KNOWLEDGE BASED DETECTION OF ROAD FURNITURE OBJECTS IN MOBILE LASER SCANNER (MLS) DATA

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March, 2014

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ABSTRACT

Road safety is of utmost importance to every road user. Road furniture objects such as traffic signs, traffic lights and lamp posts are very essential for safety driving on our roads. Maintenance of road furniture enhances our safety thus calls for need to detect, extract and document them for ease of reference. With the advancement of methods of data capture, detection and extraction of the road furniture has been becoming better every day. Methods as laser scanning have proved to capture 3D information of the feature. The purpose of this thesis is to develop an approach to detect the road furniture from MLS data. Knowledge on the characteristics of road furniture is prerequisite information to the process.

The approach of detection and classification was based on use of histogram and Minimum Bounding Box (MBB) where histogram correlation and MBB ratios are applied. First, pre-processing of the input datasets is done by segmentation and filtering where surface growing and connected component analysis is performed. Then computation of histogram correlation and MBB ratios are done on the connected components in which desired constraints for classification are defined. Next is classification which is done in two sequential steps; histogram correlation is performed to obtain object class and MBB ratios applied to refine the classification in which we obtain subclass object category. We also do enhanced kind classification which makes use of histogram correlation and distance ratio computed in MBB ratios feature space. Finally Iterative Closest Point algorithm is applied to selected segments to check for similarity by considering point-to-point correspondence.

Evaluation of the classification results was done using confusion matrix and evaluation measures completeness, correctness and quality. Lamp posts and traffic lights were found to have accuracy of 100% while traffic signs and trees achieved 87.5% and 84% respectively. Cars were poorly detected with accuracy of 47% thus its evaluation was further performed in comparison with Support Vector Machine with Forward Selection classifier in which the accuracies remain consistent.

In conclusion, use of histograms and minimum bounding box parameters for detection of road furniture is a successful approach. Enhanced classification seems to be more promising as we can handle noise stepwise than having a pipeline classification by use of constraints. This then calls for further improvement on how to implement these features in more efficient and reliable way. Finally, for Iterative Closest Point algorithm, automatic approach to selection of the initial approximation values can be investigated further to avoid bias as a result of manual selection by the operator.

Keywords
Mobile Laser Scanning (MLS), Histogram Correlation, Minimum Bounding Box (MBB), Iterative Closest Point algorithm (ICP)

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LIST OF ABBREVIATIONS

MLS	Mobile Laser Scanning
2D	Two Dimensional
3D	Three Dimensional
ALS	Aerial Laser scanning
TLS	Terrestrial Laser Scanning
TIN	Triangular Irregular Network
LiDAR	Light Detection and Ranging
PCM	Point Cloud Mapper
RGB	Red Green Blue
RANSAC	Random Sampling Consensus
PCA	Principal Component Analysis
MCMC	Markov Chain Monte Carlo
ICP	Iterative Closest Point
GUI	Graphical User Interface
CAD	Computer Aided Design
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative
MBB	Minimum Bounding Box
SVM	Support Vector Machine
FS	Forward Selection

1. INTRODUCTION

1.1. General introduction

Road furniture objects encompass all road-side objects within the road environment mainly used for road safety and control of traffic. They include traffic signs, traffic lights and lamp posts and are very essential for safety driving on our roads. They provide drivers with necessary warnings, rules and other relevant information such as distance and direction (El-Halawany & Lichti, 2011). Updated and well documented road inventories are therefore of utmost importance to the relevant authorities and organizations. This enables quick decision making for road safety improvement. This calls for the need to extract and properly document road furniture for ease of reference. The advancement in the methods of data capture has made the detection and extraction of the road furniture better. This is due to the ability of the recent methods as laser scanning capable of capturing 3D information of the feature (Terrasolid, 2012-2013).

Laser scanning technology currently exists in three modes; Air-borne laser scanning (ALS), terrestrial laser scanning (TLS) and mobile laser scanning (MLS). The difference in these methods is due to the platform in which the data is acquired but the end product is the same which is three dimensional (3D) dense point clouds of data containing X, Y, Z coordinates among other properties. In this research the focus is detection of road furniture from Mobile Laser Scanner data. This is attributed to the fact that MLS enables capturing of physical objects including road furniture in form of 3D point cloud data of urban areas inclusive of roads as can be seen in figure 1-1 below.

In most countries, road furniture objects are standardized and thus have peculiar characteristics such as shape, size and colour that define them. Figure 1-2 below shows some models of the road furniture objects. These characteristics can be analyzed and modelled and information is then collected and further analyzed to form a knowledge base for road furniture object detection. As for this study, the characteristics of the objects as captured in mobile laser scanner data is analysed and used to detect similar objects in the dataset which are then further classified according to their type.

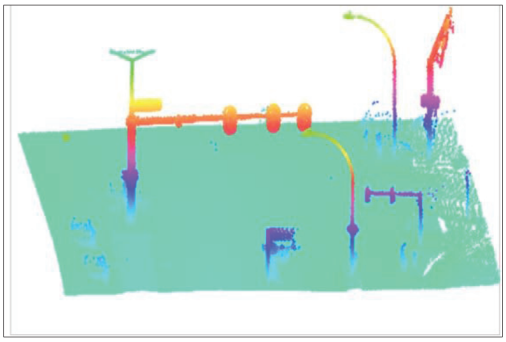


Figure 1-1: Road furniture as captured by MLS, labelled by height colour

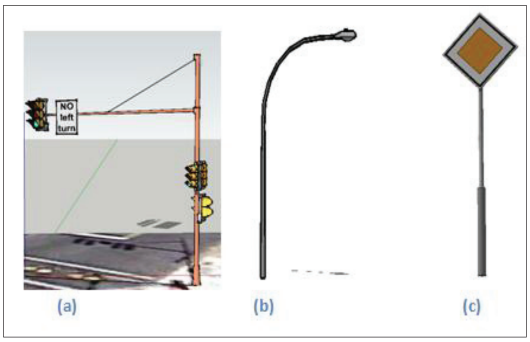


Figure 1-2: Road furniture objects; a) Traffic light, b) Lamp post, c) Traffic sign. Source (Google, 2011)

1.2. Motivation

Road transport is the most widely used mode of transport in most countries in the world. Its safety is therefore of utmost importance and the forefront issue in this sector of transport. Road furniture contributes significantly to road safety especially in countries that have voluminous road traffic. Proper knowledge of their location and status is thus important and efforts aligned in this direction are of great value. Hence the efforts applied in development of methods that facilitate road furniture object detection.

Existing methods use manual location and cataloguing of road furniture which is time consuming and tiresome (Kumar et al., 2010), therefore creating an appreciable need for automatic development of this process. Automatic detection of road furniture from MLS is one such approach, and this creates need for improvement of existing approaches that employ MLS while decreasing manual work. Additionally the MLS offers high density spatial data (Cahalane et al., 2010) and good coverage given its mobile locality on the actual roads targeted thus efficient for mapping roads and its environment (Jaakkola et al., 2008). With Mobile Mapping System, chances of inconveniencing other motorists on the road or highway during survey are very minimal since traffic need not to be stopped or detoured in order to survey the road. Other associated benefits of this system is that there is improved efficiency in data acquisition, possibility of integrating many sensors to enhance the quality of data, simplified geometry of objects and resulting images are well geo-referenced thus aid in quick object recognition (Li, 1997).

Use of Mobile Laser Scanner (MLS) data as compared to imagery is due to active 3D capture ability of MLS that enables us to capture road furniture form and location as desired with relative ease (Baltsavias, 1999). Airborne Laser Scanner (ALS) data is not good enough for detection of pole-like objects due to viewing angle and point density, as comparatively MLS offers dense point cloud with high accuracy. Also MLS has capability to capture discrete objects from multiple angles (Puente et al., 2013). Further, the mobility aspect of MLS enables it to cover large area and prevent occlusions in one continuous scan as compared to Terrestrial Laser Scanner (TLS) data that will require several scans and more equipment positions (for multiple viewpoints) which eventually will result in intensive manual work (Haala et al., 2008; Lehtomäki et al., 2010). This then renders TLS to be impractical for surveying a long stretch of roads. The closeness and continuous recording ability of MLS along the roads makes it preferable compared to ALS and TLS. Therefore, MLS can fill the gap between ALS and TLS. It is capable to collect direct geometric 3D information from road environment which can be utilized for road furniture object detection, hence the motivation for use of MLS data.

Road furniture has definite standard shapes that can be used to start the search of other similar types. Objects of the same category have similar properties in which this can be analysed and develop a method that can detect similar objects in the dataset. Interest in development of this process, thus contributes further to motivate this research on "Knowledge based detection of road furniture objects in Mobile Laser Scanner (MLS) data".

1.3. Problem statement

Detection of road furniture objects such as traffic signs, traffic lights and lamp posts still presents a considerable challenge. There is still need to improve or develop methods for capturing the form and nature of road furniture. Mobile Laser Scanner (MLS) data enables capture of physical objects along roads. However there still lies the need to identify and separate target road furniture from other captured objects. The prominence is on observing and discovering peculiar object characteristics defining the targeted road furniture types. This information is collected as base knowledge for developing a method that can detect and extract road furniture objects of interest. The main challenge then is to determine the best characteristics or properties of the objects as captured in the MLS data that can best be analysed and used to find other similar objects in the dataset to desirable levels.

1.4. Research identification

1.4.1. Research objectives and question

The main objective of this proposed research is to detect road furniture objects from Mobile Laser Scanner data captured from a sample street in Enschede. Emphasis is to apply knowledge based detection approach to automatically detect and extract road furniture from MLS data. The specific objectives and associated research questions are:

i. Establish peculiar information on characteristics of road furniture objects of interest.
   a) Which features and their characteristics define the existing nature of road furniture?
   b) What factors affect the defined nature and status of road furniture?

ii. Define the road furniture characteristics in terms of MLS data properties.
   a) How do we define road furniture based on MLS data properties?
   b) What are the characteristics of road furniture that are the least influenced by noise and low density of the data?

iii. Develop an approach to detect and extract road furniture objects of interest.
   a) Which road furniture characteristics help us differentiate between the road furniture types?
   b) How do we combine these characteristics to enable detection and extraction of road furniture?
   c) At what point do we decide that the object is detected or not?

iv. Evaluate the results of the developed road furniture extraction approach.
   a) How effective is the developed road furniture extraction process?
   b) What factors are likely to have affected the presented results?

1.5. Innovation aimed at.

The proposed approach for this study is knowledge based method which incorporates our knowledge about the objects of interest, being the road furniture. The novelty will be in specifically using a connected component representing target road furniture as base knowledge for detection and extraction of the MLS segments representing the said target road furniture from other objects captured by the same MLS data. The properties of the connected component analysed are point distribution along the object height by use of histogram and the dimensions of the object segment by employing minimum bounding box.

1.6. Thesis structure

This research has been documented in seven main chapters. Chapter 1 contains the introduction, motivation of the research, problem statement, research objectives and associated questions and the innovation and summary of thesis structure. Chapter 2 is the literature review. Chapter 3 is the description of road furniture objects. Chapter 4 describes the methodology for the detection method developed and followed by implementation and results in chapter 5. Chapter 6 presents evaluation and discussion. Finally the conclusion and recommendations are in chapter 7.

2. LITERATURE REVIEW

In this chapter, we review the concept of Mobile Laser Scanning technology in section 2.1 as a technique for data acquisition and highlight some researches on object detection in MLS data in section 2.2. We then discuss researches on road detection and extraction in section 2.3 and narrow on to the road furniture detection in section 2.4. The concept of knowledge based object detection is tackled in section 2.5. In section 2.5, we discuss about histogram matching that is applied via height wise point distribution to assess similarity of unidentified object segments to identified sample segments and finally 2.6 we give highlights on registration of point clouds specifically on Iterative Closest Point algorithm that uses point to point correspondence to determine matches between two objects.

2.1. Mobile Laser Scanning

Mobile Laser Scanning is a growing technology in laser scanning which simply can be considered as dynamic terrestrial laser scanning given the platform employed scans in motion along a predefined track (Li, 1997). Usually two scanners are mounted on the platform; one in front and the other at the rear part to allow capture of stereo images and 3D measurements (Tao, 2000). The scanner is mounted on car, train or boat (Pratihast & Thakur, 2012) as shown in figures 2-1. The system is made up of sensors, positioning (Global Positioning System) and navigation units (Inertial Measuring Unit) for spatial and time referencing unit (Puente et al., 2013). Important also to note that there is two observation modes in this system; stop-and-go and on-the-fly modes. The stop-and-go mode; scans are taken in static mode which can be panoramic or hemispherical mode typically similar to Terrestrial Laser Scanning but difference here is that the scanner is mounted on a vehicle rather than tripod. The later scans continuously in 2D (XY direction) profile mode as the vehicle move along the trajectory without stopping (Vosselman & Maas, 2010).

(a) (b) (c)

Figure 2-1: Mobile Laser Scanner platforms, (a) Boat (Alho et al., 2009) (b) Street Mapper Vehicle (c) Rail Mapper (Kremer & Grimm, 2012)

2.2. Tree detection in MLS data

Object detection in laser scanning has been the centre of many researches employing laser scanner data. Modelling of single trees in MLS point cloud was performed automatically by Rutzinger et al. (2010). The adopted workflow was automatic with three main steps; tree detection, tree simplification and tree modelling. The point cloud is first segmented and unwanted segments are removed then remaining points are grouped by connected component analysis. These components are analysed for roughness and point density ratio. Since trees have low point density ratio and high roughness due to echoes hitting the crown, the components depicting these characteristics are extracted as trees. With trees extracted based on the echoes, the point cloud is thinned using 3D alpha shape algorithm into alpha shape point cloud structure. The size is then analysed for radius of the sphere where the alpha value that tends to infinity gives convex hull and alpha value which tends towards zero returns the original point cloud. The final stage is modelling each single tree using tree model parameters which include tree height, crown width, stem height, stem width and crown shape.

2.3. Road detection and extraction in MLS data

Studies on road detection and extraction using mobile laser scanner data has been successfully carried out in the past. Wang et al. (2012) performs automatic road extraction using trajectory information from mobile laser scanner data. This is motivated by the fact that with mobile laser scanner, we get both height and side information which is helpful in obtaining driving direction and location of the road. The proposed algorithm considers every trajectory point as a seed to start the search. With two adjacent trajectory points a line segment is formed which indicates the direction of the local road patch between them.

Jaakkola et al. (2008) modelled the road surface and kerbstones on dense point cloud from vehicle-based laser scanning using retrieval algorithms. The process involved segmentation of kerbstones and road markings using image processing algorithms into intensity and height images then model the pavement as triangular irregular network on point cloud. Further, the road markings and kerbstones were modelled as raster images to allow use of raster image-processing algorithms. The raster images contain image intensity and height in which the pixel size varied as a function of the measurement distance and driving speed. Image intensity was employed for modelling road markings based on rows and columns while kerbstones were modelled using height image based on z coordinate values. To classify the road markings, the author employed area of bounding box and orientation of 4-connected segment of the image. Bounding box should be rectangular and the orientation angle is above 88° to ensure the segment is wider enough. The road surface model was accomplished by finding all the points in point cloud and create TIN by iteratively shaping it into smooth surface. The proposed method successfully found most kerbstones, road markings, zebra crossing, parking space lines and triangulated road surface that were visible in laser data with mean accuracies above 80%.

2.4. Road furniture detection

Detection of pole-like objects into different classes as flag poles, traffic poles and street light poles from unorganized point cloud was performed by El-Halawany and Lichti (2011).The adopted method was covariance based procedure for segmentation of the point cloud then the extraction of poles using local neighbourhoods based on the analysis of the relative sizes of the eigenvalues. The processing steps involved building the K-D tree, neighborhood search, computation of the covariance matrix, computation of the eigenvalues for each point , colour labelling and pole extraction. Further the poles were extracted by distance based region growing using different thresholds to ensure that no surrounding objects were included in the growing. The pole diamension was determined based on relation between the eigenvalues of the cross section and the radius of the pole.

Lehtomäki et al. (2010) developed an automatic method for detection of vertical pole-like objects in road environment. The method involved profiling and clustering of point clouds then merging and classification of the point cloud clusters to identify vertical objects. Each profile was segmented into point groups that are close to each other, and then the point groups are clustered to form a set of candidate of pole clusters. Since some poles might be divided into many clusters, merging of clusters was done and finally the candidate clusters are classified as poles or non-poles. To classify features, parameters such as shape, length, orientation and point density in the local neighbourhood of the cluster were used. The method achieved 77.7% detection of poles by manual investigation and 81% correctness.

Recognizing basic structures for road inventories was studied by Pu et al. (2011). The point cloud was first partitioned into road parts that are oriented along the road directions. Segmentation of point cloud in each road part was then performed using surface growing algorithm based on planar seed surface detection in 3D Hough space. Due to enormous amount of laser data, rough classification was done to obtain ground, on-ground and off-ground points in which the on-ground data was used for feature recognition using knowledge based feature recognition method. Characteristics of features such as size, position, orientation, shape, colour, material and topological relationship were considered as feature constraints in the shape recognition algorithm. Each segment was then compared with the feature constraints to discover potential features. For planar shapes in point cloud, convex of hull for each segment was generated and used for shape recognition for five classes of shapes that include rectangle, circle, triangle, volume and others which correspond to various traffic signs. These shapes were matched with the point cloud. Traffic sign poles and light poles, were finally extracted using percentile based pole recognition algorithm.

For clarity in the road way, road signs are designed with high reflective material. When the road is scanned by a sensor, the road signs will display points with high reflectivity. This reflectivity information can be used to extract the road signs, taking into account a simple threshold on reflectivity value and size of the resulted area (Smadja et al., 2010).

Golovinskiy et al. (2009) designed a system to recognise object in urban scene in 3D point cloud data. The system comprised of four steps; locate, segment, represent and classify the objects in the data. Locating and predicting potential objects was done based on point densities then extracted based on shape description and spatial context for example cars are found in streets usually in a line whereas the lamp posts are found on sidewalks. Classification was finally done using support vector machine according to manually labelled training set of objects achieving an accuracy of 65% of objects in the testing set. Of significance in this research, they evaluated four segmentation algorithms. They used   all the above ground points, connected components, min-cut algorithm with static radius and min-cut Automatic Radius. Min-cut segmentation performed very with best results using automatic radius than static one.

Lam et al. (2010) performed extraction of lamp posts, power line posts and power lines based on condition that posts are perpendicular to the road plane and points along the post must lie within the diameter of the post cross section circumference. With this constraint, the search is limited to space along the road data. Then line RANSAC followed by line least squares was used to determine the best estimated 3D line. Kalman filter is applied in monitoring the changes between the road local planes. To extract power lines between posts, 3D bounding box is used. The width of the bounding box is estimated using the thickness of the power line, the length is the distance between two consecutive posts and height taken is simply the local height of the post.

Awan et al. (2013) follows similar approach as Lam et al. (2010) where Kalman filtering and plane fitting algorithms are employed. Plane RANSAC and least-square fitting is applied in approximating the road section. K-d tree is then used to cluster the points in which global shape descriptors are computed from for matching. Histograms similarity measures using Earth Mover's Distance and Bhattacharyya distance were applied on each object in training database comparing against testing database. The best match considered for each object is taken based on best statistical score. The recognition rate achieved was 94.5% on diverse objects which included vehicles, poles, pedestrians, fire hydrants and street signs.

Yokoyama et al. (2011) researches on recognising pole-like objects which include streetlights, utility posts, street sings from MLS data using Laplacian smoothing based on k-nearest neighbours graph, Principal component analysis and thresholding degree of pole-like objects. The algorithm consisted of four steps; segmenting the point cloud then smoothing each segment, thirdly is to classify each point into points on pole-like objects, planar objects and others and finally evaluate the degree of pole-like objects in each segment and extract them by thresholding. These steps are illustrated in figure 2-2. Segmentation adopted was by connecting nearest points using connected k-nearest neighbours graph. Smoothing applied on segments was mainly to eliminate noise in the data, improve the recognition rate of the pole-like objects and distinguish between the points on pole-like objects, planar and others. Smoothing is achieved by applying Laplacian smoothing and recognition done by PCA. Point classification is attained by calculating eigenvalues and eigenvectors of the variance-covariance matrix of point in relation to its neighbours. With the classified points in the segments in combination with geometric properties which included height and number of points, each segment is classified into pole-like objects and others. Then the degree of pole-like objects is evaluated for the remaining unclassified segments. This method gave an average accuracy 63.9% in recognition of pole-like objects for all segments and 97.4% for correctly created segments.

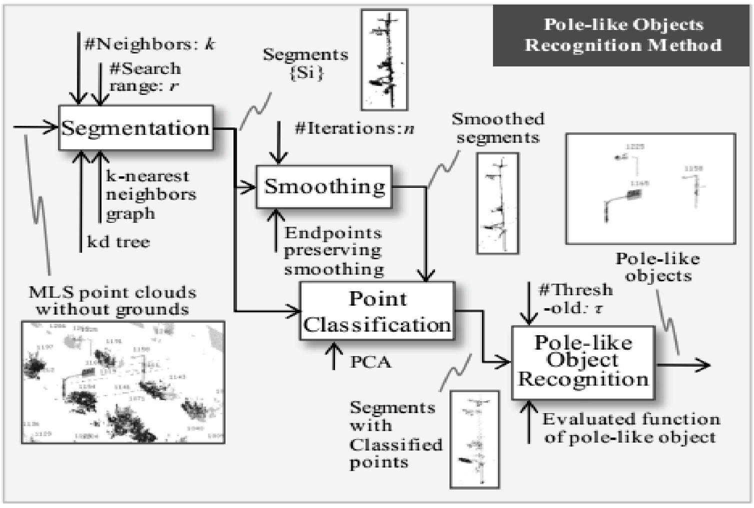


Figure 2-2: Pole-like objects recognition algorithm workflow. Source (Yokoyama et al., 2011)

Kukko et al. (2009) describes the algorithm which uses profile information of the scanner. The algorithm was developed in three stages; first, the sweeps were extracted from the data by grouping the points on the adjacent profiles. Then sweeps in consecutive profiles are clustered into poles. Finally, poles are separated from other clusters by removing too short clusters and those with too many points for example tree leaves and buildings. The algorithm gave 81% correctness result and mean accuracy of 71%.

Another way of extraction of poles was done by considering them as special case of cylinder extraction by Brenner (2009). This is done by model based approach were the assumption is that the basic characteristic of a pole is upright and there is kernel region with laser points and outside part without points .It is then analyzed as cylindrical stacks where the pole is assumed when we reach a certain minimum number of stacked cylinders as indicated in figure 2-3 below. Finally, with the stack at hand, the points in the kernel are then used to estimate the exact position of the pole.

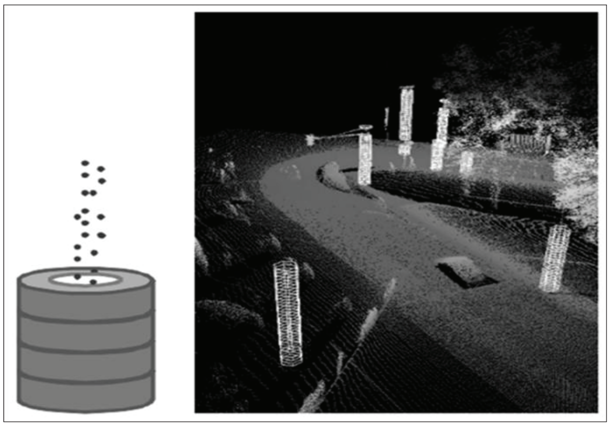


Figure 2-3: Cylindrical stacks fitted in poles. Source (Brenner, 2009).

2.5. Knowledge based object detection

Knowledge driven object detection methods are relatively new (Boochs et al., 2012). The concept applies prior knowledge about the context and the objects which is extracted from databases, CAD plans, GIS, technical reports or domain experts (Hmida et al., 2012) and also the knowledge about the shape of the object (Khoshelham, 2007).

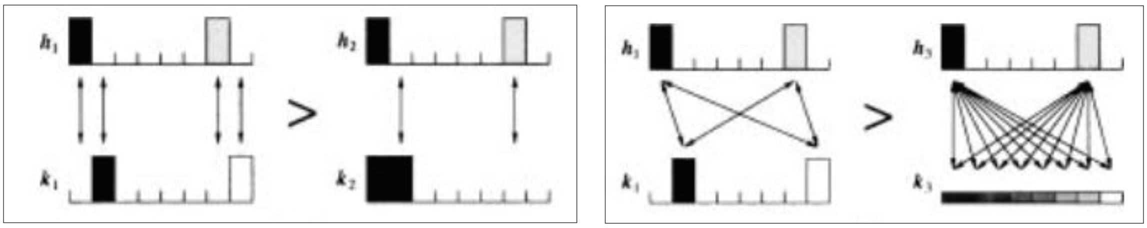
Boochs et al. (2012) and Hmida et al. (2012), performed detection of masts, signal and switchgear applying knowledge driven approach which uses different knowledge domains to select suitable algorithm. Web Ontology Language, Semantic Web rule Language and 3D processing and topological built-ins were used to allow flexible and intelligent detection. The knowledge domains were mapped through rules that are related to the geometry and topology in which suitable algorithms are selected to detect the objects. Then for verification, pre-existing scene knowledge is used.

Another knowledge based detection approach is described by Oude Elberink et al. (2013). The proposed approach utilises 3D parametric models by applying both local and global properties of the railway environment. Local properties considered are the piecewise linearity of the rail tracks whereas global properties are continuous and smooth pattern depicted by the railway lines. Detection of the railway was based on its properties which include relative height, linearity, relative position to other objects and relative position to other rail track which were implemented in four steps. First is analysing the height distribution of the points, secondly is to keep points representing linear structures, thirdly is keeping rail points that are only wire points within 2D and 3D distance and finally is to check if the gauge is constant. The RANSAC algorithm is then used to detect potential track pieces by analysing two parallel pairs of inlier points. Once they are detected, connected component analysis is performed and large components formed are classified as rail track points. To model the rail track, small pieces of rail are considered defined by their shape parameters, orientation parameters (position and rotations) of local coordinate system with respect to global coordinate system of the data. Modelling of these pieces were done using Markov Chain Monte Carlo (MCMC) algorithm. To obtain continuous and smooth model of rail track, the rail pieces are interpolated using Fourier series model. The results obtained had an accuracy of 2cm.

2.6. Histogram matching

Histogram represents a sample set of a population with respect to a measurement representing a frequency of quantitized values of that measurement among the samples. Histogram distance measure can be vector or probabilistic (Cha & Srihari, 2002). Vector histogram is considered as fixed-dimensional vector in which the vectors represent bins in fixed portions (Cha & Srihari, 2002; Rubner et al., 2000). In our study we focus on the z coordinates as the input to our histogram representation. The z coordinates represent the height of the object under consideration. The histograms of z coordinates distribution will be appropriate to obtain corresponding point frequency along the height of the object.

Histogram dissimilarity measures are used to measure match between two histograms say, $H = h_i$ and $K= k_i$. Histograms are developed with fixed bin portions as mentioned earlier. Histogram dissimilarity measures are mainly bin-by-bin which compares the contents of corresponding histogram bins and cross-bin which compares non-corresponding bins (Rubner et al., 2000) as shown in figure 2-4. Most common similarity measures are intersection, correlation and Bhattacharyya (Awan et al., 2013). The application of histogram dissimilarity measure comes in as a handy way in comparison of the target objects to be studied. This enables to determine similarity via normalised correlation between samples and unidentified objects and therefore facilitate the classification process.



(a) (b)

Figure 2-4: Histogram dissimilarity measures (a) Bin-by-bin (b) Cross-bin .Source (Rubner et al., 2000)

2.6.1. Histogram similarity measure by intersection

Histogram intersection method counts the number of points in two given sets which fall into the same bin (Grauman & Darrell, 2005). It then gives the number of pixels in the model histogram that are found in the image histogram i.e. corresponding pixels. The match value between the model histogram and image histogram is between 0 and 1 (Swain & Ballard, 1991) where 0 means no intersection and 1 means there is intersection between the model histogram and image histogram.

According to Jain and Vailaya (1996), histogram intersection is defined as follows;
Given I_R, I_G and I_B are normalized histograms of image in database and Q_R, Q_G and QB are normalized histograms of image in query, then similarity between the query and stored image is denoted by the equation

$$S_C^{HI}(I,Q) = \frac{\sum_r \min(I_R(r), Q_R(r)) + \sum_g \min(I_G(g), Q_G(g)) + \sum_b \min(I_B(b), Q_B(b))}{\min\,(|I|,|Q|)^3} \tag{2-1}$$

2.6.2. Histogram similarity measure by correlation

Comparing histograms representing an object can be achieved by taking each histogram to be a vector then the degree of match between reference object and candidate object is then given by dot product correlation. The method has been widely applied in images for object recognition where each image histogram is correlated with all stored model histograms then the model feature which yields highest correlation is taken as the match for a particular image feature. Threshold is applied to ensure strong correlation models are only selected (Evans et al., 1993). The correlation ratio is a value between 0 and 1 in which 0 means no correlation and 1 means purely correlated (Roche et al., 1998). Figure 2-5 describes how correlation by dot product is done.

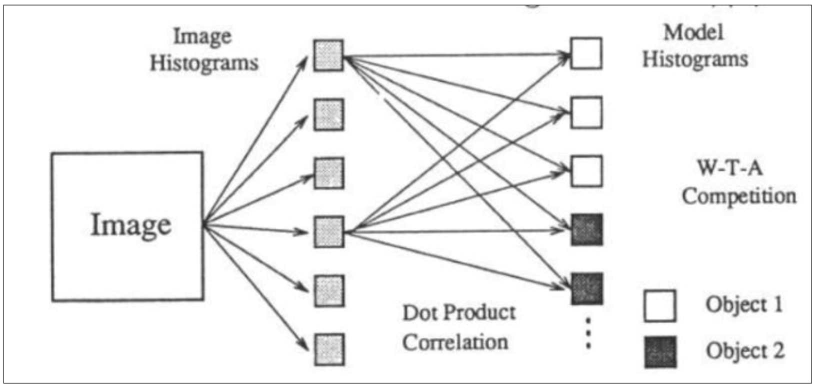


Figure 2-5: Histogram matching by correlation. Source (Evans et al., 1993)

Before we compute correlation ratio in histograms, they are first normalised to provide scale invariance (Jain & Vailaya, 1996) and convert them to unit histograms. Normalization process is simply described by Jain and Vailaya (1996) as;

Let H (i) be a histogram of an image where i represent histogram bin, then normalized histogram is denoted as

$$I(i) = \frac{H(i)}{\sum_i H(i)} \tag{2-2}$$

2.6.3. Bhattacharyya similarity measure

Bhattacharyya similarity measure is explained in (Aherne et al., 1998). This measure can be applied to compare similarity between two histograms derived from a data. The concept can be simply explained as follows;

If *Ri* is frequency for coded quantity in bin *i* for histogram 1 and *Si* is a similar quantity for histogram 2 then the Bhattacharyya statistic is given as shown in equation 2-3 as similarity measure between two histograms.

$$\sum i\sqrt{Ri}\sqrt{Si} \tag{2-3}$$

If $\sum i\sqrt{Ri} = 1$, it indicates a perfect match and therefore the two histograms are identical.

2.7. Point cloud registration

Point cloud registration process is technique that has been widely applied in registration of point clouds to match two point clouds or a point cloud and a Computer Aided Design (CAD) model. This enables determine the level of match between classified results and known samples. This can be achieved by checking their point-to-point correspondences. A typical example of matching of point cloud and CAD model has been performed by Ip and Gupta (2007). Registration of point cloud is mainly aimed at finding transformation that best aligns dataset one into dataset two usually referred as model and data (Chen & Medioni, 1992; Mitra et al., 2004).

Registration consists of matching and estimation of transformation parameters (Makadia et al., 2006). The transformation parameters are usually rotation matrix and translation vector (Liu, 2006). The most common known method of registering point clouds is by use of Iterative Closest Point algorithm. The method uses point-to-point correspondence or distance to register the datasets (Rabbani & Heuvel, 2005).

Before registration process, initial approximation parameters are needed to roughly align the model and the data. During registration process, the algorithm operates recursively as it loops until it converges at a predefined threshold value (Quan et al., 2006). The convergence or matching is achieved when the sum of squared distances between the two point clouds is minimised (Chen & Medioni, 1992; Sharp et al., 2002).

Besl and McKay (1992) describes how to register 3D shapes using ICP by giving a general framework of registration of points, line segments, implicit curves and surfaces, parametric and triangulated surfaces. They also highlighted some of its advantages and disadvantages.

The basic principle of ICP algorithm is described in (Vosselman & Maas, 2010) as follows;
Suppose we have two sets of points, $\mathbf{x}$ and $\mathbf{y}$ which are related by a rigid body transformation given as

$$y_i = Rxi + y0 \qquad (2\text{-}4)$$

where R is the rotation matrix and y0 is translation vector then the minimised sum of squares of Euclidian distances between the transformed slave point $\mathbf{x}_i$ and master point $\mathbf{y}_i$ is given by

$$e^2 = \sum_i \|Rxi + y0 - yi\|^2 \longrightarrow \text{min} \qquad (2\text{-}5)$$

The summation of distances is considered for all data points in the overlap area.

An example of point cloud and CAD model registration is shown in figure 2-6 below.

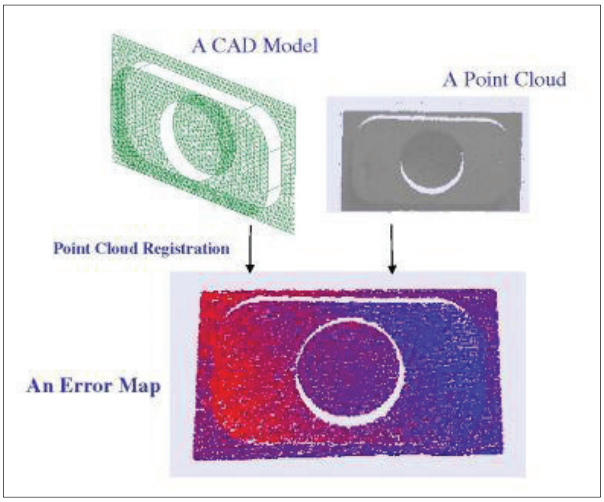


Figure 2-6: Point cloud registration between CAD model and point cloud.
Source (Quan et al., 2006)

3. ROAD FURNITURE DESCRIPTION

3.1. Introduction

The focus on this research is detection of road furniture captured by Mobile Laser Scanner. The main target objects of interest are traffic lights, lamp posts and traffic signs among others. These objects are usually above the ground surface thus their detection is focussed on detecting any object above the ground. In order to process the data, proper knowledge on their properties and characteristics is pre-requisite. This will limit the search and process time as objects to be detected will be known at hand. In section 3.2 and 3.3 we describe the characteristics of road furniture from direct view and MLS data respectively.

3.2. Characteristics of road furniture from direct view

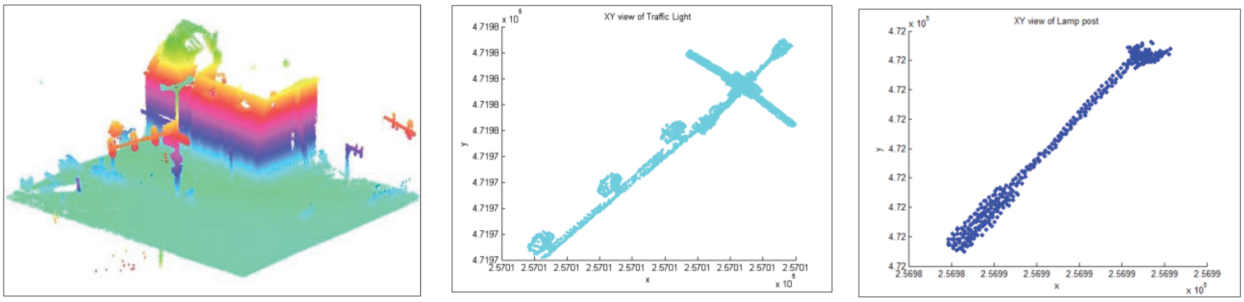
Road furniture are usually standardized in most countries thus have peculiar characteristics such as shape, size and colour that define them. Figure 3-1 shows the road furniture as they appear naturally on the road environment. These characteristics can be of great importance in detection of these objects in that when they are captured in the data, we as human beings still recognise and identify them. Some of these characteristics which can help us in detection process are enumerated as follows;

i. They are located in proximity to the road
ii. Lamp posts appear to have a pattern for example erected at some equal interval distance
iii. Traffic signs and traffic lights are commonly found at road junctions
iv. They are pole-like objects and stand at certain height above the ground
v. They have over hanging outstretched pole which is horizontal to the ground that supports the lamps or lights.
vi. Lamp posts appear to be taller than traffic lights in height above the ground.
vii. Traffic lights have their lamps erected at certain height and intervals on the outstretch pole
viii. Lamps and traffic lights have unique shapes.
ix. Road furniture has variations in terms of number of traffic signs/lights per pole, size of the lights and also there is variation of combinations of traffic signs/lights on poles.

Figure 3-1: Road furniture objects within road environment.

3.3. Characteristics of road furniture in MLS data

Mobile Laser Scanner is capable of capturing information of an object which includes X, Y, Z coordinates, reflectance value, true colour and pulse information. Road furniture as observed in MLS data is huge set of 3D point clouds. The objects appear in 3D form with their proper shape when visualized using height colour or RGB colour. When we take the XY planar view, we notice the lamp posts and traffic lights on pole out stretch occur at displacement X from vertical pole. Figure 3-2 describes MLS data from 3D and 2D views.



(a) (b) (c)

Figure 3-2: MLS data (a) Visualization of MLS data by height colour (b) XY planar view of traffic light(c) XY planar view of lamp post:

4. METHODOLOGY DESIGN

4.1. Introduction

The proposed methodology in this research is knowledge based driven approach where a connected component of an object is used to find other similar objects within the data. This means that we already know the objects of interest to study. The unknown connected component in question is compared with several other known components (training samples) to find which matches it best. The approach uses 3D (X, Y and Z) point cloud as captured by the scanner of the road sections. Pre-processing of the data is performed by segmentation and filtering of raw point cloud to eliminate unwanted zones and only keep the information for input in the next phase. The proposed way of describing the parameters of the segments is by use of histogram and minimum bounding box. Then finally a post processing is performed to check for point to point correspondence between similar segments by use of Iterative Closest Point (ICP) algorithm. Figure 4-1 gives an overview of the methodology designed.

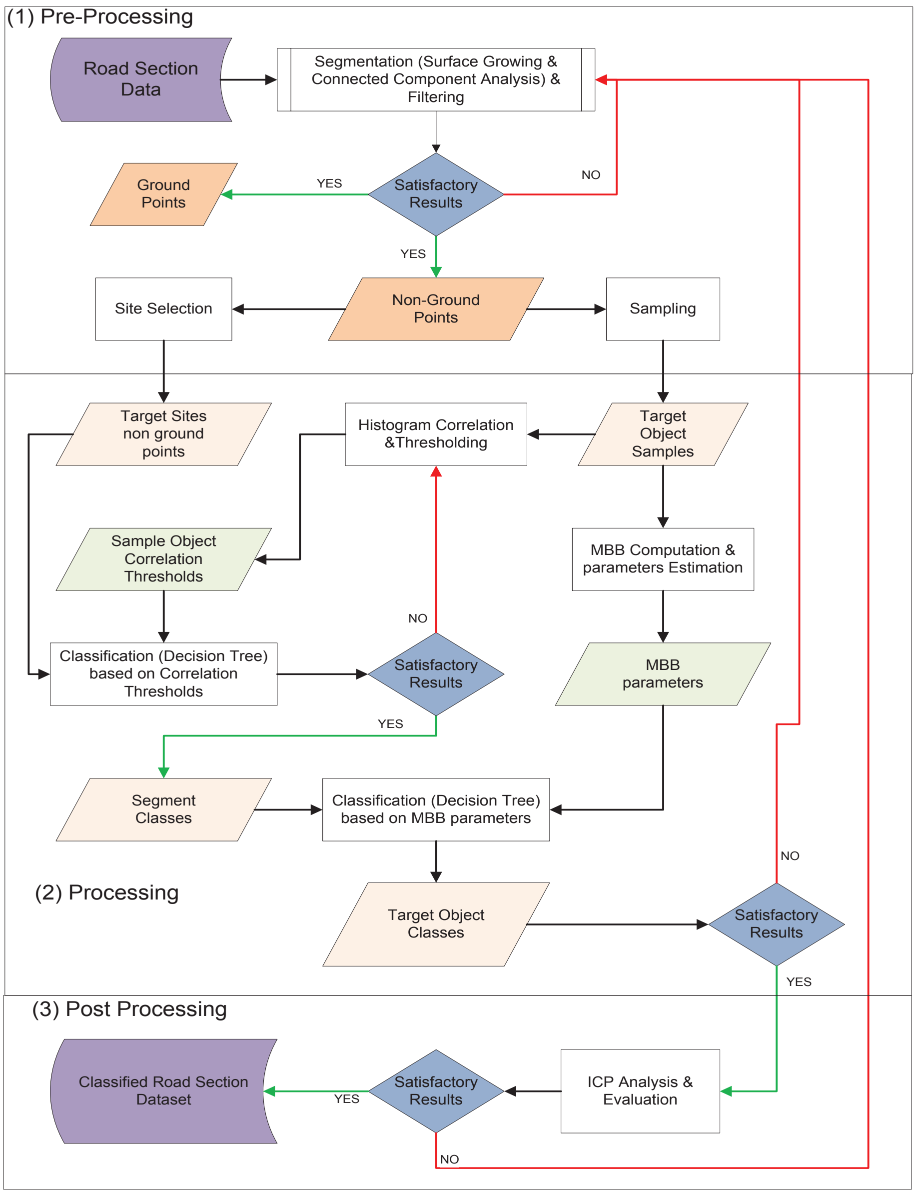


Figure 4-1: Proposed methodology work flow

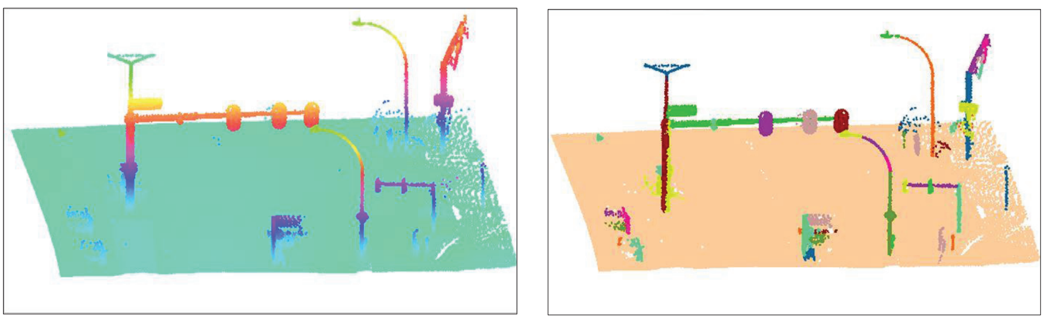
4.2. Pre-processing of data

Point cloud data contains huge amount of information as it captures the scene the way it appears naturally. Working with this huge data is cumbersome and time consuming and also can complicate the process of analysing the required information. To reduce this amount of data it is necessary to pre-process it in order to reduce computation time in analysis. This is achieved by performing segmentation and filtering as illustrated in figure 4-1.

Segmentation and filtering form the first steps in object detection process. In this study, segmentation and filtering of point cloud is needed in order to group points into object segments and remove unwanted zones. Surface growing algorithm is applied in the input data to group the points that have same properties. Since we use the surface planar model parameter, the points are grouped into planes. The ground points forms the largest plane surface which is then removed in order to remain with only above ground points. These above ground points contain mainly the objects of interest to be detected. In order to have these objects as individual segments, connected component analysis is performed on them. These processes were achieved using Point Cloud Mapper (PCM) software which is capable of performing segmentation and filtering among other processes. The output of this process provided input for extraction of samples and prepared target sites for desired segment object identification and extraction.

4.2.1. Surface growing segmentation algorithm

Surface growing algorithm is the most common segmentation algorithm especially in the segmentation of point clouds. The algorithm operates in the same way as the region growing algorithm in images. It works in two steps where first is identification of the seed surface points then the growing of the seed surface (Vosselman et al., 2004). Seed selection is done by plane fitting and analysis of residuals between each point and other points within some distance. Points with lowest residuals and below some threshold are considered to form the seed surface. Since outliers cannot be avoided in any kind of data especially laser scanner data, robust least squares adjustment or Hough transform methods are used to fit the planes to the points. Growing of seed surface is based on proximity of points, locality of planes and the smooth normal vector fields. In the first case points that are near already detected surface points within certain distance are added to the surface. The second case makes use of plane equation where a plane is fitted through all the surface points within some radius and equation is determined for each surface point. Threshold is applied to obtain candidate points to add to the surface. The later approach uses local surface normal for each point in the point cloud and angle between its surfaces normal. Within some threshold a candidate point is chosen and added to the seed surface. Figure 4-2 shows the result of surface growing algorithm defined by planar surface model.

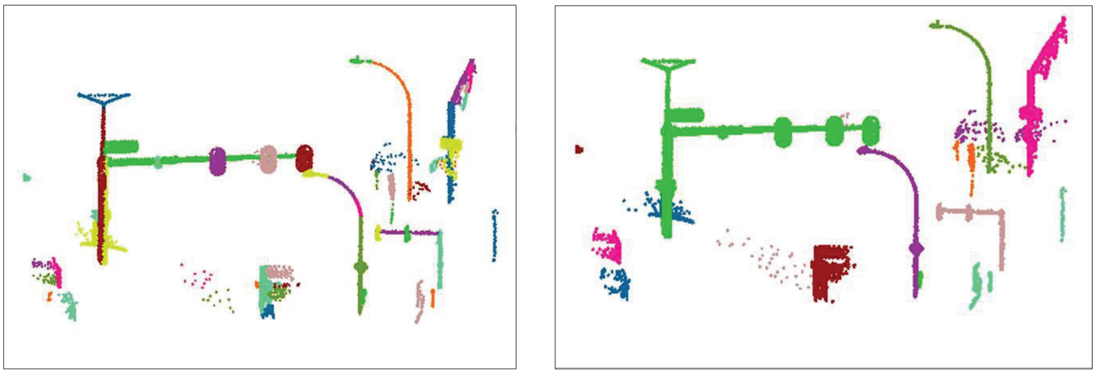


(a) (b)

Figure 4-2: Segmentation process (a) Input data, segments labelled by height colour (b) Surface growing segmentation result

4.2.2. Connected component analysis algorithm

Connected component analysis is aimed at clustering nearest points to form individual segment that represent an object (Pratihast & Thakur, 2012). The clustering of the points is influenced by maximum distance between points and maximum number of points. Similarly the algorithm starts with the selection of seed point as surface growing algorithm. Then set of points will be connected to each seed point based on threshold parameters set. The process is applied to the segments after surface growing has been performed. The connected component analysis therefore helps capture individual target objects defined by clusters of close points. Figure 4-3 below shows the result of connected component analysis on segments previously segmented by surface growing algorithm.



(a) (b)

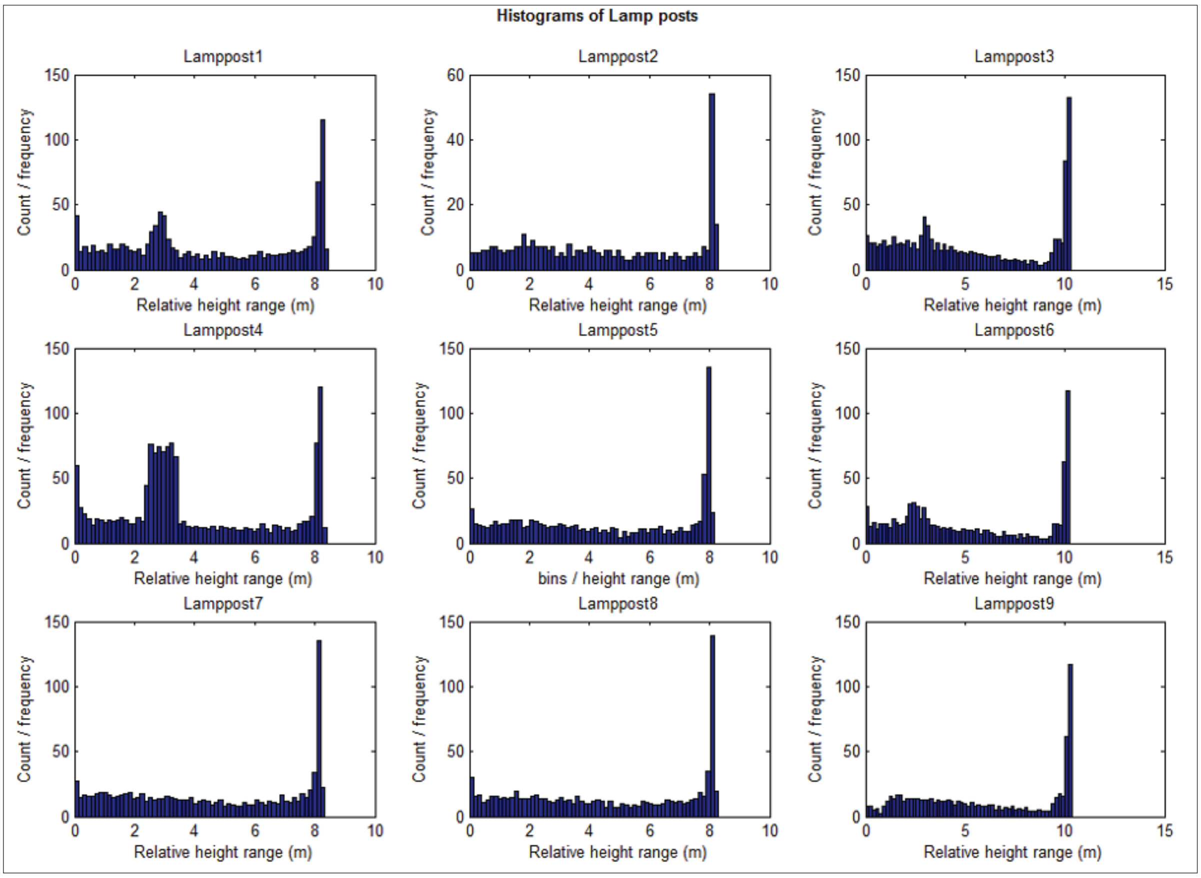
Figure 4-3: Segmentation results (a) Surface growing segmentation (b) Connected component analysis segmentation

4.3. Histogram correlation using dot product

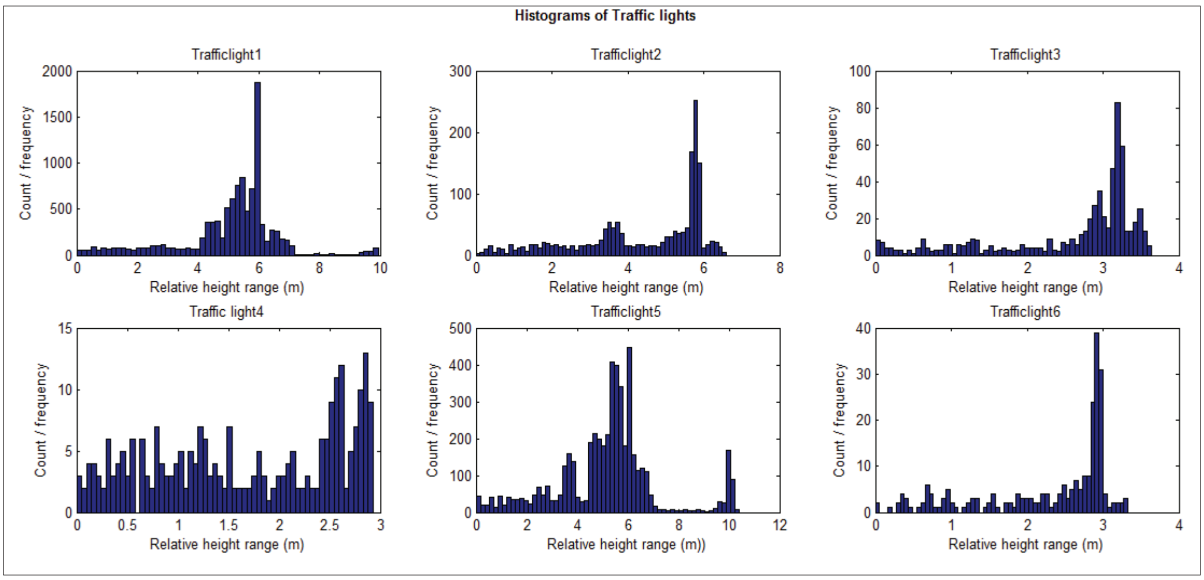
Histograms provide a graphical way of the distribution of points on the object. Histograms developed in our study were based on frequency of points per relative height of the object segment as shown in figure 4-4. It represented the frequency of points based on the height value and the bins contain point distribution along the object height. In order to obtain proper distribution of points independent of the elevation of the ground surface, relative heights of objects verses point distribution would be appropriate. Relative object height is obtained by taking the difference between the maximum *Z* value and the minimum *Z* value of the actual heights as captured on the ground by the scanner.

$$\text{Relative Height} = \text{maximum Z value} - \text{minimum Z value} \qquad (4\text{-}1)$$

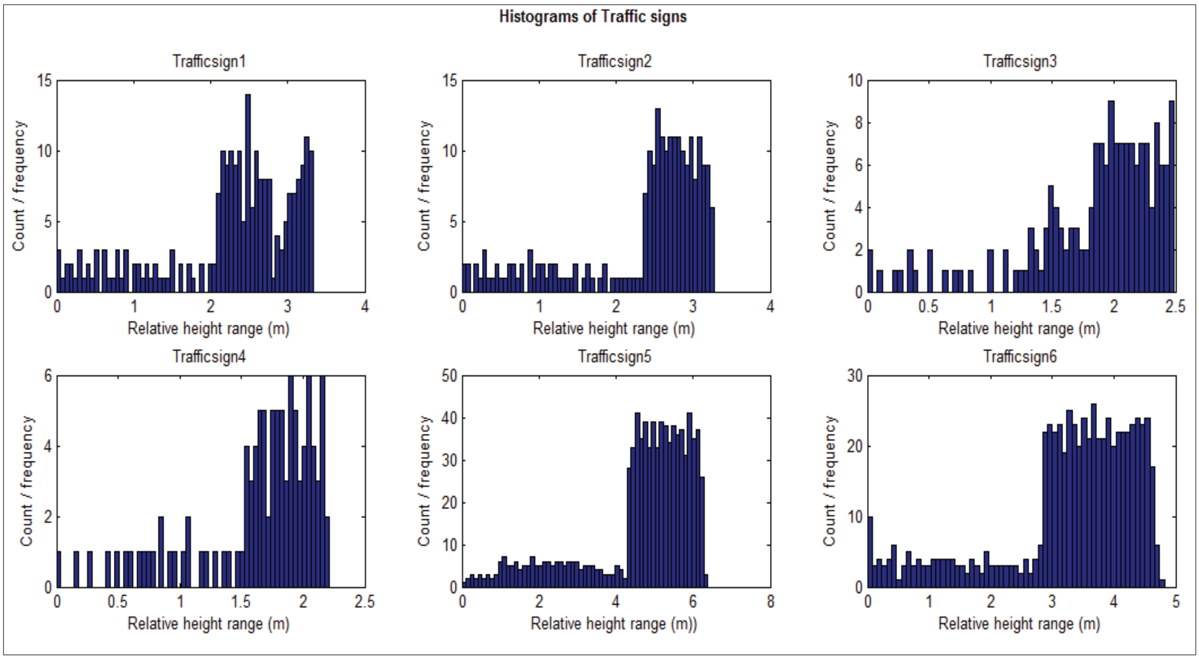
The resultant histograms are considered as vectors therefore we can compute correlation between them using dot product of vectors. Histograms are first normalised to unit vector before computation of dot product. Normalised histograms are shown in appendix 1. The dot product was computed between a number of object segments and correlation results analysed. Theoretically, if two vectors are the same then we expect to have a correlation value of 1 otherwise lower than that in which it is the case under normal circumstance due to uncertainties in the data. Segments corresponding to each other recorded highest correlation values as compared to other segments in the training dataset as presented in table 4-1.


Histograms of Lamp posts
Lamppost1
Lamppost2
Lamppost3
Lamppost4
Lamppost5
Lamppost6
Lamppost7
Lamppost8
Lamppost9
Count / frequency
Relative height range (m)
bins / height range (m)

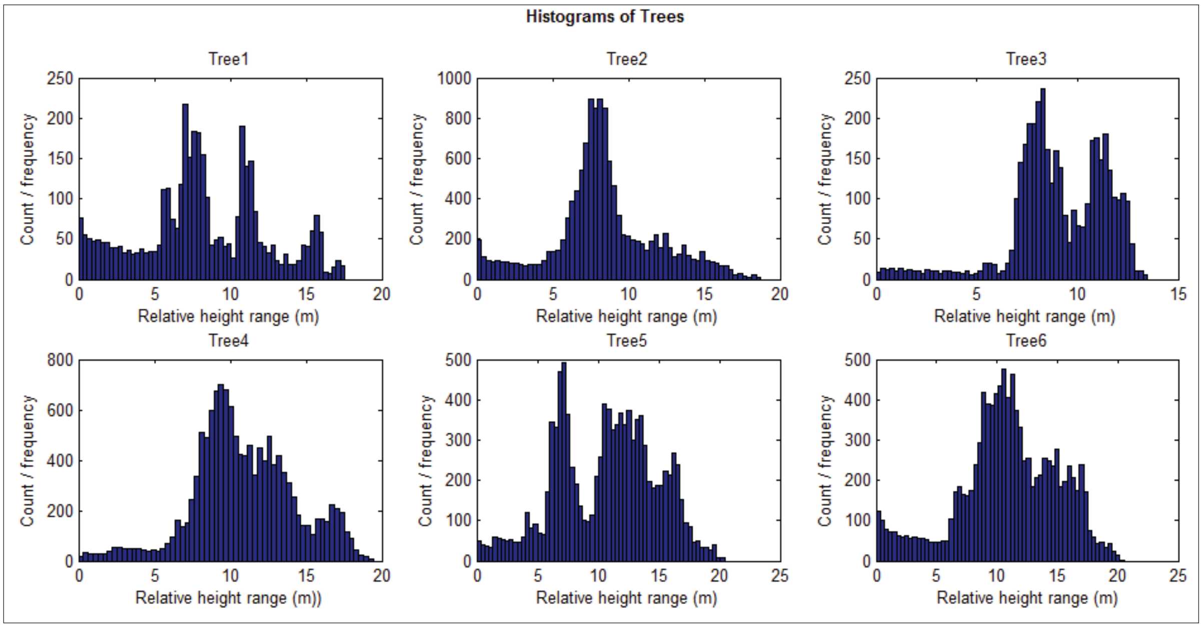
(a)


Histograms of Traffic lights
Trafficlight1
Trafficlight2
Trafficlight3
Traffic light4
Trafficlight5
Trafficlight6
Count / frequency
Relative height range (m)
Relative height range (m))

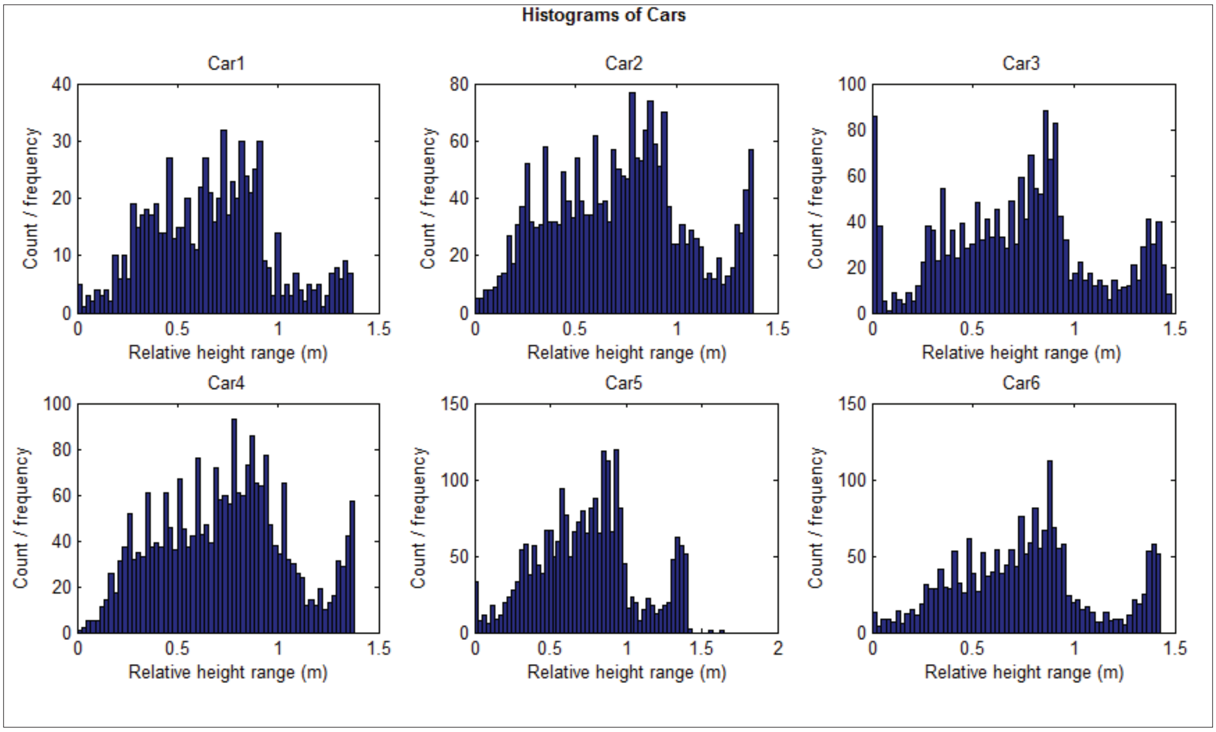
(b)


Histograms of Traffic signs
Trafficsign1
Trafficsign2
Trafficsign3
Trafficsign4
Trafficsign5
Trafficsign6
Count / frequency
Relative height range (m)

(c)


Histograms of Trees
Tree1
Tree2
Tree3
Tree4
Tree5
Tree6
Count / frequency
Relative height range (m)

(d)



(e)

Figure 4-4: Histograms for (a) Lamp posts (b) Traffic lights (c) Traffic signs (d) Trees and (e) cars

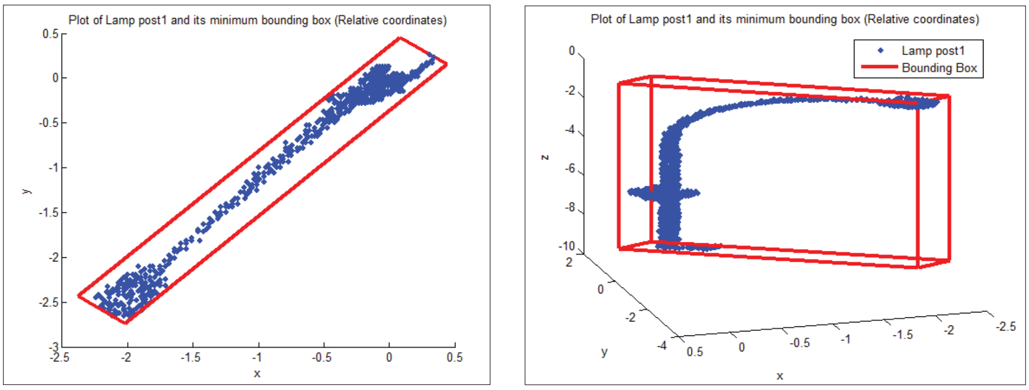
From the figures above, we notice that the segments portray differences in the shape of the histogram between the different types of object segments selected. Similar components tend to have a pattern on the shape of their histograms which actually corresponds to the distribution of the points on shape of the object itself. For instance the lamp posts, depicts a sharp rise at the top as a result of the horizontal pole holding the lamp which registers high point density at almost constant height. This information is then utilised in the development of the process of detecting similar components in the dataset based on samples selected.

Object 1	Object 2	Correlation values range
Lamp post	Lamp post	0.75 - 0.99
	Traffic light	0.25 - 0.45
	Traffic sign	0.56 - 0.62
	Tree	0.35 - 0.53
	Car	0.24 – 0.38
Traffic light	Traffic light	0.76 - 0.99
	Traffic sign	0.12 - 0.31
	Tree	0.44 - 0.68
	Car	0.13 -0.22
Traffic sign	Traffic sign	0.78 - 0.99
	Tree	0.33 – 0.56
	Car	0.36 – 0.45
Tree	Tree	0.56 - 0.82
	Car	0.11-0.32
Car	Car	0.82 - 0.99

Table 4-1: Summary of range of correlation values between sample segments

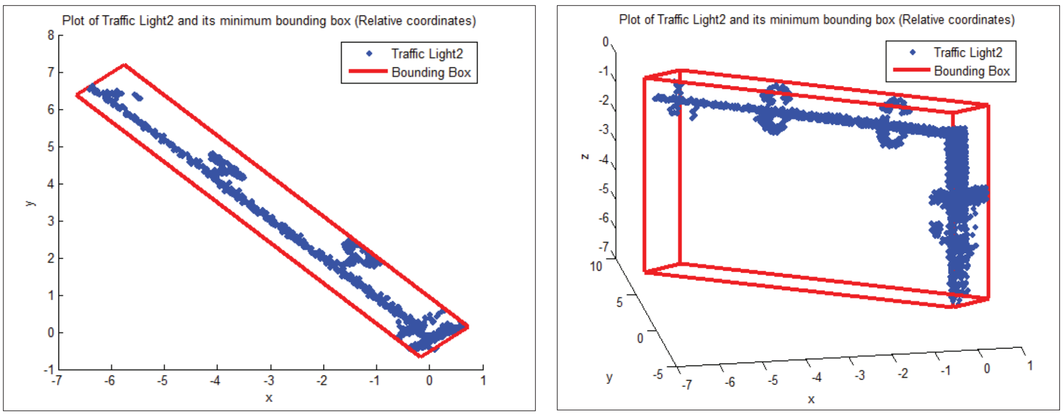
4.4. Minimum bounding box

A bounding box in context of point cloud is a box inscribed by point cloud bounded by minimum and maximum coordinates of the point cloud. The main parameters used to create it are minimum and maximum x, y and z coordinates of the point cloud (Chen & Kurfess, 2004) . The least size of box that can fully accommodate a target point cloud cluster is the minimum bounding box. This is computed based on principal components of the object defined by their extreme coordinates (Dimitrov et al., 2006). Minimum bounding box provides a surface in which we can use it to compare two or more point clouds. In this study, minimum bounding box is used to compare the dimensions of the connected components as our target is to find similar components using a known component. The minimum bounding box was developed relative to the object orientation. The resultant corner coordinates and dimensions of the bounding box are relative coordinates and dimensions of the segment as illustrated in figure 4-5 and 4-6.



(a) (b)

Figure 4-5: Plots of bounding box and Lamp post oriented to X (a) 2D view (b) 3D view:



(a) (b)

Figure 4-6: Plots of bounding box and Traffic light oriented to Y (a) 2D view (b) 3D view

The parameters of the minimum bounding box which includes length, width and height are extracted for further analysis. From these parameters, various ratios of the minimum bounding box are computed which are width to height (WH) ratio, length to height (LH) ratio and width to length (WL) ratio. A summary is presented in tables 4-2. These ratios are then plotted in a feature space to aid in visualizing how separable the objects of interest are. This is illustrated in figure 4-7.

Object	WL		WH		LH	
	max	min	max	min	max	min
Lamp Posts	0.46	0.09	0.2	0.03	0.59	0.23
Traffic Lights	0.38	0.11	0.45	0.13	1.85	0.9
Traffic Signs	1.14	0.19	0.23	0.06	0.42	0.16
Tree	1.11	0.53	0.86	0.4	1.27	0.52
Cars	0.88	0.39	1.65	0.62	3.35	1.22

(a)

Object	WL		WH		LH		H(metres)	
	max	min	max	min	max	min	Max	Min
LampPost A	0.46	0.11	0.2	0.05	0.45	0.43	8.46	8.28
LampPost B	0.15	0.09	0.07	0.04	0.59	0.46	10.50	9.08
LampPost C	0.31	0.11	0.1	0.03	0.34	0.23	10.60	10.60
TrafficLight A	0.38	0.14	0.45	0.13	1.39	0.96	10.50	9.95
TrafficLight B	0.16	0.11	0.22	0.16	1.85	1.05	6.71	6.53
TrafficLight C	0.22	0.14	0.24	0.14	1.08	0.9	3.64	3.14
Traffic Sign A	1.14	0.32	0.23	0.06	0.4	0.19	3.33	2.17
Traffic Sign B	1.07	0.3	0.21	0.06	0.37	0.16	3.27	2.21
Traffic Sign C	0.25	0.19	0.11	0.07	0.42	0.35	6.38	4.82
Tree	1.11	0.53	0.86	0.4	1.27	0.52	20.60	9.59
Cars A	0.54	0.39	1.38	1.07	3.35	2.3	1.65	1.37
Cars B	0.55	0.49	0.85	0.62	1.62	1.22	2.92	2.86
Cars C	0.88	0.67	1.65	1.53	2.1	2.04	2.22	2.01

(b)

Table 4-2: Summary of MBB ratios (a) General object category and (b) Object type per category

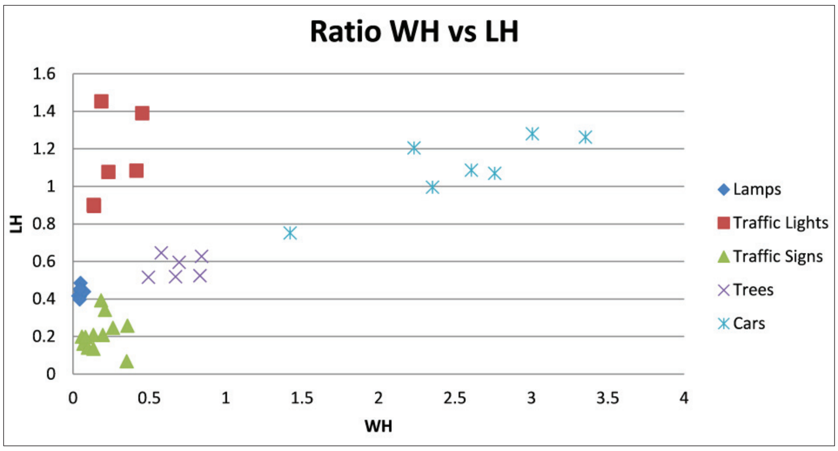


Figure 4-7: Feature space in scatter plot of ratios WH vs. LH

4.4.1. Decision tree

Separation of desirable parameters for input in classification was based on decision tree. Decision tree is a classification technique mainly applied to classify patterns through a sequence of questions. The decision tree has root node which is displayed at the top and connected by successive direct links or branches to other nodes until the terminal is reached with no further links. The classification of a particular pattern proceeds from top to bottom in which at the root node, it asks for the value of particular property of the pattern. The successive links from the root node then responds to different possible values and based on the answer, appropriate link to the next node is followed. Every decision is represented by binary decision with 'yes' on the left and 'no' on the right by convention (Duda et al., 2001). This concept was applied in separating objects into class categories.

In this approach, consideration was first given to high correlation for similar objects detection, succeeded by detection of objects satisfying the threshold limits of the minimum bounding box parameters WH, WL and LH in line with the target object class of interest at a particular stage of the proposed approach. This is illustrated in figure 4-8 below.

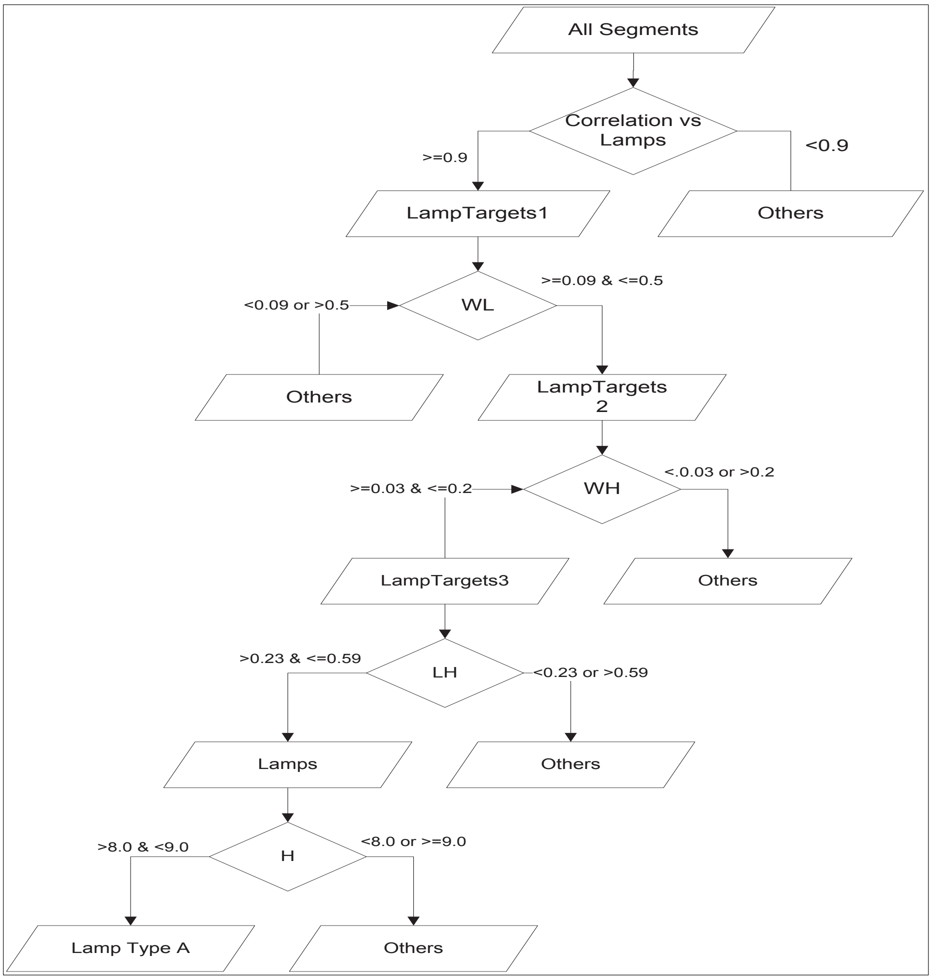


Figure 4-8: Decision tree; example for extraction of Lamp post A

4.5. Iterative Closest Point Algorithm

After we have classified the segments, we still want to determine if the right segment was labelled to the correct object class category. To perform this, we use the Iterative closest point algorithm as it enables us to check for point to point correspondence of two point clouds as applicable in our consideration. The algorithm is employed to register two segments to check for point correspondence between them. The algorithm estimates transformation parameters both the 3D rotation and translation between two sets of corresponding points by minimising their distances. Point-to-point correspondence case was applied in this study rather than point-to-plane correspondence since in our context we are dealing with point-based registration of point clouds. The procedure adopted is whereby two point clouds are imported into graphical user interface (GUI) for manipulation. Then a minimum set of three corresponding points are manually selected from the two point clouds and used to estimate initial transformation parameters. With transformation parameters already initialised, the two point clouds are roughly registered. Finally the registration is refined by manually adjusting the registration parameters which are the number of random points to be used for registration and rejection rate which is the percentage of rejecting the outlier points during registration.

The two point clouds need to be of the same dimension (n x 3) matrix containing x, y and z coordinates information of the point. Rejection rate of outliers is based on largest distance. The number of samples used for iterations, residual threshold and rejection rate are predefined. Residuals are then plotted and analysed. The residuals can clearly tell us if registration is achieved or not. The scenario can be small residuals means similar objects and big residuals not similar objects. The conclusion of registration can then be summarised into three scenarios; similar objects found, similar objects found but with additional points and no similar objects found. This was then implemented on selected point cloud segments.

5. IMPLEMENTATION AND RESULTS

5.1. Introduction

The proposed methodology designed was eventually applied to point cloud of road sections which contain a lot of information as captured by the scanner which range from road furniture, buildings, cars, pedestrians, cyclists, trees among others. This data was first pre-processed by segmentation and filtering then the resulting information contains only clusters of objects for input in the next steps. The input point cloud data contains X, Y, Z coordinates and component number since our target is to find segments that are similar with the reference segment. The analysis is based on component wise criteria.

The approach can be considered as a kind of supervised classification since we have training dataset and testing dataset involved in the classification. The training dataset was selected for the specific target objects of interest. The testing dataset on the other hand is simply the site-wide part of road section which comprises of segments of the objects as captured by the scanner. Of importance in this process is that features of training and testing set need to be same to improve the performance of classification. To perform classification, properties obtained by training the samples are taken into consideration as described in chapter 4. The approach was undertaken in three steps; by histogram correlation, minimum bounding box parameters and finally post processing by use of Iterative closest point algorithm. Figure 5-1 illustrates the entire work flow as undertaken.

Further a kind of enhanced classification is performed which combines histogram correlation and distance ratio derived from MBB ratios. This is described in section 5-5. This comes in a separate concept of implementation.

In this study, we used a total of forty nine (49) training samples which contained lamp posts, traffic lights, traffic signs, trees and cars as detailed in table 5-1. The figures showing categories of the object segment are indicated in appendix 2. Each individual object segment in the training set is manually labelled then applied in the testing dataset to recognise similar segments. The testing dataset areas were selected depending on the uniqueness of the presence of desired objects of interest. A total of eighteen (18) road section sites were selected and tested.

Object	Category types	Number of samples
Lamp post	A	3
	B	4
	C	1
Traffic Lights	A	4
	B	1
	C	3
Traffic signs	A	5
	B	5
	C	3
Tree	none	12
Cars	A	6
	B	1
	C	1

Table 5-1: Training samples

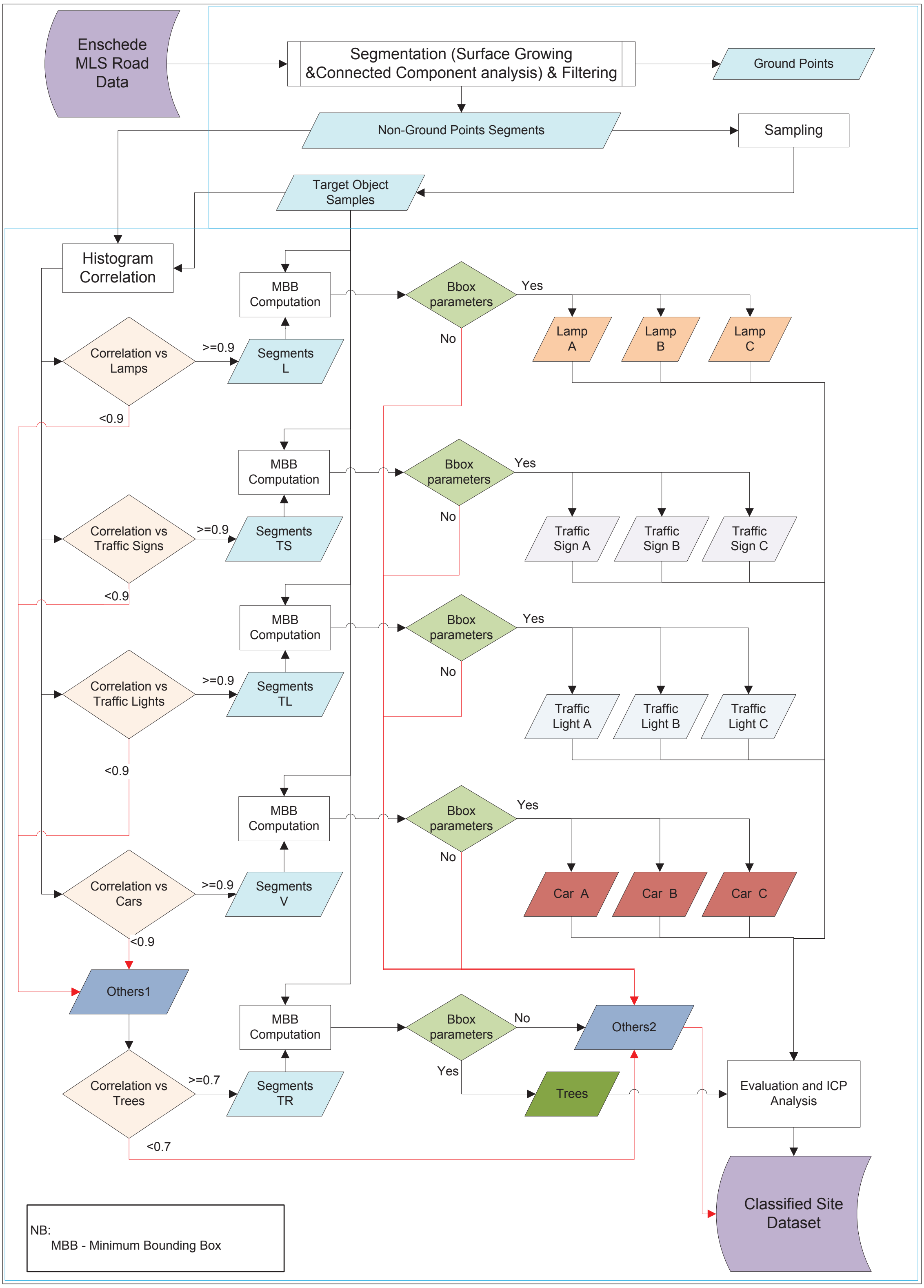


Figure 5-1: Implementation of methodology work flow

5.2. Segmentation and filtering

The focus of this study is on above ground objects. The ground surface information is not useful in our case thus we had to remove it. The process involved segmentation and filtering of the raw point cloud data where the segmentation part is aimed at getting cluster of points of individual objects in the data. Since most features in the data are man-made, plane based segmentation based on surface growing algorithm was used. The data structure K-D tree was used as it is considered more appropriate for locating nearest neighbours (Vosselman & Maas, 2010) as our study mainly focuses on having proper segments that represent an object (connected components). The number of seeds selected for detection plays an important role in the segmentation process. In our case the minimum number of seeds selected was 10 points with seed neighbourhood radius of 1.0 m. Surface growing radius of 0.3m with maximum distance to surface of 0.3 m was applied. Once the segmentation was done, the points are grouped together. The ground surface plane was then removed then the remaining points taken for the next step of clustering them. The aim of clustering the points is to have groups of them representing individual object. This was achieved by use of connected component analysis algorithm. The settings of threshold values of connected component segmentation are critical. The maximum distance between points and the number of minimum points necessary to form segment determines how well the set of points aggregate individual clusters of objects. For instance the smaller distance in places where we have lamp posts and trees together can find the lamp posts and tree grouped together into one connected component. The maximum distance between points was set to 1.0 with minimum number of points being 10. These processes were accomplished using Point Cloud Mapper (PCM) software. The result was collection of point cloud connected components for input in detection and extraction of the target objects of interest. The products of this process are illustrated in figure 5-2 below.

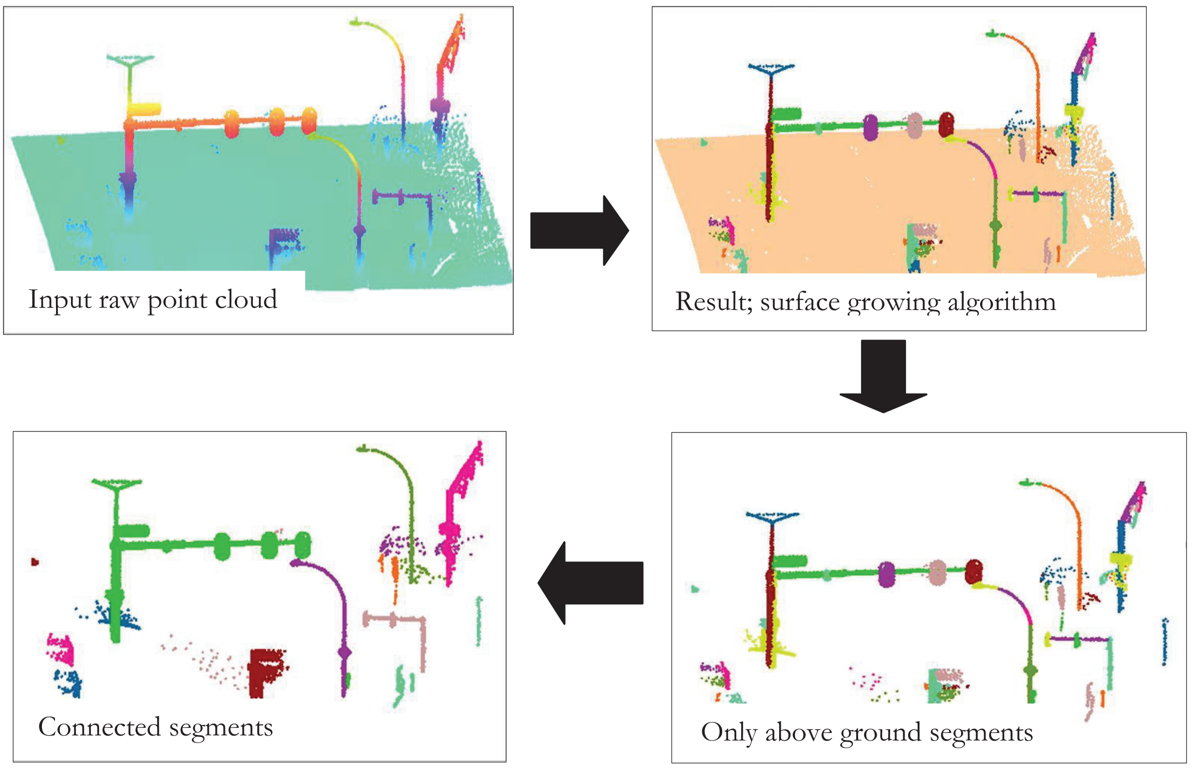


Figure 5-2: Point cloud segmentation and clustering of object points

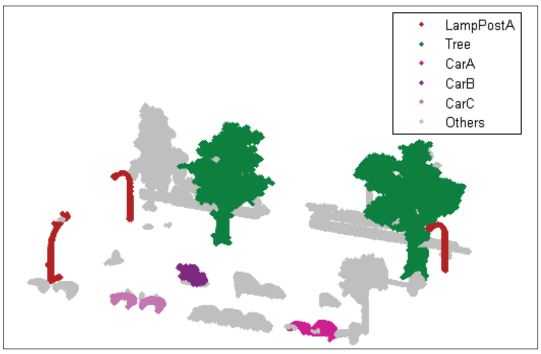
5.3. Classification based on histogram correlation and MBB parameters

The classification was done in two subsequent phases. The first phase involved computation of histogram correlation and MBB parameters, followed secondly by classification of the segments that satisfied a given threshold values from the histogram correlation and MBB parameters computation as illustrated in figure 5-1. The input dataset for analysis and classification were road sections that contained the target objects of interest which include lamp posts, traffic lights and traffic signs plus others such as building facades, pedestrians and cyclists.

The histogram correlation involved performing dot product computation of the training dataset sample segments and testing dataset segments. As mentioned earlier, the features of training dataset and testing dataset where made the same. Formations of histograms in the two cases were based on distribution of points with respect to the relative height of the object segment to make the heights independent of the elevation of the ground surface. The bin ranges of the histograms were made equal to enable us perform bin-by-bin computation of correlation. Equally important is that the histograms were normalised to provide scale invariance. The correlation values accepted for decision were adopted from the desired values found in section 4.3. This enabled us to get collection of segments that satisfy the thresholds allocated which are then further separated into their respective classes. This is accomplished by use minimum bounding box parameters.

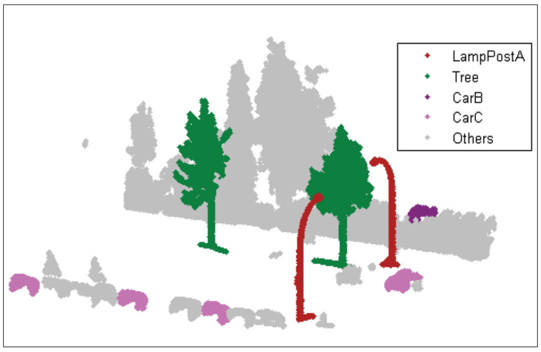
After computation of histogram correlation, the segments that satisfied a given threshold values of a given sample are then applied minimum bounding box parameters then classified to their class category accordingly. This involved decision tree usage to identify segments whose computed minimum bounding box parameters satisfied the specific limits identified as defining characteristics of specific target objects of interest to this research as explained in section 4.4.

The classification results are mainly output of the target road furniture objects which include lamp posts, traffic lights and traffic signs. Other objects considered in classification were trees and cars as these objects are also common within the road environment. The results of implementation are presented in figures 5-3 below. The objects are labelled with different colours for ease of visual identification and distinctions of the objects of interest are described by the legend.

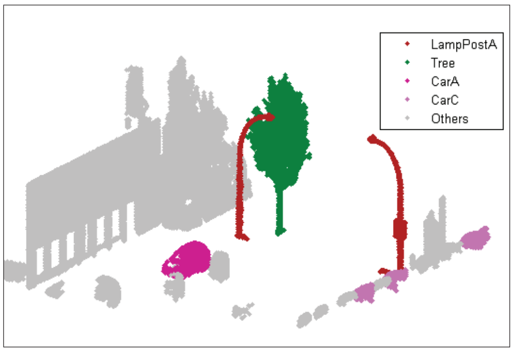


(a)

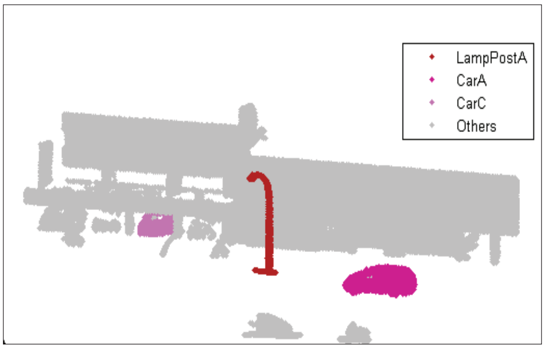
(b)


LampPostA
Tree
CarB
CarC
Others

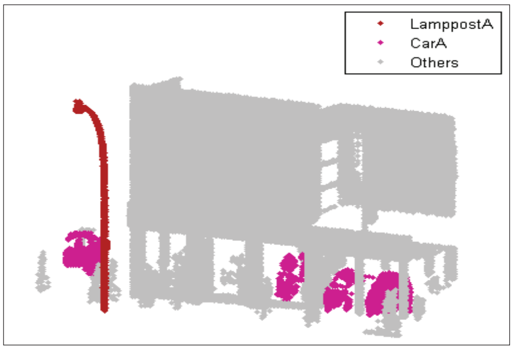
(c)


LampPostA
Tree
CarA
CarC
Others

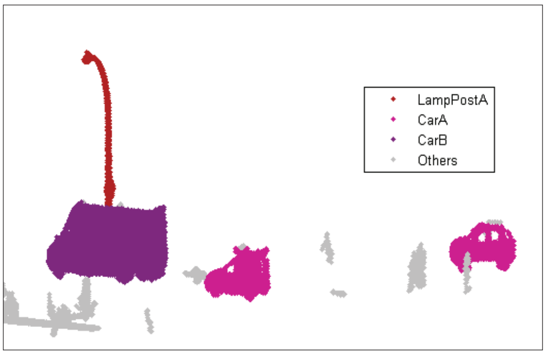
(d)


LampPostA
CarA
CarC
Others

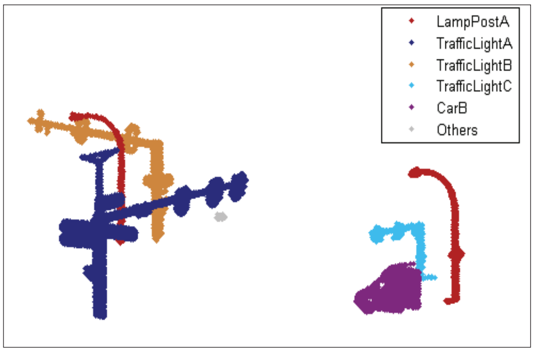
(e)


LamppostA
CarA
Others

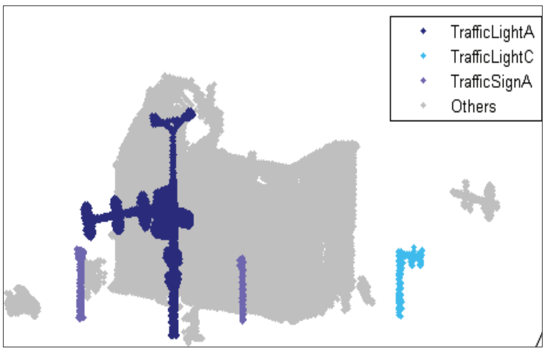
(f)


LampPostA
CarA
CarB
Others

(g)


LampPostA
TrafficLightA
TrafficLightB
TrafficLightC
CarB
Others

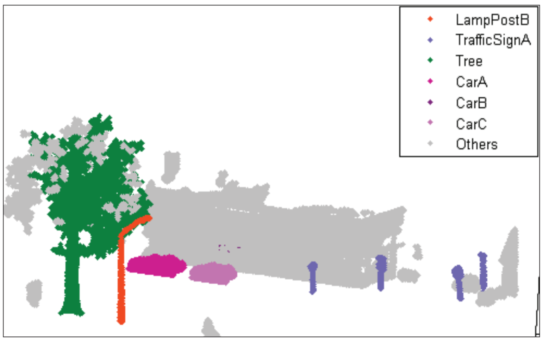
(h)


TrafficLightA
TrafficLightC
TrafficSignA
Others

(i)


LampPostB
TrafficSignA
CarA
Others

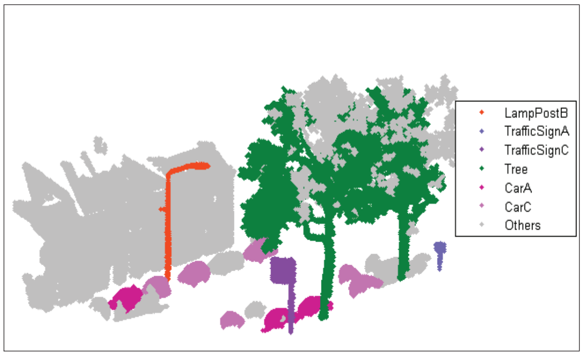
(j)



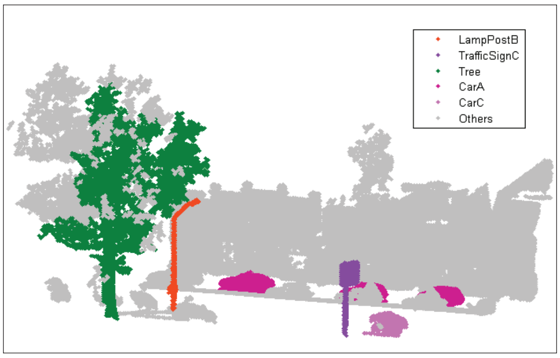
(k)

(l)

(m)



(n)



(o)

(p)

(q)

(r)

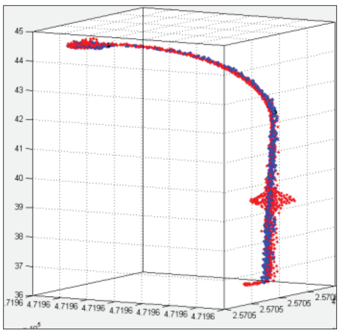
Figure 5-3: Site-wide road sections classification results

The figures display the objects considered mainly lamp posts, traffic lights, traffic signs, trees, cars and others. The others class category comprises of objects which were not classified and also objects not factored in the selection of the training samples. These include building facades, fences, pedestrians and cyclists among others. Lamp posts were classified into two categories, Lamp post A and Lamp post B as can be clearly seen that the two categories have distinct shapes. Lamp post A has a wide curved top part at the point where the almost horizontal pole holds the lamp deflects unlike Lamp post B which is slightly a small curve. Traffic lights are also seen in three different categories where traffic light A is complex segment, traffic light B and C appear similar but the traffic light C as can be seen is shorter than traffic light B. Traffic signs are also presented in three categories traffic sign A, traffic sign B and Traffic sign C according to their different shapes and designs. Trees are presented in green colour. The cars are shown in three categories A, B and C. Also from cars classification, it is seen that other objects not cars were detected as cars as can be seen in figure 5-3(q). The grey segments are others which are those segments not represented in sample selection and also the target objects of interest missed.

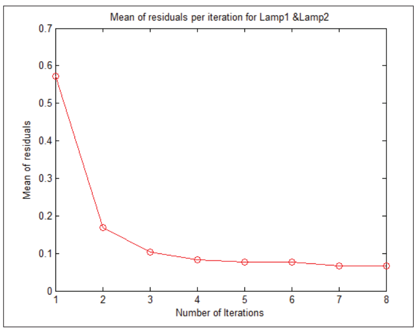
5.4. Iterative closest point algorithm

This step was performed as post processing for checking of point-to-point correspondence of the segments. The process is basically registration of two point clouds using ICP algorithm. Since the aim of our study is to find the best segment that best matches the given training samples , we need to confirm whether the segment was assigned to a given class category is correct or not in the classification step. This was done by analysing the points in the two point cloud segments. The procedure was performed manually with two point cloud of objects imported into the GUI then analysed. The parameters of registration are predefined before registration is done. The crucial parameters are the residual threshold which was predefined as 0.01m for 20 iterations. The number of random samples and rejection rate were defined by the user during refinement of the registration. The two point clouds are then registered and the residuals are analysed. The residuals obtained are between every registered point in the two point clouds. The residuals of the convergence of every point in the last iteration and the mean of residuals of all the iterations were plotted for visualization. ICP results are mainly for few selected segments.

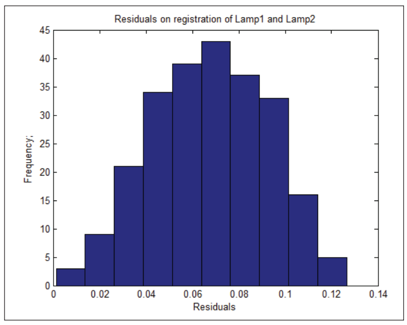
Registration of two point clouds shows two point clouds aligned to each other. The second point cloud gets aligned to the first point cloud as illustrated in figures 5-4(a, d and g). The mean of residuals of all the iterations are shown in a line graphs illustrated in figures 5-4(b, e and h). The residuals for the convergence (last) iteration as plotted in histograms shown in figures 5-4 (c, f and i).



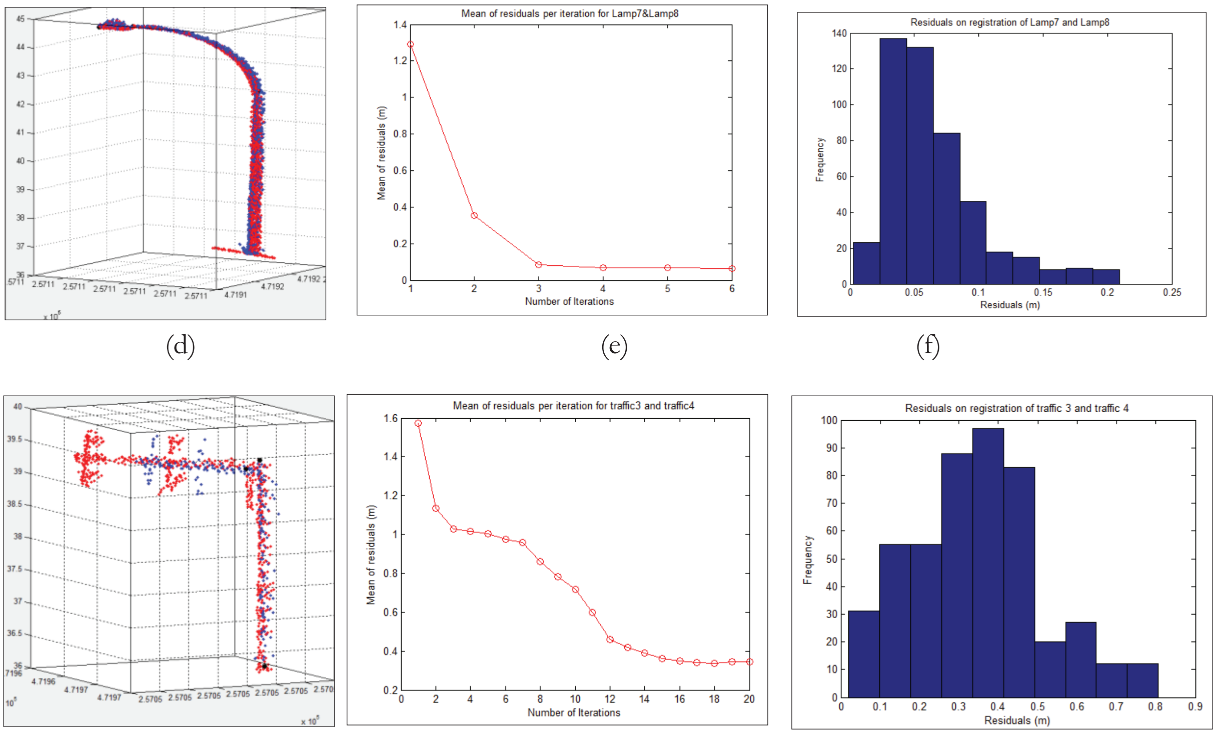
(a)



(b)



(c)



(d) (e) (f)

(g) (h) (i)

Figure 5-4: Analysis of registration using Iterative Closest Point Algorithm

From the figures, we clearly see the different sets of point cloud registered. In the case of figure 5-4(a), we see that the two lamp posts are not perfectly similar as another one have extra points from the mounted object on its pole. These then amounts to extra points on that segment. For figure 5-4(d), the two point clouds can be seen to appear similar and figure 5-4(e) shows that one of the point cloud segment has longer horizontal pole than the other thus making it to have extra points than the other one. Even the positions of their lamps are not corresponding. The line graphs shown in figures 5-4(b, e and h) clearly indicate how the convergence is arrived with the number of iterations and the final mean residual value for registration. Figures 5-4 (c, f and i) of histograms depicts the frequency of points and corresponding residuals for registration of the two point clouds.

5.5. Enhanced classification

Enhanced classification can be considered as an improvement of the implementation method previously described in which we combine both the histogram correlation and distance ratio values derived from minimum bounding box parameters. The reason we say improvement is that with this approach, we are able to analyse each segment in respect to all training samples and therefore offers opportunity to detect noise and incorrect matches. The histogram correlation values used are as explained in section 4.3. The distance ratio values were derived from the feature space described in section 4.4. From the feature space, we can clearly see the clusters of different objects under consideration. In order to analyse the separability of these objects, the likelihood of the segment to belong to a certain cluster in the feature space is computed. We first make assumption that the MBB ratios plotted in the feature space correspond to x and y then computation of the distance ratio done according to the derived formula described below.

$$\text{distance ratio} = 1 - \frac{d}{d_{max}} \qquad (5\text{-}1)$$

where d is distance given as $d = \sqrt{dx^2 + dy^2}$
for $dx = X_{sample} - X_{segment}$ and $dy = Y_{sample} - Y_{segment}$
and d_{max} is the maximum distance between samples.

This formula was derived by the logic that if an object is closer or has shorter distance to a cluster, then its distance ratio will be higher than when the distance is longer. This is attributed to the fact that closer the value of ***d*** to ***dmax***, the bigger the distance and the result ratio will be closer to value 1 then when fitted in the formula, the resultant distance ratio will definitely be close to value 0. This then will mean that the objects under consideration are not similar. Then if distance ratio is one, the objects will be considered similar. More important is that the introduction of the value 1 is to help in normalising the distance ratio.

The formula was then applied to compute the distance ratio of various training samples drawn from the data to belong to a class and also to analyse how well the parameters can separate the objects. The results are tabulated in table 5-2. The distance ratio is then later applied in selecting the segment which has the highest value with the training sample. If the distance ratio value is 1 then it means the sample and segment in question are similar where as if it is 0, then the sample and segment are not similar. Since the scenario under study is not perfect due to external factors such as noise, the distance ratio of closely similar segments will not be exactly value 1 but close to it.

Object 1	Object 2	W/L vs L/H	W/H vs L/H
Lamp post	Lamp post	0.98 – 0.99	0.98 - 0.99
	Traffic light	0.8 – 0.91	0.70 – 0.86
	Traffic sign	0.74 – 0.94	0.85 – 0.92
	Tree	0.70 – 0.79	0.76 – 0.86
	Vehicle	0.0 - 0.49	0.0 – 0.32
Traffic light	Traffic light	0.90 – 0.95	0.80 – 0.91
	Traffic sign	0.69 – 0.78	0.54 – 0.64
	Tree	0.69 – 0.76	0.67 – 0.71
	Vehicle	0.0 – 0.53	0.0 – 0.25
Traffic sign	Traffic sign	0.77 – 0.97	0.9 – 0.99
	Tree	0.72 – 0.84	0.74 – 0.80
	Vehicle	0.0 – 0.52	0.0 – 0.30
Tree	Tree	0.74– 0.91	0.92 – 0.97
	Vehicle	0.0 -0. 23	0 – 0.27
Vehicle	Vehicle	0.73 – 0.93	0.51 – 0.94

Table 5-2: Summary of analysis of distance ratio values in the feature spaces

Though the formula as applied gave appreciable results, it is likely to ignore the distribution of samples in different cluster as some clusters are bigger, some are small and distributions are different as can be seen in figure 4-7.

5.5.1. Ranking of correlation and distance ratio values

5.5.1.1. Histogram correlation

The aim is that, we assign the segment a sample that best matches it. This was done by computing histogram correlation between the segments on the site wide road section and all the samples used in the study. The segments were then ranked based on the sample which resulted with high correlation value. The ranking is done from high to low so that the correlation value which is higher than the rest is placed at the top of the ranking list. This means that the segment will be assigned the sample which scored highest correlation value. This is done for all the segments in the site-wide area of the road section. Therefore we result in a scenario were all segments are assigned to a sample segment that scored highest as shown in table 5-3.

Segment ID	Correlation	Sample ID	Sample Type
5	1	9	TrafficLightA1
28	1	48	VehicleB1
31	1	1	LampPostA1
6	0.9995018	13	TrafficLightB1
7	0.9998479	2	LampPostA2
27	0.9993437	14	TrafficLightC1
20	0.4626811	7	LampPostB4

Table 5-3: Segment and corresponding sample correlation value

5.5.1.2. Minimum bounding box parameters using distance ratio values

The second step to check for similarity of segments is by use of parameters derived from minimum bounding box. Parameters of bounding box applied were based on distance ratios extracted from feature space as described in the section 5.5 above. The distance ratio of segment to correspond to particular sample was computed on site wide part of the road. Once we have the distance ratio values, ranking is done in similar way as that for the correlation values mentioned earlier. The ranking is from high to low such that the highest value of distance ratio between segment and sample is placed at the top of the list. This was done for all the segments in the selected site of road section and we end up with the all segments in the site having assigned a sample which scored highest distance ratio value. Similar to correlation, we also check the segment and its corresponding sample that scored highest probability for it as shown in table 5-4.

Segment ID	Distance ratio	Sample ID	Sample Type
5	1	9	TrafficLightA1
28	1	48	VehicleB1
31	1	1	LampPostA1
6	0.999869	13	TrafficLightB1
7	0.976299	2	LampPostA2
27	0.921538	14	TrafficLightC1
20	0.664241	39	Tree11

Table 5-4: Segment and corresponding sample distance ratio value

5.5.2. Classification of the segment

After we obtain the segments which recorded high correlation and distance ratio values, we check if the same segment in step one was also ranked in position one in step two. If not, we compute an average then rank them again. Finally we get to assign the segment to the sample with the highest value and eventually assign it a class category appropriately as lamp post, traffic light or traffic sign based on the classes labelled in the training samples. We finally plot the classification results as shown in figure 5-5.

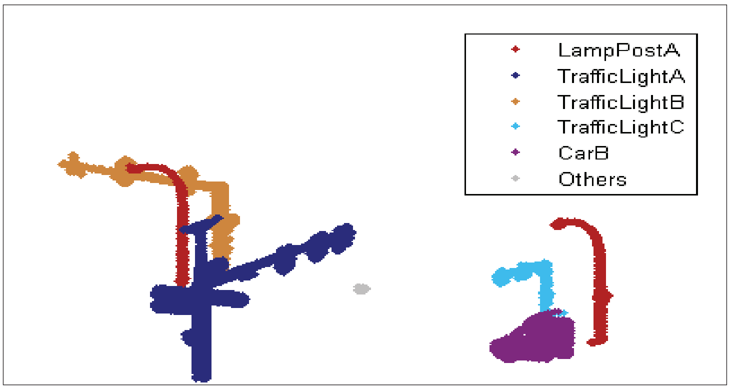


Figure 5-5: Classification result; combined correlation and distance ratio values

5.5.3. Conclusion on enhanced classification

The combination of histogram correlation and distance ratio values based on MBB ratios was found to have insight into detection and classification of segments. Combination of the two of them makes it easy to notice incorrect matches and be able to correct since we analyse each segment individually in respect to all the samples used in the study. From table 5-3, we notice that segment 20 is assigned to sampleID 7 which actually corresponds to lamp post B4, and in table 5-4 it is assigned to sampleID 39 corresponds to tree11. In correlation the segment scored 0.46 where as in distance ratio computation it scored 0.66.When we finally perform classification, we notice that the segment doesn't have a representative sample and so the reason it was assigned to any which scored high. To eliminate this, it then calls for applying thresholds in the final step of classification to ensure that only the most probable sample is assigned to the segment and wrong matches are eliminated as in the case of segment 20. This problem was encountered for segments which do not have representative samples such as building facades, fences, pedestrians, cyclist among others and there they will get assigned to any class of the samples taken in the training data. Another challenge also is still in the scaling the similarity of the minimum bounding box dimensions and this calls for proper investigation and improvement of the formula applied as described in section 5.5.

6. EVALUATION AND DISCUSSION

6.1. Evaluation of the classification results

The purpose of performing evaluation of the classification results is to help us determine how effective the classification method as employed in the dataset is. In this study, evaluation of classification results was done using the reference data manually created by counting the number of target objects of interest in the segmented point cloud data. Similarly the classified objects are counted in the classification results shown in figure 5-3. A confusion matrix was developed and also the evaluation measures namely quality, completeness and correctness were performed. Completeness represents the percentage of the reference data. Correctness represents the percentage of correctly classified objects. Quality gives the measure of how good or bad the final result is. Quality measure factors in the completeness and correctness measures together. Also important to note is that the optimum value for all these measures is 1. These measures are determined by considering four possible categories for each object. These are true positive (TP), true negative (TN), false positive (FP) and false negative (FN) as detailed by Shufelt (1999). The definitions of these quality measures are described by Heipke et al. (1997) as follows.

$$\text{Completeness} = \frac{\|\text{TP}\|}{\|\text{TP} + \text{FN}\|}$$

$$\text{Correctness} = \frac{\|\text{TP}\|}{\|\text{TP} + \text{FP}\|}$$

$$\text{Quality} = \frac{\|\text{TP}\|}{\|\text{TP} + \text{FP} + \text{FN}\|}$$

6.1.1. Evaluation of the site-wide road section classification results

The components of only the target objects of interest were manually counted and confusion matrix developed as shown in table 6-1. Counting was done on both the raw point cloud and also on the classification results. From the confusion matrix values, we computed the evaluation measures completeness, correctness and quality and results presented in table 6-2.

Classified	Reference						
	Lamp post	Traffic light	Traffic sign	Tree	Car	others	detected
Lamp post	24	0	0	0	0	0	24
Traffic light	0	5	0	0	0	0	5
Traffic sign	0	0	21	0	0	3	21
Tree	0	0	0	21	0	4	21
car	0	0	0	0	63	3	63
Missed	0	0	3	4	71		
Total	24	5	24	25	134		
Accuracy (%)	100	100	87.5	84	47		

Table 6-1: Confusion matrix of classification results

Object	TP	FN	FP	Completeness	Correctness	Quality
Lamp post	24	0	0	1	1	1
Traffic light	5	0	0	1	1	1
Traffic sign	21	3	0	0.875	1	0.875
Trees	21	4	0	0.84	1	0.84
car	63	71	3	0.470	0.95	0.46

Table 6-2: Evaluation results

6.1.2. Evaluation of cars in comparison with SVM with FS classifier

Further, in order to check the performance of the proposed method, evaluation in comparison with another classifier named Support Vector Machine with Forward Selection was done. The SVM with FS classification was performed by Li (2014) on ITC thesis titled "Automatic detection of temporary objects in Mobile LIDAR point clouds". The evaluation was performed to check the completeness, correctness and quality of cars only. From the previous evaluation, we noted that cars were poorly detected and by comparing with another classifier in the same data we can be able to pin point the performance of the proposed method. The dataset applied and result obtained is as shown in figure 6-1 below. The results of evaluation are tabulated in table 6-3.

(b)

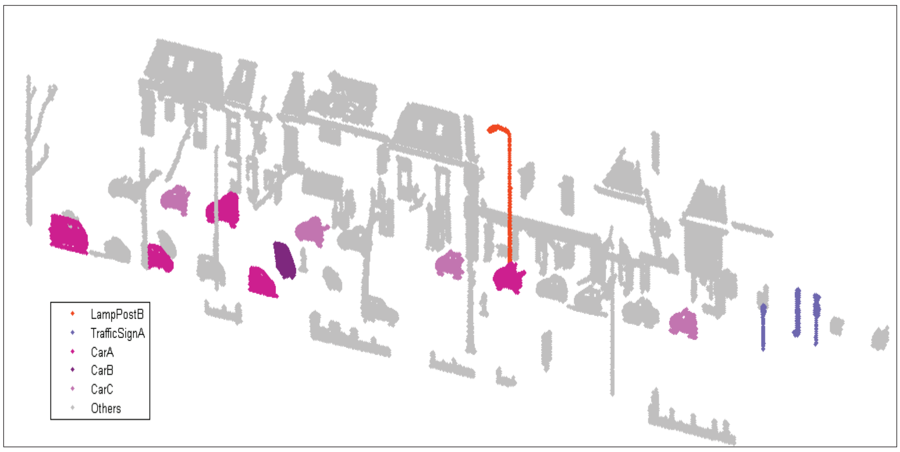


Figure 6-1: Evaluation dataset (a) Input (b) Output result

Object	TP	FN	FP	Completeness	Correctness	Quality
cars	10	11	0	0.48	1	0.48

Table 6-3: Evaluation of cars as classified by proposed method

The same dataset as classified and evaluated by Li (2014) using SVM with FS gave the results tabulated in table 6-4 below. The dataset contained 21 cars and the classification using the developed approach resulted to detection of 10 cars and 11 cars were missed. The classification as done by Li (2014) used all the cars as training and this resulted to 100% accuracy. This means that if we use all the cars as training samples in our case, then we are likely to achievethe same accuracy as obtained by use of SVM with FS classifier.

Name	Number	Completeness	Correctness	Overall accuracy
Temporary objects (cars)	1	1	1	1

Table 6-4: Evaluation of cars classified using SVM with FS

6.2. Discussion on the proposed methods

6.2.1. Discussion on Histogram correlation using dot product

Histogram correlation computation is based on bin by bin computation. Bins were constructed at equal height intervals based on the relative height of the object segment and normalised. Objects with similar heights and point distribution with increasing height achieved a greater success, a feat achieved due to the distinct pattern of the objects as visualized in the histograms as shown in section 4.3. This is seen in target objects with distinct shapes and formation that had great success as seen in results of lamp posts and traffic lights. Correlation was computed across all the site segments against target object samples and high correspondence (high correlation) segments selected for further identification based on minimum bounding box parameters. By applying a threshold of 0.9, we ensured that only segments with highest correlation values are picked for next analysis. This was found to be common for most objects except trees which were given a low value of 0.7 due to the fact that trees are more varied in nature. The good success achieved was a result of high correlation values that represented similar object types as can be seen in table 4-1.

6.2.2. Discussion on minimum bounding box parameters

The minimum bounding box parameters were proposed and computed to further assist in target object class identification. Given that it is known that different objects have a least sized cuboid into which they can be fitted, this distinctive property was ingeniously harnessed to enable differentiate between different objects. Using the Length (L), Width (W) and Height (H) of minimum bounding box, they were combined into ratios WL, WH and LH parameters that proved useful in the classification process. This was especially true to differentiate subclasses of related target object types as witnessed in the lamp posts that had almost similar shape and form with differences occurring only in their sizes especially the heights. However, target objects as cars which were of different models but almost same body size had similar minimum bounding box parameters hence making it difficult to differentiate them more successful. Also we find that trees are kind of fuzzy objects with no definite shapes to describe or relate one tree to another perfectly. This is due to the fact that trees are natural features. With these factors, the detection of trees is affected and this might be the case of the missing trees in our results as shown in figures 5-3 (a), 5-3(l) and 5-3 (r) shown in the results section.

6.2.3. Discussion on classification results

The classification results presented comprised of the target objects of interest among others. The classification was done on site wide road part as shown by the results in figures 5-3. The proposed approach achieved appreciable results especially for lamp posts and traffic lights with 100% accuracies as shown in table 6-1. These successful results are attributed to distinct shape and form of the said target objects. Having a designed shape and form, repetitively similar in other areas where they are located enabled the approach become quite a success. However, contrast to cars that tended to vary greatly and trying to pick representative samples would mean sampling nearly all captured car features. Further given that the laser captured the facade facing the laser emmitance, then the opaque nature of cars meant their back side was not captured. Even their orientation of their parking meant same object type captured from front wise would differ from same object captured side wise or rear wise. This led to minimum bounding box parameters taking the said objects as being different yet in actual sense they were of the same object type. Also some other objects which are not cars were classified as cars leading to wrong detection as can be seen clearly in figure 5-3(q). Even with these setbacks in car category, cars inside garage and behind fence were detected as shown in figures 5-3 (c, e and f). Also given the varied nature of trees and their different shapes and sizes, this meant that the threshold for trees had to be relatively low as compared to other object types (correlation 0.7) as illustrated in figure 5-1. From the classification results, we find that some trees were missed, as can be seen in figures 5-3 (a), 5-3(l) and 5-3 (r). This can be attributed to the fact that trees are varied in shape and size and getting a perfect representative sample is difficult otherwise you might sample almost every single tree in the data. Also the segmentation parameters as applied in pre-processing step seem to influence the complete detection of tree segment. Tree segmentation resulted into over segmentation thus part of the crown is being classified as others as can be seen in figures 5-3. A few trees were classified as whole which means that the tree component was well segmented. Other trees were too small to be detected and others were hanging in the air as shown in figure 6-2.

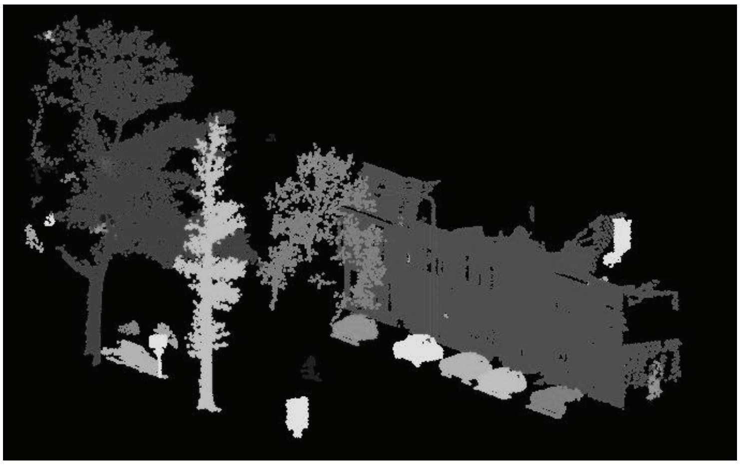


Figure 6-2: Missed small tree and hanging tree in the air

6.2.3.1. Discussion on evaluation of cars in comparison with SVM with FS classifier

Evaluation of cars was performed in comparison with Support Vector Machine with Forward Selection classifier results. From table 6-3 we find that the accuracy of cars is 48%. This almost coincides with the accuracy obtained in section 6.1.1 in which the cars accuracy was 47%. Similarly, the completeness obtained in section 6.1.1 as 0.95 is also close to the one obtained in this case which is 1. In comparison with the SVM with FS having 100% accuracy, we can say that our method cannot work well with varying objects as cars as previously discussed due to variability in shape and models thus getting appropriate representative sample is difficult otherwise you might sample almost every single car in the data.

6.2.3.2. Conclusion

Evaluation of classification results was based on reference data manually generated by counting the number of target objects of interest in the segmented point cloud data. Also, the classified objects were counted manually from classified objects in the classification. Since this kind of evaluation was based on same dataset used for training the method and classification. This therefore demands for a more proper evaluation using a larger test set and also evaluation based on external independent dataset.

6.2.4. Discussion on Iterative closest point

Iterative closest point algorithm was applied in few selected segments. The process was done manually and residuals analysed. From the figure 5-4, it is clear that segments that appear to be much similar register low residual values and converge faster with few numbers of iterations. The convergence of the residuals is gradual fall from large values to small values in which at this point the iteration stops. From the histogram, the peak shows the mean of the last iteration of convergence. The outliers of residuals appear at the far ends of the histogram. Important observation is that convergence depends on the number of random samples used for initial registration and also the number of random points and rejection rate. As indicated in figure 5-4(a), the two point clouds registered as similar but one contain extra points as a result of attachment on its pole. This is the reason why we find that the residuals of convergence span to 0.12 m. Also noticeable is that its histogram shows normal distribution of the residuals. For figure 5-4(d), the two segments are similar thus it took few numbers of iterations to converge with small mean value of residuals. For the case of figure 5-4(g), the two point cloud are not very much similar as evidenced by the residuals obtained. The two point cloud converged after many number of iterations yet with large mean residual value. This is the scenario in which the two point clouds are termed not to be similar. The approach used in registration of the point clouds proved tedious and biased since the selection of initial approximation parameters are manually done by the operator. Figure 6-3 shows black dots which indicate the areas where the three corresponding points were selected for initial approximation of registration parameters. Finding the best initial approximation parameters is by trial and error therefore any bias leads to high residuals in the registration.

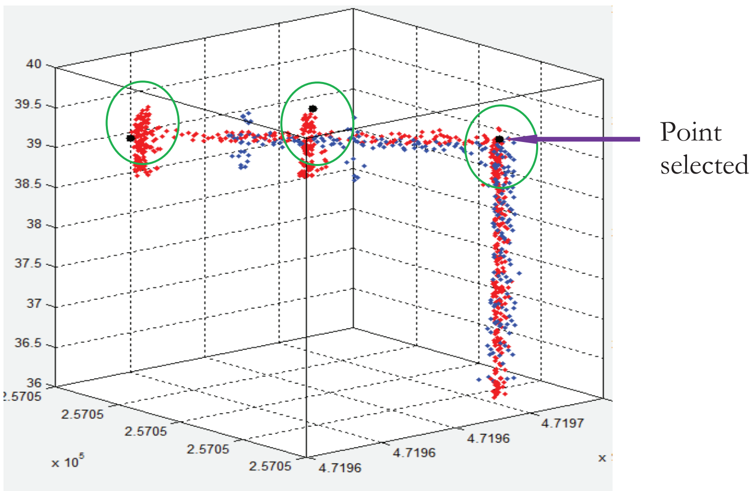


Figure 6-3: Selection of the corresponding points

6.3. Discussion on Methodology

The proposed methodology approach of using a connected component of an object to find other similar object components within the data has been proved successful. The method captured most distinct target objects with good accuracy as displayed in table 6-1 for lamp posts and traffic lights. The sequence of the methodology in extraction of objects of interest was a good approach. This is due to the fact that using correlation, the objects of different categories can register high correlation values since histogram computation is based only on the values in the bins. Depending on the values, then two objects say lamp of category A and B can be highly correlated. The strength of the method then came in when minimum bounding box parameters are introduced to give a clear cut between these categories. Objects with relatively large differences in LWH properties are easily separated as compared to objects with slight differences in their LWH properties. And this was clearly shown by the classification results in which the objects were classified into subcategories. Although the proposed approach may not be successful in all sites classification, from the results of evaluation at 100% for lamp posts and traffic lights, 87.5% for traffic signs and 84% for trees this proves it to be a promising method that can be tackled further. For cars at 47% accuracy, this may be due to greatly varying sizes and shapes of cars and also parking orientation when they were captured obscuring their ends from laser beams. This is also seen when evaluation of cars was done in comparison with another classifier SVM with FS where cars evaluation results gave consistent results with an accuracy of 48%. This may be improved if all round capturing laser techniques are applied to capture objects in full as done for trees and lamp posts that were relatively penetrable and narrow respectively. The narrowness of pole based features (lamp posts, traffic lights and traffic signs) make them be captured all round. Even though the overall approach is successful, it is likely that we cannot handle noisy segments stepwise and this is then carried throughout the classification process.

The analysis of point -to-point correspondence using Iterative Closest Point algorithm though gave a clue of matching of two point clouds, the approach was found to be tedious since the registration is done manually. Selection of initial approximation parameters is a challenge since it depends on how well the operator can locate the corresponding points clearly. This then affects the registration because the error in the initial approximation parameters is carried along the registration process yielding high residuals. This can then be improved by devising a way of selecting the initial approximation parameters automatically to avoid bias by the operator.

7. CONCLUSIONS AND RECOMMENDATIONS

7.1. Findings to the research questions

This research was accomplished by tackling the objectives associated by the following research questions and some of the findings include;

- Which features and their characteristics define the existing nature of road furniture?
  - Road furniture as captured by MLS can be defined by use of histograms and minimum bounding box parameters. This has been achieved in which the point cloud of road furniture has been plotted in histogram and minimum bounding box. The characteristic of each road furniture type has been clearly noticed in the histograms for example the lamp posts depicted high rise of points at the area where the horizontal pole holding the lamps is located. The minimum bounding box described the road furniture in a cuboid in which the features of road furniture as dimensions (Length, Width and Height) were derived.

- What factors affect the defined nature and status of road furniture?
  - Given that the histogram developed shows the distribution of points with increasing height, the proximity of points is seen in the pattern of the histogram. This is evident by the shape of histogram especially in instances of lamp posts with an attachment mounted on their poles. This area shows a sudden high rise in frequency of points at the same height level.

- How do we define road furniture based on MLS data properties?
  - MLS data offers X, Y and Z coordinates of the object. To define the road furniture in the data, segmentation was performed to group all the points that belong to an object together. The segmentation method by connected component analysis was applied after surface growing segmentation in order to have the resulting connected components being segments belonging to each individual object. The connected components actually represented the road furniture to be studied.

- What are the characteristics of road furniture that are the least influenced by noise and low density of the data?
  - As mentioned earlier, road furniture was described by use of histogram and minimum bounding box. Given that the minimum bounding box only considers the minimum and maximum x, y and z coordinates of the point cloud, the definition of road furniture using it lead to no external influence either by noise or low point density.

- Which road furniture characteristics help us differentiate between the road furniture types?
  - From the analysis of histograms, we noticed that different objects depict differences in their patterns of histograms developed. Similarly, the different objects portrayed different characteristics of minimum bounding box parameters. These were then factored into consideration in differentiating between the different types of road furniture and further used in development of the detection method.

- How do we combine these characteristics to enable detection and extraction of road furniture?
    - Given that the various road furniture objects have different properties as portrayed in the histograms and minimum bounding box, this helped in detecting them. The histogram correlation values and minimum bounding box parameters were employed in detection and extraction of the target road furniture objects. This was implemented in the classification stage to extract the desired target objects of interest.

- At what point do we decide that the object is detected or not?
    - With the interest in the study being using a connected component to find similar component, the decision of whether the correct component is found was further analysed by performing point-to- point correspondence using Iterative Closest point algorithm. This was basically registration of two point clouds. The residuals and number of iterations to convergence were analysed. Few numbers of iterations with small residuals helped to decide whether the segments are similar or not.

- How effective is the developed road furniture extraction process?
    - The proposed methodology has been proven quite a success as evidenced by the classification results. The accuracy depicted by lamp posts and traffic lights of 100% is quite impressive of the performance of the approach. Even though no ground truth data existed for evaluation, the visually derived reference data proved effective.
    - Further, the proposed method was applied to another dataset and results compared to another classifier SVM with FS for only evaluation of car category. The accuracies obtained were consistent to the ones as obtained in our classification results. This means that our approach can give consistent results with any data and so even for the objects such as lamp posts they can perform very well.

- What factors are likely to have affected the presented results?
    - Given that the results were quite impressive, other target objects were not detected well as evidenced by the cars class category. This was attributed to the fact that cars vary greatly and also the aspect in which the data was captured as orientation of the cars in a parking seem to have affected the entire car to be captured.
    - Also the segmentation parameters were found to affect the formation of connected components as witnessed in the tree segments which showed over segmentation and rendered some part of the tree not to be classified as a tree as a whole.
    - With no ground truth data existed for evaluation, the process of generating reference data manually employing visual inspection on the point cloud segments can be biased due to its dependence on the judgement of the operator.
    - Other factors might be the minimum bounding box parameters employed which is mainly based on the use of their ratios which are subjective to the shape and size of the objects.

7.2. Conclusions

The research focus was mainly on detection of road furniture in MLS data. This has been achieved by development of an approach which uses a connected component of an object to find other similar objects within the data. Segmentation by surface growing and connected component analysis was performed as pre-processing steps to prepare the connected components for analysis. The connected component parameters have been described by use of histogram and minimum bounding box where histogram correlation and MBB parameters were analysed. The procedure adopted involved computation of histogram correlation using dot product of vectors and MBB parameters, followed secondly by classification of the segments that satisfied a given threshold values from the correlation and MBB parameters computation. The classification results were evaluated for completeness, correctness and accuracy in order to investigate the performance of the proposed approach. A post processing analysis was also performed to check for point-to-point correspondence using Iterative Closest Point algorithm. The conclusions of this research are summarised as follows.

1. Surface growing algorithm was found to be appropriate for segmentation. Use of the planar surface parameter enabled the grouping of points into planes. This eventually led to the ground points forming a larger planar surface which was then removed to only remain with non-ground points for analysis. With surface growing algorithm, good segmentation parameters are necessary to achieve good results.
2. The connected component analysis segmentation proved to work well in clustering of non ground points which basically form the objects of interest. From the results, the segmentation parameters employed did not work very well for trees as they were found to be over segmented resulting into small segments especially in the tree crowns areas. Also building facades were affected resulting into over segmentation into many planes. Since they were not factored in classification, no significant effects were caused by them. The problem of over segmentation and under segmentation needs to be carefully taken care of to improve the analysis.
3. Since the study was based mainly on component wise analysis, parameters of the components were described by use histograms and minimum bounding box. Relationships between the connected segments were then based on histogram correlation and MBB ratios.
4. The proposed methodology was tested on road section dataset and proved successful with some objects attaining 100% accuracy. The histogram correlation contributed a lot to the success of the classification since the method showed high correlation between similar objects. Introducing MBB parameters in the classification played a great role in improving the classification which resulted into sub class categories. This might not have been achieved by histogram correlation alone since it relies only on bin to bin computation.
5. Enhanced classification approach combined both correlation and distance ratios obtained from MBB ratios. The approach as applied gave an insight that the method can be more successful with improvement of the formula as applied. The challenges can be encountered in areas with many and complex structures as the assignment of the sample to segments leads to multiple copies of the same sample in many segments.
6. Judging from the evaluation results, the method cannot be more effective in areas with varying objects. The cars performed poorly due to the fact that they come in different shapes and models. Also contributing factor is that the cars were captured only in one face thus leading to having a partial object segment.
7. Iterative closest point algorithm for point-to-point correspondence still poses challenges as used in this study. This is due to the fact that the process was almost fully manual as selection of initial approximation parameters were done by the user. This then poses errors in the registration as it is biased due to the expert experience.

7.3. Recommendations

A number of recommendations for further studies are as outlined below.

1. There is need to determine good segmentation parameters to ensure that the connected components of objects are not over-segmented or under-segmented. This is to ensure good components are formed which will result in classification of the segment in entirety.
2. Given the segments of building facades do not contribute that much in the detection of road furniture, filtering approach to remove them would be helpful. This is to reduce amount of data that increases computation time at the same time may complicate the detection process as small segments of facades can get classified as objects of interest.
3. The histogram matching method applied in this study was based on histogram correlation approach. Other histogram matching methods such as intersection, chi-square and Bhattacharyya can also be investigated in comparison to the histogram correlation approach as employed in this study. This can further ascertain the effectiveness of the histogram correlation method as applied in our study.
4. Since the application of MBB parameters used mainly comprised of ratios based on dimensions, other parameters such as area, volume and density can also be studied to see how effective they can be.
5. Other approach of implementation of the method can be investigated and results compared to the obtained one to determine its effectiveness and also be in position to criticize its setbacks.
6. The developed approach can also be tested with another data from other road or any urban scenario to determine its effectiveness.
7. More effort should be made on how to determine initial approximation parameters of ICP automatically since manual way still poses a lot of challenges.

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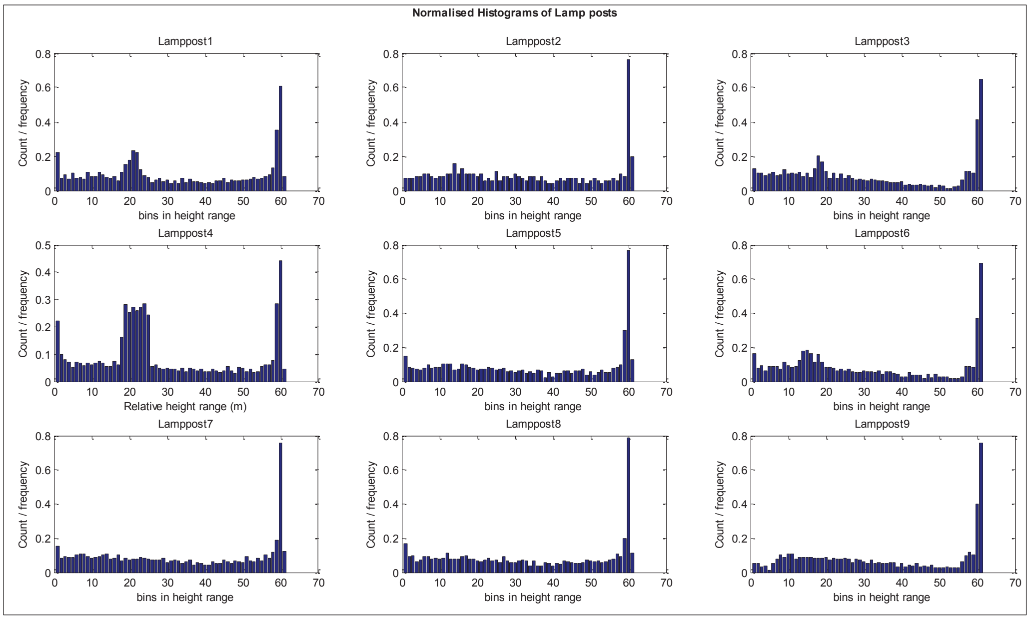
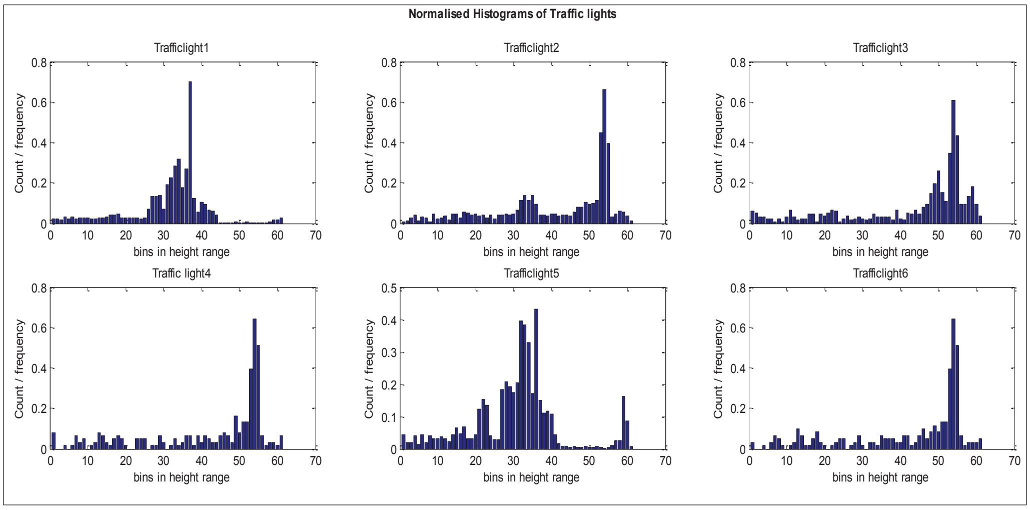
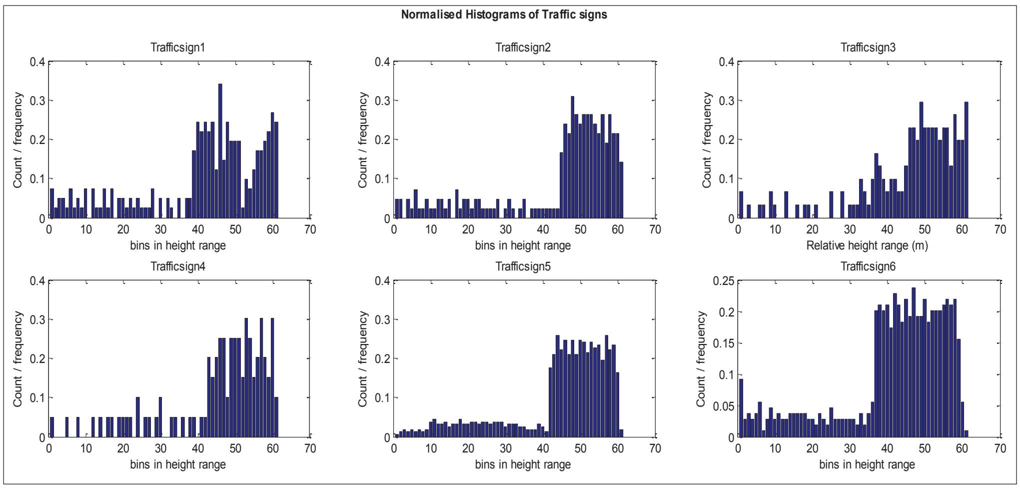
Appendix 1: Normalised histograms



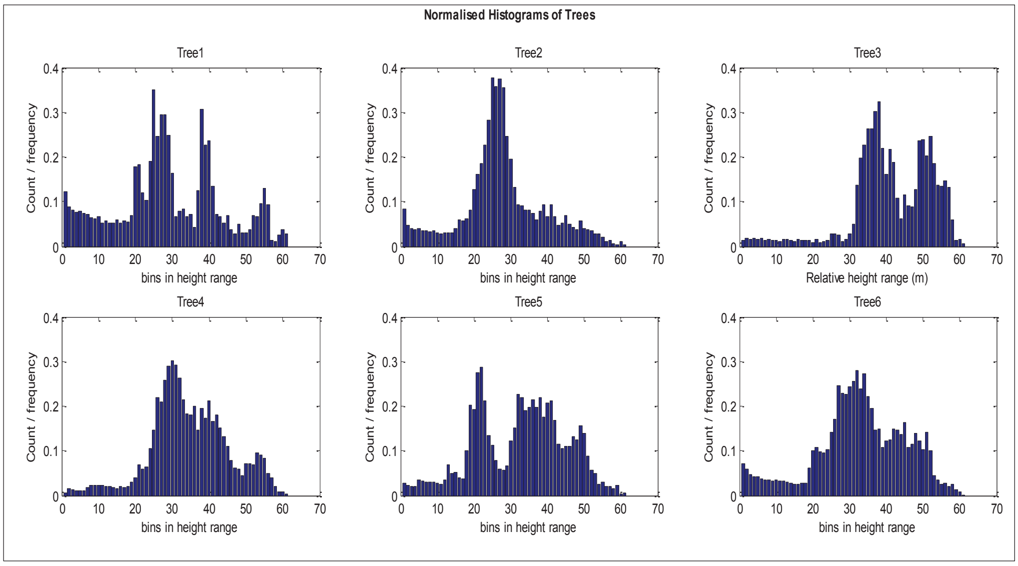
(a)



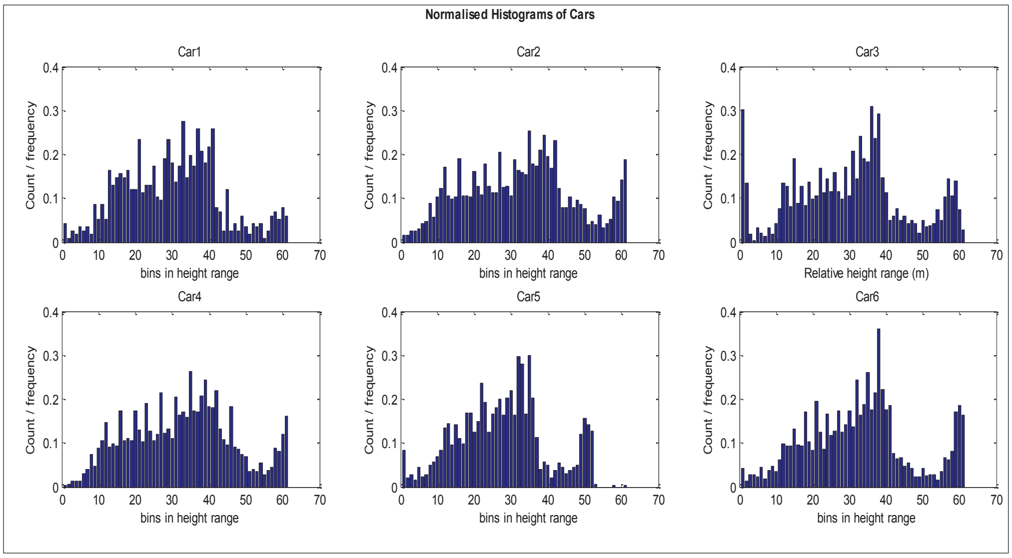
(b)



(c)

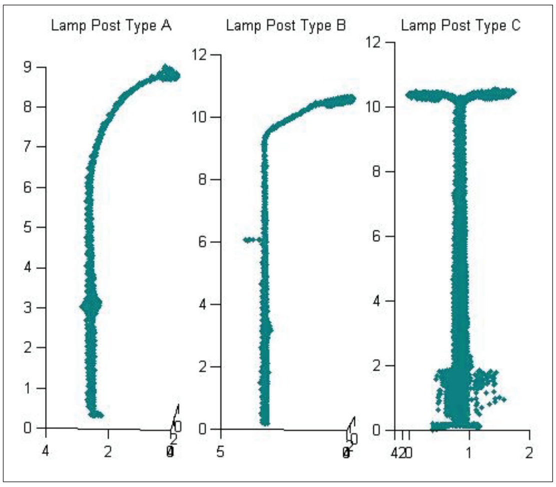

Normalised Histograms of Trees
Tree1
Tree2
Tree3
Tree4
Tree5
Tree6
Count / frequency
bins in height range
Relative height range (m)

(d)

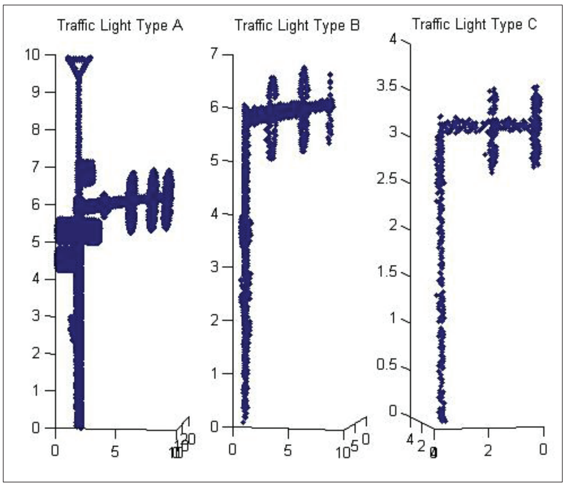

Normalised Histograms of Cars
Car1
Car2
Car3
Car4
Car5
Car6
Count / frequency
bins in height range
Relative height range (m)

(e)

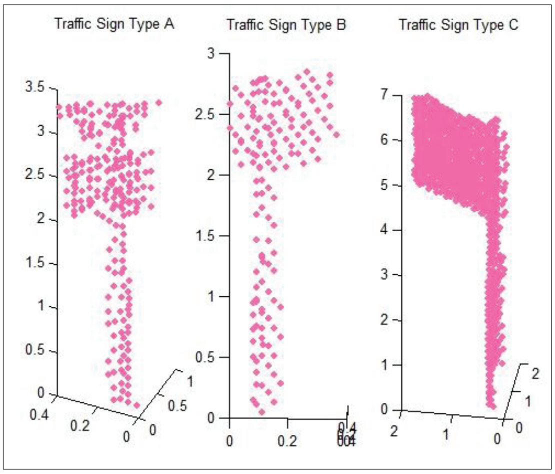
Appendix 2: Categories of object types



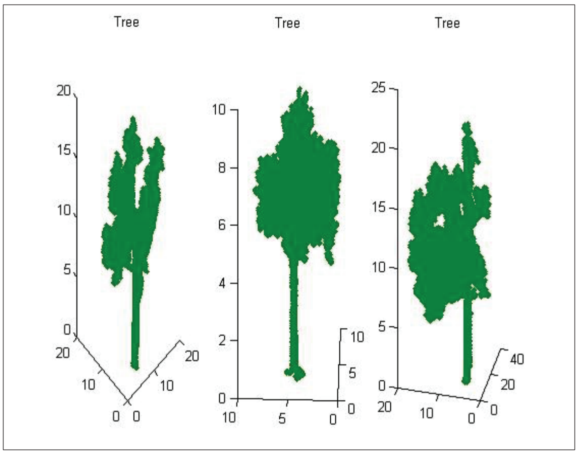
(a) Lamp posts



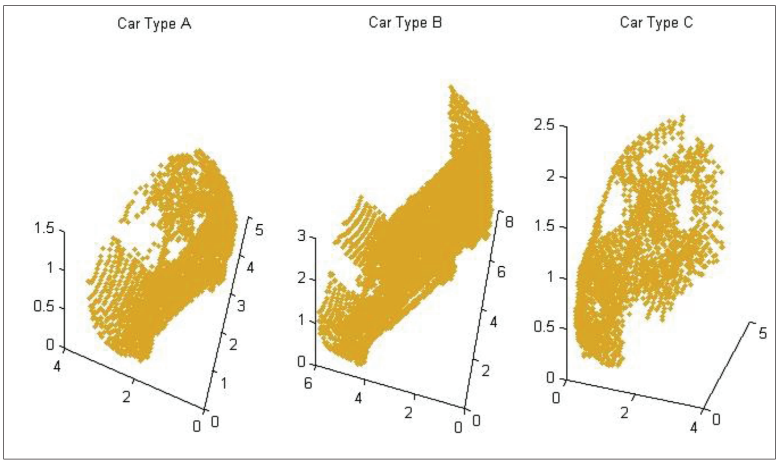
(b) Traffic lights



(c) Traffic signs



(d) Trees



(e) Cars