AUTOMATIC DETECTION OF TEMPORARY OBJECTS IN MOBILE LIDAR POINT CLOUDS

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February, 2014

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ABSTRACT

The problem of road safety is becoming serious in Europe in recent years. The current situation of the road safety is necessarily essential improved due to the climbing tendency of accidents and deaths increasing. The mobile mapping system for collecting 3D information with high quality is becoming popular in assessing the road safety circumstance. Since temporary objects are less relevant or interesting for the application on road safety assessment, they need to be removed from the MLS data. The manual detection is tedious and inaccurate since the subjective mind would be included. Therefore the automatic temporary object detection is required as it could provide valuable information rapidly and at a low cost.

An automatic temporary objects detection algorithm using mobile LIDAR point cloud is proposed in this research. There are five main phases in this proposed algorithm: laser data pre-processing, segmentation, feature extraction, classification and evaluation. First of all, the dataset is divided into 12 road parts for easy handling. In the next phase, the surface growing algorithm and connected components analysis are utilized to remove the ground surface and group unstructured laser points into objects. In the third phase, shape features, contextual features and other useful features for the detection of temporary objects especially cars are extracted as a feature table. The feature table is utilized as the input of the classification in the fourth phase. Two different classifiers are used with forward selection and backward elimination as feature selection methods for the classification. Thus the temporary objects and static cars are detected respectively. Finally, the result is evaluated by computing completeness, correctness and overall accuracy. There are two ground truths for evaluation. One is collected with six classes, which contain static temporary objects and moving temporary objects, while another one including the combination of this two classes.

The evaluation of the algorithm is carried out by comparing the result with the reference point cloud data. The evaluation of the dataset with 5 classes and 6 classes are done separately. Based on the result of the evaluation, the detection of temporary objects reaches a completeness of 1.00, correctness of 1.00 and correctness of 1.00. In addition, the detection of static cars reaches a completeness of 0.94, correctness of 0.94. A discussion following the evaluation and several recommendations for further research are given at last.

Keywords:
Mobile Laser Scanner (MLS), feature extraction, classification, object detection, temporary object detection, car detection

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1. INTRODUCTION

1.1. Motivation and problem statement

The problem of road safety is becoming serious nowadays. With the development of economy and technology, an increasing number of vehicles are being used by European in recent years. However, this situation leads to a climbing tendency of accidents and deaths occurred on the European roads which makes the road safety problem a hot issue. It is definitely necessary to improve the current situation of the road safety. There are three main areas that influence road safety: vehicle, driver behaviour and route environment or infrastructure (McElhinney et al., 2010). Among these, the environment or infrastructure safety assessment is an important aspect for the improvement of the road safety. Under this circumstance, mapping road environment and extracting information about road-side objects can help inspect the safety of the roads.

Methods for extracting information, in particular 3D objects under road environment have been developed by many researchers. The traditional methods of 3D object extraction are manual or semi-automatic detection of objects from terrestrial surveying or photogrammetry. However, these methods are time-consuming and have low accuracy owing to the operational mode. In addition, there are quite some problems in acquiring 3D data. For instance, it is difficult to obtain complete and consistent 3D objects from 2D images (Pu, 2008). Since LIDAR technology has been developed rapidly in recent years, it is commonly used by researchers due to its high accuracy and detailed geometric feature extraction of 3D spatial information.

Laser scanning technology enables the acquisition of point data by a laser scanning device mounted in three ways: in a fixed or rotary winged aircraft (Airborne, ALS), placed on ground stations (Terrestrial, TLS) (Riley and Crowe, 2006) or Mobile laser scanning (MLS) which performs as a currently developed approach for three-dimensional spatial data acquisition in a rapid and cost-efficient way (Rieger et al., 2010). ALS data has been widely used in city modelling since it gives precise georeferenced point clouds, and TLS can also provide high quality point data which is better for detailed geometric features (Holopainen et al., 2011). However, ALS cannot capture in sufficient detail all road-side objects that are necessary for road safety inspection, and TLS is very slow for capturing large areas. In comparison with ALS and TLS, MLS performs better in capturing road-side objects because of its greater flexibility and acquisition speed and capability to capture details of the road environment (Lehtomäki et al., 2010).

In terms of the application (road safety assessment) of 3D road data acquisition, permanent objects such as buildings, rivers should be preserved while temporary objects such as pedestrians, driving and parked cars should be removed from the MLS data since they are less relevant or interesting for different applications. The temporary objects can also be separated into two types: static temporary objects and moving temporary objects. Static and moving temporary objects mean that temporary objects are static or moving respectively during the period that the LIDAR point clouds are taken.

In order to remove the temporary objects, their detection in the point clouds becomes very important. Several studies have already been done to detect objects. The point clouds can be classified into detailed object classes by collecting the size, the shape, orientation and topological relationships of point clouds segments (Pu et al., 2011). There is also another method to compare the calculated feature vectors in the data with the reference object library to detect objects (Bielicki and Sitnik, 2013).

The best mode of the operational ways is automatic detection and removal of temporary objects from mobile LIDAR point clouds. In comparison with the manual and semi-automatic methods, the automatic type can operate much faster and more accurate. For instance, due to the distribution of the points, it is unreliable to select the same group of the points for the same object manually at different times. However, the program can achieve it and select the same group every time, and meanwhile the process is less time-consuming than the manual way. But the automatic way has some problems as well. The automated extraction from high density point clouds is difficult because of building shadows and trees which lead to unreliable and incomplete objects (Yang et al., 2013).

Considering the significance of detecting temporary objects from MLS data, several studies have been reported. However, still a robust and automatic technique in detecting both static and moving temporary objects is lacking. In this thesis, considering the motivation and problems mentioned above as well as the advantage of MLS, this study is motivated towards developing an automatic method for detecting temporary objects with focus on static objects (while another MSc thesis is focusing on moving objects), especially cars, from mobile LIDAR point clouds.

1.2. Research identification

1.2.1. Research objectives

The overall objective of the proposed research is to automatically detect temporary objects from mobile LIDAR point clouds, with the focus on the detection of parked cars as static temporary objects.
This main objective can be reached by defining the following sub-objectives:

1. Analyze the existing automatic static temporary object detection algorithms.
2. Extract cars from mobile LIDAR point clouds by considering different feature extraction methods.
3. Evaluate the detection algorithm after improvement.

1.2.2. Research questions

The following research questions need to be answered to achieve the sub-objectives mentioned above:

1. What characteristic properties are relevant to the detection of cars?
2. How could the shape of a car be described with some measures?
3. How to evaluate object extraction (in this research it refers to cars) from point clouds?
4. How to collect ground truth to evaluate the performance of the algorithm?
5. What is the performance (in terms of completeness and correctness) of the algorithm?

1.2.3. Innovation aimed at

The innovation intended in this MSc research is detecting static cars by considering their specific characteristic properties for instance shape features and contextual features which have not been taken into consideration by the previous researchers.

1.3. Thesis structure

The thesis is divided into 6 chapters in order to achieve the objective and answer questions which contribute to the objective. Chapter 1 includes the overall introduction of the thesis which contains the motivation of the research and problem statement and research identification. Chapter 2 reviews the theoretic backgrounds of the object detection method that are relevant to our research. Chapter 3 explains and describes the proposed method in detail. The framework of the methodology is given at first and then the explanation for each step is followed. Chapter 4 describes the implement and result of the proposed methodology for the research as well as the assessment of the training result by considering the completeness and correctness. Chapter 5 discuss the result and the evaluation of this research. In the last Chapter 6, the conclusion of the research, the answers to the questions and recommendation for future research are presented.

2. LITERATURE REVIEW

Theoretical background of this research and previous researches are presented in this chapter. Most of the existing methods follow a similar procedure: ground filtering, segmentation, feature extraction and classification. Therefore in this chapter based on these steps and in each section the related literatures are reviewed. Section 2.1 describes the principle of laser scanning and especially mobile laser scanning. Section 2.2 describes the point cloud segmentation of the point cloud data which is normally the first step for the object detection. The previous researches of the static object detection are reviewed in section 2.3. Finally a short summary of the reviewed researches is given.

2.1. Principle of laser scanning

2.1.1. Laser scanning

The technology of laser scanning has been reviewed in various of literatures (Marshall and Stutz, 2004; Vosselman and Maas, 2010). The principle of laser scanning which is generally used includes data acquisition; data processing and object extraction from LIDAR data are included in the literatures. The distance between the sensor and target can be measured by the principle. Light transit time estimation and triangulation are being used as two basic active methods for optically measuring (Vosselman and Maas, 2010).

Light transit time estimation is also known as time-of-flight or LiDAR (light detection and ranging) system. It makes a convenient way to evaluate distance by measuring the time delay which is generated by light travelling from a source to a reflective target surface and return to a light detector. Phase measurement in continuous wave (CW) lasers can also show the measurement indirectly. Figure 2-1 shows the time-of-flight principle.

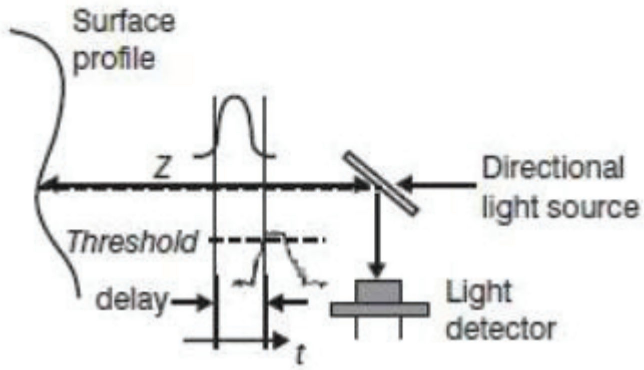


Figure 2-1: Light transit time for optically measuring 3D surface (Vosselman and Maas, 2010)

Formula 2-1 shows the calculation of the distance Z from the sensor to the target. The known velocity is c while Δ t is the time delay.

$$Z = c^* \Delta t/2 \qquad (2\text{-}1)$$

Triangulation constructs a triangle by using an illumination direction (angle) and an observation direction (angle) from the source to exploit the cosine. The triangulation principle is often used for measuring distances smaller than about 5 m while light transit time estimation is usually used for mid- and long-range laser scanners (Vosselman and Maas, 2010).

2.1.2. Mobile laser scanning

Mobile laser scanning (MLS) which performs as a currently developed approach for three-dimensional spatial data acquisition in a rapid and cost-efficient way (Rieger et al., 2010). A good overview for mobile laser scanning system with camera systems is presented in (Ellum, 2002). Mobile laser scanning (MLS) performs very well in obtaining points clouds which have high density (Pu et al., 2011). Shan and Toth (2008) give a comprehensive review of mobile laser scanning system on device and platform. Figure 2-2 indicates the components of MLS system in the research of Rieger et al. (2010). The system contains a 3D-laser scanner as a core component besides the differential GPS, Inertial Measurement Unit (IMU) and Distance Measurement Instrument (DMI). The use of 3D-laser scanner in mobile laser scanning is a new technique which gives a suitable way to acquire data for boresight alignment determination. The new method proposed a possible way to determine the boresight angles of MLS system. It analyzes the scan data if the planar surfaces of the area are provided.

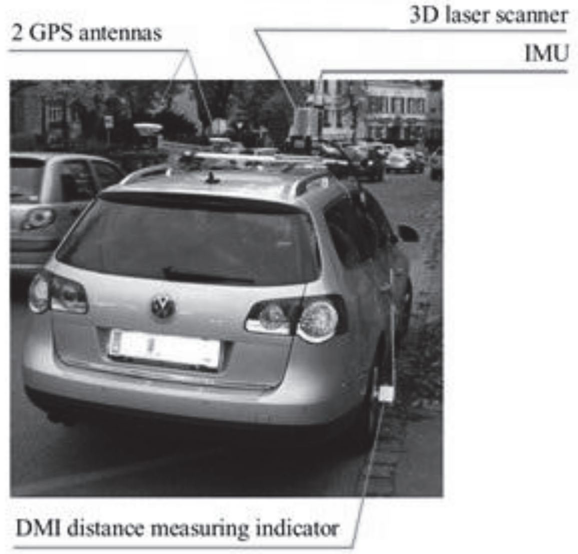


Figure 2-2: Experimental mobile laser scanning system mounted on a car (Rieger et al., 2010)

2.2. Point cloud segmentation

Normally, a large dataset contains a large amount points are given as the original dataset for the research. However, it is hard to deal with a huge dataset initially. The main objective of the laser data pre-processing is dividing the total strip into small road parts for the purpose of easy handling. In the pre-processing for detecting temporary object from LiDAR point cloud, filtering is usually the first step while segmentation is the second one. The point cloud normally involves not only the ground but also on-ground objects. The ground always contains large quantity of points. For the purpose of detecting on-ground temporary object, he points of the ground should be removed by filtering at first. Vosselman (2000) proposes a slope based filtering method which has been used by many researchers.

The amount of the point cloud is decreased after filtering. However, the dataset from any scanner is still not small enough for object detection. Segmentation which can be used to extract surface in point cloud is widely used to reduce the time consuming for computation. The scan line segmentation method is introduced by Vosselman et al. (2004) and Rabbani.T et al. (2006). Each row can be considered as scan line independently. Each scan line will makes a 3D line segments and the similar criterion is used to combine adjacent lines. Jiang and Bunke (1994) assume that a straight 3D line comes from the points on a scan line in their scan line segmentation method. A triple of line segments is presents as a seed region which can satisfy the conditions of the minimum of line segments, the minimum overlap of all segments and the maximum distance of the pairs of points on two scan lines.

Pu et al. (2011) present an intuitive method for point cloud pre-processing so as to divide the dataset into small road parts and separate the on-ground points and the ground points. In this method, they present a framework for recognizing objects from mobile laser scanned point clouds. In the first pre-processing step, the raw MLS data are partitioned along road directions as sub regions called road parts, for which the surface growing algorithms (Vosselman et al., 2004) is applied in the segmentation. The direction of the road can be acquired from either map or trajectory data. Meanwhile the length and width are specified manually. Planar seed surface detection in 3D Hough space is used for this segmentation method.

2.3. Static object detection

Various methods for static object detection have been developed after the segmentation. The two main steps in this research for static temporary object detection are feature extraction and classification. Thus in this section the literature of feature extraction and classification will be reviewed in sequence.

2.3.1. Feature extraction

In this stage features are extracted describing the difference among objects. Features generated here must distinguish object types from one another since it will be used automatically in the following stage.

The shape of objects and contextual information are the features which can be acquired easily. Golovinskiy et al. (2009) investigate both of the features in their research. The shape feature which contains the number of points of an object, the estimated volume, average height of the similar objects and standard deviation in both height and horizontal directions are introduced. The orientation of the object is invariant when the shape is described. The contextual feature which includes useful information shows the position of an object in relation with the environment. The shape feature such as size, height density will be used while contextual feature such as position (the distance from object to the trajectory) will be introduced in this research in the next chapter.

In the research of Pu et al. (2011) the knowledge based feature recognition method has been used. The main idea of the method is to develop an agent that based on computer to achieve the recognition task without manually assistance; while acquire the result similar to the manual recognition. The quality of sensor data and the complexity of the target feature type will extremely important in deciding the selection of an appropriate reason engine. Normally, data driven approach is utilized for the data that has a high quality and/or a complex feature type. Model driven approach is utilized for the data that ahs a low quality and/or a simple feature type. Authors adopt both of the approaches in their research for geometric features (for instance size, position, orientation, shape, color, material) and semantic features which are based on geometric features respectively. Besides geometric attributes the topological relations including intersect, angle and perpendicular are also taken into consideration.

M.Bremer et al. (2013) develop a method for object extraction by taken eigenvalues of each component into consideration as a feature. The eigenvalues are derived from 0.1m and 0.5m radius and each point is characterized by it. In the feature spaces an analysis is performed for the linear, planar, volumetric feature patterns for each point. The points are gathered into three classes for both radiuses. The orientation of the longest eigenvector is used for linear structure while the smallest for planar so that the vertical and horizontal structures can be derived. The orientation for volumetric structures is not defined. On both scale level the eigenvalues, eigenvectors and the vertical angles between the largest and smallest eigenvectors are calculated from covariance matrices. The advantages and disadvantages are obvious due to the different radius search method. The small geometric model and discontinuities obtain a favorable description of the 0.1m radius, however; it is sensitive to scanning patterns, data gaps and densities. In contradistinction to this, the 0.5m approach performs well in larger poles detection and planars which has lower densities as roofs is detected apparently. But the edges and discontinuities suffered blur influence in this approach which is straightly cause the volumetric patterns for object that have lower densities.

Based on the eigenvalue which has introduced above, Chehata et al. (2009) develop the feature selection method by using anisotropy, planarity, sphericity and linearity (Gross and Thoennessen, 2006). They define the three eigenvalues $\lambda_1 > \lambda_2 > \lambda_3$ as features. The discrimination among planar, edges, corners, lines and volumes can be represented by the four additional features which can describe the distribution of points in space. The four features are defined as follow:

$$\text{Anisotropy} = A_\lambda = \frac{\lambda_1 - \lambda_3}{\lambda_1} \quad (2\text{-}1)$$

$$\text{Planarity} = P_\lambda = \frac{\lambda_2 - \lambda_3}{\lambda_1} \quad (2\text{-}2)$$

$$\text{Sphericity} = S_\lambda = \frac{\lambda_3}{\lambda_1} \quad (2\text{-}3)$$

$$\text{Linearity} = L_\lambda = \frac{\lambda_1 - \lambda_2}{\lambda_1} \quad (2\text{-}4)$$

The eigenvalue λ_3 has a higher value for non planar objects than planar ones. Object which has an obvious property in one aspect will have a higher value among the four attributes. For instance, pole-like objects get a high linearity value while a low planarity value and the planarity will show a high value in plane surface conversely. By using these features, buildings will be discriminated from vegetations and pole-like objects can be easily detected.

Bounding box strategies are widely used as an intuitional approach(Chen and Kurfess, 2004). Barequet and Har-Peled (2001) introduce the algorithm for the minimum-volume bounding box and Chen and Kurfess (2004) develop several new bounding box methods. In the process of initial guessing based on the certain principle an axis-aligned bounding box method and minimum bounding box are developed. These methods are used for providing parameters with higher accuracy. The advantage of the axis-aligned bounding box method is that it is easy to implement and running fast. The performance of this method is effective when the assumption of an extremely complete point cloud and an axis-aligned point cloud are met. The advantage of the minimum bounding box is that the point cloud orientation can be compensated initially so that a more robust estimation will be provided for different point clouds. In comparison with the first method, it is particularly effective only if the assumption of whole point cloud is met. However, it is difficult to handle every point cloud by using these methods so that further improvement is still demanded.

2.3.2. Classification

Classification always plays the last stage of the previous object detection researches. Features vectors will be labelled by using classifiers. The labelled object will be obtained and each associated with a set of points.

In the literature of Golovinskiy et al. (2009), In the final phase of classification, feature vectors are labelled by using a classifier trained on a set of manually labelled objects. Background objects are not included as training set so locations away from truth objects are automatically generated as 'background'. Then several classifiers such as k-neighbors (NN) and support vector machines (SVM) are used for the classification. The completeness of the system is 65% for the objects in their test area.

A segment-based classification approach for object detection is introduced in Khoshelham and Elberink (2012) and Khoshelham et al. (2013). The previous step of segmentation groups the individual points into sets. Then features are extracted for each segments which will be used for the finally classification step. The segments are classified by a trained classifier. The main purpose of classification in statistical pattern is finding a discriminated function which is learned from training samples between features. The quantity of training samples and features and the complexity of classifiers will strongly influence the performance of a classifier (Jain et al., 2000). Khoshelham and Elberink (2012) use three classifiers for the analysis of the classifier complexity. The feature selection approach is used when the training samples is not enough for a classifier with many features. It improves the performance of the classifier obviously. The less complex classifiers give a better result when training sample takes a small proportion of features. Khoshelham et al. (2013) consider two classes to classify the segments that helps improve the result of classification. However, a sufficient training sample and an adequately training are essential to reach a acceptable classification accuracy.

2.4. Other method for object detection

In the paper of Khoshelham (2007), a new approach to the detection of 3D objects with arbitrary shapes in point clouds as an extension of the generalized Hough transform is proposed. This 3D GHT method uses a surface normal vector to replace the gradient vector. Then a 3D model is stored in a 2D R-table. After that, the method for the detection of instances of the model in a point cloud based on a voting process is described. In this paper, the author quantizes the 7D space of 3D translation, rotation and scale for object detection. This creates a trade-off between pose accuracy and computational requirements, the latter being proved to be costly. The author suggests cost-reduction strategies, for instance randomized voting process for 3D GHT algorithm.

A method for automatic object localization and recognition in 3D point clouds which based on the implicit shape models (ISM) framework is proposed by Velizhev et al. (2012). This method could recognize objects by voting for their centre locations. Users only need to set parameters for detection due to the automatic operation system. The process is split into two consecutive steps. In the first step which named object hypotheses generation, a list of putative objects represented by their associated set of 3D points can be obtained. The second step is recognition. It combines visual dictionaries and the generalized Hough transform as the implicit shape model (ISM) framework to reach the aim of recognizing and localizing objects within each component. The voting process is used here to obtain a list of potential object centres with their associated probabilities for each class.

Rusu et al. (2009) build a Point Feature Histogram (PFH) of two-point descriptors from all neighbouring points of the reference point. The authors also build a new Fast Point Feature Histograms (FPFH) by reducing the computation times through caching previously computed values or revising theoretical formulations. They use point-based representation of objects as preliminary data source. Then an innovative solution for the characterization of the surface geometry around a point is given through the formulation of a PFH 3D feature. Finally, a Sample Consensus based initial alignment algorithm method (SAC-IA) is used to search in an exhaustive FPFH correspondence space to find a good alignment solution in a faster way.

2.5. Summary

The technology of laser scanner is reviewed in this chapter and MLS performs better in capturing road-side objects due to its flexibility, speedy and detail capture capability. Based on the review of existing researches, features are not sufficiently used by the researchers and most of them focus on the detection of on road furniture detection. Therefore, a method which could quick and fully automatic extract temporary objects from the point cloud is still lack. In the next chapter, the method for automatic detection of temporary objects is introduced.

3. METHODOLOGY

In this chapter, the workflow which is used to achieve the objective of this research will be elaborated sequentially. As mentioned in chapter 2, the main process as well as the expected result of the research will be described in section 3.1. After the proposed methodology workflow given, the detailed analysis for each process will be illustrated in the following sections.

3.1. Framework of methodology

The framework of the proposed methodology is given in Figure 3-1. There are five main phases in the research: laser data pre-processing, segmentation, feature extraction, segment-based classification and evaluation.

In the first phase the total strip is divided by set parameters as length and width. All the points in each part of the strip are separated into ground points and non-ground points by surface growing algorithm at the beginning of the segmentation phase. Then, connected component analysis is applied as most of the temporary objects are considered to be a group of closest points. The components which contain few points are removed while larger components will remain. Afterwards labels will be added manually for the ground truth which will be used for the evaluation.

The following phase of feature extraction plays a significant role in the research. As the objective is detecting temporary objects especially static cars, features which can show the properties of temporary objects obviously are considered. Three types of features are described in this research: contextual features, shape features and other features. Contextual feature such as position is considered here by using the distance between the trajectory and the component. Shape features for instance size (number of points for each component), density (calculated by size and volume), minimum height (coordinate of the lowest point of the component), height of each component, area (the smallest 2D space that can cover all the points in on component). Reflective information, RANSAC, eigenvalues and their extension such as anisotropy, planarity, sphericity and linearity are applied as other features beside the above features. Then the feature table which includes all the features is made use of by classification. The advantage of each feature distinguishing objects from temporary objects will be illustrated in section 3.6.

In the fourth phase, a classification strengthened by feature selection is then performed, which assigns a label to each component. Based on the feature table, feature selection methods such as forward selection and backward elimination are applied to extract temporary objects from others. Objects with different labels as building, temporary object (static/moving), tree, lamp post and other object obtained as classified dataset finally.

The performance of the proposed method is assessed in the last phase. Both of the visual performance and labelled ground truth are used to evaluate the result. Completeness, correctness and overall accuracy of the relabelled data are calculated. If the accuracy is not satisfied enough, the work should start from the beginning again until getting the acceptable result.

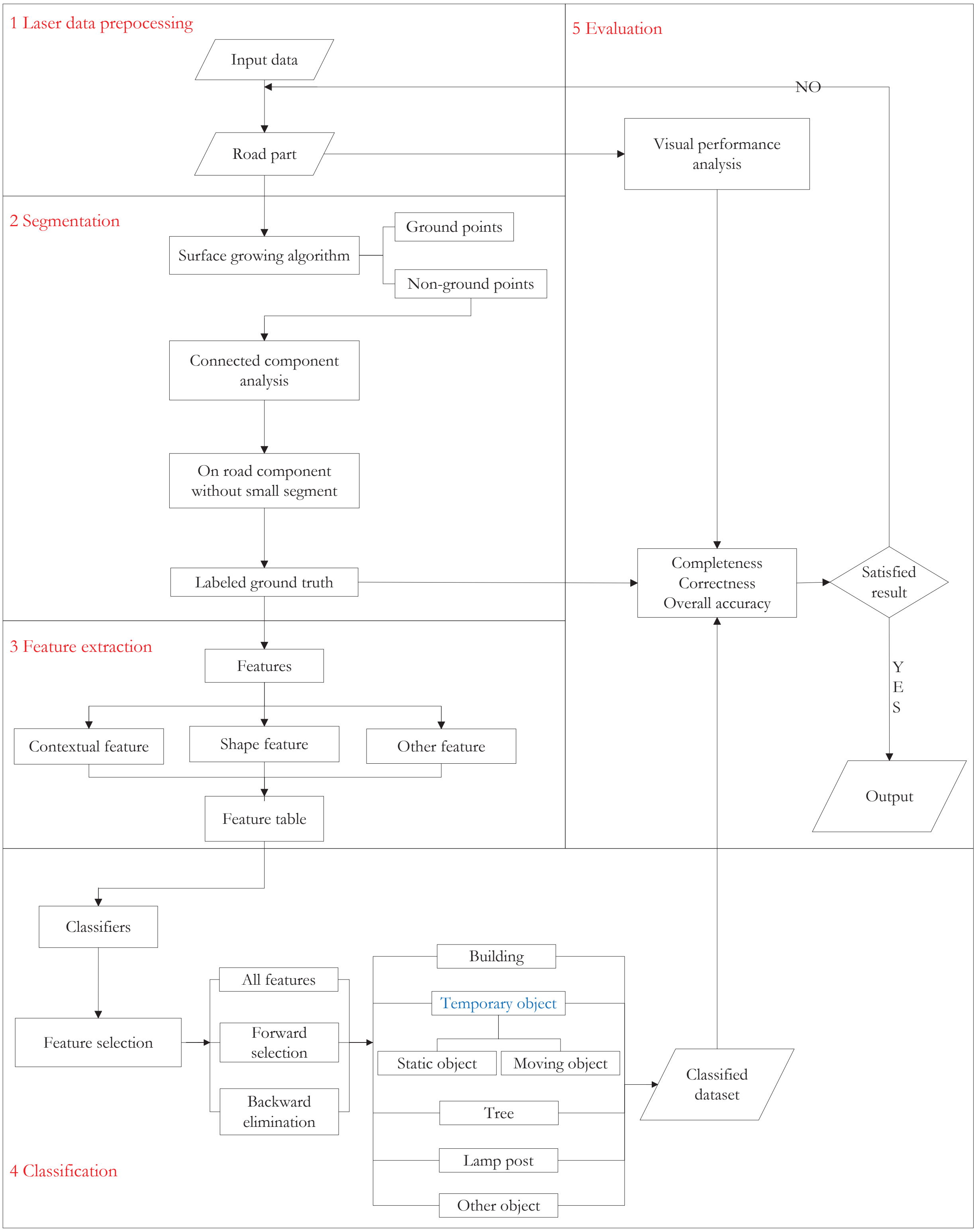


Figure 3-1: Framework of the proposed methodology

3.2. Laser data pre-processing

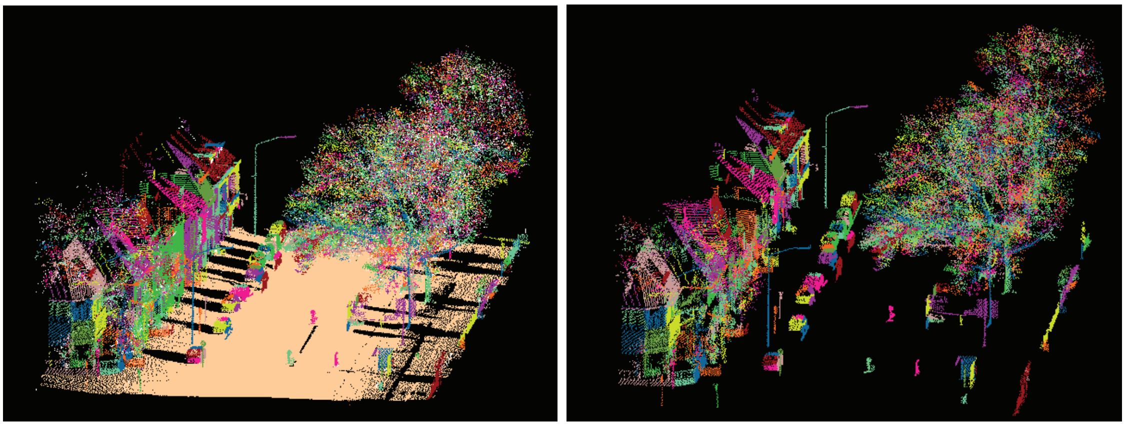
It is really a challenge to deal with a laser point cloud which including large amount of data. As shown in Figure 3-2 the dataset is partitioned into multiple parts initially and then to extract the information of interest locally. In comparison with the airborne laser data which are normally based on tiling along X and Y direction, mobile laser scanner data are usually scanned from few objects along but far away from the roads. The road direction is obtained from MLS trajectory data. The size of each road part for instance the length and width can be set up manually.

3.3. Surface growing segmentation

The surface growing algorithm (Vosselman et al., 2004) is used for the segmentation of the laser point cloud in each road part after the spatial partitioning. Surface growing algorithm in point cloud is similar to the region growing algorithm in images. The method for identify seed surfaces and principle for group adjacent points are necessary to apply this algorithm. There are various methods for seed selection, for example the brute-force method, robust least squares adjustment of planes and Hough transform-like detection of planes. In this applied segmentation method, the planar seed surface detection in 3D Hough space is utilized. Two main steps are included in the surface growing segmentation. Initially, a planar surface is taken shape by grouping the adjacent points. Least square or the 3D Hough transformation method is used for fitting planar surface to the grouped points. By including checking the residual values, the planar surface with a residual below setting threshold. In the following growing step neighbouring points within a given distance to the plane are added. Normally, as soon as a further point added to the plane the parameters of the plane are updated. However, the parameters are re-estimated after certain percentage of points added to the segment if the quantity of neighbour is large. If the defined growing criteria are exceeded after the processing, the points can be added to the segment. Since more complex objects are composed by planar segments, the derived laser segments performs good as the basic elements for the recognition of ground surfaces and walls. Besides, the comparison of normal vector of local surface which formed by the neighboring point and the growing plane can be used to check the distance to the plane. Parameters which are selected in the algorithm are not critical since it is easy to recognize the surface that mentioned above. The influence for the detection of the objects on the road surface can be ignored if the over-segmentation or under-segmentation small enough.

3.4. Removal of ground points

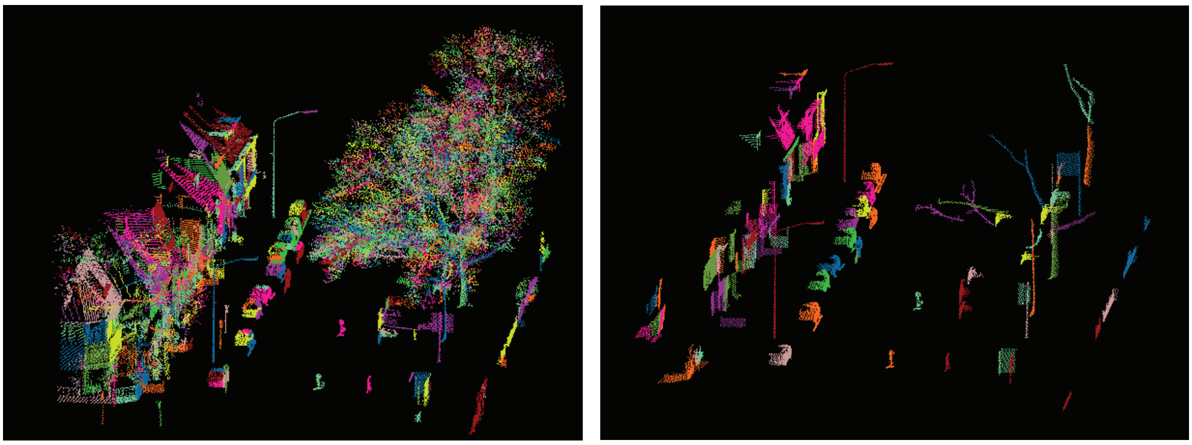
Due to the purpose of this research is the detection of the object on the ground, the ground points which always take the largest data volume are removed after the surface growing segmentation. The ground segments are recognized as the largest planes at the certain distance below the MLS trajectory. Based on the area and geometric centers the segments are analyzed. The segments pieces is grouped into one whole ground laser point cloud once they are located and meanwhile the 2D outline is generated. Other points are labeled as non-ground class since they connect to the ground but totally within the 2D outline. After the removing, the non-ground points are more significant for the analysis of the research and the amount of the points is extremely decreased. They will support the feature extraction as an input after be re-labeled with unique IDs in the next step. The performance after the remove of the ground points are shown in Figure 3-2.



(a) (b)
Figure 3-2: Segmentation performance. (a)Segments with ground points (b) Non-ground points segments

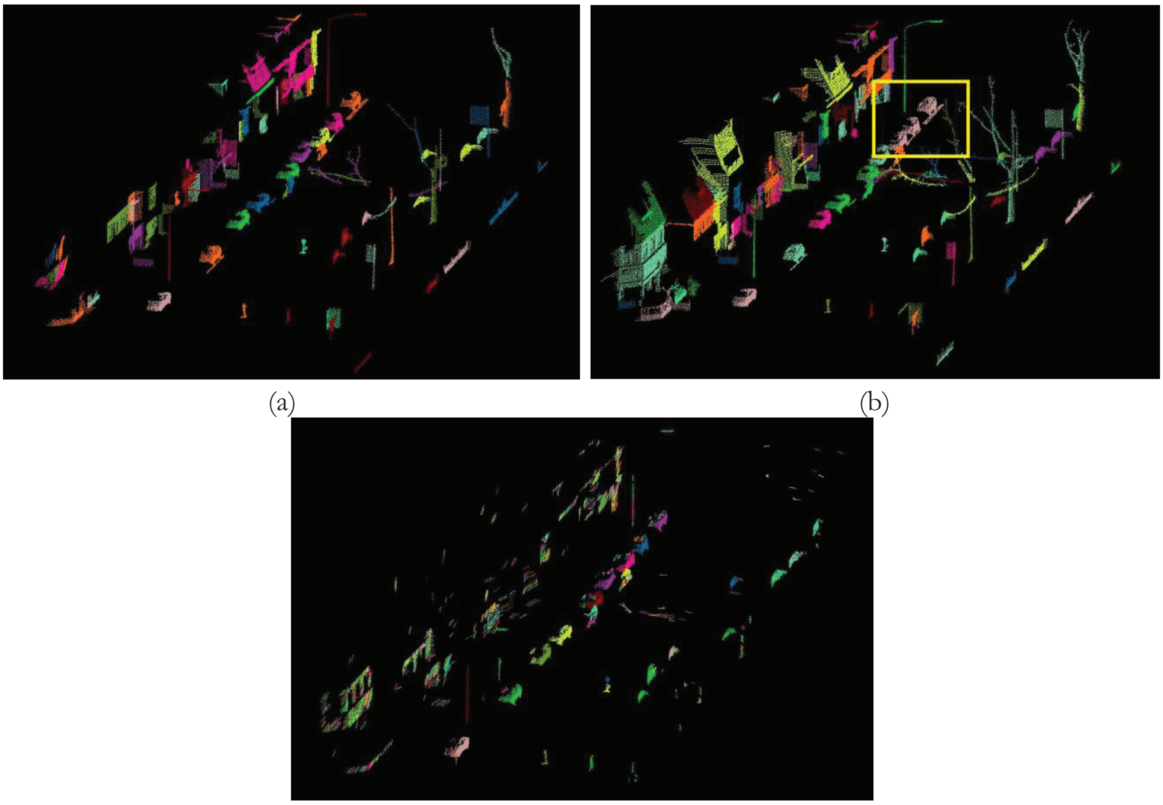
3.5. Connected component analysis

The connected component analysis is usually used for analyzing the points around the object and combining them which has similar feature. The points which is recognized as one object is shown in Figure 3-3(b). In this research, PCM is used for the connected component segmentation and the parameters of the maximum distance between points and the minimum number of points of one component need to be set. If the distance between two points within the maximum distance the two points would be merged as one component. Then the component which contains the number of points larger than the requirement would be remained while others will be removed.



(a) (b)
Figure 3-3: Result of segmentation. (a) Surface growing segmentation (b) Connected component segmentation

By using the connected component analysis, some of the objects are connected together due to the high threshold value setting. Due to this circumstance, it is extremely important to select the parameters of the segmentation carefully. For example, the under-segmentation which means two segments would be merged happens if the maximum distance between points is set too large (Figure 3-4(b)). The over-segmentation which means the supposed segment would be separated into many segments if the parameter is too small (Figure 3-4(c)). For another parameter of minimum number of points, the main objects for the research would be removed if it is set large, however; the unrelated objects would be kept if it is too small.



(a) (b)

(c)

Figure 3-4: Example of bad segmentation. (a) Expected segmentation (b) Under-segmentation (c) Over-segmentation

3.6. Feature extraction

The potential objects are represented by the segments that obtained in the previous three steps. In order to detect the objects those have different characters separately, features are extracted for describing shape and context of the object as well as some other features. Feature extraction plays an important role for the next step called segment-based classification of point clouds so that features generated in this stage must distinguish different object types one by one from the dataset. Therefore, the feature extraction method including shape feature, contextual feature and other feature is introduced in this stage.

3.6.1. Shape feature

Based on the human knowledge, the geometrical attributes of object perform as the most common features. Normally the characteristics of natural objects such as trees and bushes are different from the manmade objects such as cars and buildings. Shape features for instance size, area, density, height are introduced in this part.

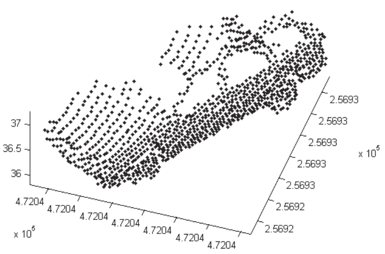
- **Size**

The number of the points of each component in the point cloud represents the size of the object. Based on the previous segmentation step, small components that contain small amount of points have been removed for example some leaves of the tree and building parts. Buildings and trees normally contain large number of points while temporary objects and lamp post have smaller size.

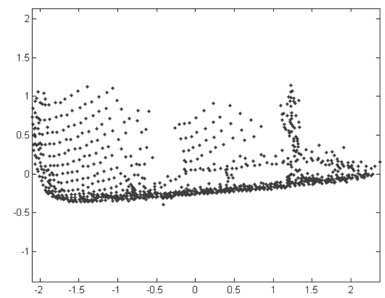
- **Area**

The measurement of area is important for the distinguishing of objects have large area from the one which has small area. For example if only consider two dimension of points, then the points would have an area of like 3 by 2 meters for cars (a small area) and for tree that will be large. It is a useful feature since for cars the horizontal projection has a certain area with small variance. It is like the most of the cars have the similar size and shape. However, for trees that could be a large value, for lamps it would be a very small value and for buildings it would also be large. Thus this feature is utilized to extract the objects have large area.

The measurement of area of the objects derives from the component after projecting on a 2D plane. It is not simple acquired from wide by length of the object. A generic function named Principal Components Analysis (PCA) is used for the calculation of area. PCA is a statistical procedure converting observations of possible correlated variables into values of linear uncorrelated variables called principal component. The PCA is the simplest true eigenvector-based multivariate analyses. The operation reveals a approach of the internal structure of the data which can explains the variance the best. PCA can use a lower-dimensional picture to visualize a dataset in a high-dimensional data space. A projection of the object is acquired from its most informative viewpoint. This can be done by using the first few principal components. Therefore, the dimensionality of the transformed data is reduced.



(a)



(b)

Figure 3-5: Area of component. (a) Component that appears in 3D space (b) Minimum area of the object in 2D space

Figure 3-5(b) shows the points that contain the maximum x and maximum y coordinate as well as minimum x and minimum y respectively. Then the area is calculated by $(x_{max} - x_{min}) * (y_{max} - y_{min})$.

- **Density**

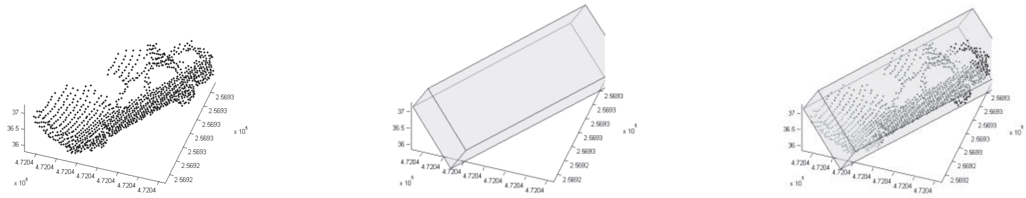
The average point density of each objects various obviously due to the position, volume and size of the component. Normally, cars have a high density since their position is close to the trajectory, the volume is small and the amount of the points for cars is high. The density for building is small because of the larger volume and lower size. The mainly reason contribute to the low density of tree is the large tree crown which makes the volume larger than any other object. Therefore this feature is significant in separating objects that have higher density from lower ones.

The volume of each object is derived by applying bounding box as mentioned in section 2.3.1. The 3D minimum bounding box computes the minimal volume of an object that completely contains the points in the set. The simple volumes are used to contain objects that have complicated geometric features in order to improve the efficiency of geometrical operation. The x, y and z perform as vectors of points in describing points in 3D space and they must be the same lengths.

Thus the density is computed as formula 3-1:

$$\text{Density} = \text{Size}/\text{Volume} \tag{3-1}$$

An example of the density is shown in Figure 3-6:



(a) (b) (c)

Figure 3-6: Process of the calculation of density of the object. (a) Size (b) Volume (c) Density

- **Minimum height**

The minimum height is the lowest z coordinates of all the points of one object. The difference among objects mainly relies on the distance to the ground. Temporary objects such as cars always stay on the ground while buildings and pole-like objects usually located on the curb stone. Vegetations such as bushes also grow in the place that has the same height as curb stone. Consequently, this feature is helpful in discriminating objects in different place.

An analysis on the average minimum height difference of each class is showed in Figure 3-7. The average minimum height is the average of several objects.

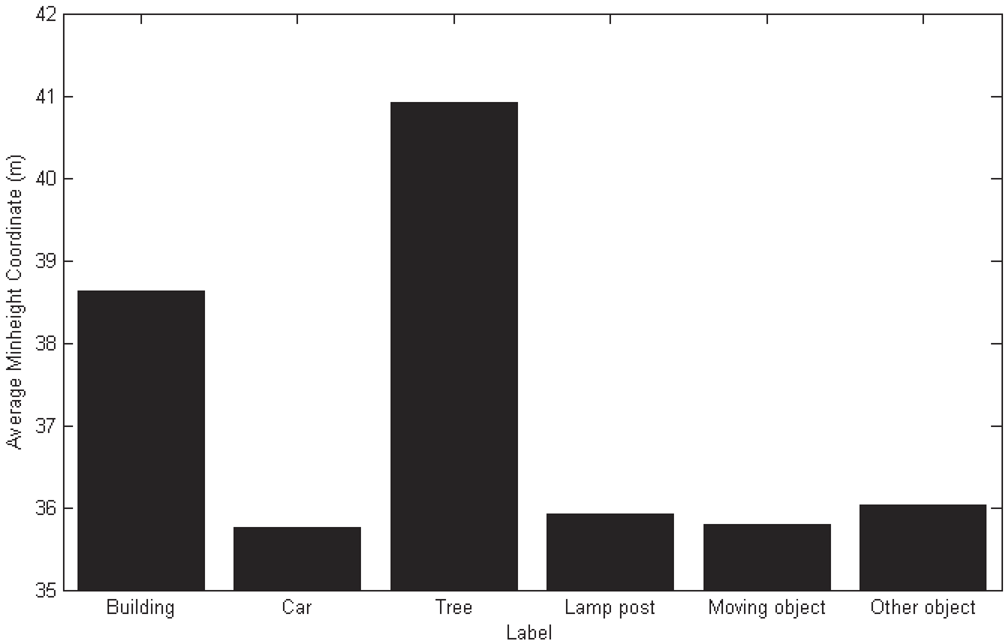


Figure 3-7: Average minimum height of 6 classes

- **Height**

The height of the object is one of the most important features as shape feature. Based on the statistical analysis, the pole-like objects are usually the highest objects which has the average height around 9m in the point clouds while the average height of cars is around 1.5m. Height is the measurement of the object in z axis from the bottom to the top. The height of the components is measured by the maximum and minimum Z value:

$$\mathrm{Height} = Z_{max} - Z_{min} \tag{3-2}$$

The analysis on the average height difference of each class is showed in Figure 3-8. The average height is calculated based on several objects in the same class.

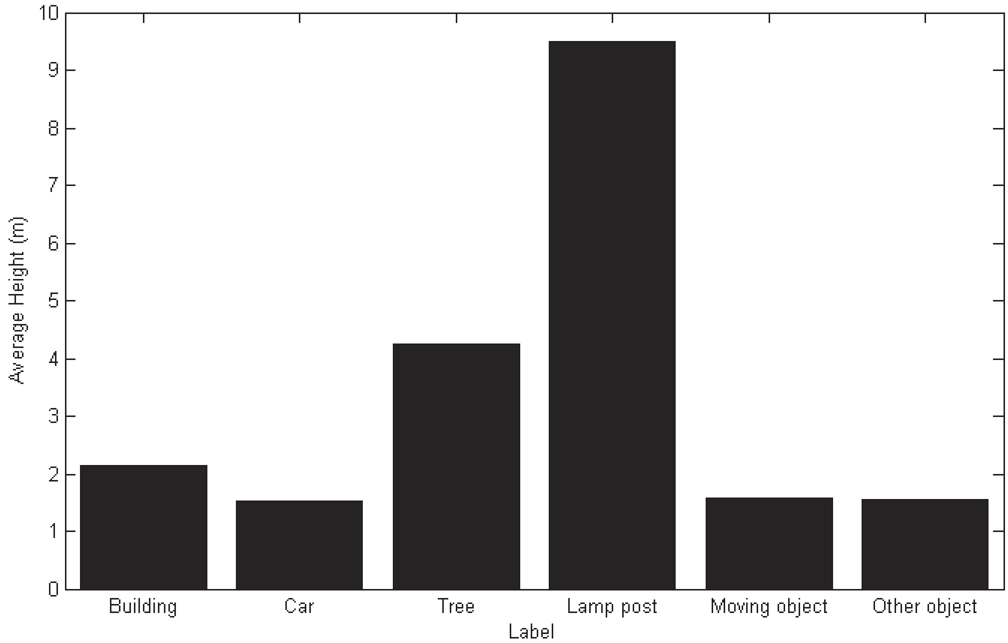


Figure 3-8: Average height of 6 classes

3.6.2. Contextual feature

The contextual feature includes the information about the position of an object related to its environment. For example, parked cars are usually staying in a line on a street as shown in Figure 3-9 whereas lamp posts are found on sidewalk and buildings are always far away from the road. These cues can be described by contextual feature.

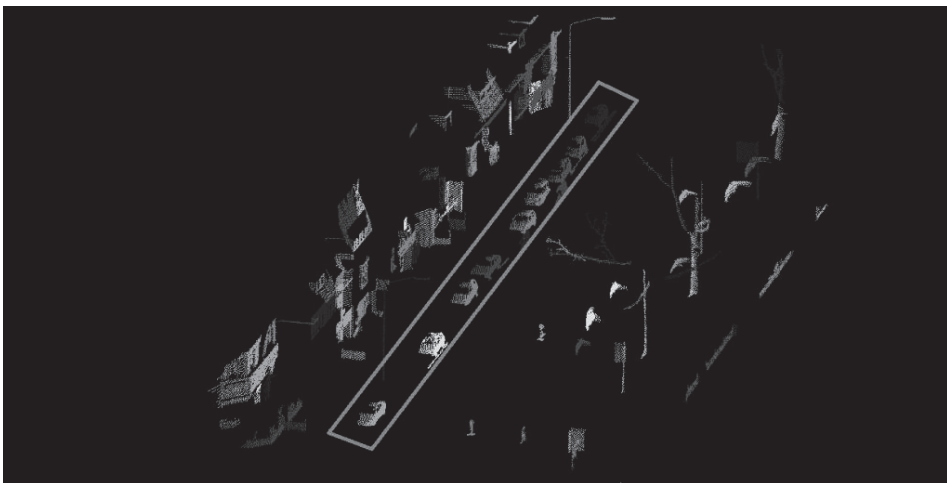


Figure 3-9: Cars stay in a line

In this research, the position is described by the smallest distance (D) from the object to the trajectory of the car which takes the sensors. The centre of the object is taken as the mean (M) of all the points in one component. The distance from the object to every point on the trajectory is calculated initially and then the minimum distance is kept. Figure 3-10(a) shows the distribution of the points in one object and the red dot represent the center which obained by computing the mean of all the points. Figrue 3-10(b) gives the position of the object to the trajectory and the blue dot is the representation of the nearest point from the trajectory to the object center.

(a) (b)

Figure 3-10: Position of the object. (a) Object and the center (b) Position to the trajectory

3.6.3. Other features

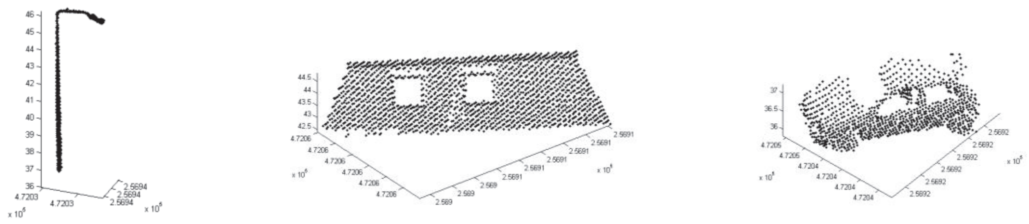
Besides the shape and contextual features extracted above, some features for describing additional properties (e.g., the reflective strength can be the representation of the material of the object) are introduced in this section. Features as eigenvalues, eigenvalue-based LIDAR features, RANSAC, reflectance information are included.

- **Eigenvalues**

Three eigenvalues describing the dimensions of objects are utilized in this research. As introduced in section 2.3.1, an analysis is performed for the linear, planar, volumetric feature patterns for each point in the feature space. These values are a particular set of scalars related to a linear system of equations (i.e., a matrix equation). These equations have been used as characteristic roots, characteristic values, proper values, or latent roots by other researchers.

The covariance matrices of components are computed as the input of the calculation of eigenvalues. Three specific eigenvalues ($\lambda_1 > \lambda_2 > \lambda_3$) are used as features. The linear structure has the largest λ_1

while the planar structure has similar λ_2 and λ_3. The vertical object such as trees and lamp post in Figure 3-11(a) can be easily derived since they have a relatively large value in λ_1 but small value in λ_2 and λ_3. Moreover, the objects which primarily based on the horizontal structure as Figure 3-11(b) have larger value in λ_1 and λ_2 than the value of λ_3 while volumetric patterns (Figure 3-11(c)) have three similar eigenvalues obviously.



(a) (b) (c)

Figure 3-11: Component with different spatial distribution. (a) Linear (b) Planar (c) Volumetric

- **Eigenvalue-based LIDAR features**

The eigenvalue-based LIDAR feature is the extension of the eigenvalues mentioned above. These additional features can help distinguishing structures such as planes, edges, corners, lines and volumes. These new features are anisotropy, planarity, sphericity and linearity which are defined from the three eigenvalues $\lambda_1,\ \lambda_2,\ \lambda_3$:

$$\text{Anisotropy} = A_\lambda = \frac{\lambda_1 - \lambda_3}{\lambda_1} \tag{3-3}$$

$$\text{Planarity} = P_\lambda = \frac{\lambda_2 - \lambda_3}{\lambda_1} \tag{3-4}$$

$$\text{Sphericity} = S_\lambda = \frac{\lambda_3}{\lambda_1} \tag{3-5}$$

$$\text{Linearity} = L_\lambda = \frac{\lambda_1 - \lambda_2}{\lambda_1} \tag{3-6}$$

The four different values show different attributes depending on the different properties of objects. For instance, the value of linearity is higher for pole-like objects than other objects, the value of planarity is higher for objects have a planar surface as roofs, the value of sphericity is higher for objects such as cars that have the volumetric characteristics and the anisotropy is higher for the objects have the property of being directionally dependent. Buildings can be discriminated from vegetations and pole-like objects can be detected by including the eigenvalue-based LIDAR features.

- **RANSAC-based feature**

Regions of points are normally not perfectly coplanar provided by the segmentation procedure. In reality, outliers may be included in these regions, for example the points on the walls, trees, cars and ground surface. Basically, cars on the ground have more points on the side and fewer points on the top and the other side. So the dominate plane is the side towards the scanner. For the purpose of detect the dominate plane, a robust plane fitting is applied to deal with these outlying points so that only these points identified as inliers are used to obtain the point-to-plane distances. The RANSAC algorithm is used for the robust plane fitting (Sande et al., 2010). Each random sample of the RANSAC should contain three points as the minimum size for defining a plane, the proportion for the outliers is 50% and 35 random samples(k) are required to guarantee in this research (Khoshelham et al., 2005):

$$k = \frac{\log(1-z)}{\log(1-b)} \tag{3-7}$$

where z is the confidence probability which is 99% means at least one sample includes error-free points, b = w^n where w is the probability that all the chosen points are within the error tolerance (here is 50%) and n is minimum number of required points which is 3 in this research for fitting a plane. The computational cost of this robust plane fitting method is affordable due to the relatively small sample size. Three normal vectors for the plane and the distance from the plane to the origin of the system are used as features.

- **Reflective information**

Reflectance strength information is introduced as feature in order to make up the limitation of the characteristic that illustrated above. The reflectance is a value of thick reflecting objects(" CIE (the International Commission on Illumination)," 2000). The internal reflection effects lead to the difference of reflectance with surface thickness when the reflection happens starting from thin layers of the material. The reflectance is the intrinsic of the surface. For example high reflection material always painted on traffic signs for helping visualization, cars are also made of metals which have high reflectance from other materials. The average reflective value of each component is calculated from the points which will be used in the next stage.

3.6.4. Summary

Based on all the features mentioned in this part, the following Table 3-1 shows the expected difference among main classes:

Table 3-1: Comparison of different classes in different features

		Building	Static car	Tree	Lamp post	Moving object
Size		Large	Small	Large	Small	Small
Area		Large	Small	Large	Small	Small
Density		Low	High	Low	Low	High
Min-height		High	Low	High	Low	Low
Height		High	Low	High	High	Low
Position(distance to trajectory)		Large	Small	Large	Large	Small
Eigenvalue	λ_1	Height	Length	Height	Height	Length
	λ_2	Width	Width	Diameter	Diameter	Width
	λ_3	Length	Height	Diameter	Diameter	Height
Anisotropy		Large	Small	Large	Large	Small
Planarity		Large		Small	Small	
Spericity			Large			Large
Linearity		Small	Small	Large	Large	Small
RANSAC	n_x					
	n_y					
	n_z					
	d	Large	Small	Large	Large	Small
Reflectance		Large	Small	Small	Large	Small

Due to the introduction of each feature, they have their own advantage in distinguishing temporary objects from other objects. For instance, temporary objects as cars always have a smaller area than buildings and trees but larger than lamp posts, they also have the highest density in all of the objects due to the volume and size and normally moving objects have a higher density since they have larger size.

3.7. Segment-based classification

The classification is the last phase of the research as mentioned in section 2.3.2. The final result is based on the segment-based classification method which is introduced in this part. Since the training sample gives a dataset including different class labels, the main purpose of classification is learning a distinguish function between patterns by using the training sample. There are four main reasons that influence the result of the classification: the number of training samples, features and class labels as well as the complexity of the classifiers. The ideal situation for training the classifier adequately is making use of a dataset with large number of training samples, high-dimensional feature space and sufficient class labels. Meanwhile, the accuracy of the classification is higher.

In order to investigate the influence of training sample size as well as the number of features, two classifiers named Bayesian linear discriminant classifier (LDC) and the linear support vector machine (SVM) (Khoshelham et al., 2013) are experimented. The equations mentioned in the following part define a linear function between each pair of labels for this research.

The linear discrimimant function is defined for solving a two-class problem as (Duda et al., 2012):

$$D_{ldc} = (\mu_1 - \mu_2)^T \Sigma^{-1} x + c \tag{3-12}$$

where μ_1 and μ_2 are the mean vectors of features respect to two different classes. Σ is the equal covariance matrix of the features to both of the classes. x is the feature vector that is going to be assign a class label while c is a constant.

In addition, the linear support vector classifier is another separating hyperplane. The parameters of this hyperplane are depending on maximizing the margin between itself and the nearest support vector from each class. The constraints are as follow:

$$y_i(\omega * x + b) - 1 \geq 0,\ i = 1, \ldots, n \tag{3-13}$$

where i is the sample, $y_i \in \{-1,1\}$ is the class label for i, and ω is the normal to the hyperplane that $\omega = \Sigma^{-1}(\mu_1 - \mu_2)$, x is the possible feature vector that lies on the hyperplane, $b = -\frac{1}{2}\omega \cdot (\mu_1 + \mu_2)$ and n is the number of samples. Parameters of the optimal hyperplane are acquired by solving the optimization problem numerically.

A large number of training samples is essentially required for training a classifier with large amount of features. The problem of insufficient training set is extenuated if the dimensionality of the feature space is decreased. The reduction can be achieved by selecting a subset of features which contribute to comparable, or improved classification accuracies, or mapping the feature space from higher dimension to lower dimension. The strategy of feature selection is adopted in this research.

Feature selection is a strategy that searching for a subset from all the features for the sake of yielding the classification result with the lowest error (Khoshelham and Elberink, 2012). Two feature selection methods are therefore used in this research:

- Forward selection (FS): an empty set is selected initially at the beginning. Then one feature is added to the classifier at one time for the evaluation of the classification error in the subsequent steps. The feature that contributes to the lowest error is selected adding to the subset. The iteration selection stops until there is no further reduction of error.

- Backward elimination (BE): the full set of feature is used at first. Then one feature is removed from the classifier at one time for the evaluation of the classification error in the subsequent steps. The feature that removes the reduction of the classification error the most is eliminated from the subset at one time. The iteration selection stops until there is no further reduction of error.

Due to the limitation of the size of the training sample, the performance of the feature selection strategy for a small dataset is far from adequate to certify whether the method is good enough or not. So it is useful to test the point cloud by using the trained classifier. More training sample that contains new characteristics can be added for a further training if necessary.

The point cloud with new label is achieved after segment-based classification. The evaluation of completeness, correctness and overall accuracy can be computed in a further stage and meanwhile, the new labelled dataset can be visualized in Cloud Compare or Point Cloud Mapper (PCM).

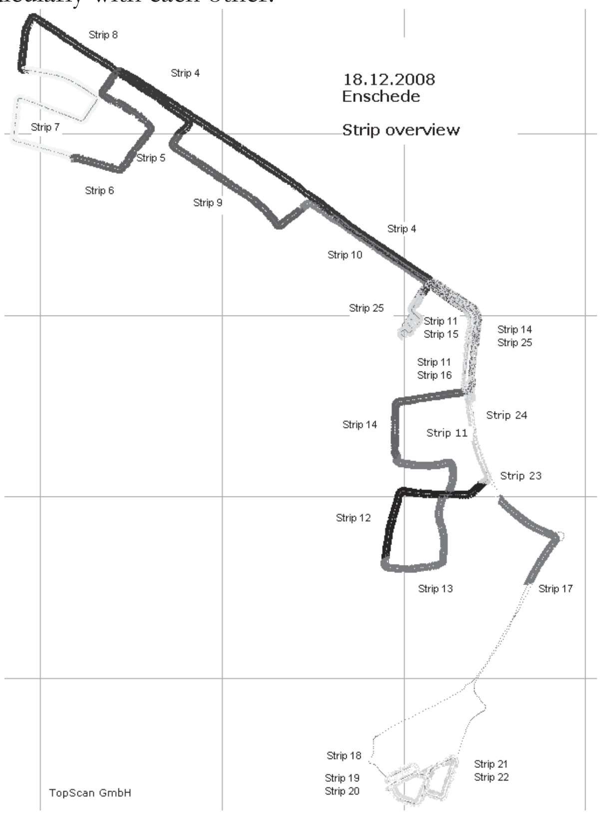
4. IMPLEMENTATION AND RESULT

In this chapter, the methodology which is described above is used in a MLS dataset and the result is given finally. Section 4.1 introduces the MLS dataset that is used in this research as well as the division of the strip into road parts. Section 4.2 describes the selection of the parameters for surface growing segmentation and the result. Section 4.3 describes the reason for the selected parameters of connected component analysis and the result of on road component without small segments. Section 4.4 shows the features which are used for classification and the common properties of the object in the same class are described. Section 4.5 describes the segment-based classification. Section 4.6 describes the evaluation of the result and the test for the total strip. Finally, the summary of the implementation and result is given.

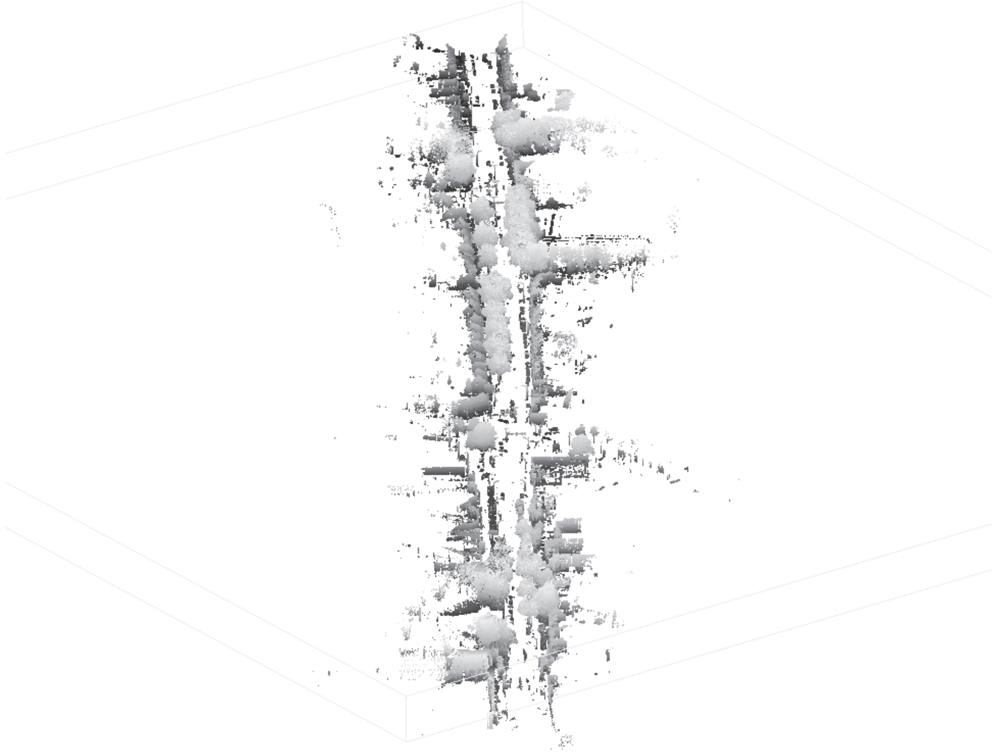
In this research, MATLAB is used for the implementation of most of the algorithms. Point Cloud Mapper (PCM) is mainly used for the procedure of segmentation and Cloud Compare is applied in the visualization of point cloud. The statistical analysis for feature extraction and classification is acquired by Excel.

4.1. Laser data pre-processing

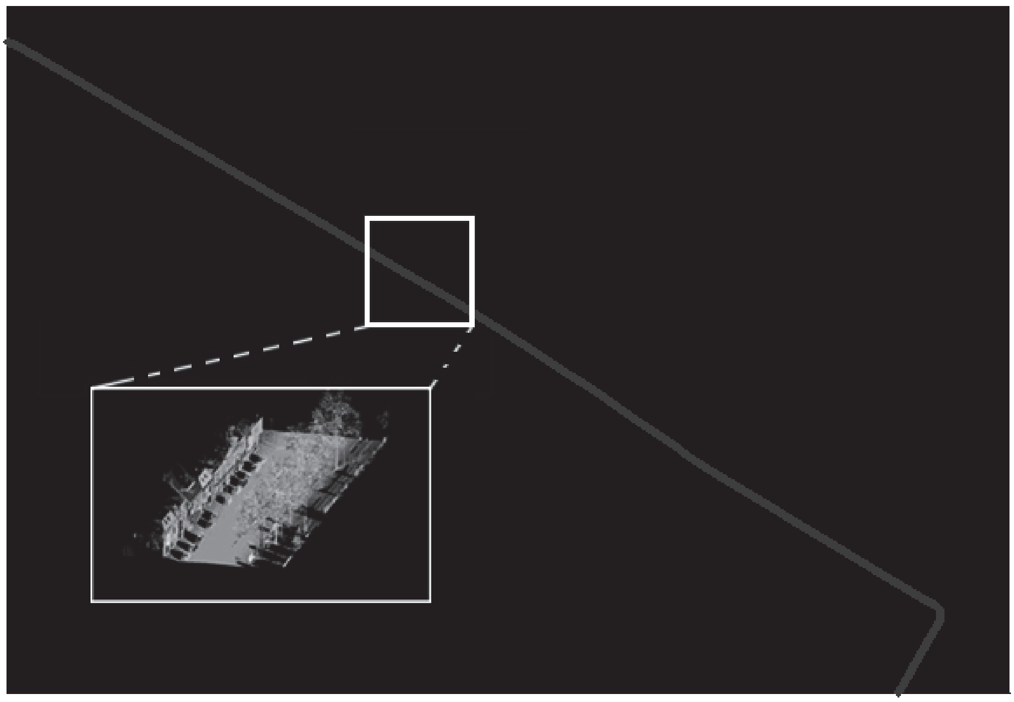
The laser scanning data set used for this research was acquired in Enschede, Netherlands in December, 2008 by TopScan GmbH. The Optech's Lynx Mobile Mapper system (Optech, 2009) is used for the collection of the dataset. Figure 4-1 shows a visualization of the data set and the one that is used here as well as the training area. There are two rotating laser scanners that stay on the top of the platform and they are amounted perpendicularly with each other.



(a)



(b)



(c)

Figure 4-1: MLS dataset. (a) Strip overview (b) Point cloud that is used in the research (c) The trajectory of laser scanner and the training sample

As shown in Figure 4-1(a), there is 22 strips in total. The strip that is used in this research is strip 4 which is the street located in front of the ITC and the overview of the laser data can be viewed in Figure 4-1(b). The testing data is the overall strip which is divided into 12 parts in the next step. Each of the part is

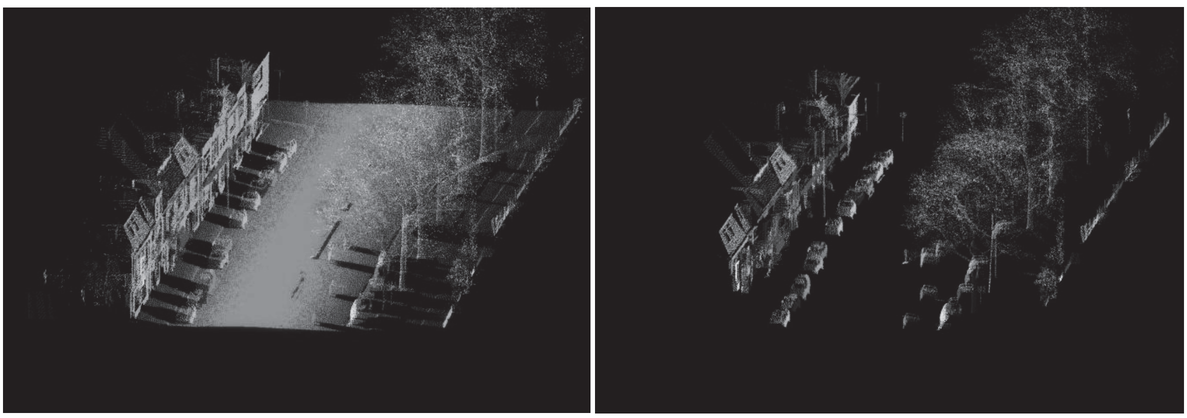
100m long and 40m wide. Part 6 is selected as the training sample for training classifiers and the strip is used as testing area to present the performance of the proposed methodology. Figure 4-1(c) shows the location of the training sample as well as the strip.

4.2. Surface growing segmentation

The surface growing segmentation is the first step after the data pre-processing and gives the on-road segments as input of next stage. Since the result would be the input of the subsequent process this phase is regarded as an important part. The MLS point cloud still contains large quantity of points while some of them for instance ground surface and building facades are not necessarily required for this research. The algorithm is used to remove the ground surface and large building facades. There are some proposed conditions which contribute to the setting of the optimal parameter values. The values are determined by considering the condition and assumption below:

- All of the on-road segments ought to be different individual component separately as much as possible.
- All of the on-road segments should separate from all the ground segments.
- All of the ground segments are assumed that have large and planar surface. Similarly, building facades should have vertical planar and large surface.
- All of the ground segments should below the trajectory. The distance from the trajectory to the ground segments should be fixed.

Based on the list about the difference between the on-ground segments and the ground and building facade surfaces. The ground and facade are easily detected. Therefore, parameters for the detection of ground and building facades surfaces of this surface growing segmentation are not critical. All the parameters setting in this part are based on the research of Li (2013) since the same dataset has been used in both researches. The surface growing radius is considered as 1.0m and the maximum distance to surface is 0.3m. The minimum threshold of ground segment and facade segment is set as 20m^2 and 50m^2 respectively while the system height is 2.4m. The tolerance of the vertical is within 7 degree for faced segment. Then ground surface is recognized if the area of the ground segment is larger than 20m^2 and satisfying the requirement of planar surface and below trajectory at the same time. Similar, the facade surface is acquainted if the area is over 50m^2 and the tolerance can meet the demand. After the detection of the ground surfaces and building facade surfaces they are removed from the laser data. The result of the on-ground segments is as shown in Figure 4-2.



(a) (b)

Figure 4-2: Result of surface growing segmentation. (a) Segments with ground and facade surfaces (b) On-ground segments

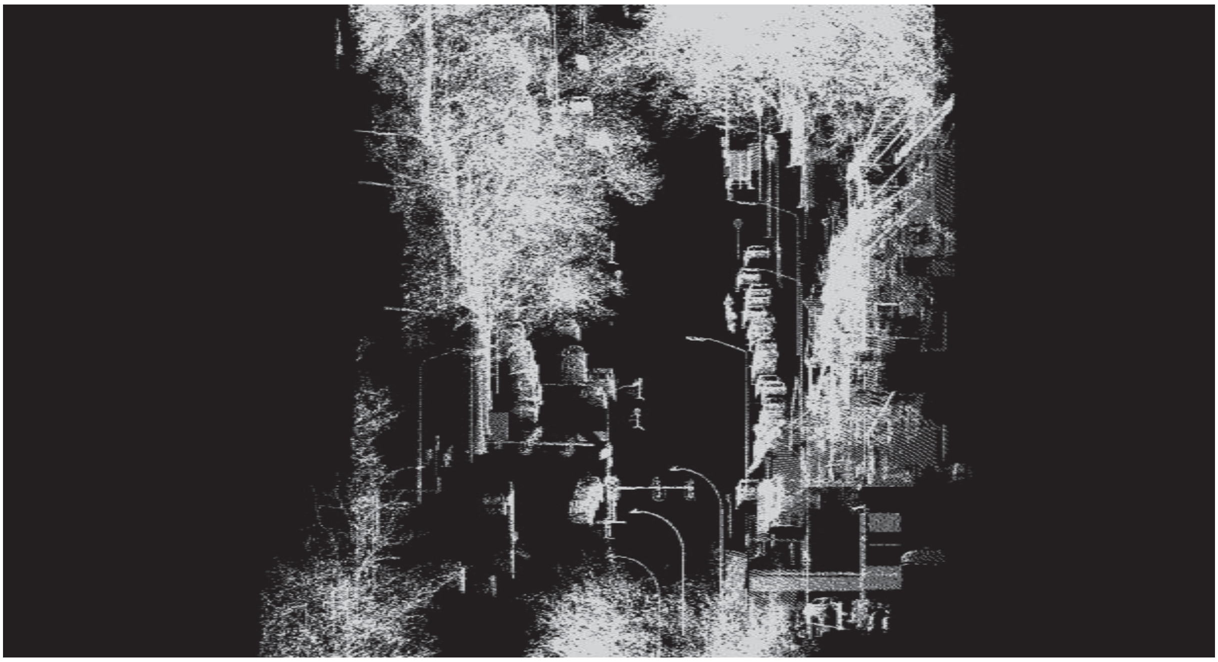


Figure 4-3: The result of the strip after surface growing segmentation

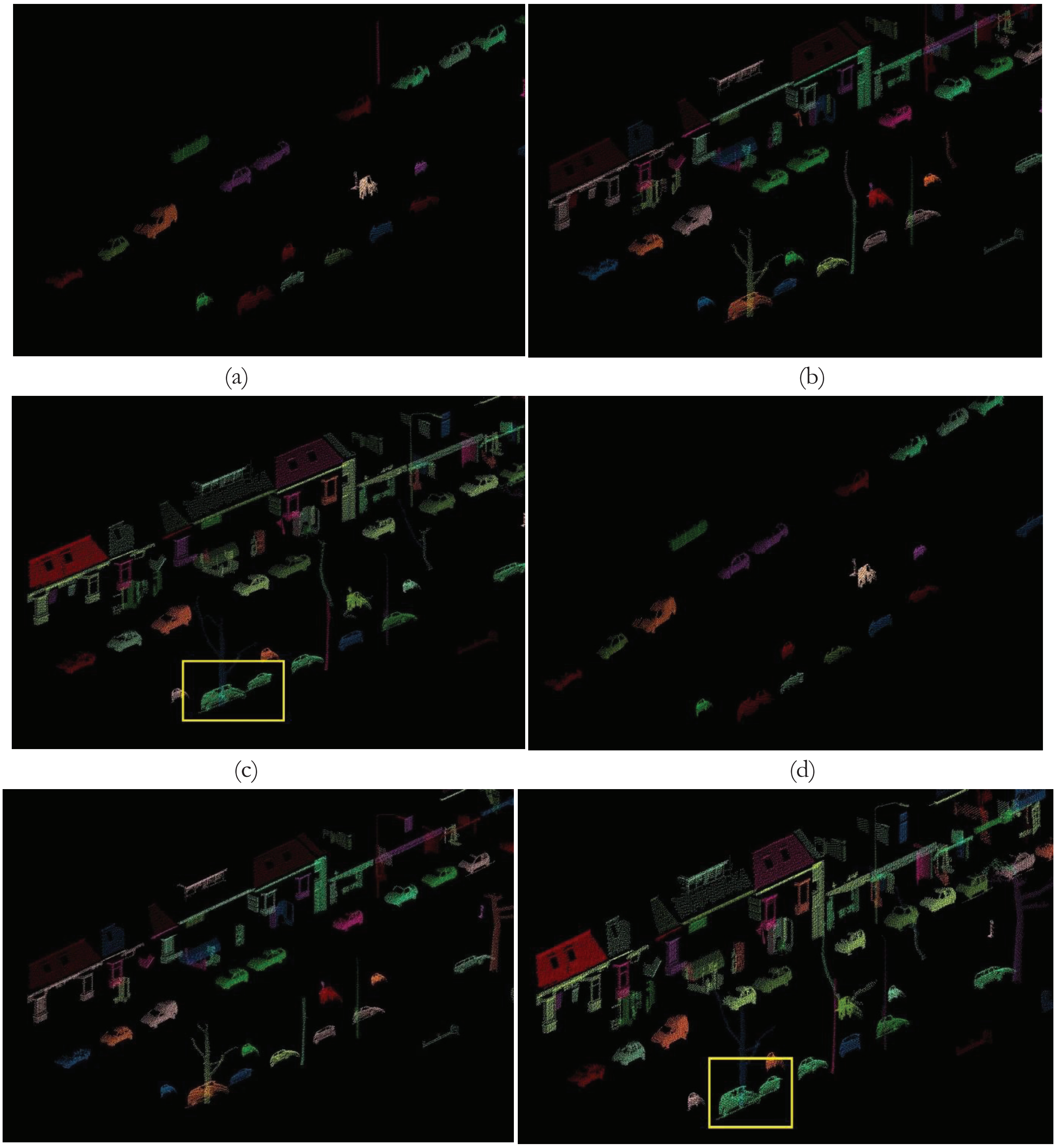
It is obvious that all the points on the ground and some large part of the building façade surfaces have been removed from Figure 4-2 and 4-3.

4.3. Connected component analysis

Based on the segmentation algorithm mentioned above, the on-road segments are generated. The connected component analysis is used and ensured each object is connected as one component so that the attribute of each kind of class can be easily acquired in the next step. The parameters of the maximum distance between points and the minimum number of points of one component are set. The parameters values that set in the analysis are examined in the training sample. The selection of different parameters for the connected component analysis is listed in Table 4-1 while the result is showed in Figure 4-4.

Table 4-1: Parameters used for connected component analysis for the same training sample

NO.	Maximum distance between points(m)	Minimum number of points
a	0.10	100
b	0.16	100
c	0.18	100
d	0.10	200
e	0.16	200
f	0.18	200



(a) (b) (c) (d) (e) (f)

Figure 4-4: Parameters used for connected component analysis for the same training sample (a) Setting 1 (b) Setting 2 (c) Setting 3 (d) Setting 4 (e) Setting 5 (f) Setting 6

Figure 4-4(a) to Figure 4-4(c) has the same minimum number of points of 100 and the maximum distance between points are 0.10, 0.16 and 0.18 respectively while Figure 4-4(d) to Figure 4-4(f) has a different minimum number of points of 200 and the distances are the same as first three group. In Figure 4-4(a) and Figure 4-4(d) most of the buildings and small components are removed which is so-called over-segmentation. The reason contribute to this is the setting of the maximum distance between points is too small which lead to there is no more than 100 or 200 points for one component. The under-segmentation happens in Figure 4-4(c) and Figure 4-4(f) which has the merged segments and has the larger maximum distance between points. Figure 4-4(b) and Figure 4-4(e) has the better result of segmentation, however; the result with 200 minimum number of points removed some of the small segments which would be used as reference in the following step. In conclusion, parameters of the analysis as the maximum distance between points is 0.16m and the minimum number of points is 100 obtained the most reliable result than others.

4.4. Feature extraction

The road part 6 is randomly selected as reference for the feature extraction and is used for training the classifier in the following phase. There are 115 segments in this part and all of them are manually labeled due to the visual effects. The information of each labeled class is showed in Table 4-2 and Table 4-3. Figure 4-5 shows the result of the label.

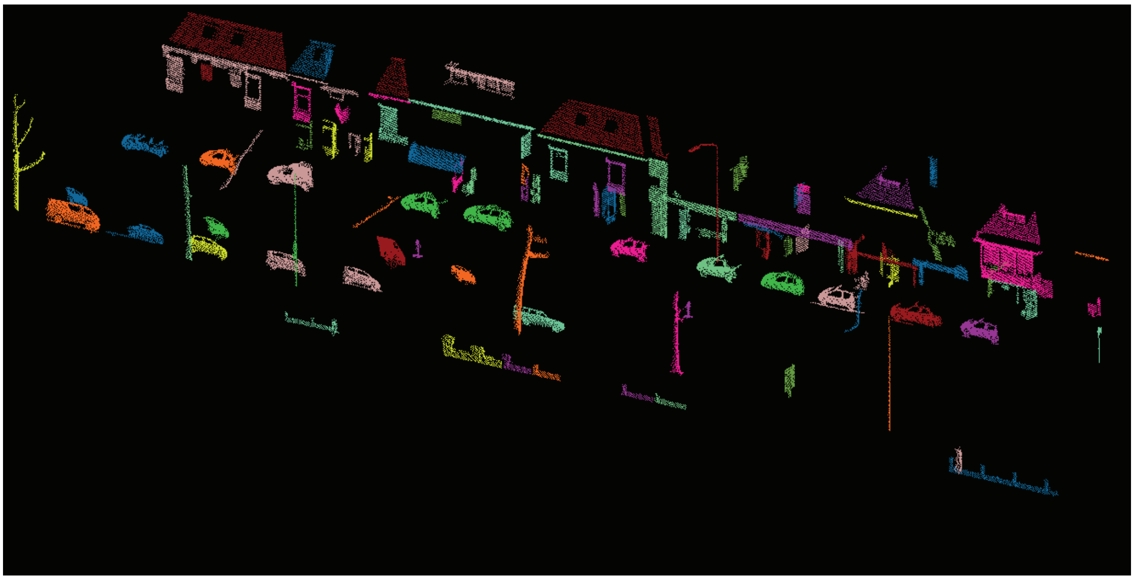
As the main objective of this research is to detecting temporary object especially static objects, the static and moving temporary objects are first labeled as temporary objects and then separately so that the different performance of the algorithm used for temporary objects detection and static cars detection can be acquired obviously. Initially, five labels are used by recognizing the static and moving temporary objects as temporary object. In the further study as showed in Table 4-3, they are labeled separately.

Table 4-2: Five labeled classes of training sample

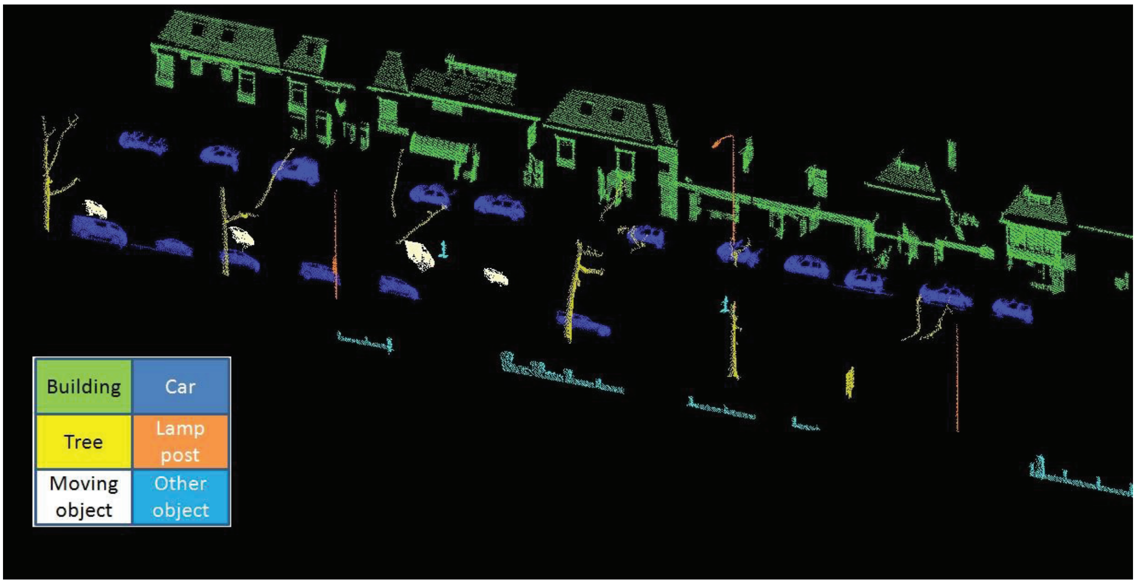
Name	Label	Object number
Building	1	61
Temporary object	2	21
Tree	3	14
Lamp post	4	3
Other object	6	16

Table 4-3: Six labeled classes of training sample

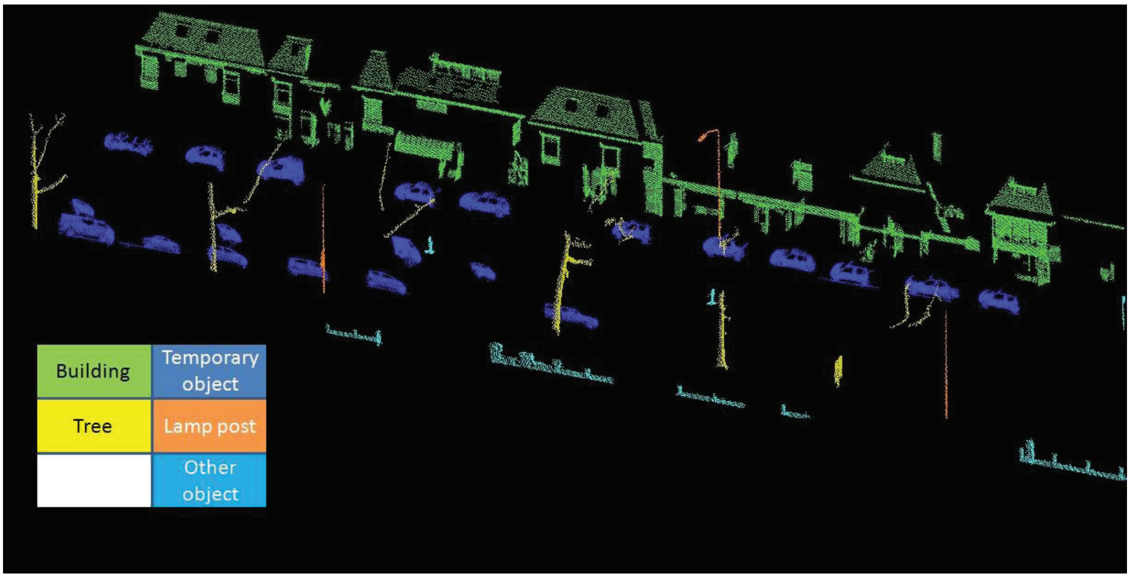
Name	Label	Object number
Building	1	61
Car	2	17
Tree	3	14
Lamp post	4	3
Moving object	5	4
Other object	6	16



(a)



(b)



(c)

Figure 4-5: Result of label. (a) Initial dataset (b) Dataset with 6 labels (c) Dataset with 5 labels

The dataset contains the x, y and z coordinates information together with reflectance information, segment numbers and labels are as input for the feature extraction. Eighteen features as size, RANSAC, eigenvalues, anisotropy, planarity, spericity, linearity, minimum height, height, area, position, density and reflectance information which have been introduced in chapter 3 are extracted. In table 4-4 and table 4-5 the overview of each feature is given for the average attribute value in training area.

Table 4-4: Average attributes value for five classes in training area

Feature	Building	Temporary object	Tree	Lamp post	Other object
Size	521.67	757.85	291.57	270.00	203.69
Area	3.48	4.42	5.04	0.49	1.97
Density	287.70	134.07	91.14	237.65	206.90

Min-height		38.63	35.77	40.92	35.91	36.02
Height		2.14	1.54	4.26	9.49	1.56
Position(distance to trajectory)		9.86	6.585	13.62	11.66	14.29
Eigenvalue	λ_1	0.02	0.05	0.05	0.002	0.01
	λ_2	0.25	0.14	0.16	0.27	0.06
	λ_3	2.09	0.82	2.45	8.37	1.45
Anisotropy		0.97	0.91	0. 97	1. 00	0. 98
Planarity		0.24	0.15	0. 09	0. 02	0. 08
Spericity		0.03	0.10	0.03	0.0003	0.02
Linearity		0.74	0.76	0.88	0.98	0.90
RANSAC	n_x	0.44	0.54	0.37	0.33	0.59
	n_y	0.66	0.81	0.40	0.43	0.61
	n_z	-0.07	-0.07	-0.13	0.0007	0.02
	d	425112.26	523527.3	295747.00	313314.83	428442.36
Reflectance		347.20	266.02	110.50	220.78	292.20

Since in the dataset with six labels only the temporary object is divided into two parts based on the dataset with five labels, the attributes in Table 4-5 of Building, Tree, Lamp post and Other objects have the same value as in Table 4-4. Only the average attribute value of Temporary object is replaced by Car and Moving object in Table 4-5 as follow.

Table 4-5: Average attributes value for six classes in training area

Feature		Car	Moving object
Size		871.94	643.75
Area		6.00	2.83
Density		110.20	157.93
Min-height		35.75	35.79
Height		1.51	1.57
Position(distance to trajectory)		6.76	6.41
Eigenvalue	λ_1	0.05	0.05
	λ_2	0.15	0.13
	λ_3	1.29	0.34
Anisotropy		0. 96	0. 85
Planarity		0. 08	0. 22
Spericity		0.04	0.15
Linearity		0.88	0.63
RANSAC	n_x	0.54	0.52
	n_y	0.81	0.83
	n_z	-0.14	0.20
	d	521441.52	525613.33
Reflectance		175.64	356.40

After the feature extraction of the training dataset, the result would be used in the classification and evaluation part. In addition, features for the strip 4 as testing dataset need to be extracted as well. The value of each feature cannot be showed in table since the total strip has no label. However, the segments have the similar features should have the similar values.

4.5. Segment-based classification

The feature table is acquired after the feature extraction which is used as input for the segment-based classification. As introduced in section 3.6, the two most separable features in the feature space are selected to have a preliminary analysis of the separability of features. Then two classifiers as Bayesian linear discriminant classifier (LDC) and linear support vector machine (SVM) are experimented. Besides the two feature selection methods (forward selection (FS) and backward elimination (BE)) mentioned in section 3.6, all features are selected to train the classifiers as well. In section 4.5.1, the training dataset with 5 classes is used for the classification and in section 4.5.2 the training sample with 6 classes is used. Finally, the total strip is tested by the trained classifiers.

4.5.1. Dataset with 5 classes

The feature table contains eighteen features with 5 classes performs as the input for the classification. The two most separable features of height and size of each segment are selected as showed in Figure 4-6. Despite this only lamp post which contains 3 segments has been separated obviously from all the segments which are not good enough. So the feature selection methods are used for higher accuracy.

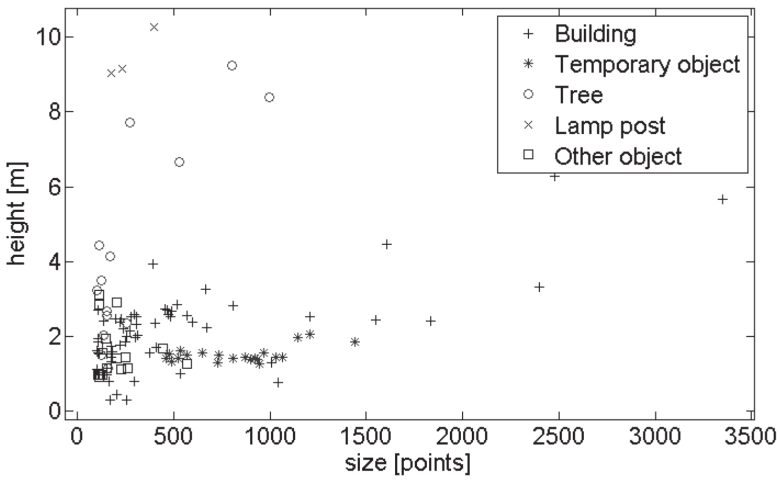
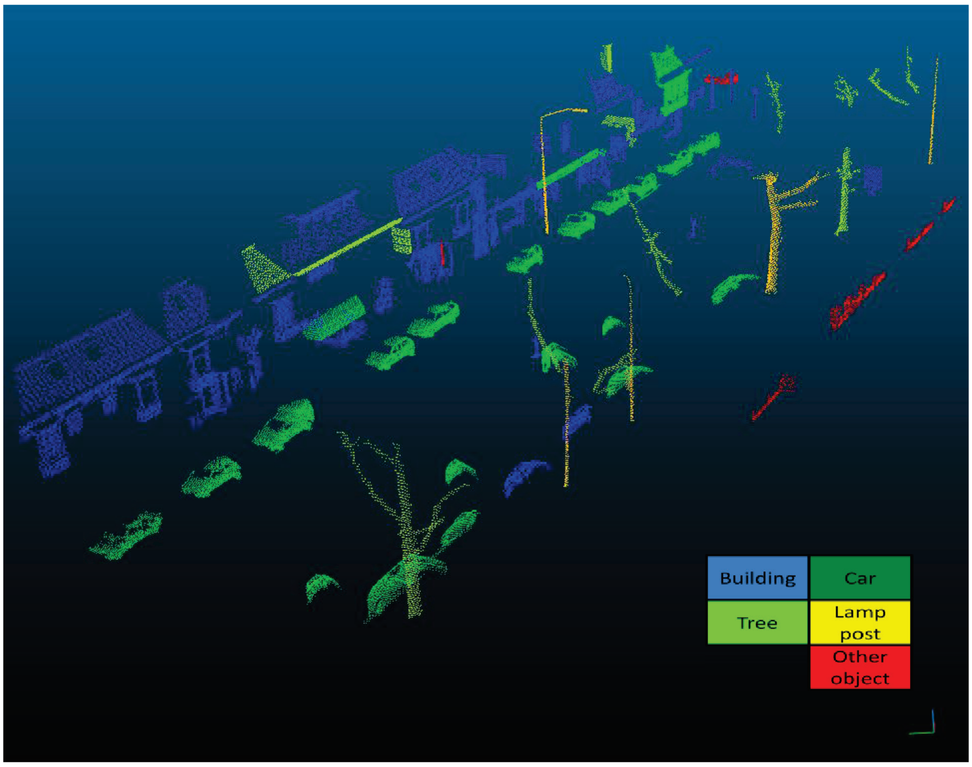


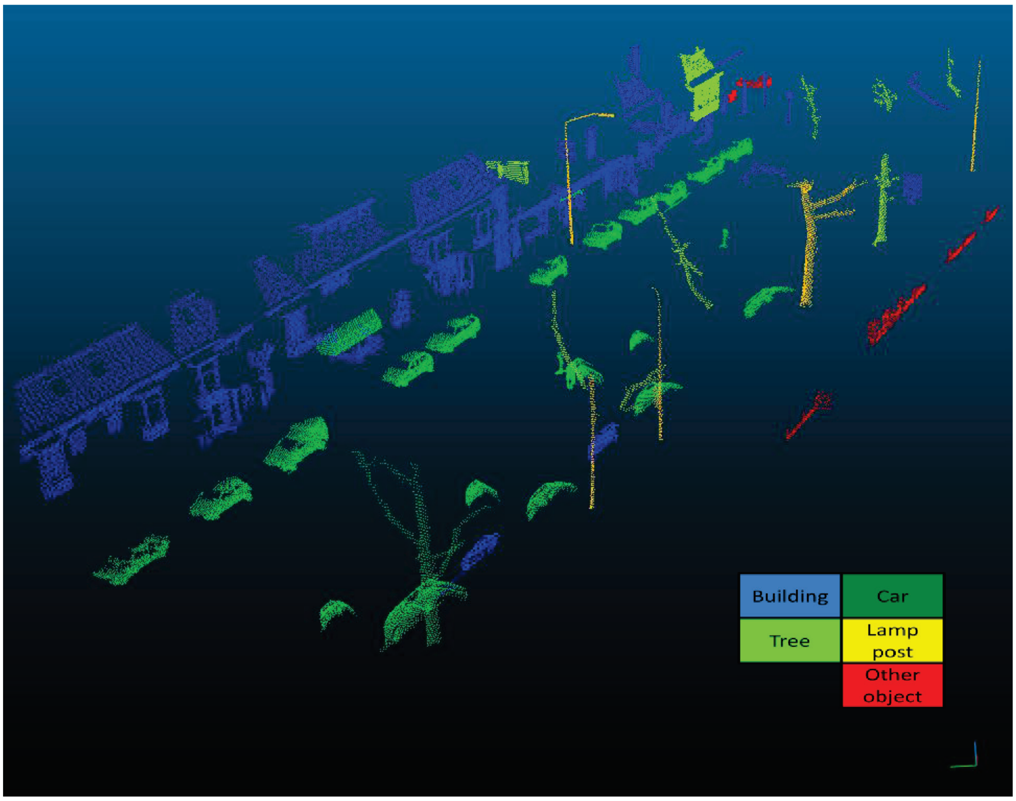
Figure 4-6: Two most separable features for 5 classes

4.5.1.1. Result with LDC

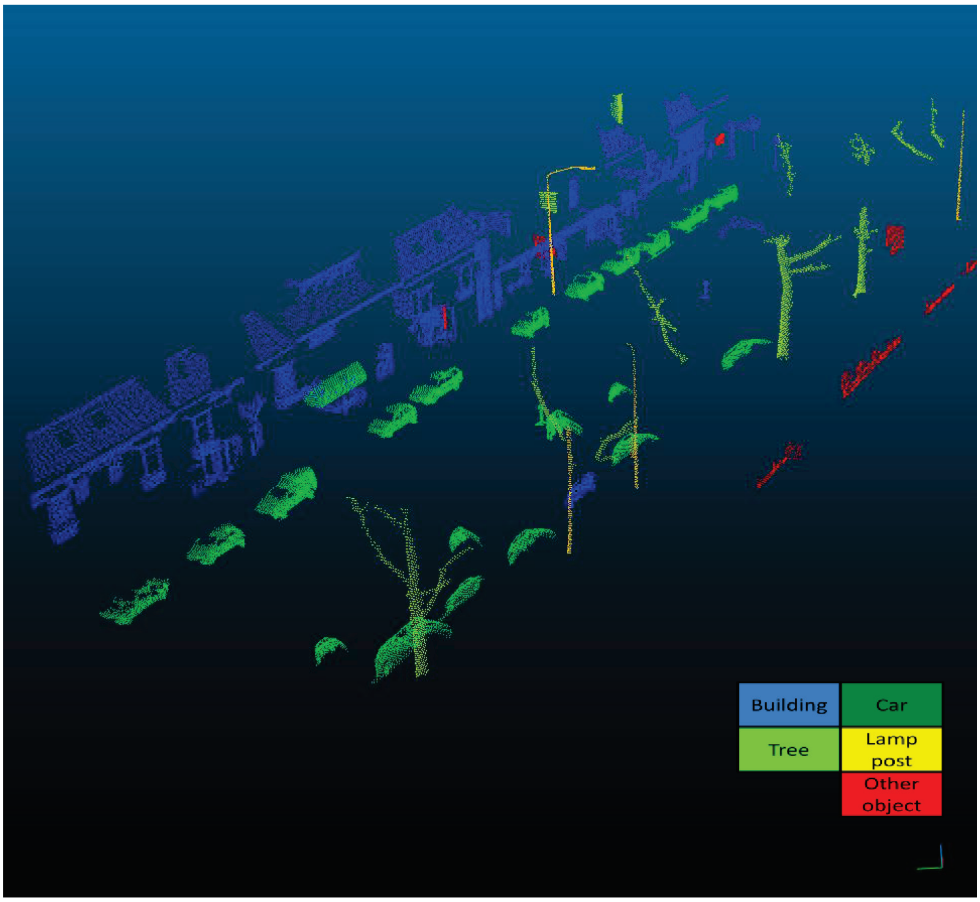
The Bayesian linear discriminant classifier (LDC) is trained by the training dataset at first and three selection methods as all features selection, forward selection (FS) and backward elimination (BE) are used respectively. Figure 4-7 shows the result of each feature selection method.


Building
Car
Tree
Lamp post
Other object

(a)


Building
Car
Tree
Lamp post
Other object

(b)

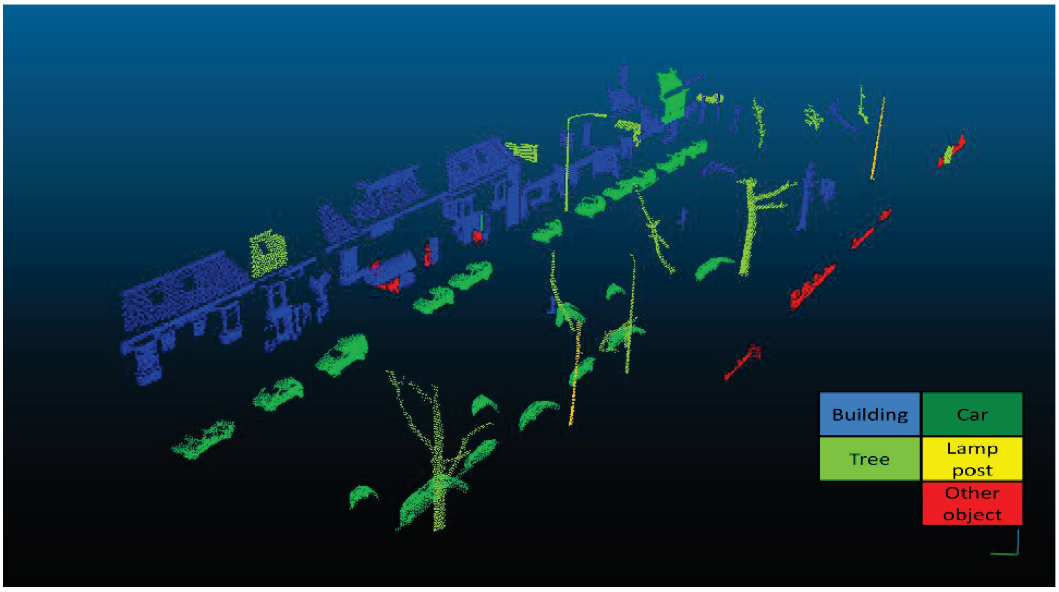


(c)

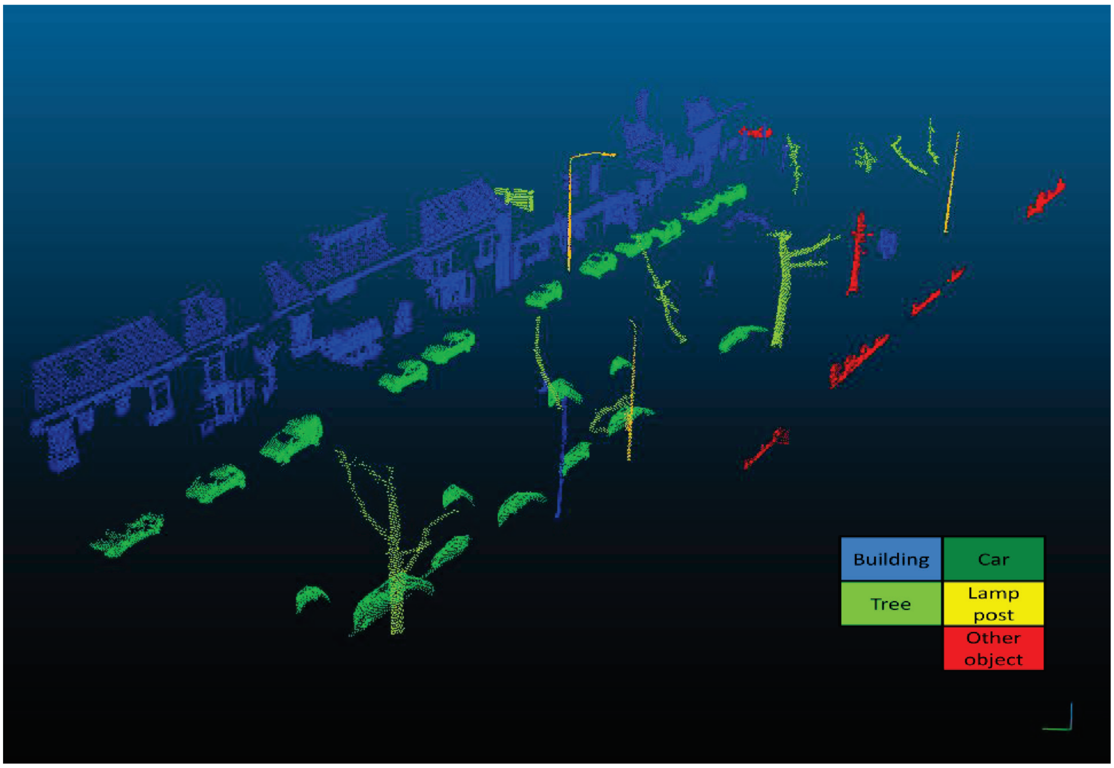
Figure 4-7: Result by different feature selection methods of LDC for 5 classes. (a) All features (b) FS (c) BE

4.5.1.2. Result with SVM

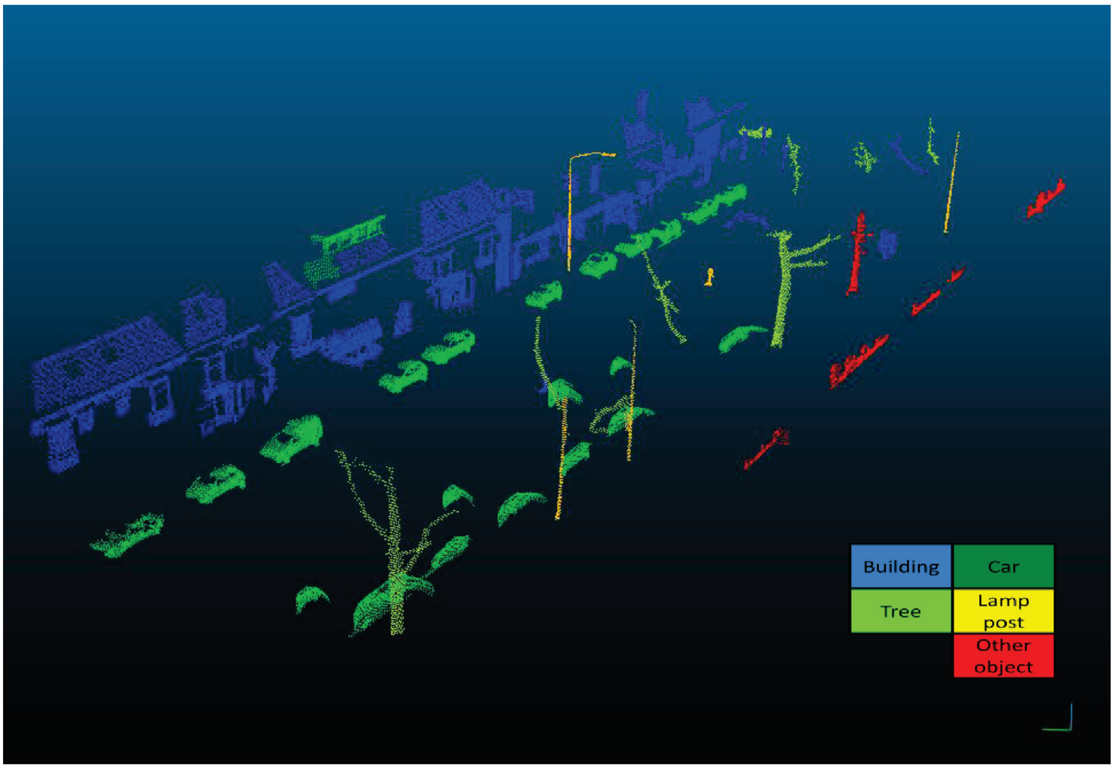
As the training method of LDC, The linear support vector machine (SVM) is used at first and three selection methods as all features selection, forward selection (FS) and backward elimination (BE) are used respectively. Figure 4-8 shows the result of each feature selection method.



(a)



(b)



(c)

Figure 4-8: Result by different feature selection methods of SVM for 5 classes. (a) All features (b) FS (c) BE

4.5.1.3. Feature selection result table for 5 classes

The selected features for different classifiers with different feature selections methods for 5 classes are as follow:

Table 4-6: Result of different feature selection methods for 5 classes

		FS(LDC)	BE(LDC)	FS(SVM)	BE(SVM)
RANSAC		X			X
		X	X	X	
		X		X	
				X	X
Size			X		
Eigenvalue	λ_1	X			
	λ_2			X	X
	λ_3		X		X
Anisotropy					
Planarity				X	X
Spericity					
Linearity					X
Minimum height		X	X	X	X
Height		X	X	X	X
Area			X		X
position		X	X	X	X
density		X	X	X	
Reflectance					X

Normally, it is not necessary to use all features in the classification for the high accuracy result. Thus features which have been selected by different selection method are important in illustrating the performance of the classifier. The selected features of each selection method are listed in Table 4-6.

4.5.2. Dataset with 6 classes

Based on the result of classification with 5 classes, the class of temporary object is divided into static object which named as car in this research and moving object. The feature table contains eighteen features with 6 classes performs as the input for the classification. The two most separable features are selected as showed in Figure 4-9. As the result of 5 classes, the two most separable features are feature 5 and feature 14 as well. Only one more class added here. Therefore the same feature selection methods are used for higher accuracy.

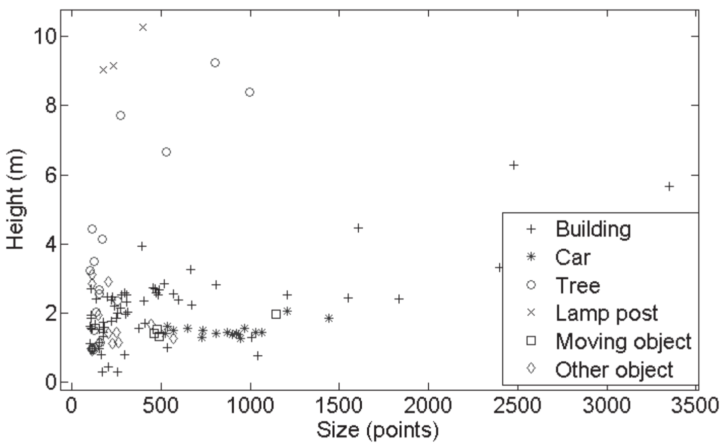
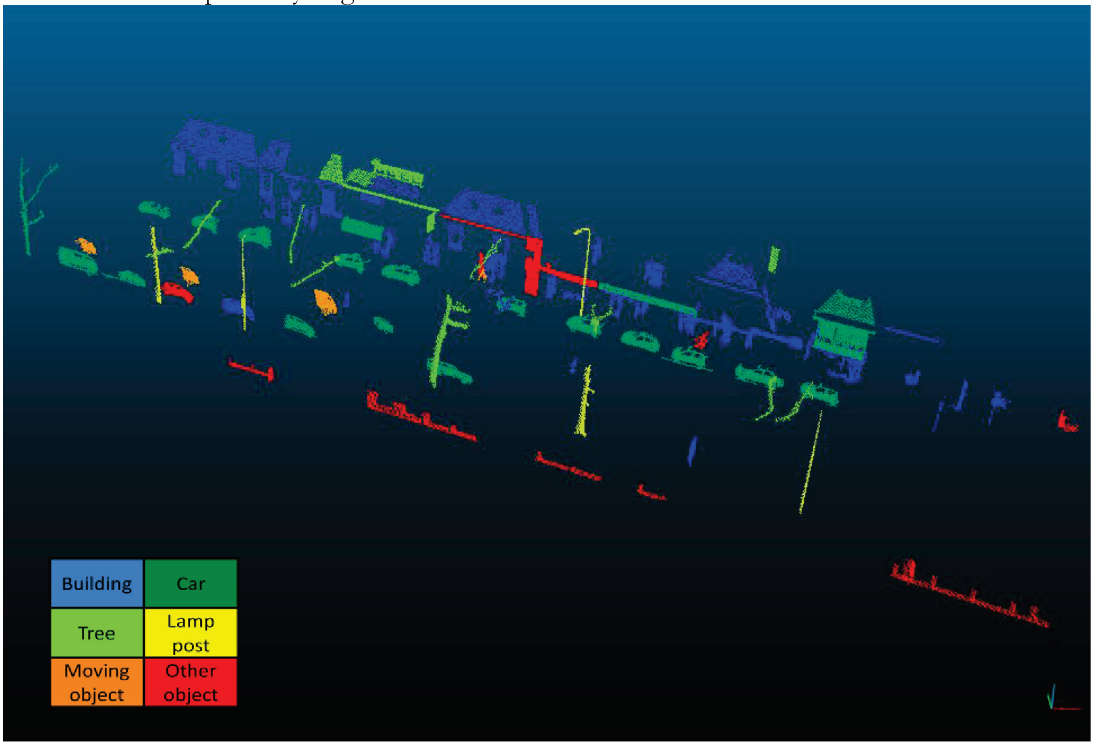


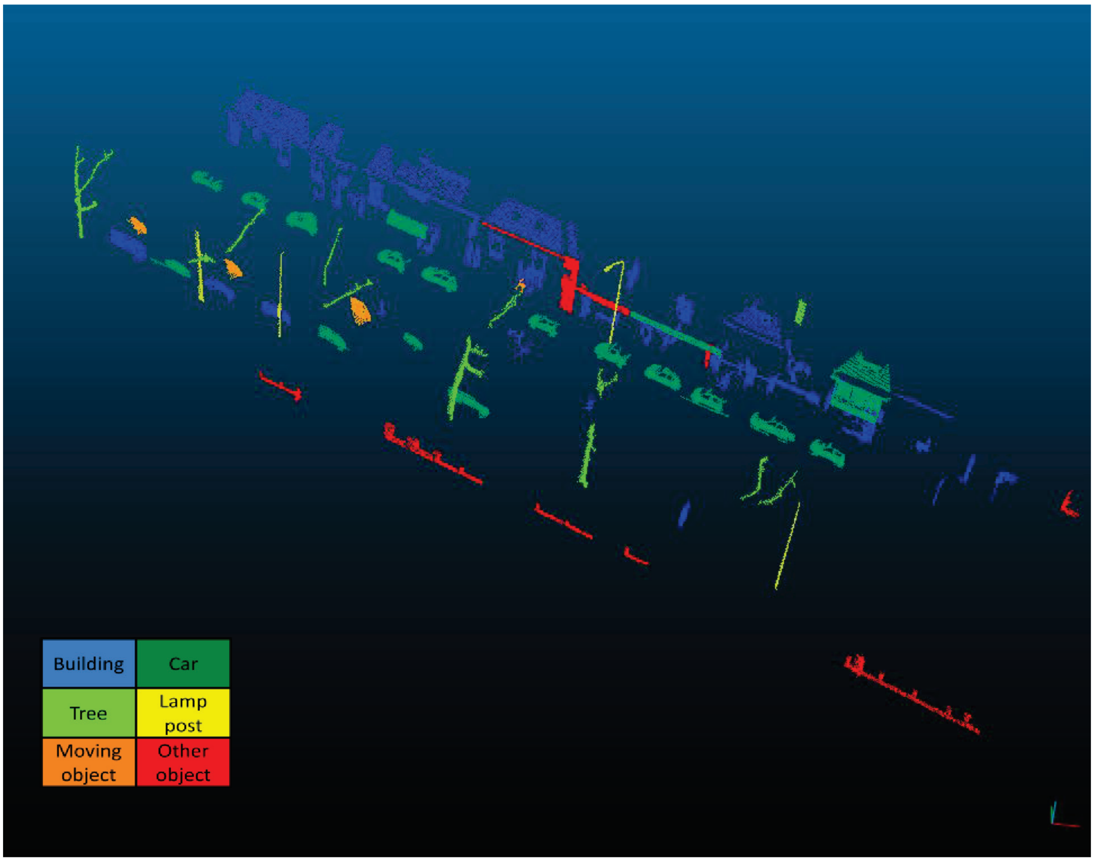
Figure 4-9: Two most separable features for 6 classes

4.5.2.1. Result with LDC

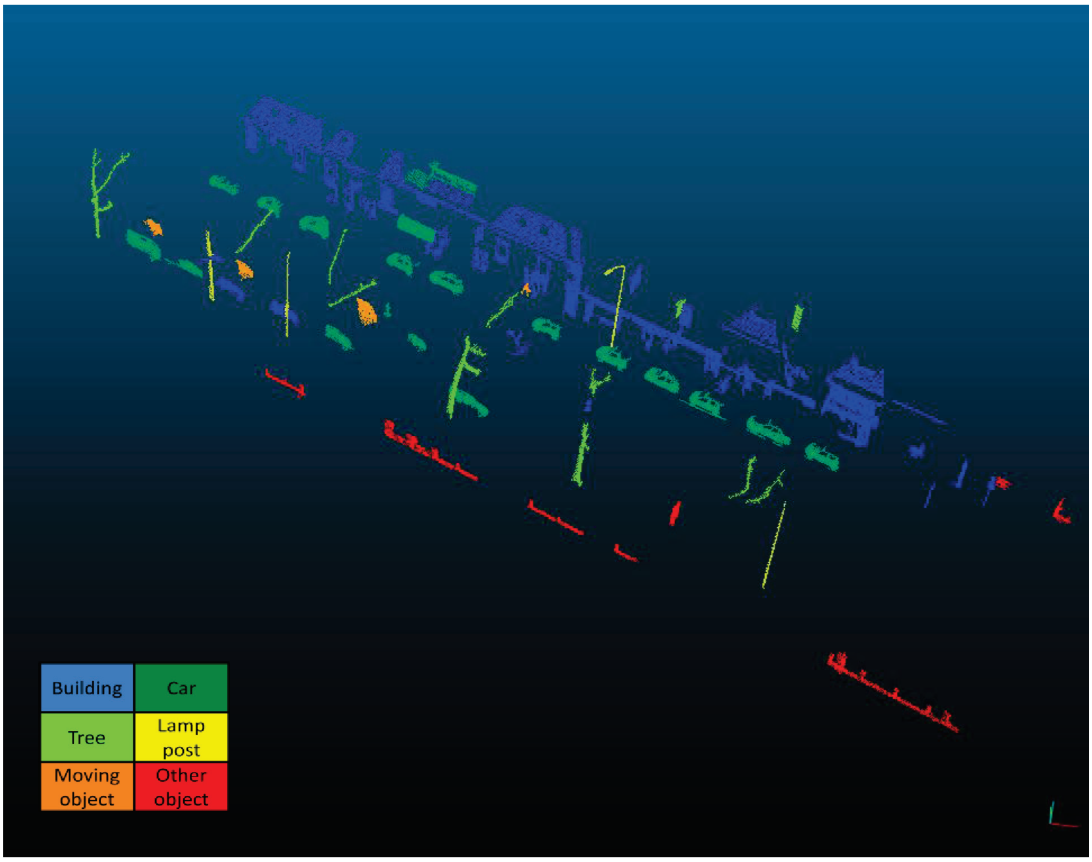
As mentioned for 5 classes, LDC is trained firstly and then three selection methods as all features selection, FS and BE are used respectively. Figure 4-10 shows the result of each feature selection method.



(a)



(b)

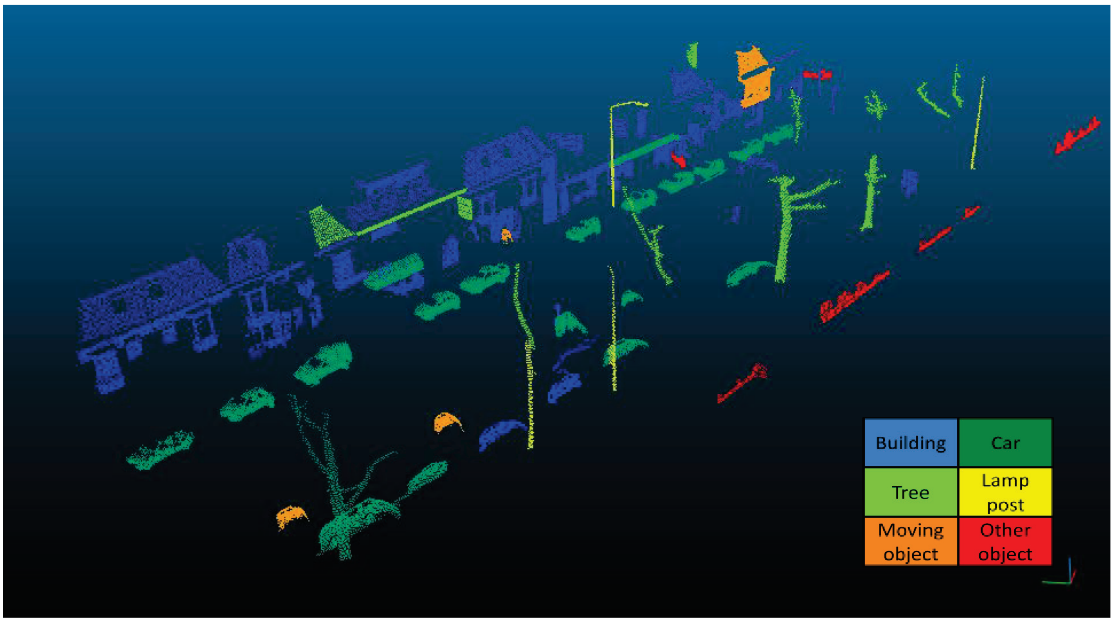


(c)

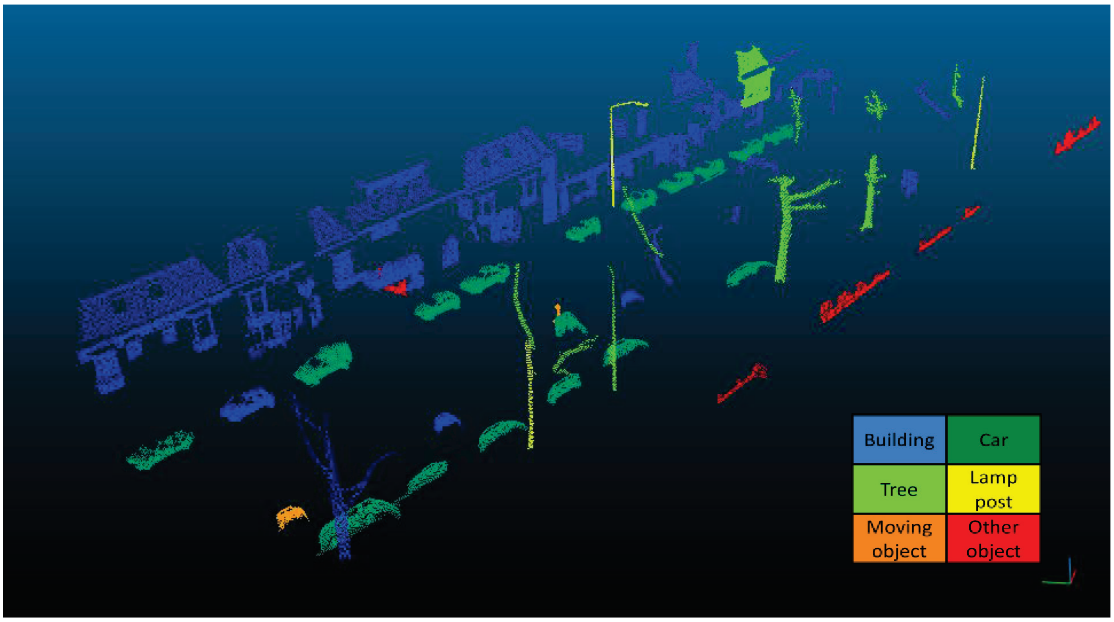
Figure 4-10: Result by different feature selection methods of LDC for 6 classes. (a) All features (b) FS (c) BE

4.5.2.2. Result with SVM

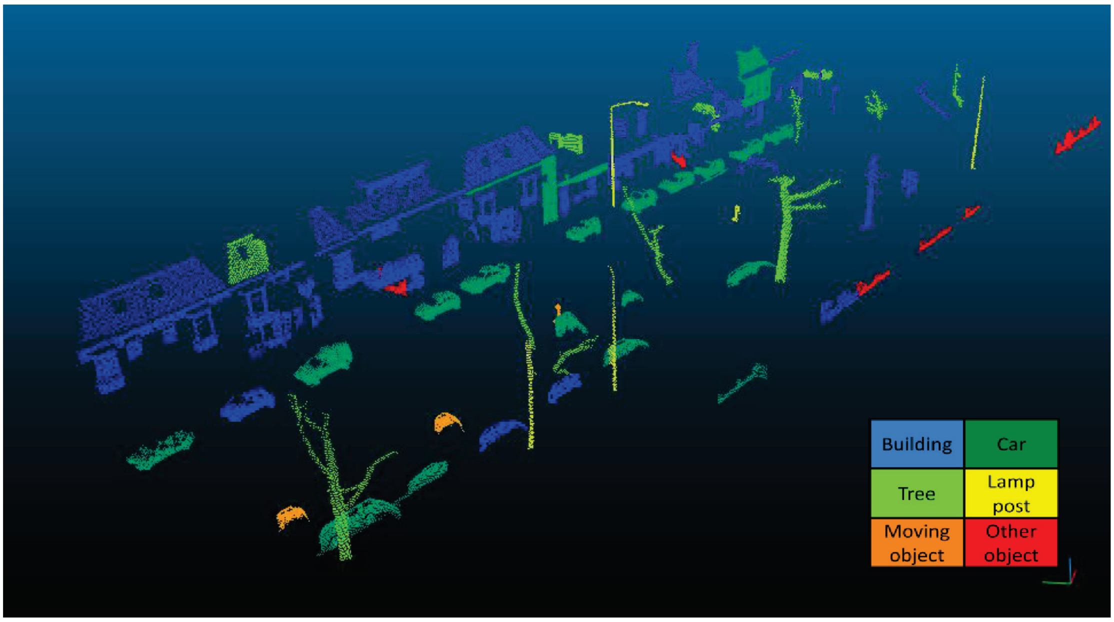
SVM is applied together with all features selection, FS and BE. Figure 4-11 shows the result of each feature selection method.



(a)



(b)



(c)

Figure 4-11: Result by different feature selection methods of SVM for 6 classes. (a) All features (b) FS (c) BE

4.5.2.3. Feature selection result table for 6 classes

The selected features for different classifiers with different feature selections methods for 6 classes are as follow:

Table 4-7: Result of different feature selection methods for 6 classes

	FS(LDC)	BE(LDC)	FS(SVM)	BE(SVM)
RANSAC	X		X	X
	X		X	
	X	X	X	X
	X	X	X	X
Size	X		X	X

Eigenvalue	λ_1	X			
	λ_2	X		X	
	λ_3	X	X	X	X
Anisotropy		X		X	
Planarity		X			
Spericity			X	X	X
Linearity					X
Minimum height		X	X	X	X
Height		X	X	X	X
Area		X	X		X
position		X	X	X	X
density					X
Reflectance		X			X

4.6. Evaluation of the result

The result after classification contains 5 classes or 6 classes based on the training dataset is used here. The conclusion can be made from Figure 4-7, Figure 4-8, Figure 4-10 and Figure 4-11 that some objects such as buildings, cars, trees, lamp post and other objects has been recognized as others. Therefore the evaluation of the result is significant to show the performance of the proposed algorithm.

4.6.1. Strategy of evaluation

Reference dataset which has been labelled in the feature extraction is used to evaluate the classified result. Since the temporary object can hardly be checked by field investigation, the visual check of the dataset and photograph check are necessarily important. After using the proposed algorithm each type of object has a unique label tag value as the reference dataset. The classified result is expected perfectly match the reference dataset.

The quantitative evaluation is carried out as automatic assessment. The classified points are automatically overlying with the reference points and checking whether the classified points has the same label tag value with the reference points when they have the same segment number. The True Positive (TP), False Positive (FP), False Negative (FN) and True Negative (TN) are defined as follow:

- TP (True Positive): the number of objects in result correctly classified as expected objects.
- TN (True Negative): the number of objects in result correctly classified as other objects (not expected objects).
- FP (False Positive): the number of other objects in the result classified as expected objects.
- FN (False Negative): the number of expected objects in the result classified as other objects.

For example, cars and other objects are included in the reference as well as the result. TP means the number of objects correctly classified as cars. TN means the number of objects correctly classified as other objects. FP means the number of other objects classified as cars and FN means the number of cars classified as other objects.

The completeness, correctness and overall accuracy which is introduced by Khoshelham et al. (2010) are used for completing the error assessment:

- Completeness:

$$\text{completeness} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{4-1}$$

- Correctness:

$$\text{correctness} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{4-2}$$

- Overall accuracy:

$$\text{overall accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{4-3}$$

The completeness means the percentage that objects in the reference has been correctly detected by the proposed algorithm. For example, the percentage of cars in the reference is detected by the algorithm. The correctness means the percentage of the correct detection of the object in the reference. For example, the correctly detected cars in the result correspond to the reference. The overall accuracy indicate the accuracy of the classification algorithm in classifying expected objects as expected objects and other object as non-expected objects. The optimum value of the completeness, correctness and overall accuracy is 1.

4.6.2. Evaluation of the result

The evaluation based on the strategy is showed in this part. This step is implemented by using MATLAB and the three values are calculated to reveal the performance of the result.

Table 4-8: Evaluation result of 5 classes by using LDC with all features

Label	Name	NO.	Completeness	Correctness	Overall accuracy
1	Building	61	0.89	0.84	0.86
2	Temporary object	21	0.90	0.86	0.88
3	Tree	14	0.71	0.77	0.74
4	Lamp post	3	1.00	0.60	0.75
6	Other object	16	0.63	0.91	0.74

Table 4-9: Evaluation result of 5 classes by using LDC with FS

Label	Name	NO.	Completeness	Correctness	Overall accuracy
1	Building	61	0.93	0.88	0.90
2	Temporary object	21	0.90	0.79	0.84
3	Tree	14	0.57	0.80	0.67
4	Lamp post	3	1.00	0.60	0.75
6	Other object	16	0.69	1.00	0.81

Table 4-10: Evaluation result of 5 classes by using LDC with BE

Label	Name	NO.	Completeness	Correctness	Overall accuracy
1	Building	61	0.92	0.89	0.90
2	Temporary object	21	0.95	0.91	0.93
3	Tree	14	0.79	0.85	0.81
4	Lamp post	3	1.00	0.75	0.86
6	Other object	16	0.63	0.77	0.69

Table 4-11: Evaluation result of 5 classes by using SVM with all features

Label	Name	NO.	Completeness	Correctness	Overall accuracy
1	Building	61	0.85	0.84	0.84
2	Temporary object	21	1.00	0.91	0.95

3	Tree	14	0.64	0.56	0.60
4	Lamp post	3	0.33	0.50	0.40
6	Other object	16	0.50	0.67	0.57

Table 4-12: Evaluation result of 5 classes by using SVM with FS

Label	Name	NO.	Completeness	Correctness	Overall accuracy
1	Building	61	0.98	0.87	0.92
2	Temporary object	21	1.00	1.00	1.00
3	Tree	14	0.71	0.91	0.80
4	Lamp post	3	1.00	1.00	1.00
6	Other object	16	0.63	0.91	0.74

Table 4-13: Evaluation result of 5 classes by using SVM with BE

Label	Name	NO.	Completeness	Correctness	Overall accuracy
1	Building	61	0.98	0.88	0.93
2	Temporary object	21	1.00	0.95	0.98
3	Tree	14	0.64	0.90	0.75
4	Lamp post	3	1.00	0.60	0.75
6	Other object	16	0.56	0.90	0.69

From the table above, the result of temporary object detection by using SVM classifier gives higher accuracy of the three values than using LDC classifier. Moreover, the detection by using SVM with FS gives the best result as completeness of 1.00, correctness of 1.00 and overall accuracy of 1.00 which mean all of the temporary objects have been detected and none of other objects has been detected as temporary objects. Meanwhile, the accuracies of the lamp post detection are 1.00 as well which is higher than others.

Table 4-14: Evaluation result of 6 classes by using LDC with all features

Label	Name	NO.	Completeness	Correctness	Overall accuracy
1	Building	61	0.84	0.85	0.84
2	Car	17	0.88	0.75	0.81
3	Tree	14	0.64	0.75	0.69
4	Lamp post	3	1.00	0.6	0.75
5	Moving object	4	0.75	0.75	0.75
6	Other object	16	0.63	0.71	0.67

Table 4-15: Evaluation result of 6 classes by using LDC with all FS

Label	Name	NO.	Completeness	Correctness	Overall accuracy
1	Building	61	0.89	0.83	0.86
2	Car	17	0.82	0.78	0.80
3	Tree	14	0.79	0.92	0.85
4	Lamp post	3	1.00	0.75	0.86
5	Moving object	4	0.75	0.75	0.75
6	Other object	16	0.63	0.83	0.71

Table 4-16: Evaluation result of 6 classes by using LDC with BE

Label	Name	NO.	Completeness	Correctness	Overall accuracy
1	Building	61	0.92	0.88	0.90
2	Car	17	0.88	0.79	0.83
3	Tree	14	0.71	0.83	0.77
4	Lamp post	3	1.00	0.75	0.86
5	Moving object	4	0.75	0.75	0.75
6	Other object	16	0.69	0.92	0.79

Table 4-17: Evaluation result of 6 classes by using SVM with all features

Label	Name	NO.	Completeness	Correctness	Overall accuracy
1	Building	61	0.89	0.83	0.89
2	Car	17	0.89	0.75	0.81
3	Tree	14	0.64	0.82	0.72
4	Lamp post	3	1.00	0.75	0.86
5	Moving object	4	0.50	0.50	0.50
6	Other object	16	0.63	0.91	0.74

Table 4-18: Evaluation result of 6 classes by using SVM with FS

Label	Name	NO.	Completeness	Correctness	Overall accuracy
1	Building	61	0.97	0.81	0.88
2	Car	17	0.94	0.94	0.94
3	Tree	14	0.57	0.80	0. 67
4	Lamp post	3	0.67	0. 67	0. 67
5	Moving object	4	0.25	0.50	0.33
6	Other object	16	0.56	0.90	0.69

Table 4-19: Evaluation result of 6 classes by using SVM with BE

Label	Name	NO.	Completeness	Correctness	Overall accuracy
1	Building	61	0.89	0.82	0.85
2	Car	17	0.82	0.74	0.78
3	Tree	14	0.64	0.69	0. 67
4	Lamp post	3	1.00	0.60	0.75
5	Moving object	4	0.50	0.67	0.57
6	Other object	16	0.44	0.78	0.56

From Table 4-14 to Table 4-19, still, the detection by using SVM with FS gives the best result as completeness of 0.94, correctness of 0.94 and overall accuracy of 0.94 which mean most of cars have been detected and few of other objects has been detected as cars.

The results of the classification by using different classifiers with three feature selection methods are showed from Figure 4-12 to Figure 4-17. It is obviously that the result by using SVM with FS for temporary object detection performs the best which reach the classification error of 0 by comparing Figure 4-12 and Figure 4-13. From Figure 4-14 and Figure 4-15 the result by using SVM with FS for cars detection performs the best which reach the classification error of 0.06. Figure 4-16 shows the comparison of all classifiers with the feature selection method. It is obvious that SVM performs better than LDC in detection of temporary objects. In Figure 4-17, the SVM performs better in detection of static cars than LDC.

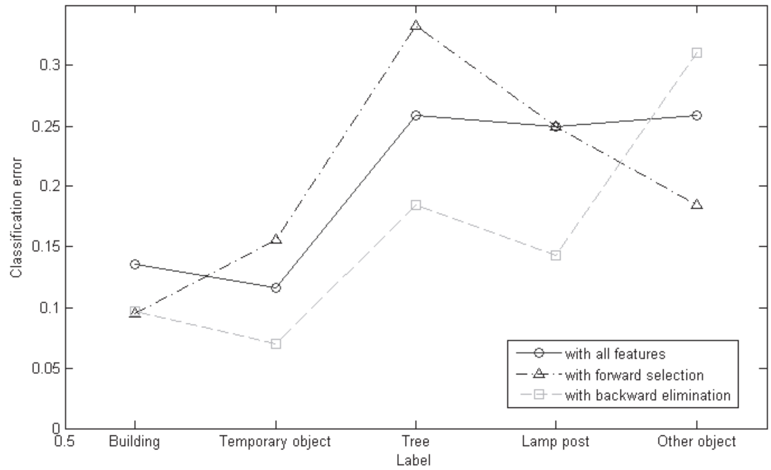


Figure 4-12: Result of 5 classes by using LDC

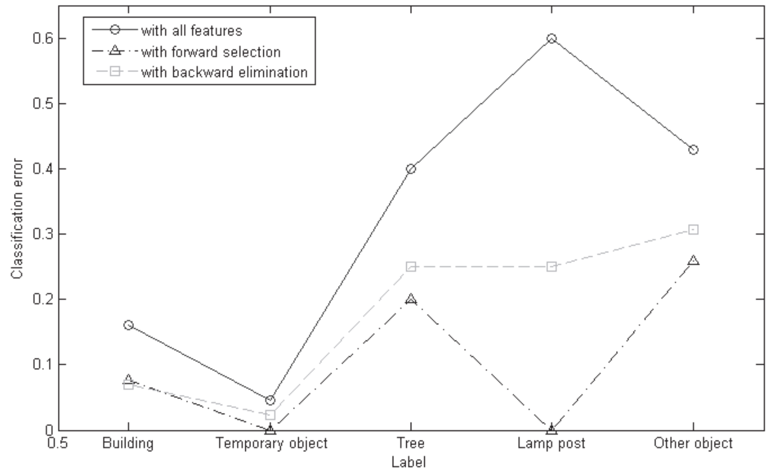


Figure 4-13: Result of 5 classes by using SVM

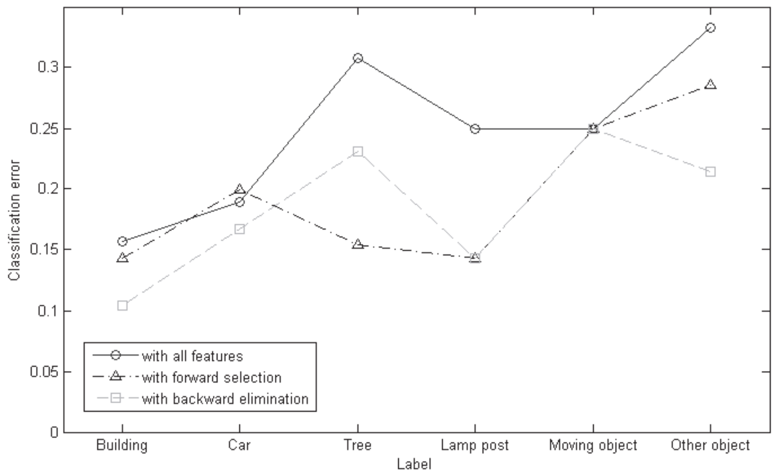


Figure 4-14: Result of 6 classes by using LDC

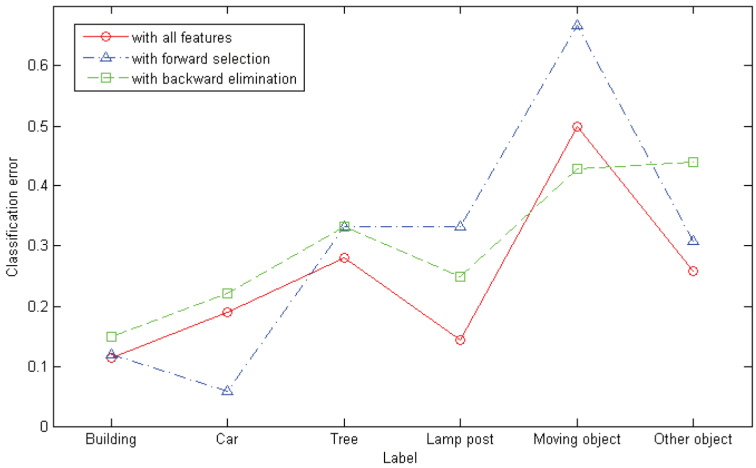


Figure 4-15: Result of 6 classes by using SVM

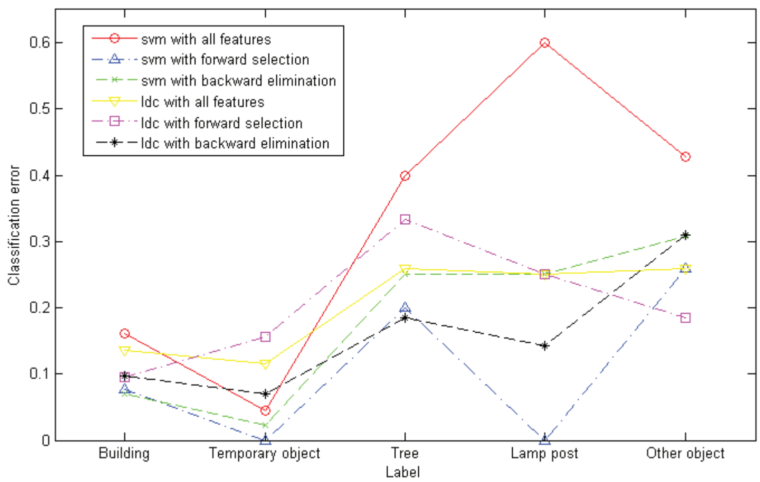


Figure 4-16: Result of 5 classes by all methods

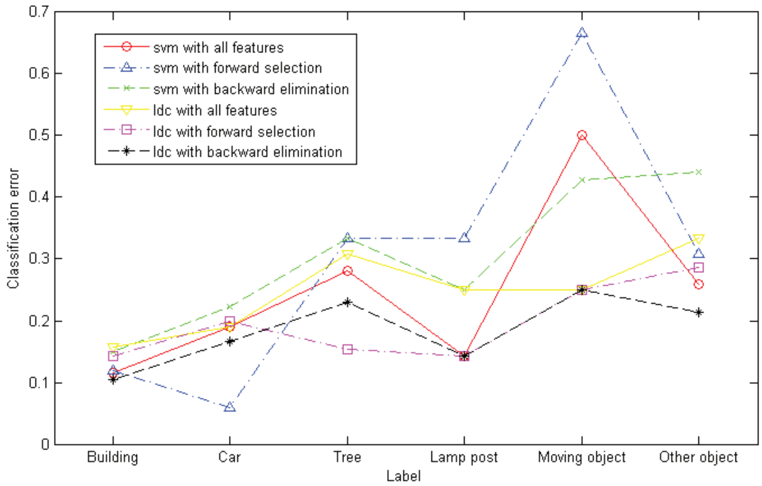
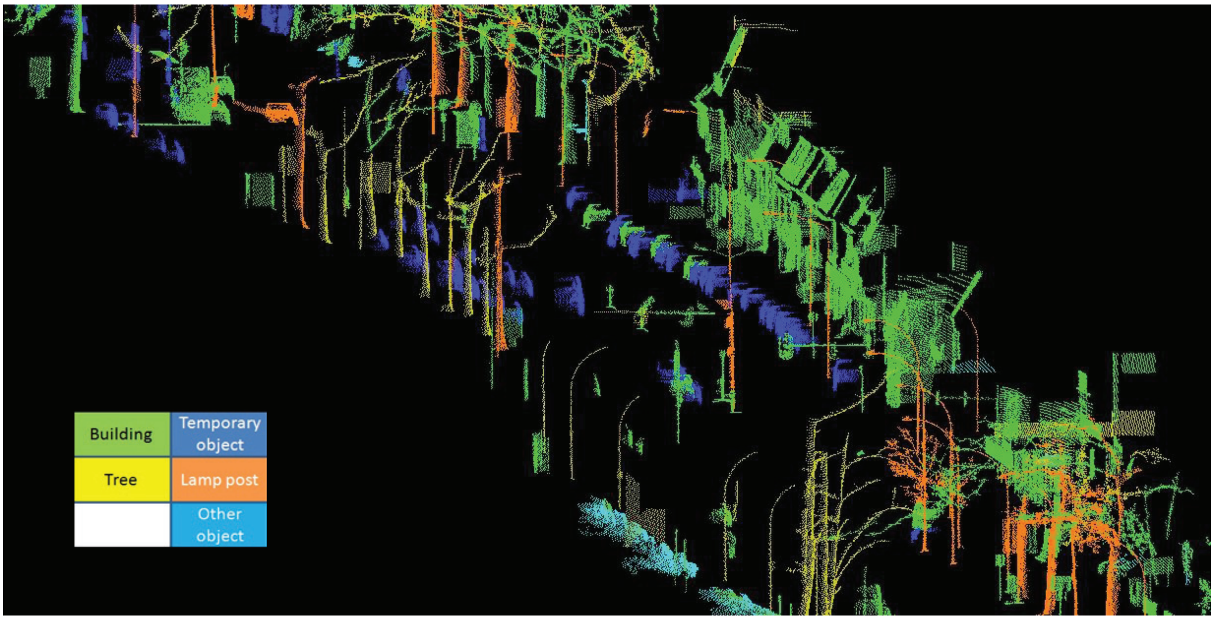


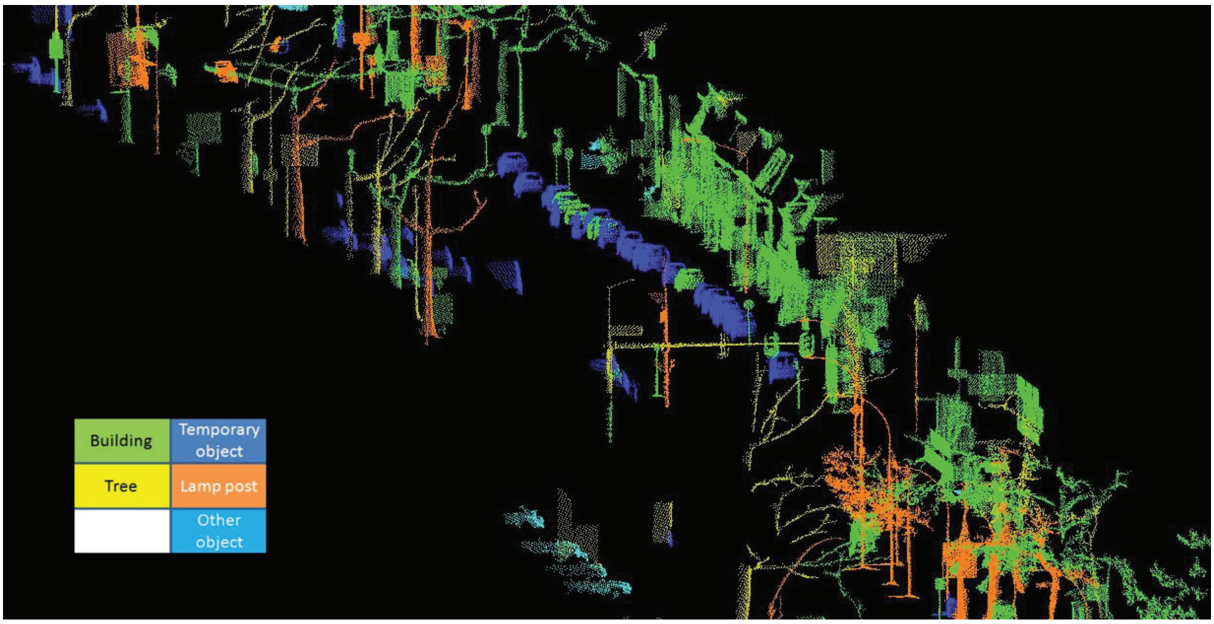
Figure 4-17: Result of 6 classes by all methods

4.6.3. Testing of the total strip

The classifiers have been trained by the training samples as above. Then the trained classifiers are used for testing the point cloud of the total strip from both sensors. The total strip is the combination of all road parts after the connected component analysis which contains no ground points. The data of strip only contains only the x, y and z coordinates and the segment number. The features of the strip are extracted firstly, and then the feature table performs as the input of the classification by the trained classifiers. The SVM with forward selection trained by dataset with 5 classes is used for the testing respectively. The result of the testing is showed in Figure 4-18. The legends are the same as Figure 4-5.



(a)



(b)

Figure 4-18: Result of the test of SVM with forward selection. (a)Sensor 1 tested by trained classifier (b) Sensor 2 by trained classifier

4.7. Summary

In this chapter, the proposed algorithm is implemented for the training sample and tested by the total point cloud from both sensors. Parameters are selected through statistics analysis and examined in the training area to get the optimal result. Five types of objects as building, temporary object, tree, lamp post, other object are classified in the road environment. Six types of objects which divide temporary object into static cars and moving objects are also classified. Though the results for training dataset and the tested strip are good enough by visualization, still some missing detection and false detection exist. The quantitative evaluation of the result is described to indicate the performance of the algorithm and discussion of the proposed algorithm and result is included.

The results are evaluated in this chapter to show the performance of the proposed algorithm. The automatic evaluation is used and the completeness, correctness and overall accuracy are computed by comparing the result dataset with reference dataset automatically. The automatic evaluation method reduces the time consuming in comparing with the manually visual check. It is convincing that the proposed algorithm is feasible in the detection of temporary object especially static objects since an accurate completeness and correctness of the training dataset is acquired and the testing result performs well.

5. DISCUSSION

The result and evaluation of detection of temporary object especially static cars by using the proposed algorithm has been listed in chapter 4. In this chapter, the performance of each stage of the algorithm is discussed. Finally, a summary of the performance is given.

5.1. Discussion of proposed algorithm

5.1.1. Discussion of the surface growing algorithm

During the surface growing algorithm the ground has been removed from the laser point cloud of strip4 successfully. The number and the quality of static cars has been checked after the operation and obtained the following results.

Table 5-1: The number of cars before and after road feature extraction

Number of part	Car number(strip4)	Car number(raw)
0	2	2
1	1	1
2	3	3
3	32	32
4	0	24
5	1	1
6	17	17
7	13	13
8	4	4
9	0	0
10	8	8
11	4	7

The Table 5-1 shows that most of the results are in good quality since they have the same number of cars as the raw data. However, the result in part 4 and part 11 are not good enough. For part 4, the main reason depended on the width we set that lead to some of the cars which located far away from the road had been removed together with some part of the buildings. For part 11, the cut of the raw data which depends on the setting of the length of the road part contributes to the missing of the data as well as the reason mentioned as part 4.

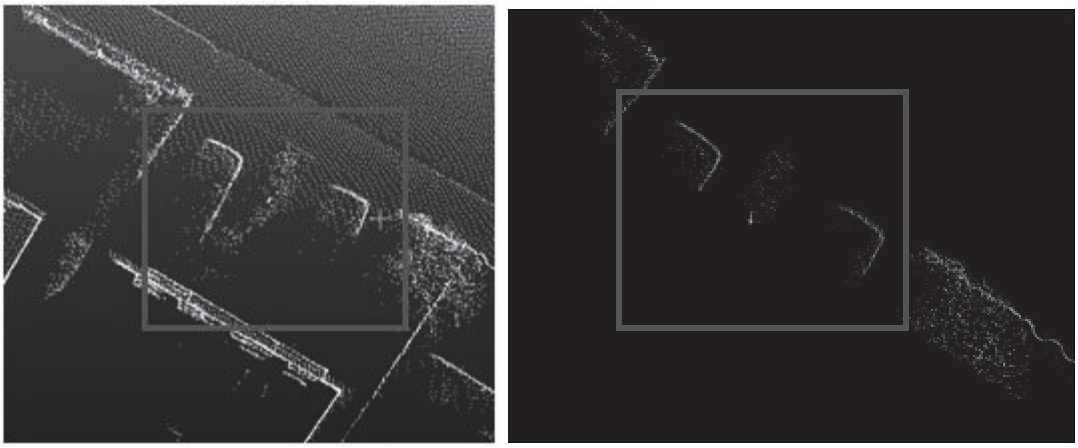


Figure 5-1: Missing cars away from road

Figure 5-1 shows the first reason of the missing of the cars that part of the car has been removed together with the buildings. The left figure comes from the raw data which shows parked cars clearly. The right figure comes from the data after the operation which shows only part of cars.

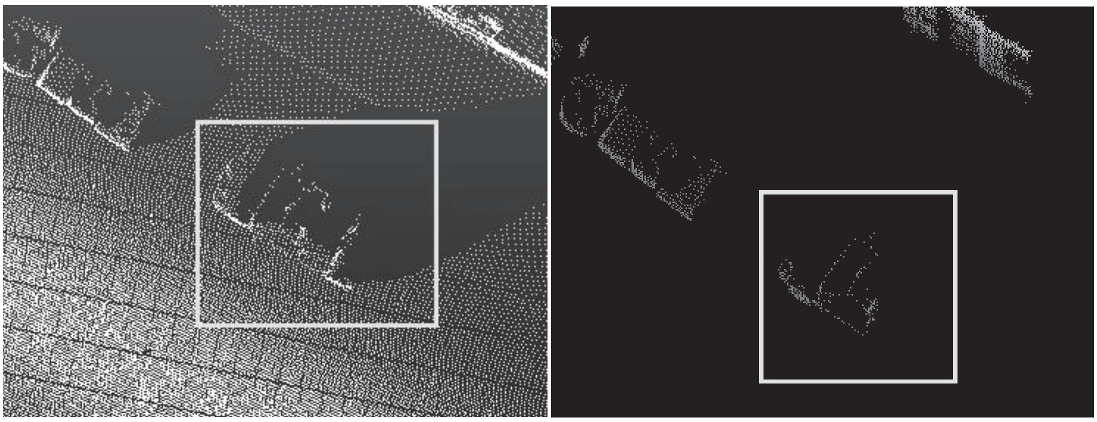


Figure 5-2: Missing cars by cutting the data

Figure 5-2 shows the second reason of the missing of the cars that the car has been divided into two parts. The left figure come from the raw data which shows a complete car which has been cut in the right figure. Both of the reason could lead to the decrease of the accuracy for the detection of cars in the first step.

5.1.2. Discussion of the connected component analysis

In the connected component analysis the parameters of the maximum distance between points and the minimum number of points of one component have been set to obtain the expected segments. However, some small segments have been removed from the point cloud especially for tree crown as shown in Figure 5-3. Meanwhile, small segments which have been removed from cars would change its basic characteristic. For instance if the segment on the top of the car has been removed the height of the car would be reduced. Moreover, some of the components have been merged together due to the set of the parameters as in Figure 3-3. The merged components can contribute to the mistake in feature extraction as well. In addition, small segments like buildings may be detected as others which have the similar attribute.

(a)

(b)

Figure 5-3: Error in connected component analysis. (a) Dataset before the analysis (b) Dataset after the analysis

5.1.3. Discussion of the feature extraction

The feature extraction is the main work of this research and the decided features are extremely important for the classification. Although 18 features have been extracted, some of them are rarely used in the classification while some of them contribute to the error. The difference between the result and the expected result can be obtained by comparing Table 3-1, Table 4-4 and Table 4-5.

- Size: The expected size of the buildings and trees should be the largest, however; the temporary object has taken the largest part. The main reason for this is the crown of the trees has been recognized as small segments which have been removed in the previous step. The buildings have been separated into smaller segments than expected. This may cause the result that other objects be detected as cars.

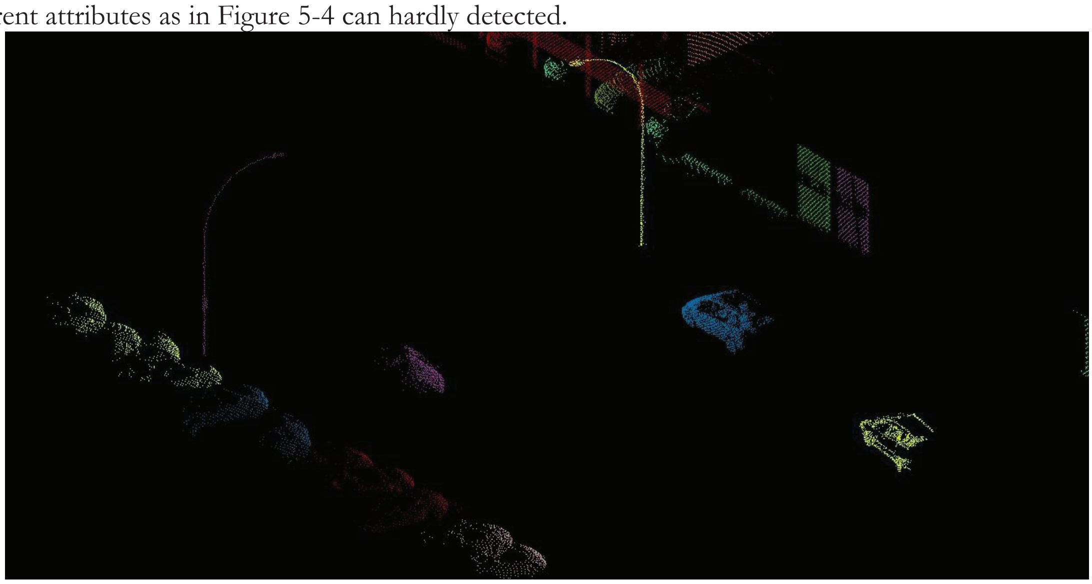
- Area: As mentioned for size, the area of some segments of buildings and trees are not large enough as expected. The average area value of buildings even smaller than temporary objects. The removal of small segments and the segment strategy can contribute to this error.
- Density: The density of building is exceeding larger than expected due to the volume of the segments much smaller than expected.
- Height: The main problem of the lower height for buildings may lead the miss detecting buildings as cars since most of them have a similar height.
- Position: The trajectory of the sensor is not the centre of the road which will lead to the result that the similar objects located on both side have different value for position.

By analyzing the feature selection in Table 4-6 and 4-7 the conclusion can be summarized that features as eigenvalue λ_2, anisotropy and linearity are the most rarely used features while the minimum height, height and position have been used in all the feature selection strategies. λ_2 performs as the second value in eigenvalue which can hardly describes the attribute alone. The performance of this value would be better if using together with other eigenvalues. The reason for the rarely use of anisotropy is that most of the objects has a high value which is difficult in distinguishing different classes. The linearity performs well in the detection of pole-like object, however; the value for the buildings and temporary objects are almost the same due to the existed error by connected component analysis.

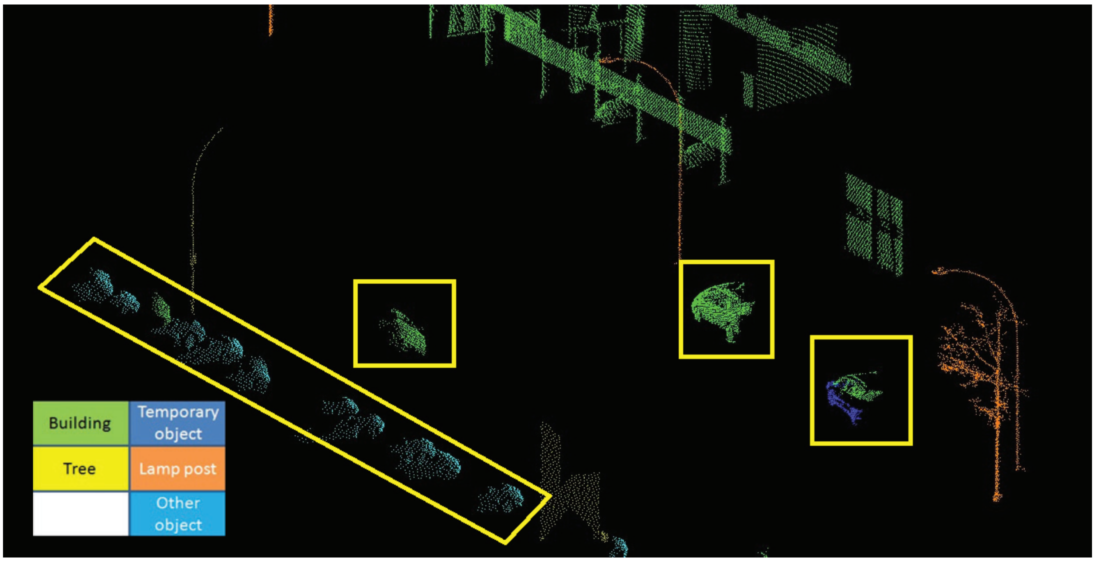
5.1.4. Discussion of the segment-based classification result

The finally result after classification is evaluated in section 5.1.2. The proposed algorithm produces a reliable result. The completeness, correctness and overall accuracy for temporary object detection are higher than that of detecting static cars and moving objects by using different classifiers with different feature selection methods respectively. The main reason for this is that static cars and moving objects have large number of similar features which would contribute to the miss detection. As visualised in Figure 4-10 and 4-11, the moving objects are easily recognized as static cars by the proposed algorithm. In addition, as mentioned above, some of the buildings segments have almost the same characteristics as cars so that both of them may be detected as buildings and vice versa. Therefore, the accuracy would increase when the static cars and moving objects combined as temporary object since there would be no more miss detection between them.

In order to confirm the proposed algorithm, the point cloud of total strip from both sensors has been used as testing data. As shown in Figure 4-16, most of the temporary objects that share the similar attributes as the training dataset have been detected. However, the temporary objects which include different attributes as in Figure 5-4 can hardly detected.



(a)



(b)

Figure 5-4: Miss detected temporary object. (a) The original dataset (b) The miss detected temporary object

Temporary objects which are showed in Figure 5-4(b) are missing detected as buildings or other objects. This is mainly because of the small training dataset. Thus some samples have the same attributes of these temporary objects are added in the training dataset to train the classifier. Then the following Figure 5-5 gives the better after the improvement.

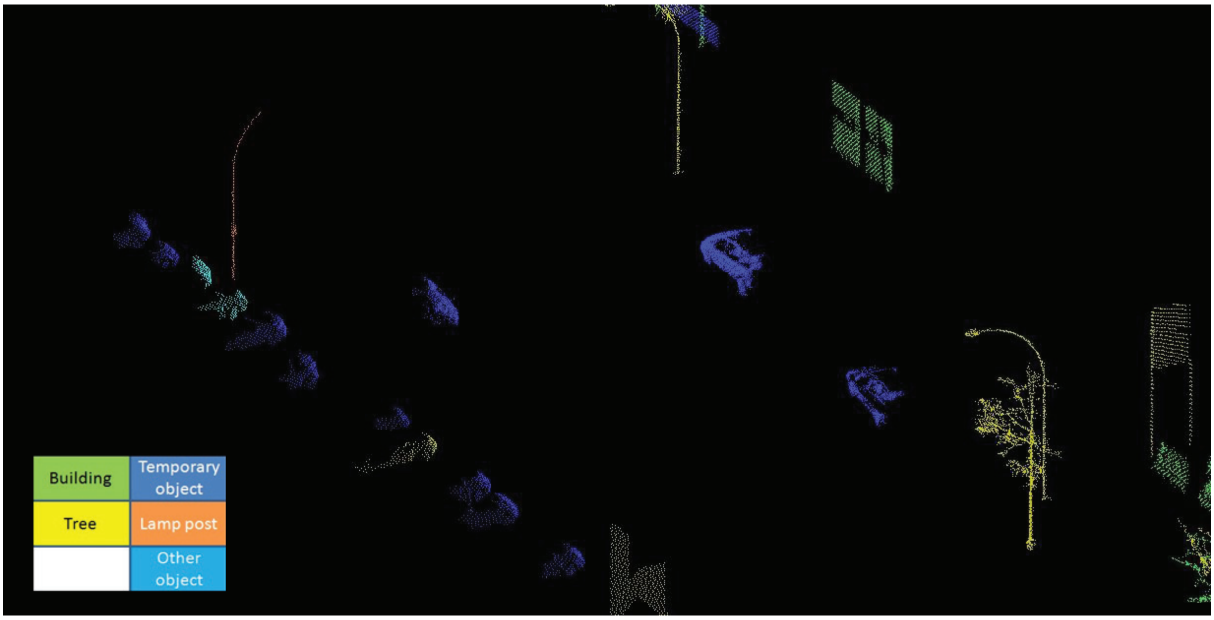


Figure 5-5: Result of total strip after improvement

The result has been clearly improved for the detection of temporary object. However, still some static cars have been missed detected. The other attributes such as size, density, and area may lead to the error.

5.2. Summary

In this chapter, the result with existing error has been discussed. There are three main errors sources: error from the dataset, error from the method and error from the assessment method. The error from the dataset such as some part of the object including no point cannot be avoided. Errors from the surface growing algorithm, the connected component analysis, feature extraction and classification have been discussed and the errors have been reduced as much as possible for high accuracy. The manually labelled reference dataset includes some defect over the recognition experiment. The ground truth do not have sufficient reference component for each class and there might be some mistakes during the recognition of the object visually. The result by testing the strip using an improved training dataset performs quite well which confirms the utilization proposed algorithm

6. CONCLUSIONS AND RECOMMENDATIONS

6.1. Conclusions

The main objective of the proposed research is to automatically detect temporary objects from mobile LIDAR point clouds, with the focus on the detection of parked cars as static temporary objects. There are five main phases to achieve the objective: laser data pre-processing, segmentation, feature extraction, classification and evaluation. In the first phase the total strip is divided into 12 road parts which can be easily operated in the following step. Then the surface growing algorithm is used in the second phase to group the unstructured laser points for the sake of remove the ground points and preserve the non-ground points. The connected components analysis removes small components then the labels are added for the ground truth. In the next phase of feature extraction, 18 attributes are picked up into a feature table for the dataset with 5 classes and 6 classes respectively. The feature table is utilized as the input of the classification phase. In the fourth phase, the LDC and SVM classifiers are used with FS and BE feature selection method for the classification. Thus the temporary objects especially static cars are detected. The last evaluation phase gives the analysis of the result by using completeness, correctness and overall accuracy.

The proposed algorithm is verified by the testing dataset then. The dataset of the total strip performs as the testing dataset. The reference datasets are generated by manually labelling every component into 5 classes and 6 classes. The dataset with 5 classes contains building, temporary object, tree, lamp post and other object while the dataset with 6 classes includes building, car (static), tree, lamp post, moving object and other object. The trained classifier by the training datasets is used to test the point cloud of the strip from both sensors. The accuracy for the training sample performs well in the evaluation result. Simultaneously, the result of the testing dataset is achieved with high accuracy for the temporary object. Moreover, the automatic method which developed in this research reduces the calculation consuming. Some conclusion is summarized by analyzing the evaluation result.

- The surface growing algorithm is an effective method for the removal of ground surface and large building facades. The parameters on the surface growing algorithm cannot be very critical since the ground and large building facades can be easily detected.

- The connected component analysis ensured that the laser points in one component have been grouped so that the attribute of each kind of class can be easily acquired in the next step. Parameters of the maximum distance between points and the minimum number of points of one component are set to avoiding over-segmentation and under-segmentation.

- The feature selection phase plays an important role in this research. 18 features are extracted here. Shape features as minimum height, height and position are the most significant feature in all the feature selection methods. However, features such as anisotropy, reflectance information and the second eigenvalue are rarely used in both classifiers.

- The classification is done by using two different classifiers with three feature selection methods based on the feature table. Besides temporary objects especially cars, other objects such as trees, lamp posts are detected as well. During the classification, the SVM cost a longer time for training than the LDC. However, the performance of SVM is better than the LDC. The classification can be applied in the indoor object detection as well as the road environment object detection by analyzing the properties of objects.

- The proposed algorithm is feasible in detecting temporary objects especially cars based on the achieved result. The detection of temporary objects from the training sample reaches a perfect result that all the objects have been detected completely and correctly while the overall accuracy is 1.00 as well. For the detection of static cars, the completeness and correctness also achieved a high value as 0.94 and meanwhile, the overall accuracy is 0.94. The result in the testing dataset shows a quite good performance which confirms the utilization of the proposed algorithm.

6.2. Answers to research questions

1. What characteristic properties are relevant to the detection of cars?

The geometrical attribute of objects based on human knowledge performs as the most common features. Shape features for instance size, area, density, minimum height and height are used for detecting cars. The densities of cars are always the highest among all the objects. The minimum height always is the smallest one since cars stay on the ground directly. The feature and height can detect cars indirectly since they can be used to separate pole-like objects from cars while size can be used in distinguishing buildings from cars. In addition, the contextual feature includes the information about the position of an object related to its environment is taken into consideration. Since cars are always staying in a line on a street the contextual feature is an important property. Besides the shape and contextual features extracted above, additional features as eigenvalues, eigenvalue-based LIDAR features, RANSAC need to be extracted as well. The eigenvalues of λ_1, λ_2 and λ_3 of cars have the least difference and spericity are the highest among objects since they have volumetric patterns. The distance from the original to the cars are the largest since they located as the furthest objects.

2. How could the shape of a car be described with some measures?

As mentioned above, size, area, density, minimum height and height are used as features for describing a car. The size of a car is represented by the number of the points in the component. The minimum area is measured for describe the space occupied by a car. The density is calculated based on the position, volume and size of a car. Normally, cars have a high density since its position next to the trajectory, the volume is small and the amount of the points for cars is high. The minimum height of a car is the lowest z coordinates in the component. Temporary objects such as cars always stay on the ground so that they have the lowest minimum height among all objects. The height of a car is one of the most important features in describing the shape. Based on the statistical analysis, the average height of cars is 1.5m.

3. How to evaluate object extraction (in this research it refers to cars) from point clouds?

The accuracy of completeness, correctness and overall accuracy are calculated for evaluating the object extraction. Besides, the trained classifiers are used for the testing strip to show the performance of the algorithm. More training samples are added for increasing the accuracy for the testing dataset.

4. How to collect ground truth to evaluate the performance of the algorithm?

The randomly selected road part 6 is manually labelled as ground truth after the connected component analysis. There are two different ground truth dataset. The one with 6 classes contains buildings, cars (static), trees, lamp posts, moving objects and other objects. The one with 5 classes includes the combination of cars (static) and the moving objects as temporary objects based on the labelled result of 6 classes. For improving the result of testing dataset, 20 more samples in other parts have been added into the ground truth with the same labels.

5. What is the performance (in terms of completeness and correctness) of the algorithm?

The evaluation of the detection of temporary objects especially static cars are carried out by comparing the result with the reference point data. The completeness, correctness and overall accuracy are calculated for evaluating the performance of the proposed algorithm. The evaluation of the dataset with 5 classes and 6 classes are done separately. Based on the evaluation, the completeness and the correctness for the detection of temporary objects are 1.00 as well as the overall accuracy. The completeness and correctness for the detection of static cars are 0.94 as well as the overall accuracy. Therefore the proposed algorithm gives a persuasive accuracy for the detection of temporary objects especially static cars.

6.3. Recommendations

The result with high accuracy is obtained by the feasible proposed algorithm. However, due to the limitation of time and knowledge, improvement based on this research is still needed in the further study. Some recommendations are listed as follow:

- The parameters of surface growing segmentation and the connected component analysis are based on the examination of the training dataset. However, the parameters are not convincing enough since the parameters may not the optimal setting. Therefore an objective method for parameter selection would contribute to the result with higher accuracy.

- 18 features have been taken into consideration in the feature extraction section. Since some features have been rarely used in the classification, the representation levels of the features need to be carefully thought of before the feature extraction so that only useful features would be used. In addition, more features such as Fast Point Feature Histogram can be taken into account in the further research.

- The proposed algorithm has only one training dataset and one testing strip. More testing datasets would be better in convincing the proposed algorithm. Since the limitation of the amount of components in one class, the training samples are not sufficient enough to train the classifier for testing a large dataset. So more training part would contribute to a better result of the detection of temporary object especially cars.

- As shown in the result, both of static cars and moving objects are missing detected as buildings. Simultaneously, some of the buildings have been recognized as cars. This reduces the correctness of the detection of temporary object obviously. So it would be essential to remove the buildings in the first two phases in later work.

- Due to the limitation of time, only two classifiers and three feature selection methods have been used here. Although a result with quite high accuracy obtained finally, analysis based on more classifiers and feature selection methods would be better in separating different classes.

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