of existing algorithm: The main shortcoming in (Pu et al., 2011) is that threshold value of the diameter constrain is too small to filter lot of trees and other candidate pole-like objects, which lead to the low detection rate of poles, especially trees. For instance, one road part in Figure 3-8 shows that after using existing filtering criteria, all of trees are removed.

- Improvement: To improve the tree detection, it is necessary to adjust the given threshold value to keep the trees as much as possible. Number of trees will be kept if the given filtering threshold increases. Statistical analysis is carried out to determine the optimal threshold value.

Owing to occluded and thick tree trunk in road environment, tree detection is difficult by using existing algorithm. A new tree detection method should be taken into consideration, which will be introduced in section 3.4.

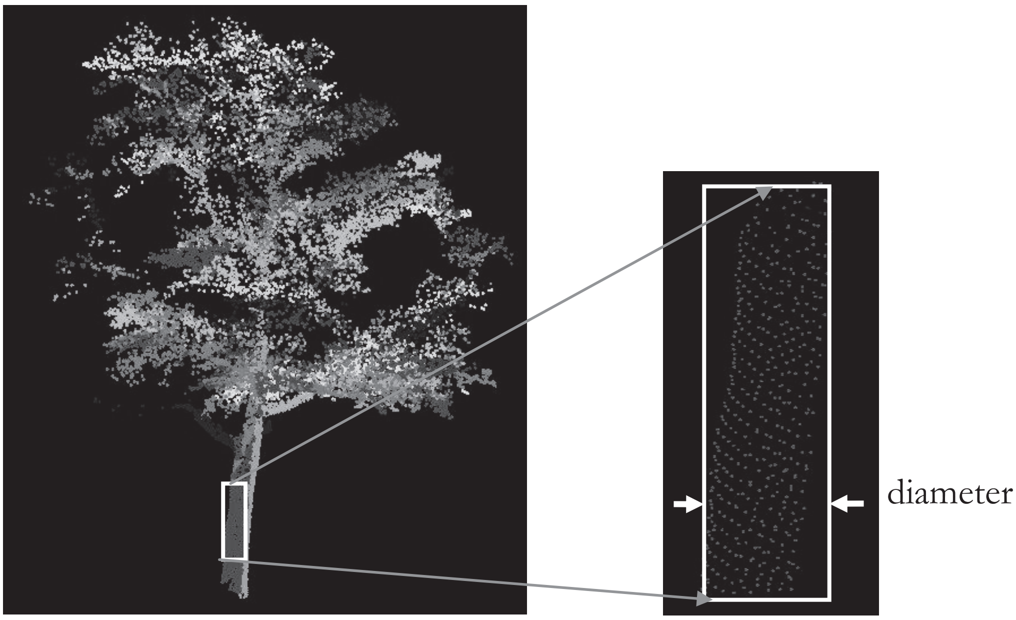
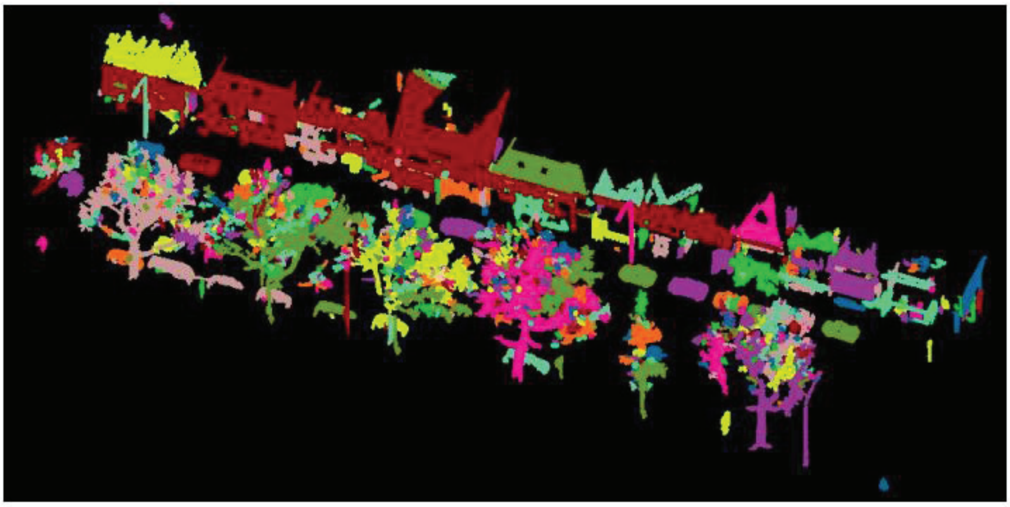
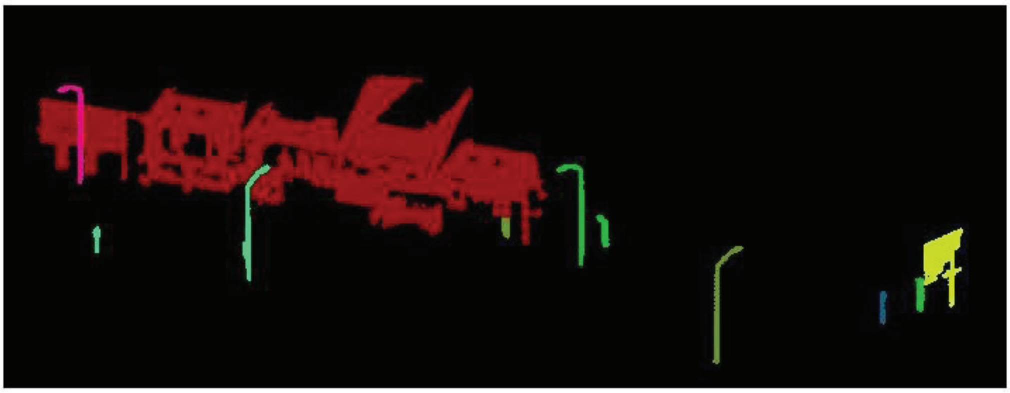


Figure 3-7: Each section is selected to check whether the segment can be labelled



(a)



(b)

Figure 3-8: Existing filtering result, (a) before filtering (b) after filtering

3.4. Rule-based tree detection

In reality, there are trees have not tree trunk visible in laser point cloud but which are considered as the potential objects of interest (Figure 3-9). Since no tree trunk and thick tree trunk are visible in the point cloud, there are large amounts of missing detected trees in the existing algorithm (Table 3-1). For the limitation of existing percentile-based algorithm, it is difficult to detect all kinds of trees, there should be another tree detection method proposed to increase the tree detection accuracy.

Therefore, a rule-based tree detection method is developed in this section to detect the tree which has no tree trunk or has relatively thick tree trunk in the point cloud, and then separate the tree from other on-road objects. Similar with the rule-based collapsed building detection in (Oude Elberink et al., 2011), two kinds of attributes are taken into consideration to build the rules.

Figure 3-9: Two undetected trees where trunks are occluded (Pu et al., 2011)

In rule-based classification method, each of the selected training areas contains tree, building, lamp post, traffic light and traffic sign. For each component in point cloud, a list of geometric and radiometric attribute are calculated. The attributes are proposed to detect tree and then separate component of trees from other on-road objects such as lamp posts or buildings.

3.4.1. Geometrical attribute

In the city environment, in terms of the human knowledge, the characteristics of natural objects are different from the manmade objects such as building or cars, a number of geometric attributes are commonly utilized to extract the vegetation:

- **Height**:

Height is a measure of the object in Z axis from the bottom to top. The tree near roadside should be higher than a given threshold value. The maximum and minimum Z value of each component data bound gives us a measure of the component height:

$$\text{Height} = \text{Maximum Z value} - \text{Minimum Z value} \tag{3-1}$$

- **Area**:

Area is a measure of area for the Minimum Bounding Rectangle (MBR) derives from the component after projecting onto 2D plane. The area of MBR is a sharp indicator can be used because the projections of traffic pole furniture usually shows long and narrow linear projection while trees have large 2D projection owing to tree crown. After getting the length and width of the MBR, the area is calculated as:

$$\text{Area} = \text{width} * \text{length} \tag{3-2}$$

However, in the actual situation, some fences are connected to the bottom of trees, which will deform the shape of projection. To avoid the effect of fence, section above 2m from bottom of the component is selected. Then the selected sections are projected onto ground and generate the MBR. As the result, length and width of MBR are calculated to check the area of the projection, it can fulfil area constrain if the area is greater than a given threshold value.

- **Ratio**:

As the reason mentioned above, the road traffic furniture shows long and narrow linear projection most times while trees have no regular shape but usually the length and width of MBR are relatively close (Figure 3-10 (b)). Thus the ratio is an important index to extract the tree, which is calculated as:

$$\text{Ratio} = \frac{\text{width}}{\text{length}} \tag{3-3}$$

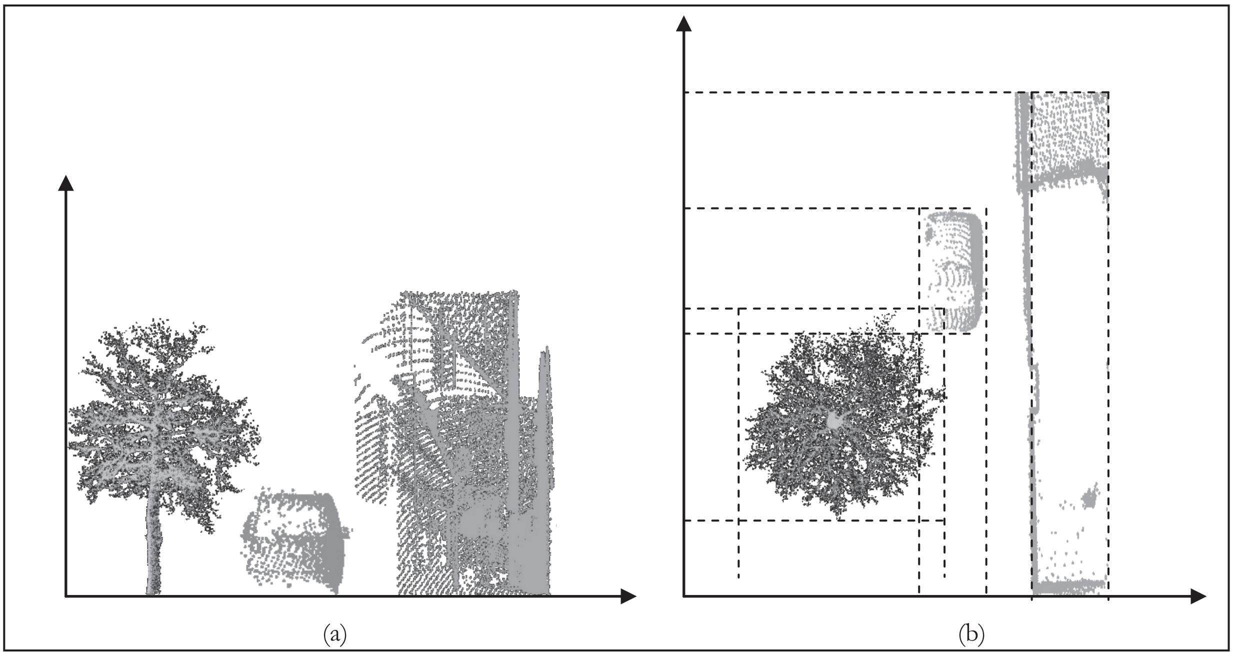


Figure 3-10: Geometric attribute, (a) component height from horizontally view (b) area, ratio of component MBR

3.4.2. Pulse count information

In addition to the geometric attribute, radiometric information of laser point, especially the pulse count information is also an important factor to detect the tree. In the road environment, vegetation has rough surface, which causes multiple pulse count. However in most buildings, last and first pulse data are similar depending on the material of façade. During measurement of trees, certain percentage of a laser footprint would be reflected by the branches and leaves of trees, other parts will penetrate the foliage and finally be reflected by building at roadside in Mobile Laser Scanner. Therefore, the number of multiple pulse count points in tree should be higher than man-made objects. Figure 3-11 shows the pulse count information of laser points in vegetation and man-made objects.

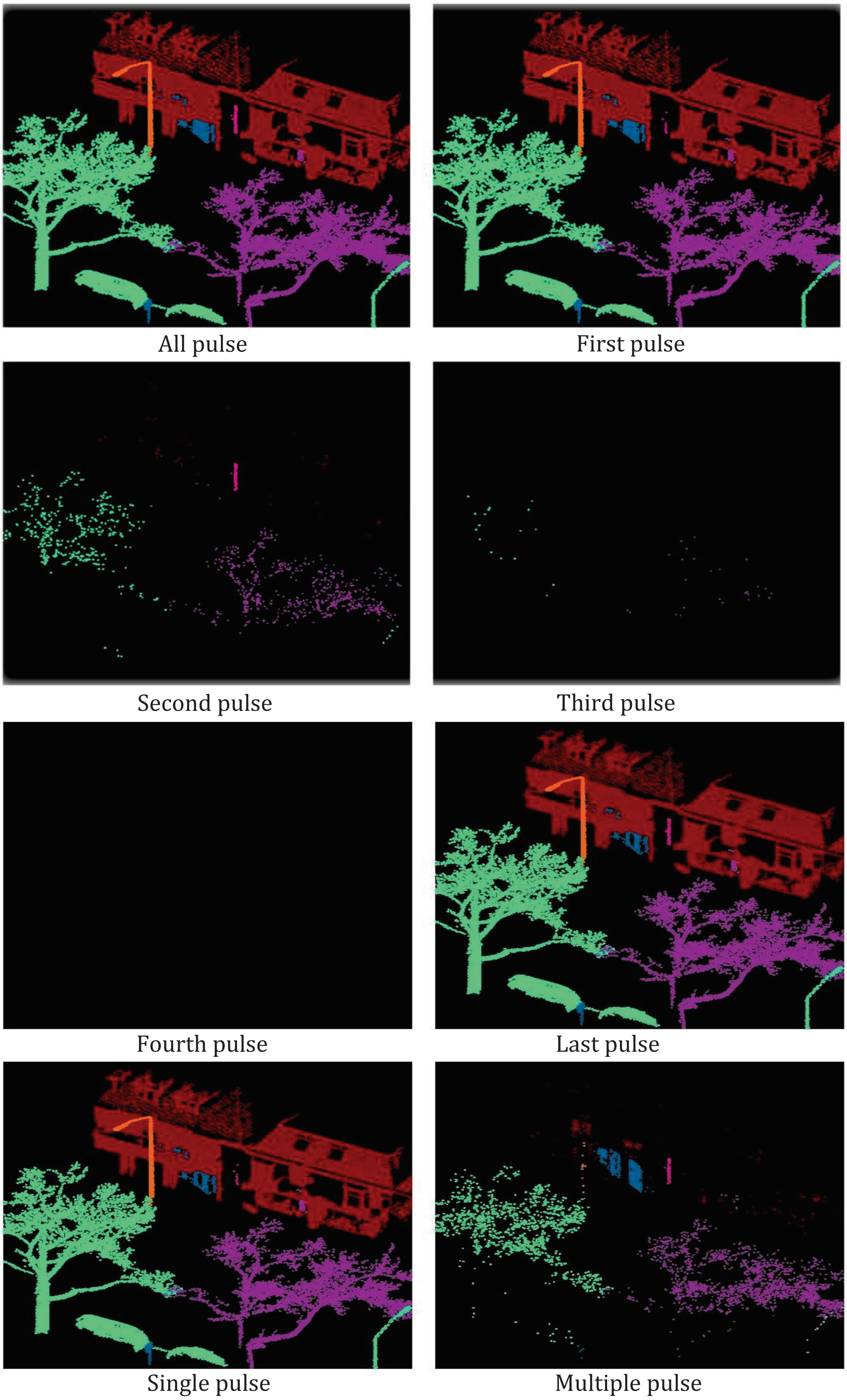


Figure 3-11: Pulse count information visualization

For this reason, multiple pulse count information can be used to separate tree and other man-made objects. The percentage of multiple pulse count in each component is calculated by counting the total number of points with multiple echoes. One component is probably a tree if the percentage of multiple pulse count exceeds given threshold value. The value is obtained through the equation shown below:

$$\text{Percentage} = \frac{\text{the number of points with multiple pulse in component}}{\text{total number of points in component}} \tag{3-4}$$

3.4.3. Decision tree on detection rule

After statistically analyzing each type of objects in training areas, the information about the above geometric attributes and pulse count information can be derived as input parameters of the developing decision tree for the rule-based detection. The automatic tree detection is based on a count system where a counter is defined for each component to count the number of time to meet the above conditions; at the end, sum up the count per component. Whether the component can be recognized as tree depends on the final count value. The component with the count value 3 or 4 can be considered to meet constrain as a tree and derive the outcome of classified tree. As a result, a set of automatically detection rules from the decision tree are produced, and then these rules are used in the testing areas to detect the trees. Determine on the parameters of decision tree will be discussed in section 4.3.

- Defect of existing algorithm: There are some occluded and thick tree trunks in the point cloud, due to the harsh filtering threshold values formulated in the existing algorithm, many trees have been removed, which resulting low tree detection rate.

- Improvement: Since the proposed rule-based tree detection algorithm is adopted, reflectance strength information of point cloud is taken into consideration. Based on such significant feature combining with geometric information of the component, tree can be recognized well through current proposed algorithm.

3.5. Percentile-based algorithm

In this research, the percentile-based pole detection algorithm is used to determine the pole-like objects. Using percentile-based algorithm performs better than regular method to extract the pole-like objects, because it analyzes section of pole instead of whole candidate pole to avoid the missing detection of the tilted poles or the poles have dense vegetation around the bottom.

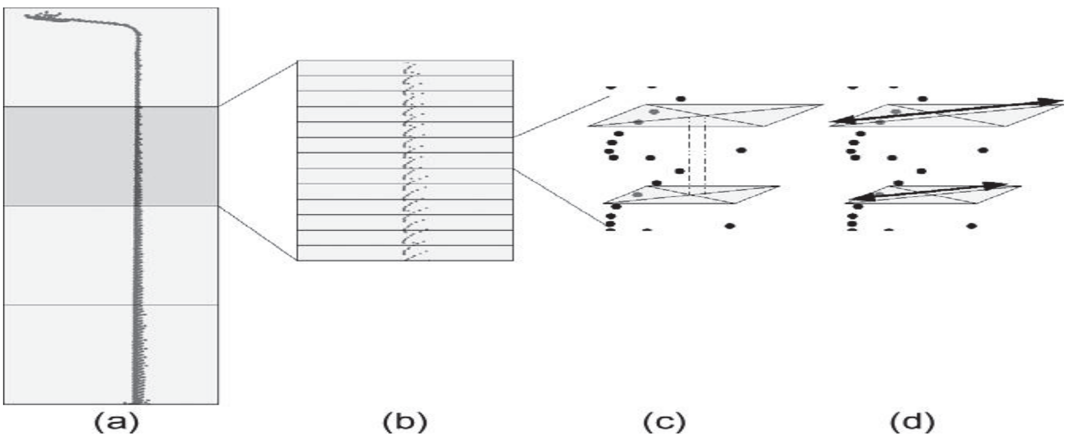


Figure 3-12: Principle of percentile-based pole detection algorithm.

The principle of percentile-based pole detection algorithm is shown in Figure 3-12: (a) Divide the whole candidate component into several sections and select one section as test part. (b) Slice section into multiple horizontal slices (c) Check the deviation of centre position between neighbouring two slices (d) Check the length of diagonal and difference between two adjacent slices diagonals. A counter is defined to count once if these four values are within given threshold simultaneously. At last, if the count is greater than a given threshold value, this selected section can be recognized as pole. As a result, such whole component is labelled as vertical pole-like object. The schematic diagram of calculation on centre position deviation and diagonal different is shown in Figure 3-13.

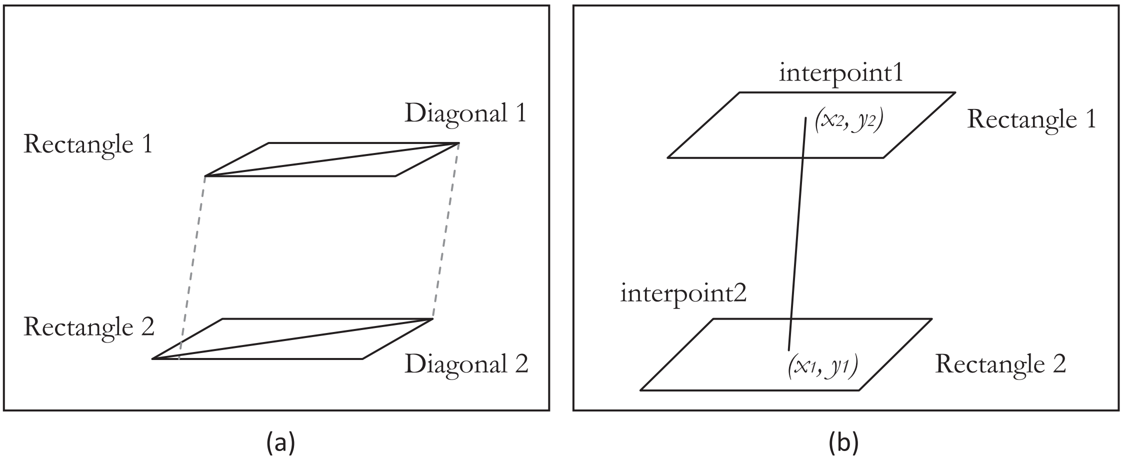


Figure 3-13: Indexes used to detect the poles, (a) diagonal difference calculation (b) displacement calculation

- Defect of existing algorithm: Five parameters utilized in the pole detection algorithm are tabulated in Table 3-2. Due to the harsh threshold values used in the existing algorithm, some poles were missing detected.

- Improvement: To improve the detection accuracy of pole detection, each parameter of pole detection should be optimized to get the best detection result. For this reason, statistical analysis of the threshold values to get the optimal values for each parameter will be carried out in section 4.4.1.

Table 3-2: Description about parameters of pole detection

Parameter	Description
parts	Height of part between two rectangles
maxdiagpart	Maximum diagonal of part
diffpos	Difference between two adjacent rectangular midpoints
diffdiag	Difference between two adjacent part diagonals
numparts	Number of parts fulfil the above conditions

3.6. Knowledge based classification

In (Pu et al., 2011), the rest segments after removing the vertical pole part are assessed to differential types of objects. The existing method simply classifies the pole-like objects into four categories: poles, trees, road signs and others. The more classes are classified, it is more beneficial to improve the transportation safety in the actual traffic environment. Therefore, except for the trees, it is important to further identify the transport facilities such as traffic signs, traffic lights or the furniture near road like lamp posts and others. After removing the pole part from the entire pole, a number of distinction attributes are analyzed.

Strong clues can be generated by the laser points with the feature description to determine the most likely pole type.

There are several considered geometric information to differentiate types of pole, i.e., size, shape, maximum height, MBR ratio of rest part points. In addition to the geometric information, since the characteristic of traffic sign in traffic system, almost all of the traffic signs are painted by special material with high reflectivity for better visualization. Thus the reflection intensity information of laser point would be beneficial for the algorithm improvement.

- **Size**

The term size refers to the size of segments on the additional structures of pole. After removing the vertical pole from the pole-like object, if the size of the remaining segment is less than 10, such segment can be classified as other pole, includes flagpole, bare pole, etc.

- **Shape**

Shape information can be used as an important element to distinguish types of pole, because man-made objects usually have regular and common shapes. In most cases, the traffic sign is rectangle or circle, the top of traffic light and lamp post is long and narrow linear shape. The tree points are irregular distributed in 3D space.

- **Maximum height**

Based on statistical analysis, we find that the lamp post is often the highest object, except tree, which around 9m in the road environment. And all of other types of poles are lower than tree and lamp post. An analysis on height difference between lamp post and other kinds of pole-like objects is shown in Figure 3-14. From this figure, it is convincing that the height information can be used on lamp post extraction.

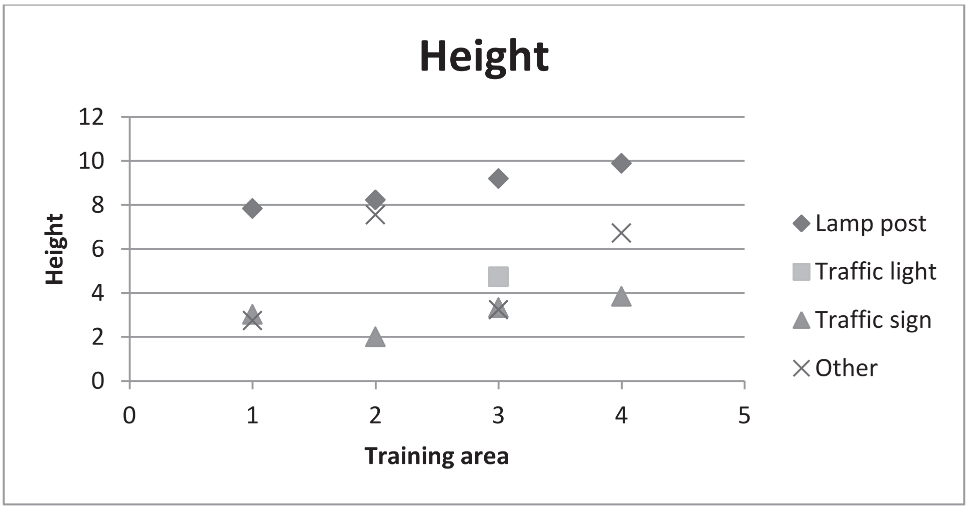


Figure 3-14: Average of object height, for 4 classes in 4 training areas

- **Reflection intensity information**

According to the international practice, for the various applications in the nighttimes and low-light visibility, high reflection material are painted on the traffic signs for better visuals, is shown in Figure 3-15. Due to the limitation of only coordinate information used in the existing algorithm, reflectance strength information can be introduced to extract the traffic signs.

(a) (b)

Figure 3-15: High reflection material on traffic signs: (a) in Europe (b) in China

Each type of pole is selected to demonstrate the high reflection values in traffic signs and other pole-like objects. The number of points with high reflective values in component is calculated. From Figure 3-16, we notice that traffic sign contains number of points with significantly higher reflection values than others. This is investigated as it could give us significant indicator useful to extract the traffic signs in further classification.

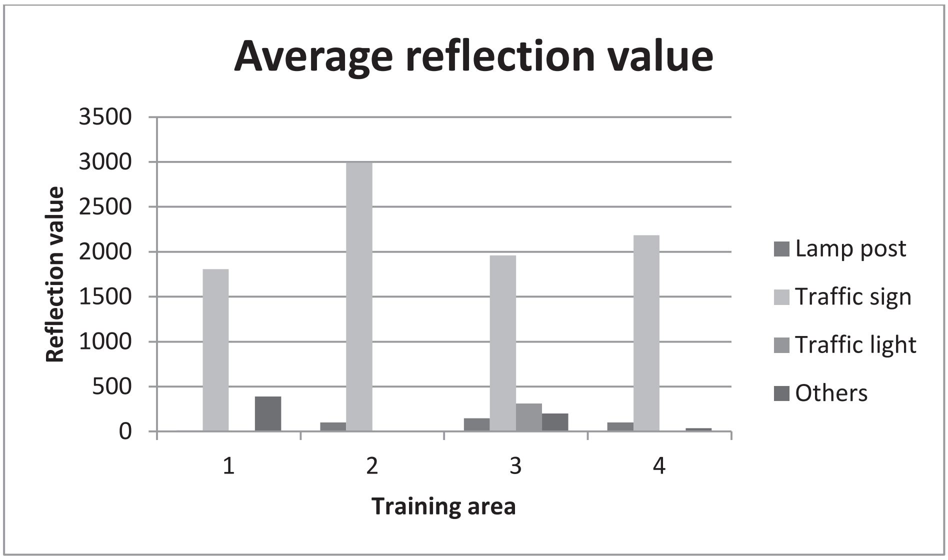


Figure 3-16: Average reflection value for 4 classes in training areas

- Improvement: In order to improve the existing algorithm, Different pole-like object definitions are developed according to five classes, and several geometric attributes and spectral information are calculated to extract types of poles. After introducing the reflection information, the traffic sign can be classified more accurately.

3.7. Statistics analysis

To obtain the statistics, C++ programming is used to investigate the features. The programming is operable in an executable file format and running by typing command. The laser file format is used as input and an optional choice for desired outputs. The statistical output is in “txt” format and then to be transferred to a “csv” format and opened in Excel for analysis. The main output of program is laser file, which can be saved in a chosen directory and visualized in PCM.

The feature attribute contains: the height of component, area of MBR, ratio for length and width of component MBR, percentage of multiple pulse count points in component, size of segments, ratio of shape matching, maximum height and number of points with high reflective value in component.

From the derived text file, both of the geometric and spectral attributes values of each component are summarized by Excel to get the statistical result. The simple schematics diagram below (Figure 3-17) summaries the derivation of the statistics.

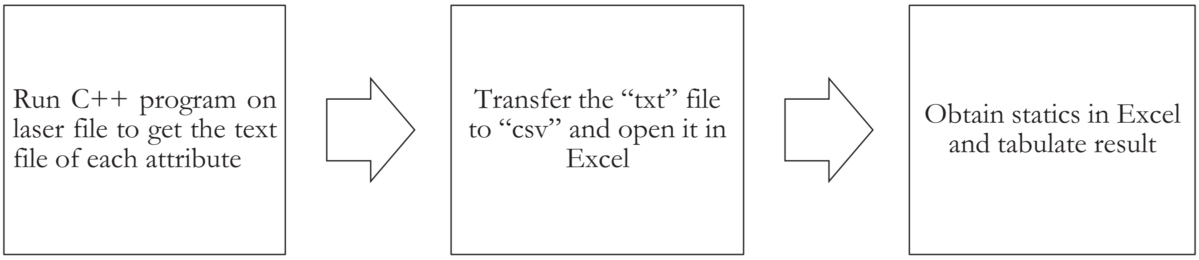


Figure 3-17: Workflow for compiling statistics

4. IMPLEMENTATION AND RESULTS

This chapter firstly introduces the dataset used in this research and then presents the implement of the methodology described in chapter 3. As mentioned before, most of the algorithms were implemented in C++ while the statistical analysis for detection and classification was obtained in Excel. The segmentation processing was done applying the function provided by the Earth Observation Department of ITC in PCM, as well as the visualization of results. In this chapter, Section 4.1 describes the mobile laser scanner dataset and testing areas used in this research. And section 4.2 describes the selection of threshold values in rough classification while section 4.3 describes threshold values selection and shows the result of tree detection. Section 4.4 describes the result of the pole detection and further classification. At last, a summary of the result is described in section 4.5.

4.1. MLS dataset

The MLS dataset used in this research is obtained by TopScan GmbH in December, 2008 using Optech's Lynx Mobile Mapper system (Optech, 2009) from a site located in Enschede, an eastern city of Netherlands. Two rotating laser scanners, for which each of them is oriented at 45 degree with the vehicle driving direction, are amounted perpendicularly with each other on the back of the platform. The mobile vehicle drives with speed of 50km/h and measurement frequency of 100 kHz per scanner. There are total 20km of road was scanned. The specification of the MLS system is listed in Table 4-1.

Table 4-1: Specification for LYNX mobile mapper V100 (Optech, 2009)

LYNX MOBILE MAPPER	V100
Parameter	
Number of lidar sensors	1-2
Camera support	Yes, 2 x 2 Mpixel
Maximum range	100 m, 20%
Range precision	±8 mm, 1 σ
Absolute accuracy	±5 cm (1 σ)[1,2]
Laser measurement rate	100 kHz
Measurements per laser pulse	Up to 4 simultaneous
Scan frequency	150 Hz
Scanner field of view	360° without obscurations
Power requirements	12 VDC, 30 A max. draw
Operating temperature	-20°C to +40°C (extended range available)
Storage temperature	-40°C to +80°C
Laser classification	IEC/CDRH Class 1 eye-safe
Vehicle	Fully adaptable to any vehicle

The testing data used in this research contains 9 road parts, each of them is 50m long and 40m wide. Four of the nine road parts were selected to study in this research as training area, and the total nine road parts are used as testing areas to show the performance of the proposed algorithm (Figure 4-1).

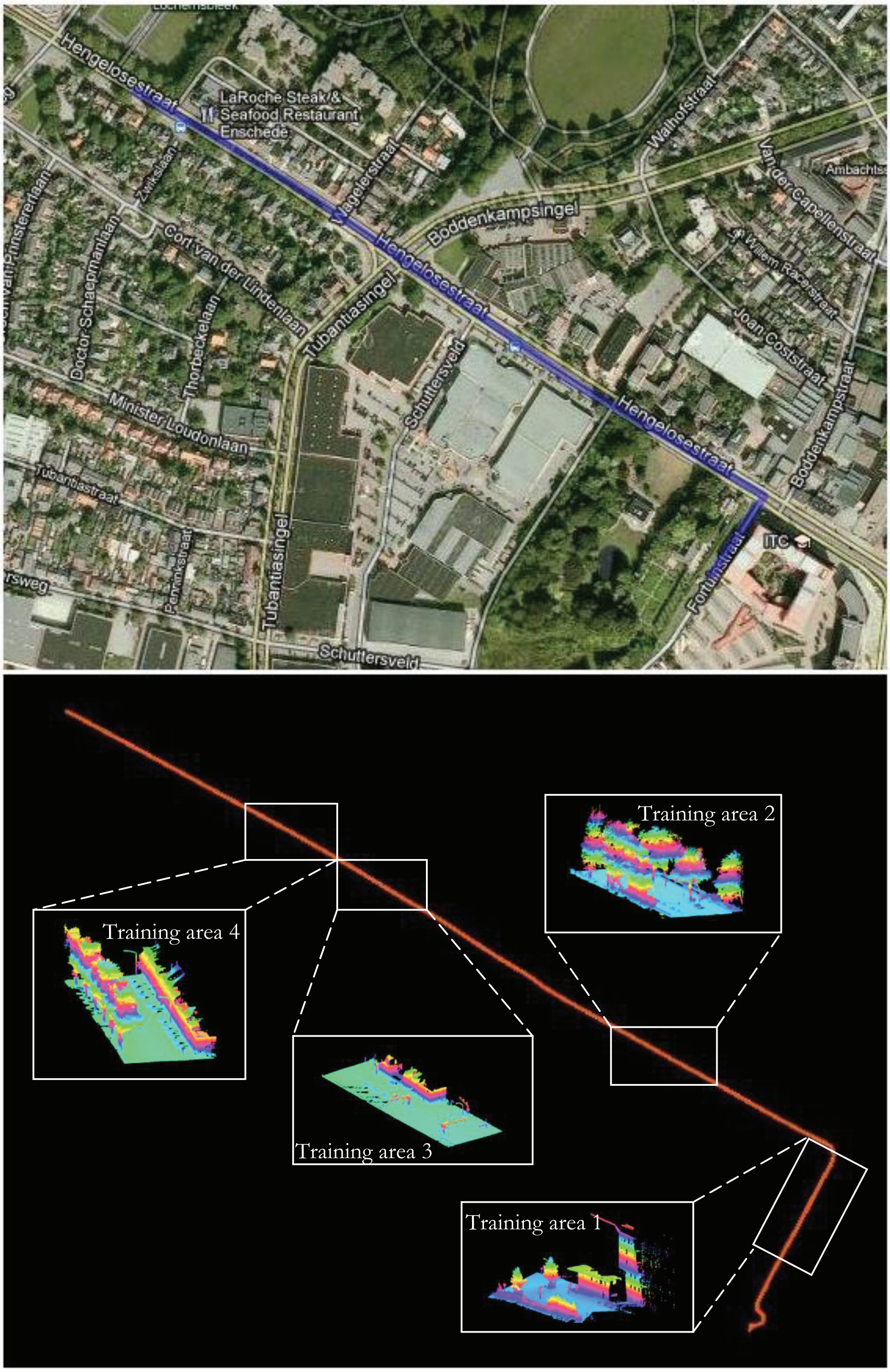


Figure 4-1: The trajectory of laser scanner and selection of 4 training areas

4.2. Rough classification

4.2.1. Segmentation threshold

Rough classification, which includes the segmentation and filtering the unwanted points, give the kept on-road segments as input of next phase. It is regarded as an important process in this research, because the result of rough classification would be used as input for the subsequent detection process. If the rough classification cannot filter the unwanted points well or over-filter the points of interest, the pole detection will not generate a reliable result. First step of rough classification is segmentation, which based on surface growing algorithm to remove the ground surface and large building facades. And then connected component analysis groups the points into component. There are several conditions proposed in the segmentation algorithm to get the optimal parameter values. Based on the condition and assumption listed below, parameter values are determined from statistical analysis on the four training areas:

- All ground segments are assumed as the segments with large area and planar surface at a certain distance below the trajectory, all building facades ought to have vertical planar surface with large area.
- All ground segments are separated with the on road segments.
- All on road segments should be connected as different individual component as much as possible.

The first step of the rough classification is to remove the ground surface and facades. Because the ground and facade surface are easily detected in the laser data, parameters on the surface growing algorithm is not much critical for the on-road object detection. The surface growing algorithm parameters were considered as surface growing radius is 1.0m and maximum distance to surface is 0.3m. After statistically analyzing on the training areas, minimum area threshold of ground segments is set as 20m^2 and facade segment is set as 50m^2. The system height of this research is 2.4m. This means that if area of one segment is greater than 20m^2 and performs planar surface under the trajectory, this segment can be recognized as ground surface. For the same reason, if area of a segment is over 50m^2 and within the vertical tolerate of 7 degree, it should be recognized as facade. After fulfilling above conditions, the ground surface and building facades were removed.

The second step of rough classification is filtering the segments far away above the ground. To prevent the impact of the objects flying in the air, the height of object bottom from ground surface were calculated, and as a conclusion, the segment bottom above 1m from ground were classified into off-ground segments and would no longer be considered as points of interest. Eight objects were added into the on-road segments by current algorithm while these had been removed in the previous algorithm. The derived on-road segments would be processed in the following steps.

Once on-road segments generated, to get the attributes of component for object detection, connected component analysis was performed and ensured each wanted object was connected as one component as far as possible. For getting the threshold values of the maximum distance between points parameter in connected component analysis, the distance between two points in the laser point cloud was surveyed as an average value of 0.1m. As a result, parameter values of connected component analysis were examined in the training areas. The selection of connected component segmentation parameter and visual analysis was carried out to get the optimal threshold values listed in Table 4-2.

The process requests the individual objects connected into one single component. Through visual examination on the immediately result shown in Table 4-2, we could find that when using maximum distance between points with 0.23m, the connecting get a more reliable result than other values. Based on such observation, parameters of connected component analysis were considered as maximum distance between points is 0.23m and minimum number of points in component is 10.

Table 4-2: Parameters determination for connected component analysis

	Maximum distance between points (m)	Minimum number of points	Remarks
Training area 3/4	0.15	10	Buildings were divided into many small parts, lamp posts were split into several components, so-called over-segmentation
	0.20	20	Buildings were divided into many small parts, lamp posts were split into several components, one lamp post was connected with tree
	0.23	10	Buildings were still segmented into some components, all other individual objects were grouped into different single object
	0.25	20	Buildings were still segmented into some components, several lamp posts were connected with trees, so-called under-segmentation

4.2.2. Filter criteria threshold

Once the connected component analysis was done, the filter criterion was carried out using a given threshold cut_max_diameter to remove the unwanted segments. In the existing algorithm, the threshold value is set too critical (0.6m) to filter the segments. After statistically analyzing all the segments selected from pole-like objects in the training areas, Figure 4-2 shows the average radius was calculated as 0.43m. To ensure all thick tree trunks can be kept after the filtering criteria, several values were selected to get optimal threshold. Because of the average radius of 0.43m, the cut_max_diameter should be greater than twice the radius. In this step, the threshold value is tested from 1m. Table 4-3 tabulated the parameter selection for filter criteria using the different threshold values and Figure 4-3 shows the result of connected component algorithm and the filter criteria with different threshold values.

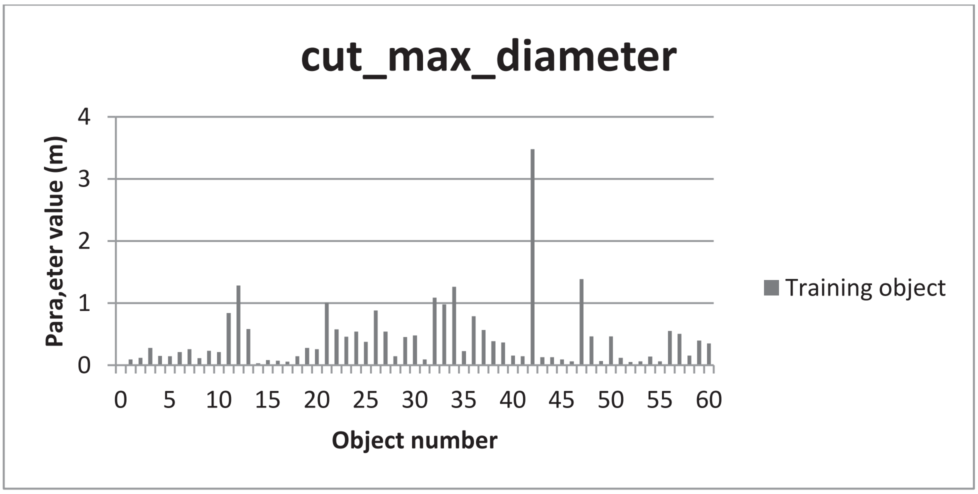
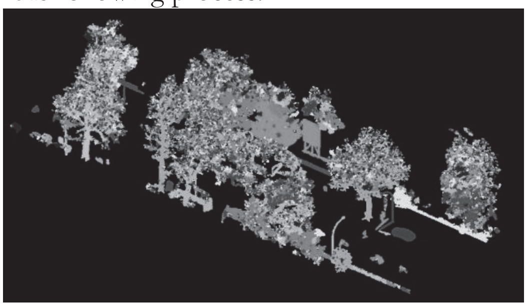


Figure 4-2: Filtering parameter analysis in pole-like object in 4 training areas

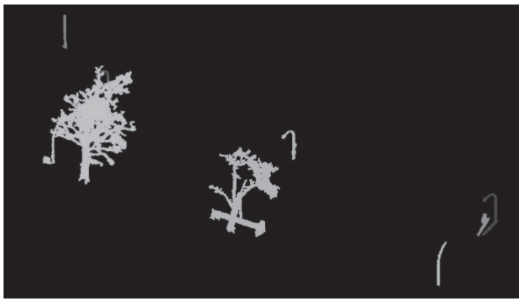
Table 4-3: Parameters determination for filter criteria

	cut_max_diameter threshold (m)	Remarks
Training area 1	0.6	All of trees were removed
	1.0	All of trees were removed
	1.5	One tree was removed
	2.5	All trees were kept
Training area 2, 3 & 4	0.6	Most of the trees, cars were removed
	1.0	Trees with thick tree trunks, most of cars were removed
	1.5	Trees with thick tree trunks were kept, most of cars were removed
	2.5	Trees contains tree trunks occluded by dense leaf were kept, almost all of cars are removed

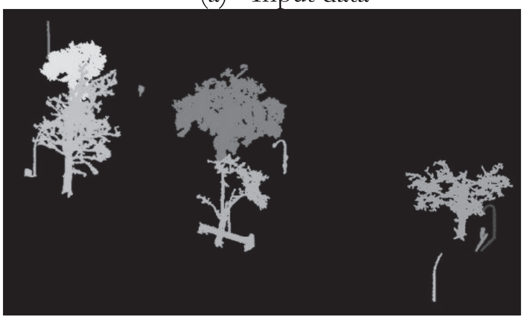
To keep more trees, the filter criteria value should be increased, however some unwanted segment would also be kept, which shown as the segment within white circle in Figure 4-3(e). These segments would be filtered in the following process.



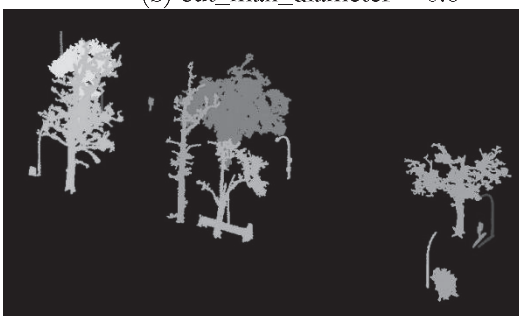
(a) Input data



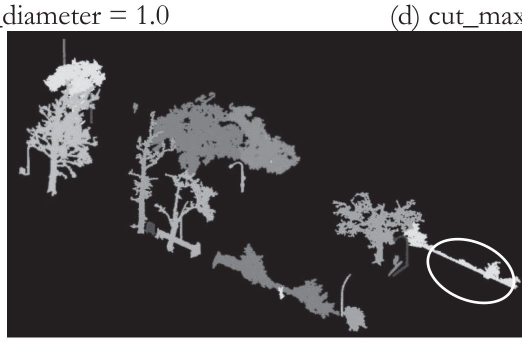
(b) cut_max_diameter = 0.6



(c) cut_max_diameter = 1.0



(d) cut_max_diameter = 1.5



(e) cut_max_diameter = 2.5

Figure 4-3: Results of filtering criteria with different threshold values

- Improvement: The improvement in this phase is through statistically analyzing radius of the segments, find an optimal threshold value to filter the unwanted segments and keep most of the thick pole-like objects like trees, and also find a trade-off between the thick pole and unwanted segments. In the existing algorithm, a lot of trees were removed because of the harsh threshold value. After statistically analyzing rectangular diagonal of the pole, value 2.5m which can get the best result was formulated. As a result, most of missing trees in the existing algorithm were kept in this research.

4.3. Rule-based tree detection

Because of limitations of the existing algorithm, rule-based tree detection was introduced in section 3.4. To separate the trees from other on road objects, several geometric and spectral attributes were calculated. Components in the training areas of five classes were analyzed to get the signature of each class. In Table 4-4 an overview is given for the average attribute value of these features in the training area per class.

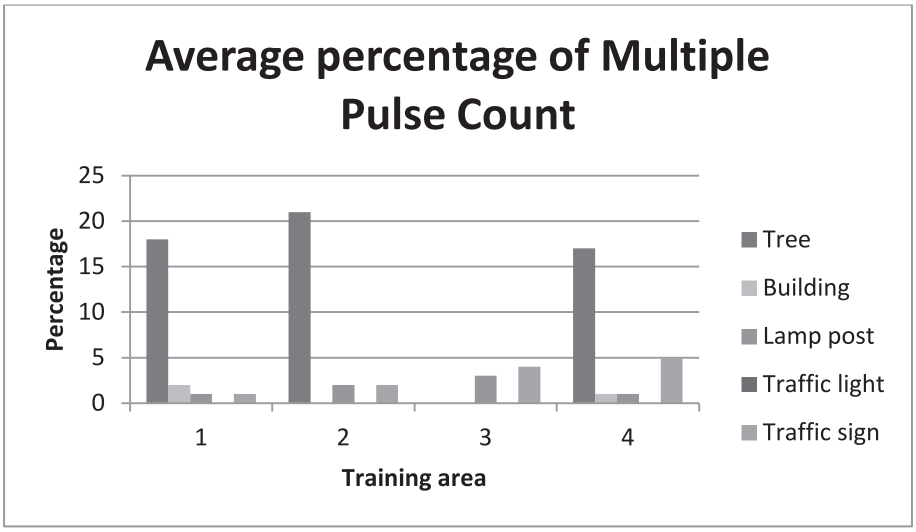
Table 4-4: Summary of average attributes values in training areas

	Percentage of MPC	Area (m^2)	Ratio of w/h	Height (m)	Size
Tree	18	194.83	0.64	16.7	11054
building	1	161.86	0.22	12.2	20730
Lamp post	2	1.45	0.08	9.91	209
Traffic light	0	3.23	0.20	5.88	1917
Traffic sign	3	0.31	0.27	3.25	291

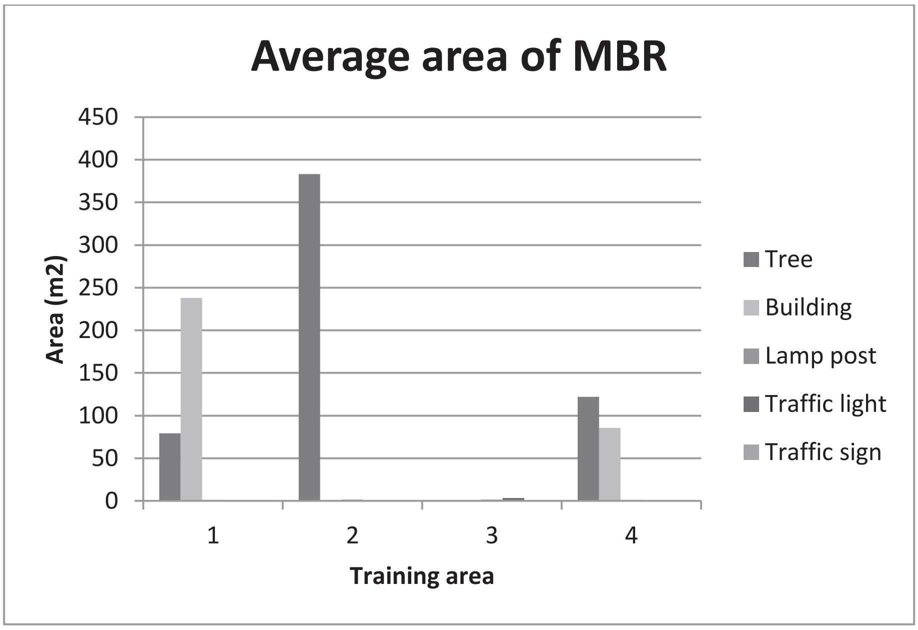
Figure 4-4 gives more insight in how the attributes in each component can be applied as important elements to detect tree. In this figure, the average values of each attributes for all samples in four training areas were calculated. From Figure 4-4(a) we found that the percentage of multiple pulse count points in tree was clearly higher than other pole-like objects; (b) indicates that the average minimum bounding rectangle area of tree crown in each training area is over $50m^2$ and clearly greater than other pole-like objects. Figure 4-4(c) shows that the ratio of MBR in tree is higher than other pole-like objects and average greater than 0.5, (d) shows the statistical analysis result of the component height, and we noticed that the average height of tree in each training area is over 10m. In additional to the geometric attributes, it was recognized that the parameter Percentage of MPC is a good factor to distinct vegetation and other road furniture. In total of 21 trees, 6 buildings, 11 lamp post, 18 traffic sign and 5 traffic lights were analyzed, although the number of samples is limited, it clearly shows that the selected attributes were convinced to be used to detect the tree. From the statistical analysis of the training areas, the following values in Table 4-5 were chosen as threshold to create a decision tree for the rule-based classification.

Table 4-5: Threshold values to meet the conditions for rule-based classification of vegetation

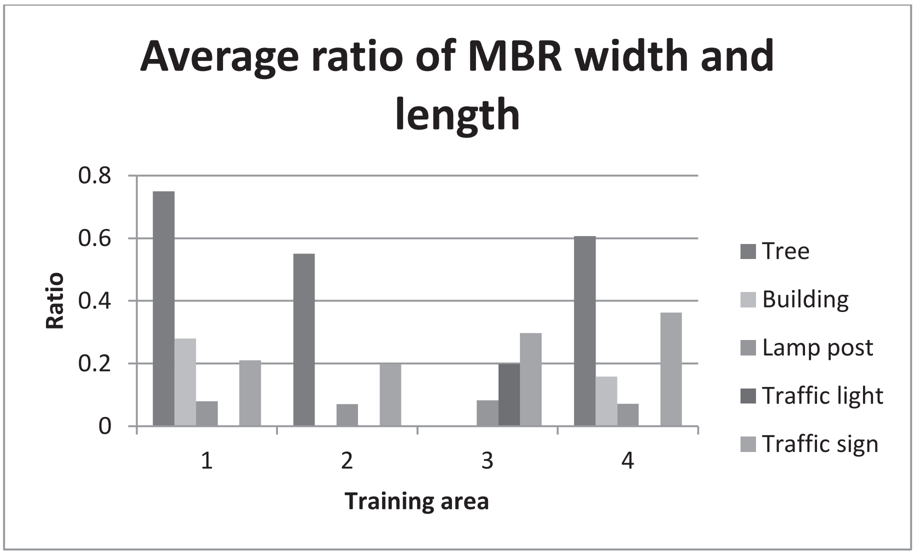
Parameter	Threshold value
Percentage of MP count	8
Area (m^2)	15
Ratio of width and length	0.5
Height (m)	10


Average percentage of Multiple Pulse Count
Percentage
25
20
15
10
5
0
1
2
3
4
Training area
Tree
Building
Lamp post
Traffic light
Traffic sign

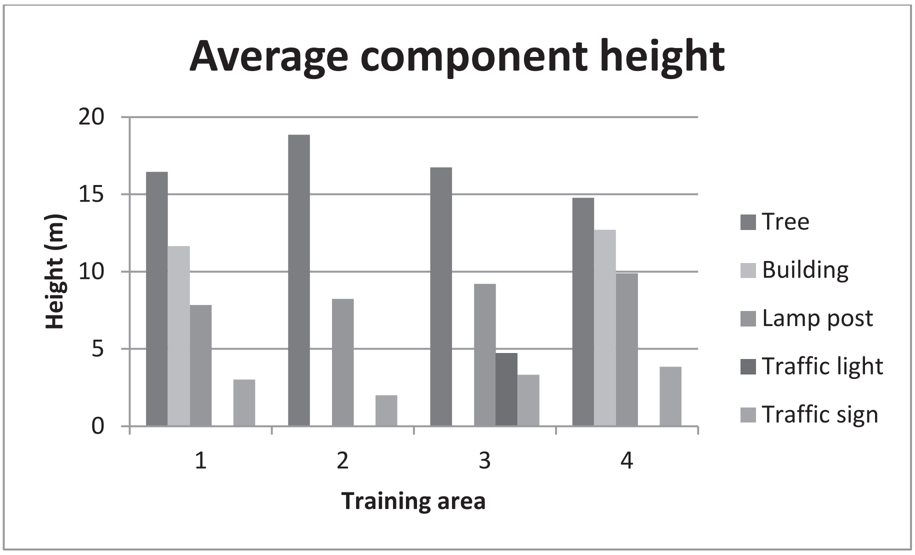
(a)


Average area of MBR
Area (m2)
450
400
350
300
250
200
150
100
50
0
1
2
3
4
Training area
Tree
Building
Lamp post
Traffic light
Traffic sign

(b)


Average ratio of MBR width and length
Ratio
0.8
0.6
0.4
0.2
0
1
2
3
4
Training area
Tree
Building
Lamp post
Traffic light
Traffic sign

(c)



(d)

Figure 4-4: Feature values in component: (a) percentage of Multiple Pulse Count (b) area of MBR (c) ratio of width and length of MBR (d) height of component, for 5 classes in 4 training areas

The automatically rule-based detection algorithm is based on a count system where the counter is defined to count the number of time to meet the conditions in each component. If one attribute value is greater than the corresponding threshold value, it is counted once. At the end, after judging all four attribute values for each component, sum up the count per component. Whether the component can be recognized as tree depends on the final count value. If the count number is great than 3 (3 or 4), the component can be considered to meet constrain as a tree and derive the outcome of classified tree.

- Improvement: As a result, the improvement of the existing algorithm here is to increase the tree detection accuracy. With the rule-based detection method, many missing trees in the existing algorithm were detected. Figure 4-5 shows the result of rule-based tree detection algorithm. From this figure, it is noticed that almost all of the trees are kept and detected using the developed rule-based algorithm.

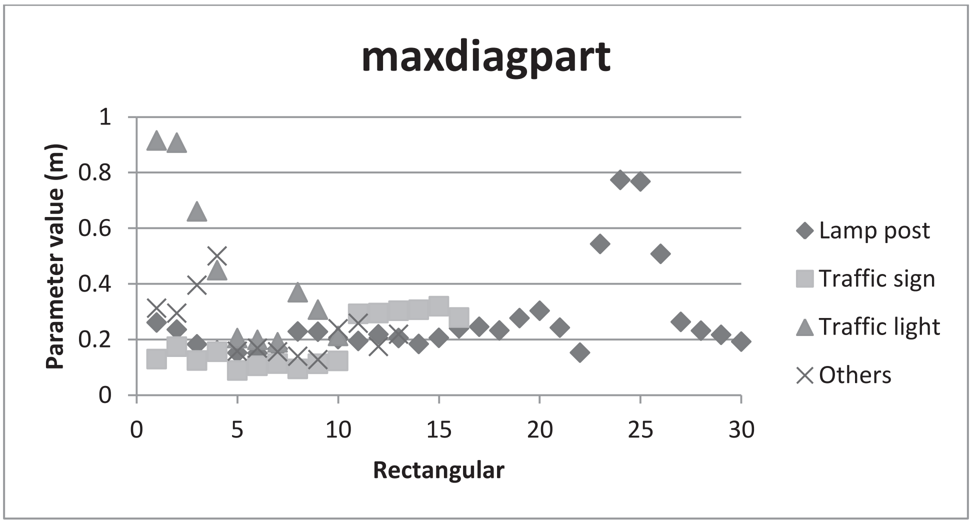
Figure 4-5: Detected trees by rule-based algorithm

4.4. Pole-like objects detection

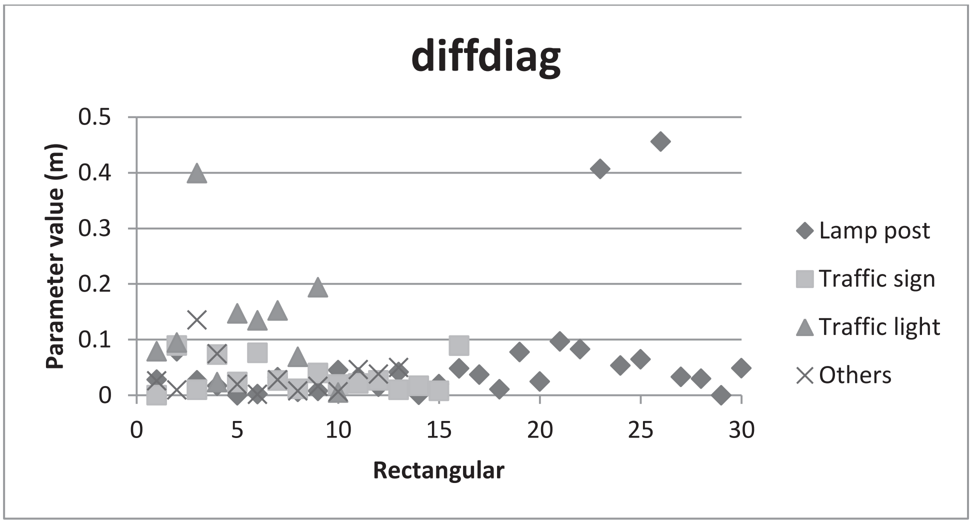
Once the introduced tree detection was completed, percentile-based algorithm was used to extract the pole-like objects from the remaining point cloud, and knowledge-based algorithm was carried out to conduct the further classification.

4.4.1. Percentile-based algorithm

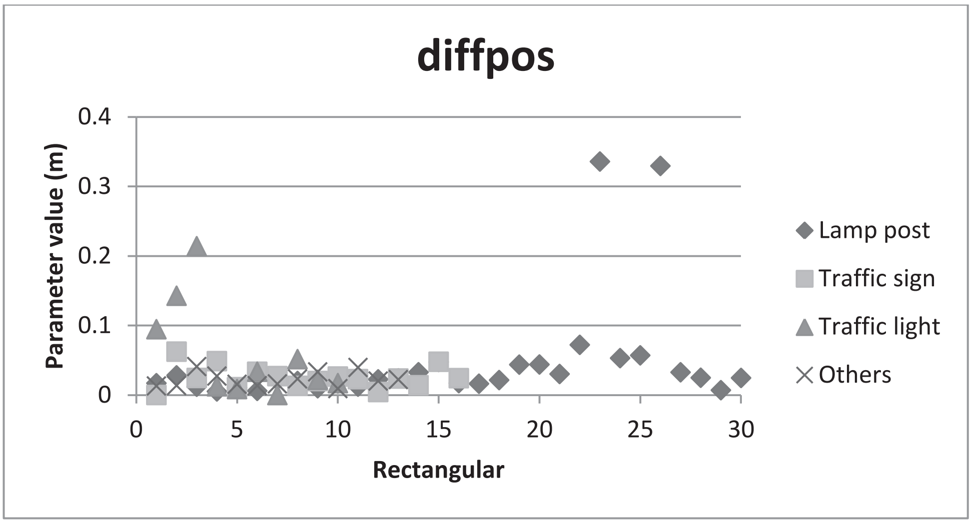
In the percentile-based algorithm, one of quartering in the component was selected in the pole detection. Each section was then sliced into multiple slices. For every two adjacent slices, minimum bounding rectangle was derived from points between the slices. For the pole detection, length of rectangle diagonal (maxdiagpart), difference between the adjacent rectangle diagonals (diffdiag) and distance between the adjacent rectangles midpoints (diffpos) were checked. In this case, a Boolean type of classification was made. If the three parameters based on two adjacent rectangles are smaller than the given threshold values simultaneously, this sub-section between the adjacent slices was counted once. After counting the considered section, in case the count is greater than a given number, this component can be labelled as pole-like object.



(a)



(b)



(c)

Figure 4-6: Statistical analysis for parameters selection in percentile-based algorithm. Three parameters performed in four classes

In this research, the second section quarter up from the ground surface was chosen as the considered section for pole detection. The reasons are that, on one hand the additional structures were often apparent in the upper part of the pole-like object; on the other hand it meant to avoid the problem caused by the tree crown in the upper part of tree. The height between two slices was determined as 0.25m. The reason is that if the value is too small such as 0.1m, there would be too few points between slices can be used to derive the rectangle; if the value is too large while the pole is short at the same time, there will not be sufficient rectangles to utilize in the pole detection. To complete the parameter statistical analysis, 30 rectangular from lamp post, total 16 rectangular from traffic sign, 15 rectangular from traffic light and 13 rectangular from other pole in the training areas were calculated. Figure 4-6 shows the statistical analysis of parameters diffdiag, maxdiagpart and diffpos in different types of pole-like objects from four training areas. The statistical results gave more insight about the general parameter values of each type of pole. Figure 4-6(a) showed that most of the parameter maxdiagpart values in the second section of lamp post were within 0.5m, the very high abnormal values were caused by the additional structure attached on the lamp post and traffic light. Figure 4-6(b) and (c) indicated that almost all of the parameter diffdiag and diffpos values in the selected section were within 0.3m, similarly the abnormal values were caused by attached structure on the pole. As the statistical analysis explained above, the parameters thresholds were determined as shown in the Table 4-6. After counting the rectangles that meet constrains of pole detection, through statistics, the component with count number greater than 2 was recognized as pole-like object. Figure 4-7 shows the detected pole-like objects by utilizing percentile-based algorithm.

Table 4-6: Threshold values to meet the conditions for percentage-based pole detection

Parameter	Threshold value (m)
Length of diagonal (maxdiagpart)	0.5
Distance between adjacent midpoints (diffpos)	0.3
Difference between adjacent diagonals (diffdiag)	0.3

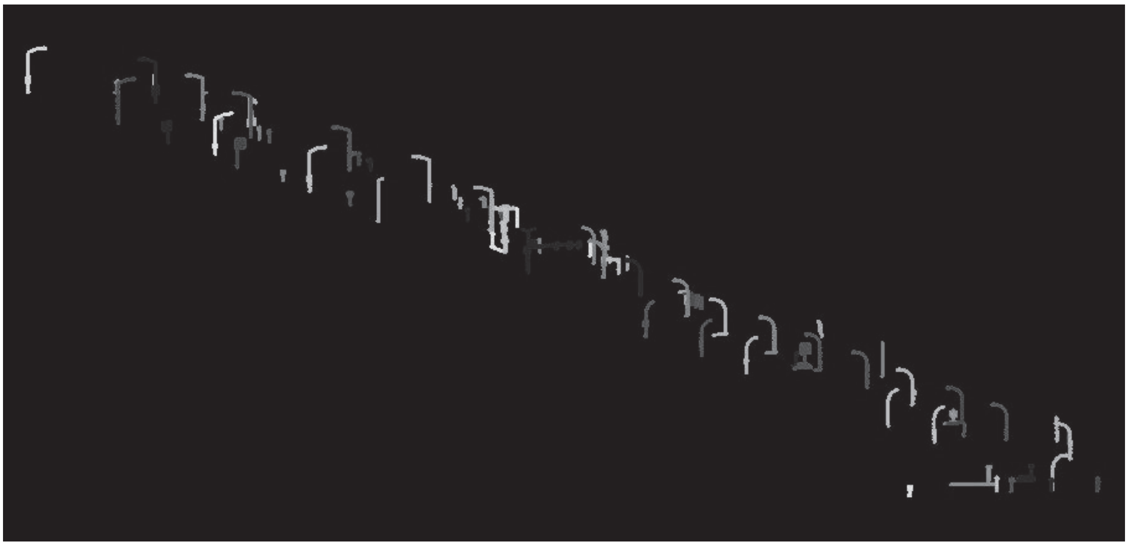
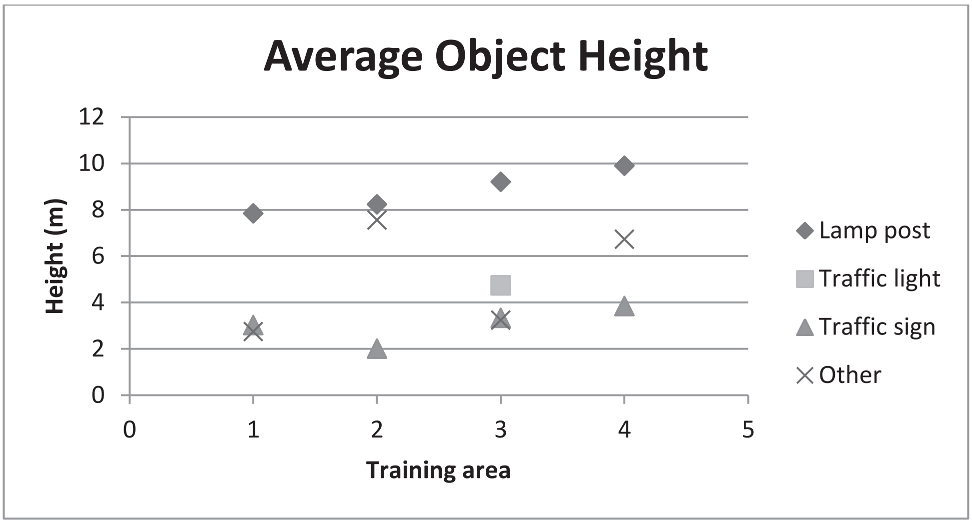


Figure 4-7: Detected poles by percentile-based algorithm

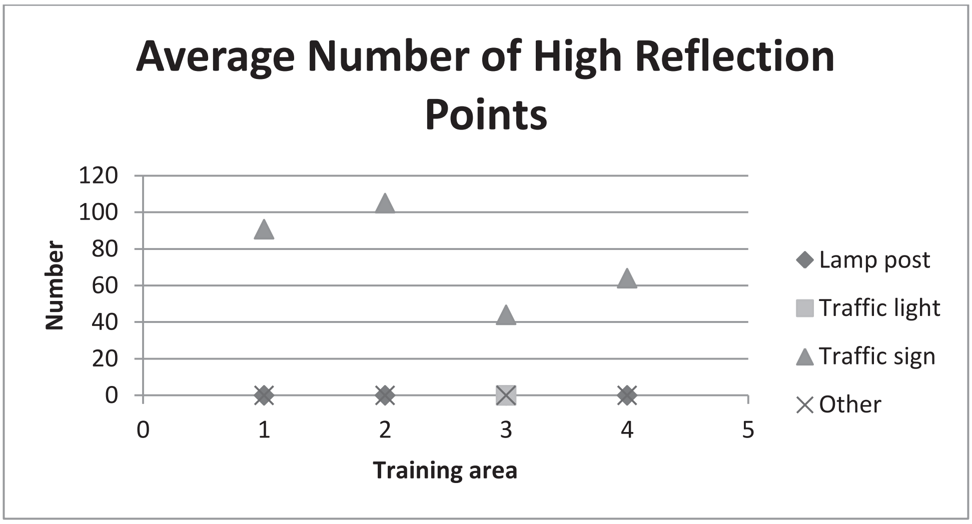
- Improvement: In the existing algorithm, due to inappropriate threshold values setting, the pole-like objects detection rate is not good enough. However, through statistically analyzing the parameter values in the four training areas, optimal threshold values were formulated to get more reliable result. As a result, most of the pole-like objects can be recognized using the proposed percentile-based algorithm, and then be used as the input data for the further classification.

4.4.2. Knowledge-based classification

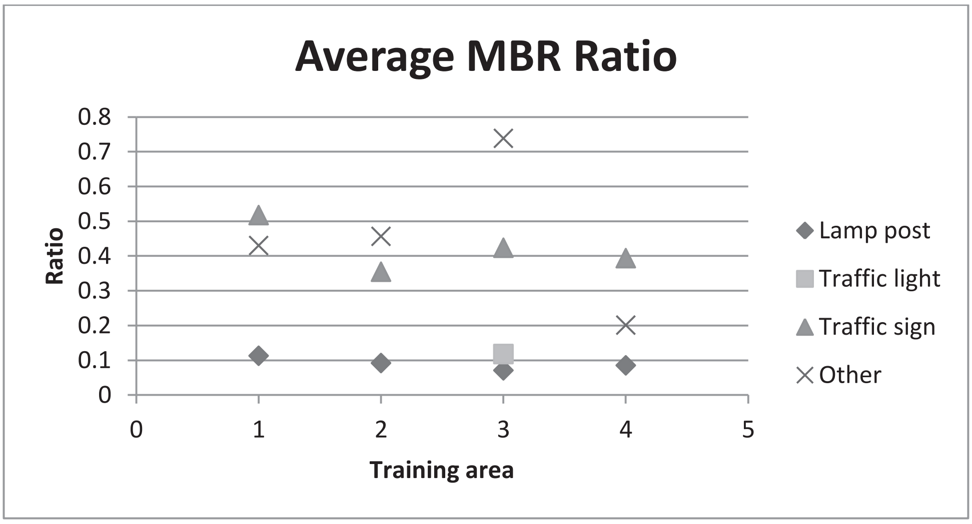
After the percentile-based algorithm, the pole-like objects were detected. In the traffic environment, more classes are classified, it is more beneficial to the traffic safety. As a result, knowledge-based classification was utilized to distinct different types of pole-like object. Based on the features characteristic described in section 3.6, all the pole types can be organized and defined. The definition of each pole type is tabulated in Table 4-7. Based on the geometric and spectral attributes discussed in section 3.6, height of object (maximum height), ratio of MBR generated by the remaining points after removing vertical pole (ratio) and number of points with high reflection values (point number) were calculated. The average attribute values of all samples in each training area were depicted in Figure 4-8. In Figure 4-8, each sign represented the average value of all samples in this training area. The average height of the object in each training area was compared in Figure 4-8(a), we noticed that lamp post was the highest object on road after separating tree from other on-road segments; and (b) showed that the average number of high reflection points in traffic sign is significantly higher than other types of pole; (c) indicated in each training area, the average ratio of width and length based on the minimum bounding rectangle in lamp post and traffic light was lower than other kinds of pole-like objects and performed linear shape while others were close to rectangular. The reason why only one training area contains the traffic light is that only the third training area in the testing data includes traffic light and neither of other road parts have such pole. The small square sign in Figure 4-8 represented the average value of five traffic lights in the third training area. Based on the result of statistical analysis, parameter values used in this knowledge-based classification algorithm were determined as also listed in Table 4-7.



(a)



(b)



(c)

Figure 4-8: Statistical analysis for the parameters selection in knowledge-based algorithm, for 4 classes in 4 training areas.

Table 4-7: Definition and determine of threshold for further classification

Type	Feature characteristic of remaining point cloud	Size	Height (m)	Number of high reflection points	Ratio	Horizontal/ Vertical area (m^2)
Tree	3D irregular point distribution	--	--	--	--	>15
Lamp post	The highest object in road environment, linear shape on the top view	--	>= 7	--	<=0.25	--
Traffic sign	Rectangle or circle shape and contains sufficient high reflectance points	--	--	>=7	--	--
Traffic light	At least above 2m from ground surface, another kind of linear shape except lamp post	--	--	--	Width>=0.3 Length>=2.5 Rectangular or circular	--
Others	Remaining poles which do not meet the above conditions	<10	--	--	--	--

However, the actual situation is that there will be several different types attached in one pole-like object, thus a priority rule was proposed to determine types of these kinds of mixed poles. And the final calssifed pole-like objects result by using percentile-based pole detection and knowledge-based classification algorithm is shown in Figure 4-9, each object is coloured by different types: lamp post: yellow, traffic light: white, traffic sign: blue and others: orange. The priority rule for classification is listed below:

- If the object includes tree type, it is recognized as tree;
- If the object includes traffic light, it is recognized as traffic light;
- If the object includes lamp post but no traffic light, it is recognized as lamp post;
- If the object includes traffic sign type but no traffic light and lamp post, it is recognized as traffic sign;
- If the object just includes others, it is recognized as other pole.

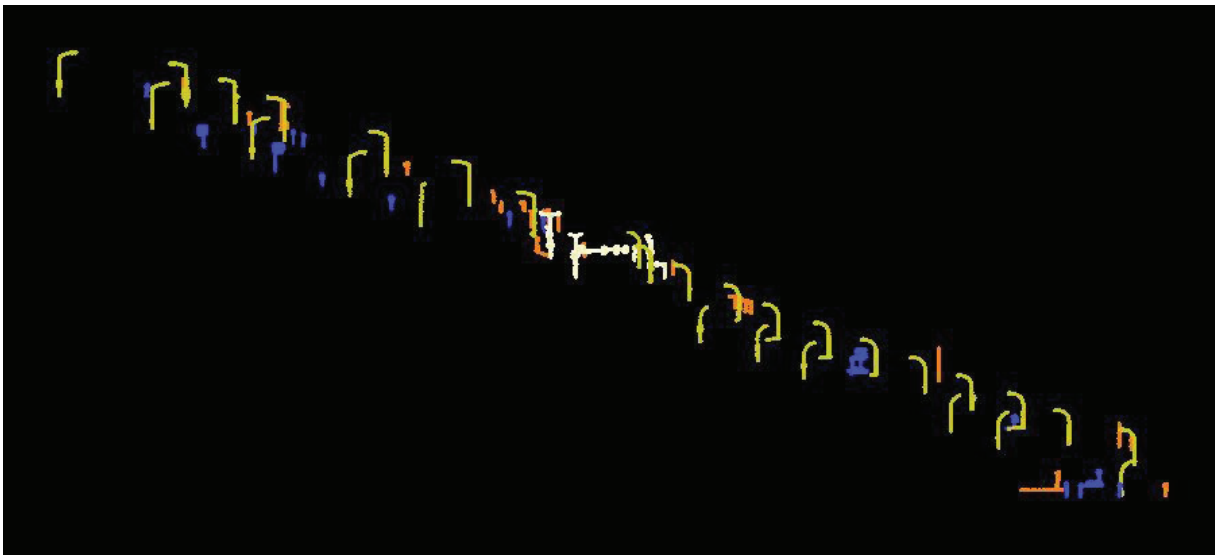


Figure 4-9: Detected poles in testing areas coloured by type

- Improvement: Due to the limitation of only using coordinate information in the existing algorithm, the further classification did not get an accurate result based on the detected pole-like objects. However, thanks to the statistical analysis about reflectance strength information and several adopted geometric attributes, more classes and higher accuracy can be achieved using this proposed algorithm.

4.5. Summary

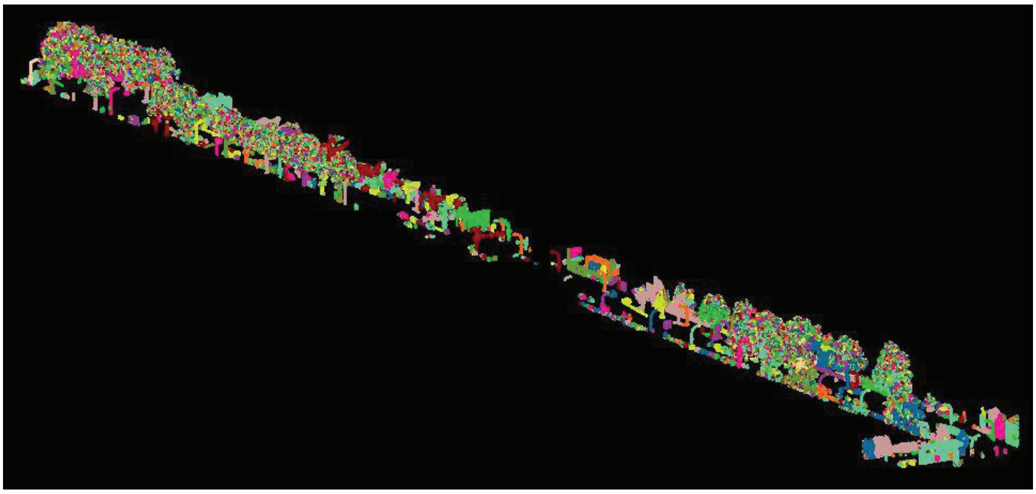
In this chapter, the proposed algorithm was implemented and tested by nine testing areas. Parameter threshold values were selected through statistics analysis to get the optimal result. Totally five types of pole-like objects were classified in the road environment, including the tree, lamp post, traffic light, traffic sign and others. From visual examination on Figure 4-5 and Figure 4-9, it can be concluded the algorithm is able to detect majority of pole-like objects. But at the same time, there will be missing detection and false detection. In chapter 5, quantitative evaluation of the detection result will be described to give an insight view of the performance of the proposed algorithm.

5. EVALUATION AND DISCUSSION

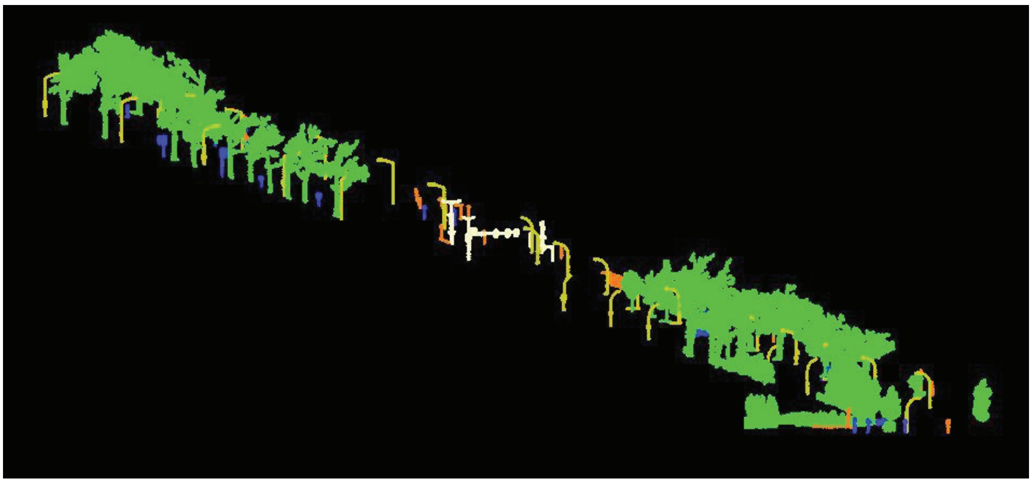
In chapter 4, detection result has been derived from nine testing areas by using the proposed pole-like objects detection algorithm. Performance of the proposed detection algorithm will be analyzed in this chapter. The evaluation strategy will be described firstly in section 5.1, and then discussion on the performance of proposed algorithm is put forward in section 5.2. Finally, a summary of the performance of proposed algorithm is described in section 5.3.

5.1. Strategy of evaluation

After classifying the pole-like objects, classified result contains five different types of pole-like objects: tree, traffic light, traffic sign, lamp post, and others. The input data and classified result are shown respectively in Figure 5-1. From Figure 5-1(a), the input data is coloured by component, we notice that there are varies of objects such as trees, poles, buildings and cars in the input data. And Figure 5-1(b) shows final result of different types of pole-like objects were already detected by proposed detection and classification algorithm, the output dataset coloured by each pole type: tree: green, lamp post: yellow, traffic light: white, traffic sign: blue and others: orange.



(a)



(b)

Figure 5-1: Result of the detection algorithm, (a) input data (b) output classified result

To evaluating the classified result, reference dataset was produced through visual examination and labelling each component manually in accordance with these five types of pole. A total of 696379 points were recorded in the reference dataset. To avoid the problem in explaining the performance of point cloud, field investigation and photograph checking are necessary. After pole-like objects detection, each type of pole-like object has a unique label tag value while the reference also has the unique label tag value. In normal situation, the classified result is expected to have a good result which can match the reference dataset perfectly. However, this kind of ideal result is difficult to achieve in the laser data.

In this chapter, two kinds of quantitative evaluation were carried out: automatic point wise assessment and visual examination based object wise assessment. The first one was executed by automatically overlying the classified points with the reference point cloud and checking whether each point in result dataset had the same label tag value with the reference point in the same location. If the same point in the result dataset has been extracted correctly corresponding to the reference dataset, this point can be recognized as true positives (TP) as well as the False Positives (FP), False Negatives (FN). The definition of each error type is tabulated in Table 5-1. This step was implemented with C++ language and final result was shown with varies of factors include completeness, correctness and quality.

Table 5-1: Error assessment in evaluation

	Reference is true	Reference is false
Result is true	True Positives (TP)	False Positives (FP)
Result is false	False Negatives (FN)	True Negatives (TN)

For completing the error assessment, completeness and correctness are calculated similar with the definition described in (Heipke et al., 1997) shown as equations below :

- Completeness:

$$completeness = \frac{\mathrm{TP}}{\mathrm{TP+FN}} \tag{5-1}$$

The completeness is the measurement that percentage of the reference data which explained by the extracted result. For example, the percentage of pole-like objects in reference data was detected by the proposed detection algorithm in this research. The optimum value of completeness is 1.

- Correctness:

$$correctness = \frac{TP}{TP+FP} \tag{5-2}$$

The correctness is the measurement of percentage of correct detected objects. For example, the correct detected pole-like objects in classified result correspond to reference dataset. The optimum value of correctness is 1.

- Accuracy quality:

$$accuracy = \frac{\mathrm{TP}}{\mathrm{TP+FP+FN}} \tag{5-3}$$

The accuracy is the measurement about the “goodness” of the classified results. The optimum value of accuracy is 1.

The evaluation result based on point is tabulated in Table 5-2. From this table, we notice that the types of tree and traffic light have a good overall accuracy, and the high correctness rate indicates that the algorithm is accurate enough to classify poles based on correct detected pole-like objects. The others pole has the lowest accuracy rate mainly because large amount of false detection.

Table 5-2: Evaluation result based on point statistics

Pole Types(Point number)	Completeness	Correctness	Accuracy
Tree (638453)	0.95	0.96	0.92
Lamp post (25330)	0.84	0.99	0.84
Traffic sign (13588)	0.82	0.99	0.82
Traffic light （11131）	1	0.74	0.74
Other pole (7877)	0.41	0.55	0.31

The second evaluation based on object wise comparison was carried out through visual examination. It is supposed that human operator can correctly recognize each considered component. Confusion matrix has been used to show the performance of the proposed algorithm and presents possible improvement in Table 5-3. The detail of error assessment will be discussed in section 5.2.

Table 5-3: Confusion matrix of the detected result

Enschede dataset		Visual inspection						False positives (%)
		Tree	Lamp post	Traffic sign	Traffic light	Others	Total detected	
Algorithm	Tree	45	0	0	0	0	45	0
	Lamp post	0	29	0	0	0	29	0
	Traffic sign	0	0	17	0	0	17	0
	Traffic light	0	0	0	5	1	6	16.7
	Other	0	0	2	1	10	13	23.1
	Missed	9	5	7	0	2	25	
	Total visual	54	34	26	5	13	135	
	Detection rate (%)	83.3	85.3	65.4	100	76.9		

5.2. Discussion of proposed algorithm

5.2.1. Discussion on the rule-based algorithm

The improvement in this research is to develop a rule-based tree detection algorithm, which increased the tree detection significantly higher compared with the existing algorithm. In the existing algorithm, only 63.5% of trees were detected, while from Table 5-3, it is noticed that over 80% of tree were detected and no one is false positive in this research. It indicates that by using the rule-based tree detection algorithm, the detection accuracy of the tree increase significantly.

Although the tree detection accuracy has already improved clearly, there are still several missing detected trees. One of the reasons for the missing detection is that all of the poles of interest are considered as the objects at least within 1m above to the ground. Since several trees were hanging in the air, which lead to the missing detection was shown in Figure 5-2(a). Another reason is the characteristic of tree. The proposed tree detection algorithm relies on the pulse count information and projection area of tree crown. Since some trees only include a small amount of leaves in the tree crown, and perform like other kinds of poles, at the same time the thick tree trunks exceed threshold values of the percentile-based pole detection, these trees are missing detected (middle tree in Figure 5-2(b)).

(a) (b)

Figure 5-2: Missing tree detection analysis, (a) one missing tree hanging in the air (b) one missing tree

One solution on the former problem is to increase the tolerance of the on-road segments and taking these kinds of hanging objects into consideration. To avoid the problem of latter situation, the threshold values for the tree detection and pole detection need to be selected carefully to ensure detecting this kind of trees as much as possible. Notwithstanding its limitation, the proposed rule-based algorithm increases the tree detection accuracy clearly, which indicates that the rule-based algorithm is feasible on tree detection.

5.2.2. Discussion on pole-like objects detection result

Pole-like objects detection is done mainly to separate poles from unwanted points. The ideal result should be that all of the poles are labelled as pole to be input for next step and all of the unwanted points would not be considered any more. After statistically analyzing the adopted parameters, optimal threshold values can be utilized to improve the detection accuracy. Therefore, we can notice that over 70% of pole-like objects (here it is defined the poles except trees) are detected through this proposed algorithm from Table 5-4, which is more accurate than the existing algorithm (Table 3-1). Based on the evaluation result, it is demonstrated that after optimising threshold values in percentile-based algorithm, the proposed algorithm is feasible to apply to detect pole-like objects in laser data.

Table 5-4: Evaluation result on pole-like object detection

Object (point number)	completeness	correctness	accuracy
Pole-like objects (57926)	0.80	0.88	0.72

There are several bottlenecks which reduce the detection accuracy in this proposed algorithm. The main reason of the missing pole detection is the point number between the selected slices. In the detection algorithm, one section was selected as considered section to determine whether this object was a pole or not. Because the few number of points in the selected section, it is hard to collect the rectangular in detection process, such as derive the minimum bounding rectangle for each subpart, or count the number of the rectangle, which should be at least 2 rectangles in the selected section. Figure 5-3 shows a typical scenario of missing pole detection. In the left figure, one section is selected as test section, however in the right figure, there are only two points inside the subpart derived by two adjacent slices, it is not sufficient to create minimum bounding rectangle, which resulting a problem in the pole detection. Meanwhile, since the selected section is too short to collect enough rectangles, these pole-like objects have been missing detected. It is difficult to completely avoid such problem: if the section between two adjacent rectangular is selected as high as possible to ensure the generation of rectangular, there would not be sufficient number of rectangular can be utilized in pole detection. This problem could be improved if we consider an optimal trade-off between the derivation of rectangular and the number of rectangular.

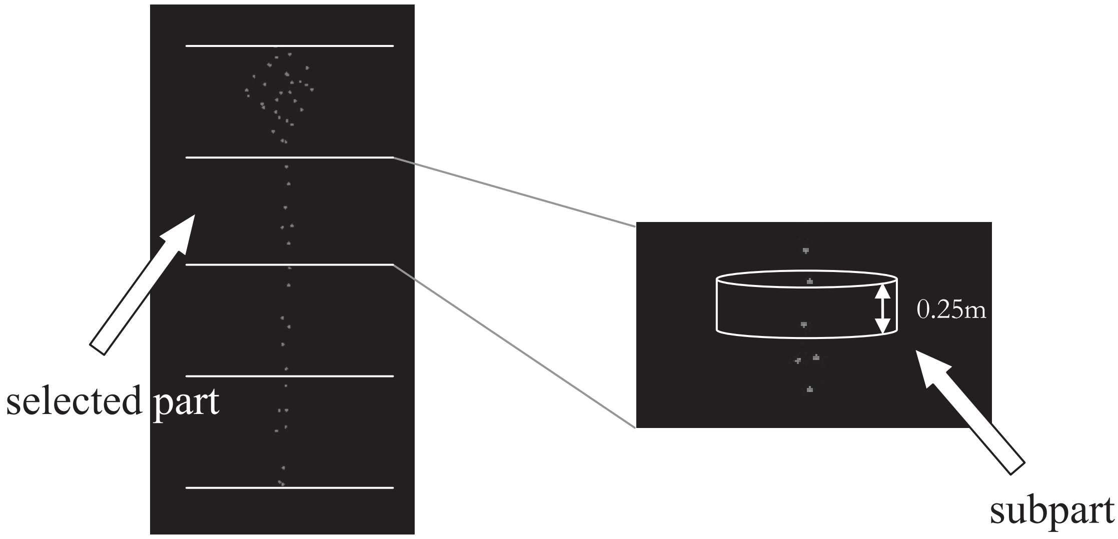
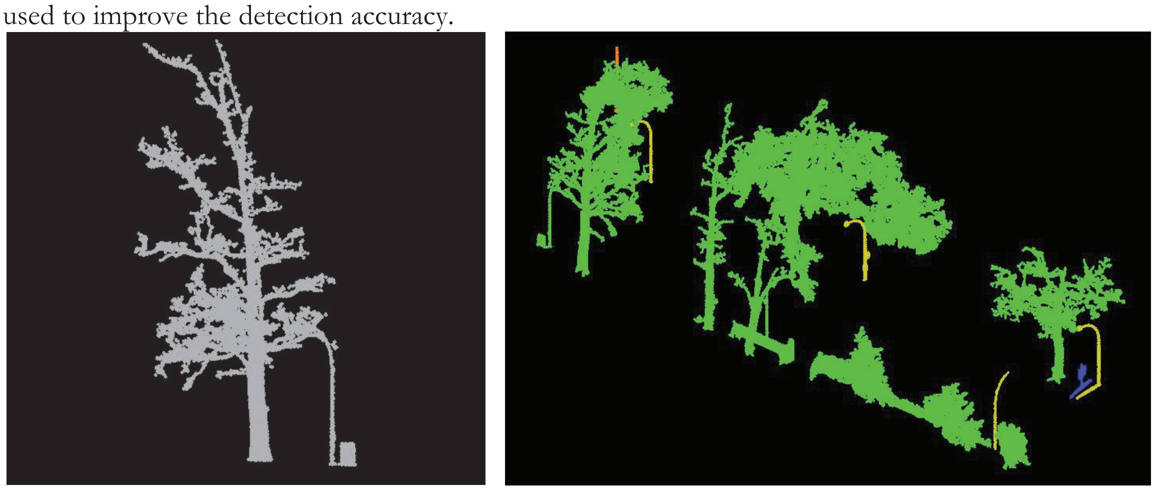


Figure 5-3: Missing pole detection analysis

Another reason of the missing detection is the hanging poles caused by the input data quality. Some poles in the testing areas "fly in the air" because are locating behind the fence at the bottom of pole-like objects or occluded by other objects. Due to the on road objects are defined as the objects within 1m close to the ground surface, the hanging objects are removed before the pole detection step, which resulting the missing detection. Similar with the problem in tree detection, a solution for such problem is to increass the tolerance of the on-road segments in order to take these kinds of hanging segments into consideration.

The third reason of the missing detection is that several lamp posts have been connected with tree, which is shown in Figure 5-4(a). It is difficult to completely avoid such problem because the lamp post is indeed connected with tree branches in reality. To improve this problem, contextual information can be utilized to give a hint of location of such pole-like object. From Figure 5-4(b) we can notice that four of the six regular distributed lamp posts have been detected, the rest two missing lamp posts are connected with trees. Once the contextual information is introduced, the location information of pole-like objects can be used to improve the detection accuracy.



(a) (b)

Figure 5-4: Missing lamp post analysis, (a) one missing lamp post (b) regular distributed lamp posts

The last reason for the low accuracy is the false detection caused by other objects, which are recognized as pole-like objects incorrectly. The false extraction occurred in the pole detection are mainly on the false detection of the building structures. Since there are glasses on the building facades along the road (Figure 5-5(a)), laser beam penetrates through the glass and then hit furniture inside of the buildings. Because of location of these objects, they are connected with building by connected component analysis. At the same time, they perform like pole-like objects. For these reasons, many of the furniture inside the buildings are detected as pole-like objects incorrectly, resulting arise of the false detection rate in the proposed algorithm (Figure 5-5 (b)). Due to the material of building facades, for example the glass in this research, this kind of problem is difficult to avoid. One solution is that, in premise of ensuring the other single object connected into individual component, connect the objects inside building with the building as much as possible. Another solution would be using a filtering constrain to remove the segments behind the building facades once the facades have been detected.

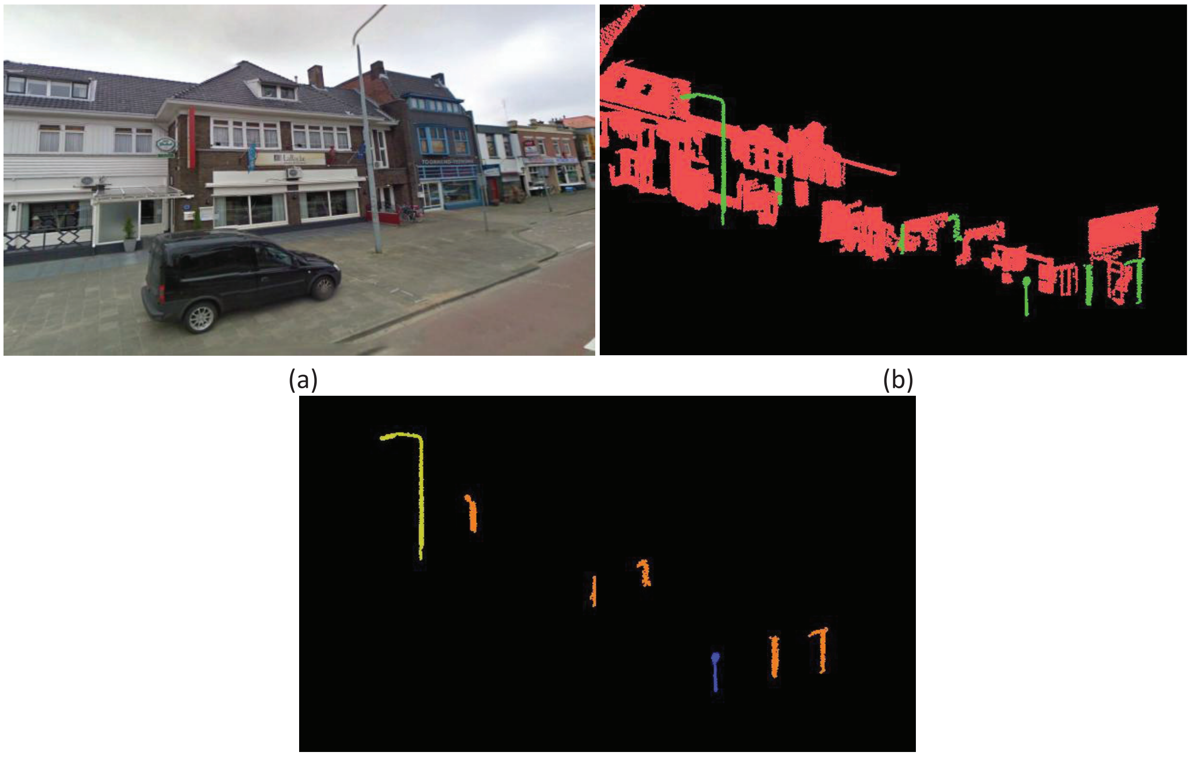


Figure 5-5: False pole detection, (a) glass on the building facades along the road (Google map) (b) false detected pole-like objects (c) false classification based on the incorrectly detected poles

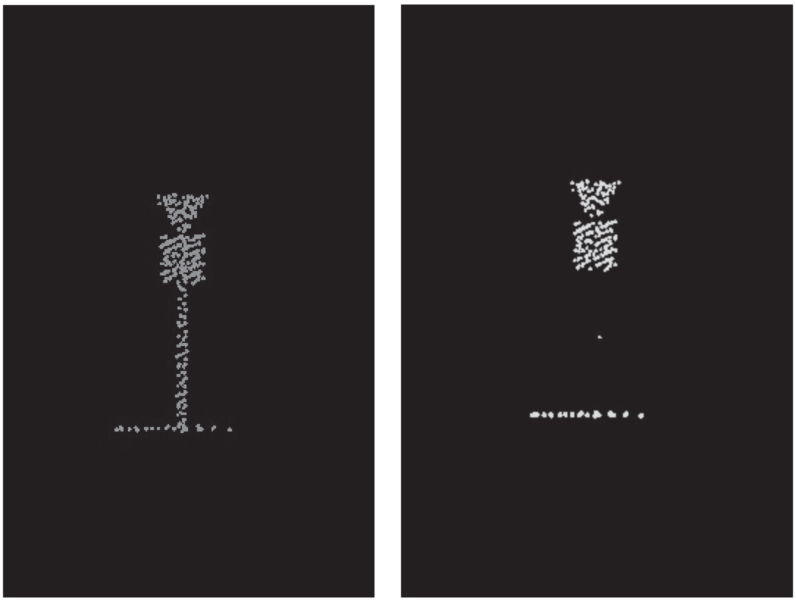
5.2.3. Discussion on further classification result

One improvement in this research is presented as proposing more specific classification, which produces more reliable result than the existing one. In the existing algorithm, detection rate of poles, road signs and others is 20%, 60.8% and 81.8% respectively while in this proposed algorithm, the detection accuracy of five different types of pole: tree is 92%, traffic sign is 82%, lamp post is 84%, traffic light is 74% and others is 31%. This indicates that the proposed knowledge-based classification performs better and improves different types of pole-like objects' detection accuracy in varying degrees except others. Although the proposed classification cannot success under all circumstances, this proposed classification algorithm still works well on distinction of different types of pole on regular and typical characteristic of pole-like objects and is demonstrated feasible to apply in the actual application

From Table 5-2, we can notice that the detection accuracy of other pole is the lowest in five types of poles. The main reason is the false detection occurs in percentile-based pole detection step, which mentioned in section 5.2.2. Because of false pole detection, the attributes of these objects are calculated in further classification phase, as a result, these objects are classified into others (Figure 5-5(c), others: orange, lamp post: yellow, traffic sign: blue).

Another observation is that not all the traffic signs have regular shape or contain high reflection points. Traffic sign in the road environment often performs circular, rectangular, triangular, and also a combination with different shapes. There are some traffic signs containing different signs mounted on one pole such as the one shown in Figure 5-6. From Figure 5-6(b), it is observed that after removing the straight pole part, the remaining segments are used to determine which pole type they belong to. However, since both of the matching rates of this segment with MBR and MBC are low, and also there are not many high reflectivity points in this object, this object are classified into other pole. As reviewed in the chapter 2, imagery can provide much rich texture and colour information, which is efficient for the traffic sign extraction, can be utilized if imagery data is available.

Another difficulty on classification is that there are different appearances in same type of pole-like object, and conversely similar characteristic of different types of pole appear in laser points. It is impossible that one method can work perfectly in all situations. Therefore, based on the evaluation result, it is demonstrated that the proposed knowledge-based algorithm increase the classification accuracy clearly when compared with the existing algorithm.



(a) (b)

Figure 5-6: False traffic sign classification, (a) one missing detected traffic sign (b) remaining segments used in classification

5.3. Summary

From the error assessment result, it is noticed that both of tree and traffic pole-like objects detection increase through proposed algorithm in this research. By proposing a new rule-based tree detection algorithm, over 90% of trees points are detected correctly while only 63.5% in the previous existing algorithm. After optimizing threshold values through statistically analysis, 80.9% of traffic pole-like object points are detected and 87.5% of them are correctly recognized. A new knowledge-based classification algorithm is proposed to further classify the detected pole-like objects. 82% of traffic sign, 84% of lamp post, 74% of traffic light and 31% of others are classified correctly, in which all of the pole types' detection accuracy except others increase clearly. Although the proposed classification cannot success under all circumstances, it is still convincing that the proposed algorithm is feasible in the pole-like objects detection.

After the detection, two different evaluation methods are used to show the performance of the proposed algorithm comprehensively based on the point wise and object wise. At first, the evaluation is carried out automatically through matching the result dataset with reference dataset based on point wise. The entire detection and classification algorithm is processed automatically in C++ programming language. By the automatically evaluation, the accuracy of the objects detection can be calculated directly. The advantages of the automatic evaluation include that, on the one hand, it will reduce much time consuming on manual visual examination and calculation consuming. On the other hand, the immediately evaluation result is beneficial to the algorithm optimization. Once the evaluation result is generated, a new optimization loop can be carried out and then check the result immediately. Then an object wise evaluation is proposed through visual examination to show clearly how the algorithm performs. From the evaluation result, it concludes that the proposed algorithm obtains improvement in different aspects and achieved more reliable performance than the existing algorithm.

6. CONCLUSION AND RECOMMENDATION

6.1. Conclusion

The main objective of this research is to optimize detection algorithm of pole-like objects in mobile laser scanner data based on existing algorithm by (Pu et al., 2011). The procedure consists of five phases: at first, rough classification is applied using surface growing algorithm to group unstructured laser points together, in order to remove the ground surface as well as the large building facades, and keep the on-road segments as input in next phase. In the second phase, connected component analysis is utilized to connect laser points into component. Once a series of geometric and pulse count information are calculated, a rule-based tree detection algorithm is determined to detect the trees and separate them from other on-road objects. In the next phase, by using percentile-based pole detection algorithm, the pole-like objects are detected from the remaining on-road objects. In the fourth phase, knowledge-based classification is put to use on the detected pole-like objects, based on the characteristic of segments after removing the vertical pole part from each component, to further classify the detected poles. The last phase is the evaluation, which looped throughout the entire optimization process to achieve the optimal result.

The performance of the proposed algorithm was validated then. The testing area comprises nine road parts, which including five types of pole-like objects: tree, lamp post, traffic sign, traffic light and others. The reference dataset is generated through labelling each component manually corresponding to the same five types based on human visual examination and image interpretation. Once the evaluation is completed, the evaluation result is checked to determine whether the result is good enough to meet the satisfied output. If the result is not good as output classified laser points, the optimization would start again and loop straight forward until getting the satisfied accuracy. From the evaluation result, we notice that the overall accuracy for the pole-like objects is feasible to detect the pole-like objects. Although the final detection accuracy is not very high in this research, it still achieves an improvement when compared with the existing algorithm, and it is demonstrated the possibility of applying the proposed processing in the actual application. Meanwhile, this proposed algorithm worked automatically enough to reduce extra calculation consuming and onerous human visual examination. Several conclusions can be stated through analyzing the evaluation result.

- Since the difficulty in separating the sharp edge between two objects, such as the edge between building facade and road surface, surface growing algorithm is an efficient method to remove the ground surface and large facades well. By redefining the on-road segments, many removed pole-like objects in the existing algorithm were kept and taken into consideration again in this research.
- Connected component analysis can group the laser points in the same object together. After the component is derived, the attribute of component features can be used to determine a decision tree for rule-based tree detection. The area of MBR, ratio of width and length of MBR, height of component, percentage of multiple pulse count points of each component are used in the rule-based tree detection algorithm. In which, the pulse count information not utilized in the existing algorithm, was proven to be the most efficient attribute on the tree detection.
- Based on the evaluation result, it was noticed that over 90% points on tree were detected correctly from the unstructured laser points. It demonstrated that the proposed rule-based algorithm was convincing to be used for tree detection in actual application.
- From the achieved confusion matrix of the error assessment, the proposed automatic knowledge-based classification was demonstrated to achieve an improvement of the existing algorithm, even if it cannot success under all circumstances.
- Due to additional structures attached on the pole, percentile-based pole detection algorithm was much better than taking the whole component into consideration. After statistically analyzing the

adopted parameters, optimal threshold values were determined and then generated higher pole detection rate than the existing algorithm.

- The classification was done based on the object features in the road environment, however it can applied in other environment such as urban, indoor, through analyzing the characteristics of objects to define different object features.
- The achieved result indicated that the proposed framework was feasible to detect and classify the pole-like objects on road environment. Based on the evaluation result, more than 90% of tree points were detected correctly, more than 80% of pole-like objects were detected from the unstructured laser point cloud and in which 87.3% of pole points were detected correctly on the already detected pole objects. It is concluded that, after proposing a new rule-based algorithm and knowledge-based classification, a large percentage of missing poles in the existing algorithm can be detected correctly. After statistically analyzing the adopted parameters, the detection accuracy is obviously improved than the previous one.

6.2. Answers to research questions

- Analyze the existing pole-like objects detection algorithm
  - What are the factors affecting the performance of the algorithm?

  After analyzing the existing algorithm, several problems were found. One point is the threshold values for segmentation, filtering and detection algorithm need optimization. Then, existing algorithm is too harsh to detect occluded and thick tree trunks, so that another detection algorithm is needed to propose.

- Improve the existing pole-like objects detection algorithm
  - What is the more suitable classification of the road furniture including further categories?

  In the existing algorithm, laser points were classified into three categories: ground surface, on-ground segments and off-ground segments. Only on-ground segments were taken into consideration in the next steps. However, some segments of interest were included in the off-ground points. Thus, classifying the points into ground surface and on-road and near road segments, which including the previous on-ground and part of off-ground segments, would keep more potential pole-like objects as input for next step.

  More classes were classified, more beneficial to the traffic application. Therefore, after detecting the pole from road environment, the pole-like objects would be classified into five types: tree, lamp post, traffic light, traffic sign and others to specific the pole-like objects in traffic environment.

  - How to optimize the parameter setting, e.g. threshold values, in the extraction algorithm to reduce the influence?

  After calculating the objects attribute from training areas, statistical analysis was carried out to determine the optimal threshold value for each parameter, and then build decision tree for further process.

  - How can we detect the tree trunks with dense foliage or branches, as well as the poles occluded by some other objects?

  A rule-based tree detection algorithm was developed in this research to detect the tree with dense foliage or thick tree trunk. The rule-based detection algorithm used the pulse count information of laser points, which was verified as the most efficient element, and a series of geometric attributes to determine the best rules of decision tree to be used in the tree detection algorithm.

- How can we distinguish different types of pole-like objects from the 3D laser point clouds?

A knowledge-based classification algorithm was adopted in this step, which focused on the characteristic of remaining segments of each component after removing vertical pole. The size, height, shape and reflection intensity information of segments were utilized to classify different types of pole.

- Are there any other data resources can be used to improve the detection accuracy?

As mentioned above, due to the characteristic of different road furniture, not only the coordinate information, but also the pulse count information and reflection intensity information can be utilized in this research to improve the pole-like objects detection and classification.

- Evaluate the detection algorithm after modification
    - What is the completeness of the pole-like detection algorithm after improvement? What is the correctness of the pole-like detection algorithm after improvement?

Evaluation was automatically carried out in this research by point wise comparison of automatic classified point data and reference point data, which corresponding to five types of pole: tree, lamp post, traffic light, traffic sign and others. Completeness, correctness and accuracy were used to show the final result and performance of the proposed algorithm. Based on the evaluation result, we noticed that the proposed algorithm can classify 91.2% of trees, 80.8% of traffic sign, 84.2% of lamp post, 74.1% of traffic light and 30.5% of others based on point wise in road environment. In addition to this, object wise assessment was also presented to show the algorithm performance, in which 83.3% of trees, 85.3% of lamp posts, 65.4% of traffic sighs were detected correctly; all of the traffic lights were detected while 16.7% were false detected and 76.9% others pole were detected in which 23.1% of them were false positive detection.

6.3. Recommendation

The proposed algorithm is validated to get basically accurate result. However, since the knowledge and time limitation, some aspects need further work and several recommendations are listed below based on the current research:

- The proposed algorithm has been tested on part of the overall dataset, so if there is enough time, the proposed method can be tested by the whole dataset even another dataset which locating in another street or city or country.
- In this research, proposed rule-based tree detection algorithm has detected the trees with large tree crown or containing number of multiple pulse count points. In the future work, the trees, which include small tree crown or have limited pulse count information need further research.
- Other objects but not the pole-like objects would affect the detection accuracy has been discussed in section 5.2.2. In the further research, it is possible to remove all of the segments behind the facades once the building facades have been detected, which based on the general knowledge that objects behind the facade will not be the pole-like objects of interest. After removing such objects, the detection accuracy would be more accurate.
- Since the lamp posts are often distributed regularly in both sides of road (Figure 5-4(b)) which has been discussed in chapter 5, the contextual information can be used to give a hint on the location of lamp post if it is connected with or occluded by other objects like trees.
- Since the much richer texture and colour information provided by imagery is beneficial to recognize the traffic sign based on knowledge recognition, which is discussed in section 5.2.3, the combination of laser points and imagery should be investigated in the future.

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