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SRAVANTHI MURALI
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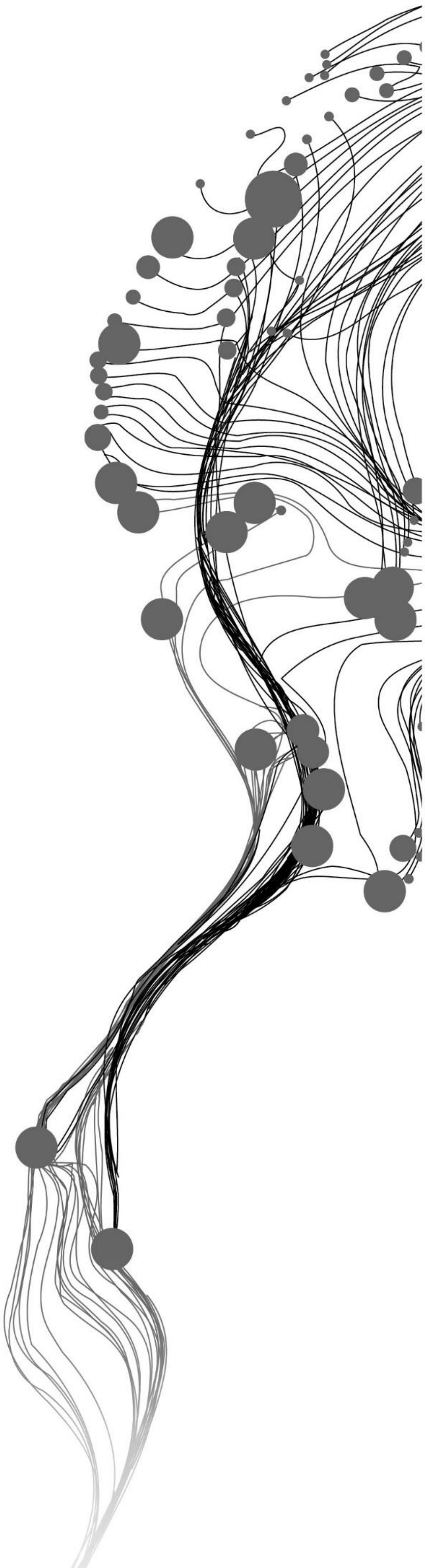
SUPERVISORS:
Dr. ir. Oude Elberink, S.J. (ITC)
Prof. Dr. ir. Vosselman, M.G.(ITC)



MAP SUPPORTED CLASSIFICATION OF MOBILE LASER SCANNER DATA

SRAVANTHI MURALI
Enschede, The Netherlands, [February, 2018]

Thesis submitted to the Faculty of Geo-Information Science and Earth Observation of the University of Twente in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation.

Specialization: Geoinformatics

SUPERVISORS:
Dr. ir. Oude Elberink, S.J. (ITC)
Prof. Dr. ir. Vosselman, M.G.(ITC)

THESIS ASSESSMENT BOARD:
Prof. Dr. ir. Stein, A (Chair)
Dr. R.C. Lindenbergh; Delft University of Technology; Optical and Laser Remote Sensing

DISCLAIMER

ABSTRACT

Mobile laser scanners (MLS) help in capturing highly dense point clouds from ground perspective. They can be used to capture various scenes both outdoor and indoor. The most common outdoor scene is a street scene in an urban setting. These dense point clouds contain a lot of detail. Thus, the task of filtering, data reduction and classification are important tasks to obtain meaningful information from the raw point clouds. One of major challenges of using mobile laser scanned data is to extract useful information rapidly with minimal compromise to the quality of the results.

Large scale 2D topographic maps are a ready source of information often containing large details. The most obvious information that can be used from the topographic map is the location information of a particular object. Besides that, maps are also rich in metadata which includes information such as object types and sometimes even object dimensions. The information pertaining to the objects in the map can thus be exploited for point cloud classification.

Classified point clouds are useful for a large number of applications. They can be used for automatic object detection and recognition, asset management, to create 3D city models for visualization etc. The goal of this research is to achieve the point cloud classification with the help of the knowledge derived from the map. A street scene is used to carry out this study. The polygon, polyline and point map features are used to classify the point cloud data into relevant classes.

The proposed methodology initially prepares the map and LiDAR datasets. Each map layer corresponds to an object class. The raw point cloud is labelled into 3 height labels i.e. ground points, just above ground points and above ground points. The LiDAR points are first classified using the polygon map features. This is performed by a point in polygon operation. Not all of the LiDAR points are considered for this operation. The class of the polygon map feature determines the LiDAR points of a specific height label to be considered for the point in polygon operation. Mostly, points at ground level are classified by polygon map features. Those LiDAR points that are above the ground then undergo a connected component segmentation. For each of the point cloud component, the closest map point is identified and the component is assigned the class of the corresponding map object. A visual accuracy check is carried out to test the initial results. The methodology is also extended to handle some of the remaining unclassified points. Finally, an accuracy assessment is performed to determine the classification results.

The proposed methodology was implemented on 3 different MLS datasets each containing around 12 million points covering an area of ranging between 70,000 and 90,000 square metres. The point cloud is classified into 21 classes. The accuracy of the classification ranges between 87% and 92%. The proposed approach can be extended to handle for many more classes as available in the map.

Keywords: mobile laser scanning; LiDAR; 2D map; fusion; classification;

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1. INTRODUCTION

1.1. Motivation and Problem Statement

3D point clouds are rich sources of information. They are simply a collection of points arranged together closely. Each point contains location attributes in the three-dimensional space. Point clouds help in assessing the geometrical and spatial information of objects and are used in a huge number of applications such as urban planning, asset management, utility mapping, forestry, civil engineering, cultural heritage mapping and documentation etc. They are produced by high quality laser scanning equipment that can be used to capture data from airborne, terrestrial and mobile platforms.

Mobile laser scanning involves capturing 3D point cloud information from a ground level perspective. In comparison to other laser scanning techniques, mobile laser scanning has several advantages which has been captured well by Zhu & Hyyppa, (2014). According to them, data captured by airborne laser scanning is in top-view which does not provide adequate high-resolution data for ground-based modelling. Oftentimes, the data is required to be captured from complex terrains. The mobile lasers can be used in such environments by fitting the laser scanner to cars, vans, boats, trolleys and even backpacks. Most mobile scanners are fitted with GPS and IMU and contain single or multiple scanners which can be set to obtain different point densities, several scanning angles and ranges to the objects. Point cloud datasets captured from mobile laser scanning techniques provide better point density, improved access to ground surface information and is a cheaper option for many applications as against airborne techniques (Zhang, Wang, Yang, Chen, & Li, 2016).

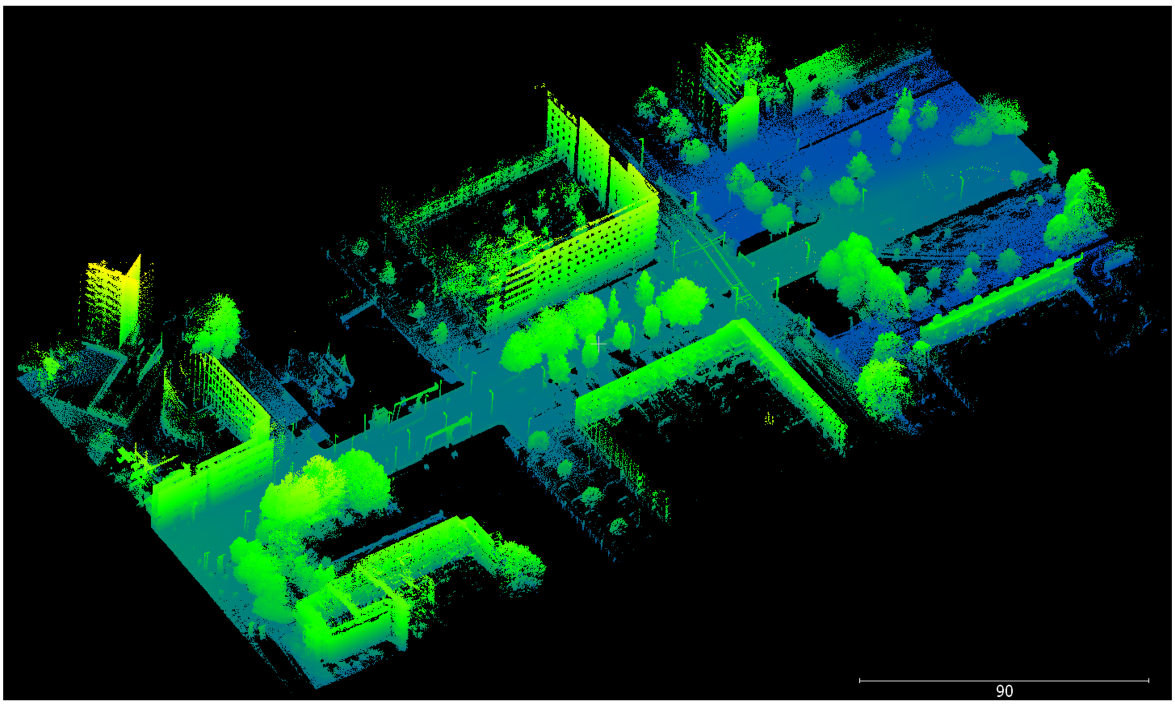

Figure 1: A subset of MLS point cloud colorized by height

3D point clouds usually are captured for an entire scene. The initial steps of segmentation and classification must be performed to make them beneficial for various applications. The point cloud data is captured for various scenes ranging from simple to complex. The point density, occlusions and noise play an important factor in point cloud segmentation and classification. Therefore, this is a widely researched topic with an intent to come up with innovative solutions that can be used for generic and specific purposes.

There exist several techniques to automatically classify point clouds. The most commonly used segmentation procedures involve edge based detection (Sappa & Devy, 2001), region growing (Arastounia, 2012), model fitting using RANSAC (L. Li et al., 2017) and Hough Transform, attribute based segmentation (Serna, Marcotegui, & Hernández, 2016), machine learning segmentation and graph based segmentation (Golovinskiy & Funkhouser, 2009). The success of these methods largely depends upon the point cloud density, noise or computational efficiency. There also exist many novel methods for point cloud classification such as building shape descriptors (J. Wang, Lindenbergh, & Menenti, 2017) or clustering segmentation results using Gaussian map (Yinghui Wang et al., 2013). A range of computer vision techniques such as conditional random fields (CRF) (Niemeyer, Rottensteiner, & Soergel, 2012) and data fusion techniques such as using aerial images (Beger, Gedrange, Hecht, & Neubert, 2011) and ortho images (Neubert et al., 2008) have also been explored for point cloud classification. However, these methods rely on extracting objects based on geometry and fail to give satisfactory results with increasing scene complexity.

The several techniques mentioned above are used to classify point cloud features of similar types. For example, point cloud classification for urban scene involve classification of pole like objects such as traffic lights, lamp posts and street lights (D. Li, 2013). In a railway environment, point clouds are mostly classified for railway tracks (Yang & Fang, 2014) or similar features such as contact cables, catenary wires (Arastounia, 2015). Instances of research involving point cloud classification of objects of different dimensions are limited to buildings, roads, low vegetation and trees. Often, they yield results of low accuracy, especially for trees (Kemboi, 2014).

This research explores the possibility of classifying features by data fusion of MLS point cloud and large scale 2D topographic map. Large scale 2D topographic maps are a ready source of information which contain object types and their locations. The information in these maps can be leveraged for point cloud classification. Issues such as varying point cloud densities and noise could be handled better. The map can also be used to classify the point cloud data in more detail as against the traditional classes of building, terrain and vegetation.

1.2. Research Identification

This research uses the large scale 2D map to classify the point cloud data. The LiDAR points were assigned to the features represented in the map. Points that did not belong to any of the map object class was assigned to the 'unclassified' class. Points corresponding to cars or pedestrians are examples of such points.

The following elements were taken into consideration

- Registration errors - During the overlay of the two datasets, there may be a shift in the datasets owing to minor geo-registration errors. The influence of these errors was observed and discussed.
- Object appearance - The appearance of objects in LiDAR dataset and map vary. For example, the buildings on the 2D map will be a polygon feature. In the LiDAR dataset, the building façade might have protruding features that do not fall within the extents of the polygon feature of the map data. Also, there might be intra-class variations of objects and details of appearance of those objects is not present in the map.

- Temporal resolution - The temporal inconsistencies between the LiDAR point cloud data and the topological map is considered. Points that remained unclassified or the differences in the number of class objects present in the map and LiDAR point cloud is attributed to differences in temporal resolution between the datasets.
- Extra features – The objects in the point cloud such as cars or humans which is not be present in the topographic map was also considered and discussed upon.

The map supported classification of point clouds can be performed for any dataset that has large scale detailed map information. Examples of users who can benefit from this research include municipalities for street furniture inventory, railway infrastructure companies for asset management and maintenance etc. The classification results can also be extended as training samples for machine learning and deep learning algorithms.

1.2.1. Research objectives

The main objective of this research is to assess the feasibility of map supported classification of mobile laser scanner data. To meet the main objective, the following sub-objectives must be fulfilled.

a. To correctly assign the classes defined in the map to the point cloud data
b. To account for differences in the dataset
c. To assess the quality of the classification

1.2.2. Research questions

In order to meet the aforementioned research objective, the following research questions must be answered.

Sub-objective 1

i. Which set of points belong to the objects in the topographic map?
ii. How does the appearance of objects in the map vary from the point cloud?
iii. What are characteristics that should be assigned to the map object?

Sub-objective 2

i. Which objects appear in the point cloud but do not appear in the map?

Sub-objective 3

i. What is the accuracy achieved in the classification?
ii. What are the factors influencing the achieved accuracy?
iii. What is the influence of registration errors between the datasets?

1.3. Innovation

The innovation in this research is the data fusion of mobile LiDAR point cloud with large scale 2D maps for classification of objects. Classification of LiDAR point data to extract objects of interest have been investigated by several people. So far, object classification methods include introduction of novel methodologies or integration of good features of several existing methodologies. Minimal research has been conducted for point cloud classification using fusion of two or more datasets. Mostly, high resolution aerial images have been used to complement feature extraction and classification. Fusion of maps and point cloud data has been primarily investigated for 3D reconstruction techniques. Thus, this research particularly aims at achieving point cloud classification using 2D maps for object classification.

1.4. Project Set-up

The research project will be carried out in three parts:

- Data Pre-processing
- Map based classification
    - Polygon feature matching
    - Point feature matching
- Accuracy assessment

1.4.1. Method Adopted

In the first part, the BGT map will be analysed to finalize the number of classes that will be used to classify the LiDAR file. The two datasets are then checked for registration errors. This is to ensure that there exists no systematic shift between the two datasets.

In the second part, the LiDAR points are matched to the features in the map. Map features include polygon, polyline and point features. The polyline features are converted to polygon by assigning them with minimum width depending on the feature type. Polygon features are used to match corresponding parts in the point cloud. Then, the point map features are used to classify LiDAR points. The remaining unclassified points are handled by setting generic rules. The final stage involves an accuracy assessment. A visual accuracy check is performed to check the results of the classification.

1.4.2. Thesis Structure

The thesis is organized into eight chapters. In the first chapter, the motivation for the research, the problem statement, the main objective and specific objectives of the research are elaborated. The second chapter deals with related work in point cloud segmentation techniques and work done in fusing maps with LiDAR data. The third chapter introduces the datasets used in this research. The fourth chapter explains the steps of the proposed methodology and its implementation on the chosen datasets. The fifth chapter presents the results. The sixth chapter evaluates the results obtained. The seventh chapter discusses the methodology. The eighth chapter is dedicated to summarizing the thesis and presenting the conclusion and recommendations.

2. RELATED WORK

2.1. Mobile laser scanners

A laser scanner helps capture 3D spatial information of objects and even entire scenes of various sizes at flexible distances in a wide range of environments. Mobile laser scanners help capture 3D information of whole scenes such as roads, railways etc. at a faster rate with effective geo-referencing and registration (Vosselman & Maas, 2010).

Mobile mapping systems consisting of laser scanners, positioning and orientation systems and digital cameras are mounted on vehicles such as cars and vans such that the scene can be captured as the vehicle moves along with the road traffic. Figure 2 (Position Partners, 2018; Sigma LLC, 2013) shows the Topcon IP-S3 scanner and the general setup of the mobile mapping system.

The laser scanner emits light pulses at a high rate and captures the objects in the scene of capture. It can emit up to one million pulses per second. The laser scanner captures the range, scan angle and the intensity of the returned laser pulse. The positioning and orientation system consists of the IMU (Inertial Measurement Unit) and the GNSS receiver. They help in linking the captured coordinates to a spatial reference system. The IMU and GNSS together with the wheel rotation counter continuously capture data to calculate the exterior orientation parameters. The digital camera can be used along with the laser scanner. This captures the RGB information of the objects and this can be assigned to the laser points.

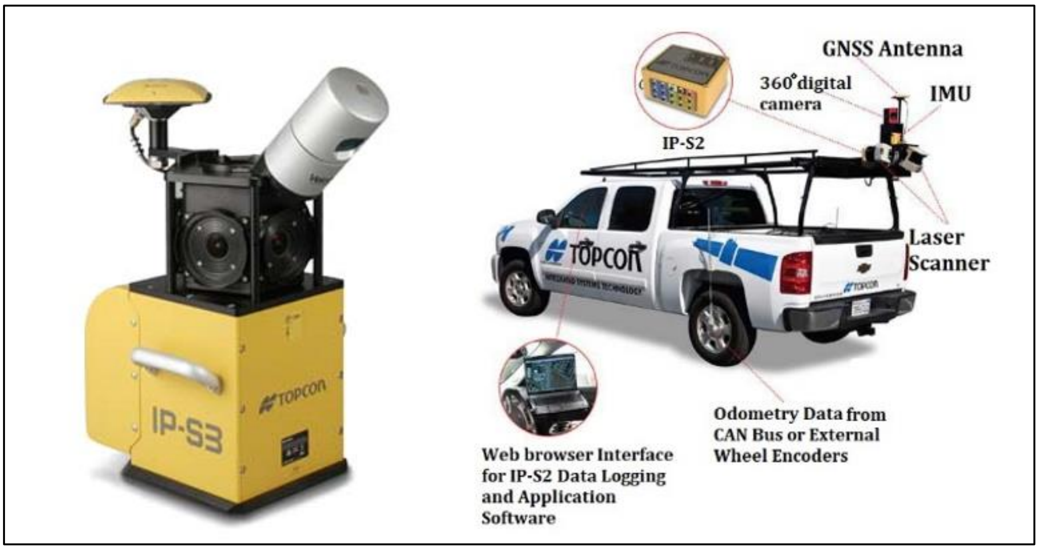

Figure 2: MLS Scanner and Scanning setup

Since the mobile mapping system involves capturing points from a moving surface, the sensors are attached to rigid platforms. They are calibrated for mutual offsets. The possibility of unsteadiness resulting from irregular driving surface such as holes or bumps might cause mutual displacement. Therefore, recalibration might be required. In addition, the precision of mapping might also be affected by the GPS signals in an urban environment. Hence, the data captured from mobile mapping systems might be subject to post processing in order to make the data as accurate as possible.

The data captured from mobile laser scanners yield very dense point clouds. Depending on the environment they are captured i.e. in road scenes, railways, archaeological sites, construction sites or disaster struck areas, the foremost step of segmentation and classification must be performed to make the point cloud useful for further analysis.

2.2. Segmentation and classification of Point clouds

Extraction of point clouds features by segmentation and classification has been done in many ways. A review of segmentation and classification techniques has been well captured by Grilli, Menna, & Remondino, (2017) and Nguyen & Le, (2013) where the advantages and disadvantages of basic segmentation techniques have been explored. According to the review, edge based detection yields fast segmentation results but the accuracy of the results is affected by noise and uneven point density. While the other methods such as region growing, model fitting, graph based methods are robust to noise and outliers, they also have their shortcomings in terms of accuracy or computational capacity. The accuracy of the region growing method depends on the initial location of seed points. The boundary regions are also prone to inaccuracies with respect to estimating normals and curvatures. Methods such as region growing, model fitting, attribute based segmentation and graph based segmentation are sensitive to point density and are computationally intensive.

Research has been conducted to extract features of interest by classification of point cloud data in railway, road and indoor environment. Objects such as poles, traffic lights and street lights are the predominant ones being extracted in a road environment (X. Li, 2015; Pu, Rutzinger, Vosselman, & Elberink, 2011; Tang & Zakhor, 2011). This has been achieved using a number of techniques such as building shape descriptors and performing template matching (J. Wang et al., 2017), using 2D enclosing algorithms (Vakautawale, 2010), and by histogram correlation (Kemboi, 2014). The techniques used in railway environment do not vary significantly. Automatic classification involves template matching to extract railway centrelines and performing vertical plane fitting from railway tracks to extract contact cables and catenary wires (Arastounia & Elberink, 2016). With respect to integrating data from two datasets, high resolution aerial imagery has been used to extract railroad centre lines where image processing techniques have been applied (Zhu & Hyyppa, 2014).

Largely, 3D object reconstruction of roads, buildings and trees have been performed using 2D maps and LiDAR point data. Elberink, (2010) uses the 2D map to obtain points in a location of object of interest and transfers the height data from the point cloud to the 2D map to reconstruct the 3D object. Haala, Brenner, & Anders, (2001) use building floor plans to reconstruct building objects by drawing surface normal to the building plane. Vosselman & Dijkman, (2001) propose a method to use the building footprint to reconstruct the buildings by first assigning a one is to one relationship between building roof and building floor and then fitting a plane to reconstruct the building roof. Y Wang & Elberink, (2016) make use of topographic map data to classify point clouds obtained from airborne laser scanning. However, the quantitative accuracy of the classification is not ascertained due to lack of ground truth.

2.3. Fusing Maps with LiDAR data

The previous section elaborated on the various segmentation and classification techniques for mobile laser scanner data. The techniques implemented concentrated on developing methods to automatically classify the raw point cloud with no additional information. The main focus of this research is to use the information already present in the map to achieve point cloud classification.

2.3.1. 3D Object Reconstruction

There exists research focussing of using the already available 2D map data with LiDAR data for 3D object reconstruction i.e. mainly for building objects. Building footprint delineation, building roof reconstruction and building façade reconstruction have been the general area of research. Using the map, it is easy to identify the laser points belonging to a building object which influences the processing steps for those set of LiDAR points. Hofmann, Maas, & Streilien, (2002) demonstrate that by fusing maps with point cloud data, maps offer a good trigger point for object classification.

Vosselman & Dijkman, (2001), use ground plans to extract the roof planes such that they have a 1:1 relationship. The ground plan is then segmented based on extending concave building outlines and the points inside the segment are projected to 2D to analyse those that fall into a plane using 2D Hough transform and the ridge lines are determined followed by hypothesising the height jumps to assign the roof faces to segments in a 1:1 relationship. The other method is to fit models to the roofs and add/delete the segments from the initial model as check to see if the point clouds are belonging to the model. The second method works with low point density but could show wrong roof models.

Haala et al., (2001) also use the building ground plans which are decomposed to generate rectangular shapes of the building primitives. Using the laser DSM, surface normals are drawn to the building planes. The assumption is that building roofs are planar with steady slope and the eaves are at the same height. The texture mapping is done from terrestrial images.

Elberink & Vosselman, (2006) pre-process LiDAR data by segmenting the data using surface growing. Seed surface is obtained by Hough transform for plane fitting. The topographic map is densified by adding more points on polygon boundaries (to help assign correct height data to each polygon). The two datasets are fused such that the laser points of same segments are assigned to the growing polygon in topographic data based on points being also in same plane. Multiple height for each point in the map is estimated, polygons are reconstructed in occluded areas and surface TIN is created to visualize the 2D data in 3D.

Vosselman, (2003) used maps to reconstruct roads and trees for city modelling. For modelling roads, the laser points in the street parcels have been selected by producing a mask. Laser points belonging to cars or other objects in street are removed using morphological filtering using height data. To reconstruct road terrain as 3D, second order polynomial is fitted to the triangulated surface obtained from laser points and map points. The edges of roads and road crossings which do not provide a smooth terrain are evaluated for Eigen vectors using road curvatures to smoothen the visualization. Trees are identified using local maxima of laser points. The tree crown modelling is not very successful owing to point density issues. Water is modelled by obtaining histogram of heights of points in water parcel and a height of 0.4 m below sea level is assigned to these models. To model roofs, the height was set to 90% of the height of laser points in the building areas.

All the above mentioned methods use the map to find the location of laser points on which the methodology can be implemented upon. Other map attributes are not taken into consideration.

2.3.2. 3D Topography

Maps are also used to obtain the 3D topography from the 2D map. The advantage of using maps with laser scanned data includes is that the height information which when appropriately combined with data from the 2D map provides faster, accurate and automated generation of 3D maps (Elberink & Vosselman, 2006a).

(Elberink & Vosselman, 2006) select a random laser point is for surface growing. The nearest points are identified using k nearest points. A 3D Hough transform is applied to those points to check if there are minimum points available to be set in a plane. If yes, the parameters of the plane are increased by least square fit. Thus the seed surface is finalized for surface growing. Each map point is assigned heights of the laser points nearest to it. The map object is assigned height based on the height of the plane that is fitted through the points closest to it. Map objects with same height are checked if they share a similar 3D boundary by applying topological rules. A surface model is obtained with Delaunay triangulation between map points and laser points thus attempting to add 3D information to 2D maps

Koch & Heipke, (2006) semantically correct the 2.5 data by integrating the topographic vector map with the DTM. The DTM is triangulated. The topological objects that are line are converted to polygon like objects by using the width attribute to create a buffer. Height from TIN is given to the topological objects with constraints. When overlaying, new points are introduced in areas where topological object boundaries intersect the DTM TIN and new triangulations are introduced where topological object boundaries have new points (like buffered roads). The horizontal constraint ensures points in same bounding area get mean height or same height. Tilted plane ensures that height assigned does not exceed a particular slope and height of other objects are assigned based on neighbouring objects.

Here the height information from the laser points have been assigned to the map. The map attributes as such have not been utilized. Again, the map is used as a guiding point for the location of the (x, y) coordinates.

2.3.3. Map for Segmentation and Classification

(Hofmann et al., 2002) performed a research on the knowledge based building detection using a 2D topographic map. The methodology proposed initially subjects the laser data to be rasterized. The rasterized laser data undergoes segmentation by region growing technique using height data as most relevant parameter. The map data was vectorised and centre coordinates of houses was stored. The centre coordinates of buildings points in laser data are compared to the vectorised map containing information about houses. Those buildings that were wrongly classified as houses were further classified using local standard deviation of height information of the laser points. In addition, the laser segments were analysed for trees being included with buildings. This was evaluated based on elevation data and the segments were divided sublevels and super levels. The buildings were also detected based on building location, size and shape for rural and urban areas. This information was mostly assumptions and not metadata in the map. Though the map was used to detect buildings, the major shortcoming of the proposed methodology is that the segmentation process used includes a lot of manual intervention. It is also highly time consuming. Despite the results showing higher accuracy percentages, the classification technique is not considered robust because of high manual intervention in segmentation and attribute setting. Also, the map was used only for detection of one class of objects i.e. buildings.

(Yancheng Wang & Elberink, 2016) used the map information to segment the point cloud. The point cloud was segmented into four main classes i.e. buildings, vegetation, roads and water. Each class was segmented based on rules. To guide the segmentation process, point attributes were calculated to be able to the group points based on proximity in combination with constraints on local geometric features. Features like flatness, normal, segment size, max height difference was used in this segmentation process. Therefore, for each class these parameters were checked for a set threshold. All the segments complying with the set parameters were segmented to belong to the relevant class. The advantages of this method is that because the segmentation was map guided, the segmentation procedure was cleaner. This meant that it was clear which points were useful for further processing. However, the accuracy assessment not done due to absence of reliable and independent ground truth data. In addition, no explicit check was performed to determine whether the points actually belong to the neighbouring polygons.

All the aforementioned studies deal with airborne laser data. This research mainly focusses on using mobile laser scanned data and large-scale maps for object classification. However, a few elements must be taken into consideration for a map supported classification such as registration errors, variation in appearance of objects and temporal resolution of two the datasets.

3. DATASET

The datasets used to perform the map supported classification includes

- Mobile laser scanned data
- Topographic Map

3.1. Data Acquisition

3.1.1. Laser Data

The mobile laser scanned data was obtained using the TopCon IP-S3 scanner. This laser scanner also consists of the positioning and orientation system. It consists of an Inertial Measurement Unit (IMU), GNSS receiver (GPS and GLONASS) and a vehicle odometer. The precise positioning and attitude can thus be calculated in a dynamic environment.

The rotating LiDAR sensor of the IP-S3 can capture the scene with a rate of 700,000 pulses per second. There are 32 internal laser scanners which cover a complete 360-degree view around the system during each rotation. This feature eliminated the need for multiple scanners because the gaps resulting from obstacles or dead-angles are effectively minimized. The MLS dataset for this research was acquired by mounting the equipment on a car.

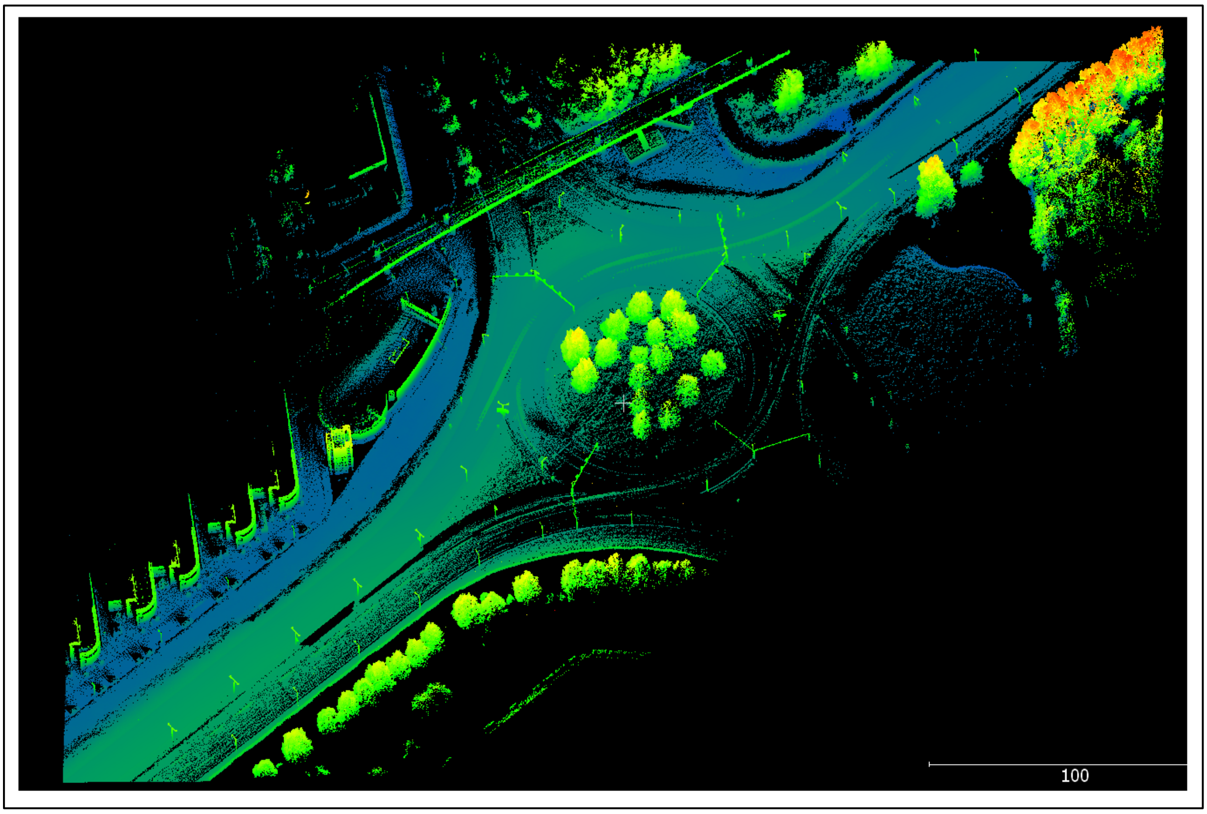

Figure 3: Data subset 1 of the raw MLS point cloud colorized by height

3.1.2. Topographic Map

The topographic map of the same area was downloaded from the Dutch National SDI i.e. the PDOK. This portal provides reliable and most current geo-spatial information of the Netherlands. The Basisregistratie Grootschalige Topografie (BGT) was 2D topographic map that was used. Figure 4 shows a small subset of the topographic map downloaded from the PDOK.

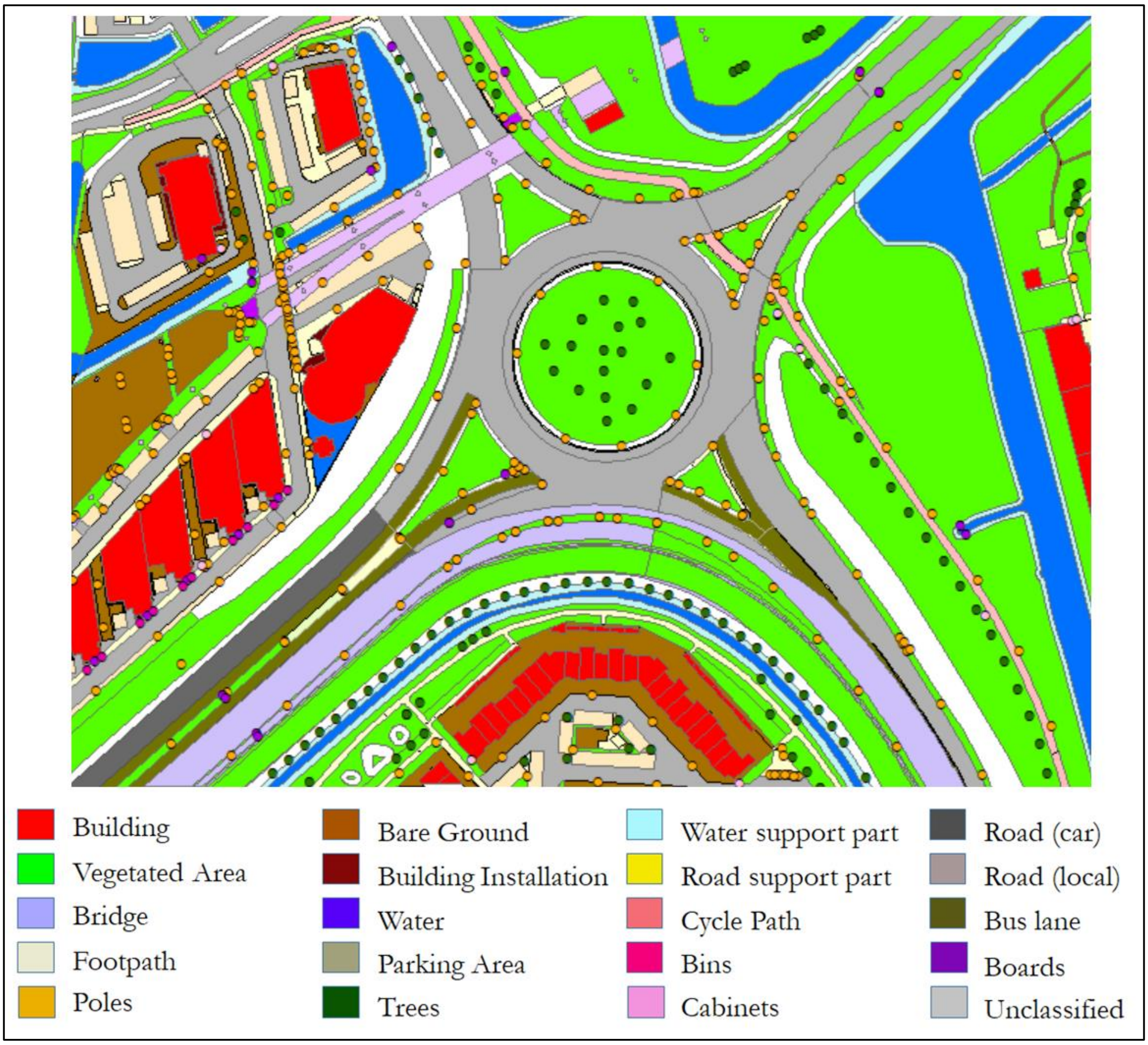

Figure 4: The 2D map as downloaded from PDOK

3.2. Dataset details

The data is captured in the Rotterdam area of The Netherlands. The captured dataset spans a radius of 5 sq.km and a length of 30 km. It majorly captures the street scene at the boundaries of Rotterdam Centrum, part of the residential district of the township of Kralingen Crooswijk and the major highway around Het Lage Land, Prinsenland, Oosterflank and Schollevaar. The data thus involves objects such as buildings, bridges, poles, trees and many other objects common to residential areas and highways.

The raw mobile laser scanned data thus has captured has the information with respect to the 3D coordinates in space i.e. (x, y, z), the time, the intensity and point source ID. The average point density is around 220 points per square meter for the entire MLS dataset.

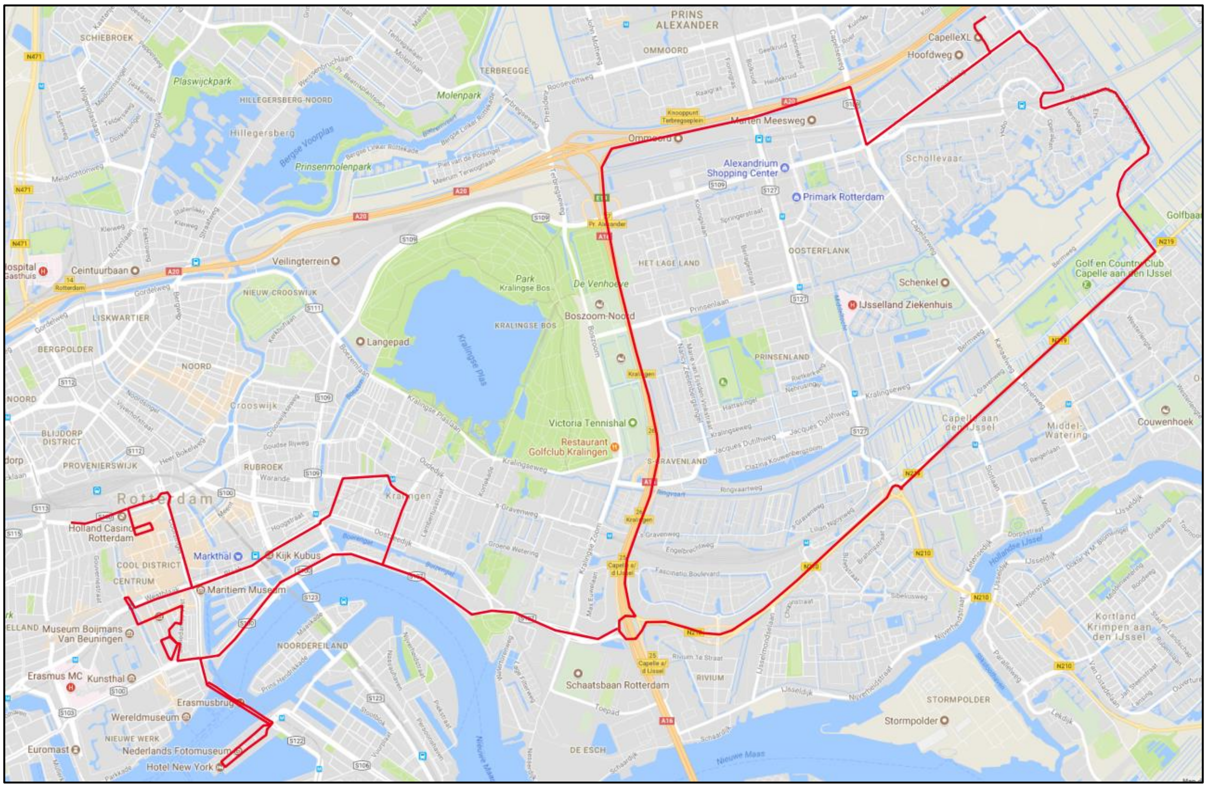

Figure 5: Extent of the MLS data capture area (highlighted in red)

A large scale topographic map of the same extents has been used from the PDOK. The large scale topographic map is downloaded in the gml format and has information about the whole area in 34 layers. Some examples of the map layers include buildings, street furniture, roads, waterways, trees, vegetated areas etc.

3.3. Data subsets

For the purpose of this research three subsets of the total dataset were used. For convenience, the three data subsets are henceforth referred to as dataset 1, dataset 2 and dataset 3 respectively. The datasets thus chosen were such that almost all the map features i.e. the 34 layers were captured in their extents.

Dataset 1 is a highway. This scene consists of objects that are clearly distinguishable and has minimal clutter. There are many vehicles captured in this dataset. The raw point cloud of dataset 1 is presented in figure 3. Dataset 2 is an area that consists of some business establishments near a residential area. The area does not contain a lot of vehicles or pedestrians but it contains a large number of objects such as poles and boards. Dataset 3 is an area near the Rotterdam Centrum and is a very busy area with public transport such as trams and buses. There are also other vehicles and many pedestrians. Figure 6 shows the location of these datasets. Figure 7 shows the raw point cloud of these datasets 2 and 3.

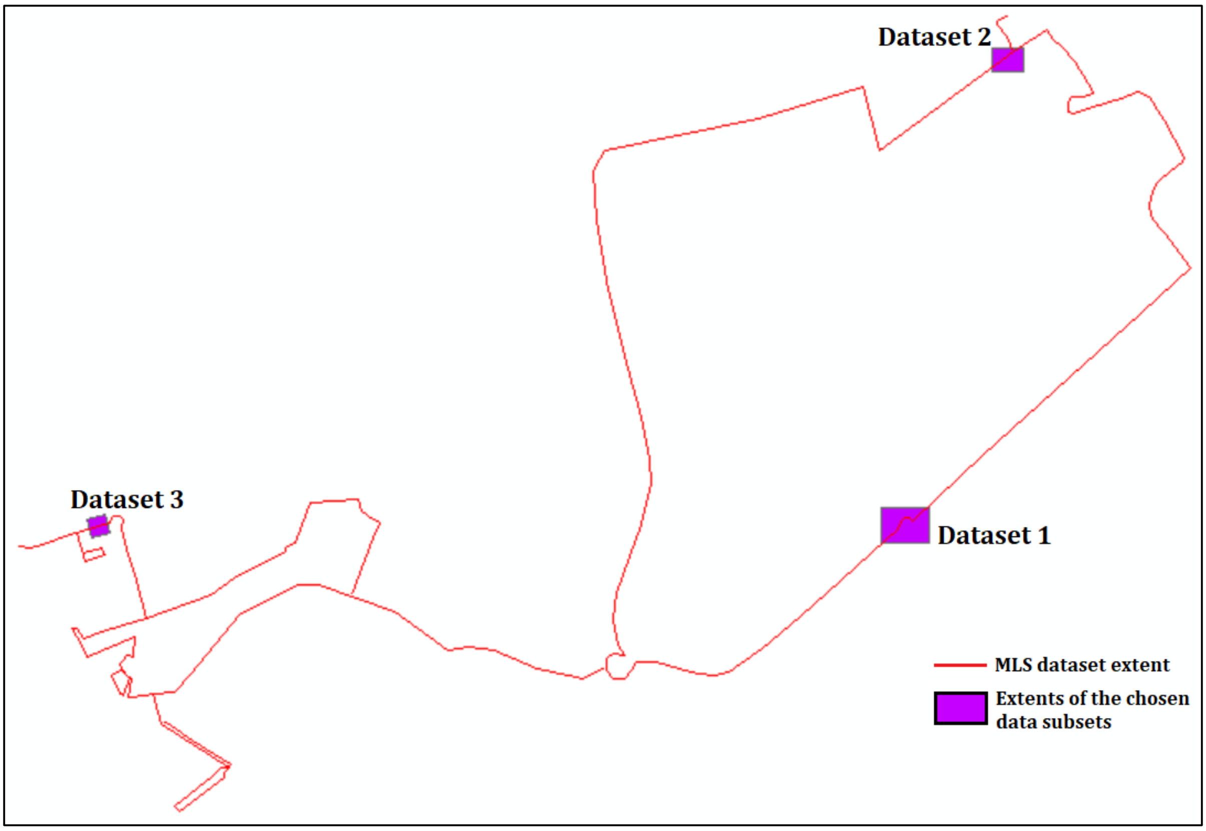

Figure 6: Location of chosen datasets against the extent of MLS data (in red)

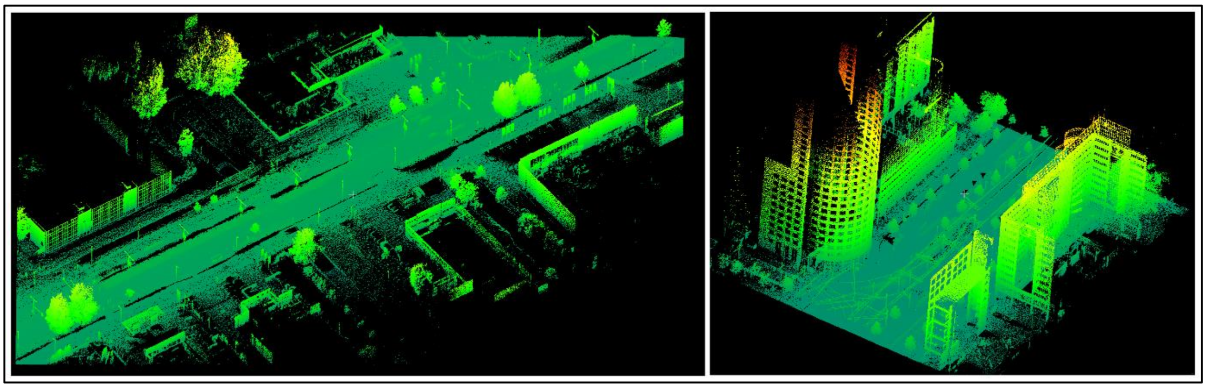

Figure 7: Snapshots of Dataset 2 and Dataset 3 (colorized by height)

4. METHODOLOGY AND IMPLEMENTATION

4.1. Methodology Overview

The steps involved in map based classification is broadly divided into 3 steps.

- Data Pre-processing
- Map based classification
    - Polygon feature matching
    - Point feature matching
- Accuracy Assessment

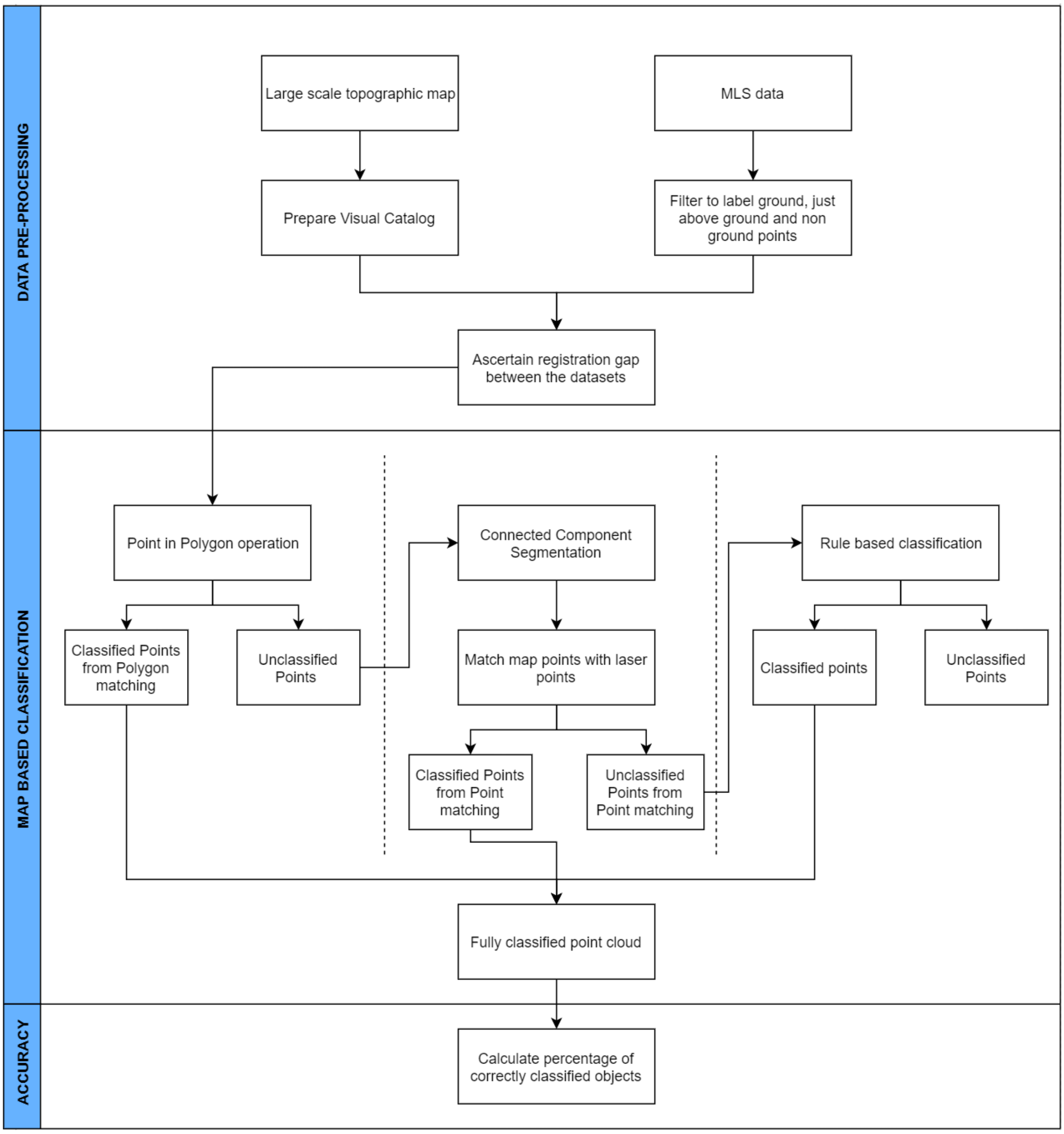

Figure 8: Overall methodology proposed

4.2. Data Pre-processing

4.2.1. Visual assessment of map and LiDAR data

In order to perform the map supported classification, the map was first assessed for the total number of features that it contained. The features on the map i.e. the polygon features such as buildings, vegetated areas and polyline features such as railway tracks and point features such as poles, boards etc. were visualized in the point cloud. Most of the features such as poles, trees and buildings were easy to locate and visualize in the point cloud.

The bins and boards for example are of different sizes and shapes. Clutter and occlusions hinder their visualization in the raw point cloud. The additional map attributes such as type of the feature helped in approximating the size and shape of the object. In addition to this, Google street view images were used to augment better understanding of certain features.

A detailed visual catalogue (as presented in appendix A) was prepared to understand the appearance of each map feature in the map and in the point cloud. The visual catalogue thus helped in finalizing the classes that were used for the classification purpose. Some classes were not clearly distinguishable in the point cloud but they could still be used for classification purposes. Examples of such classes include bare ground, vegetated area etc. Some other classes were marked distinctly in the map but they could not be clearly distinguished in the point cloud. Examples of such objects include water drains or sensors.

In the dataset obtained for this project, the BGT map contained a total of 34 features. Each of the features is a layer in the map. Every layer was visualized in the map as well as in the LiDAR dataset. Google street view images were also utilised to augment the efforts. For example, figure 9 shows the building feature in the map, in the LiDAR dataset and in the Google street view.

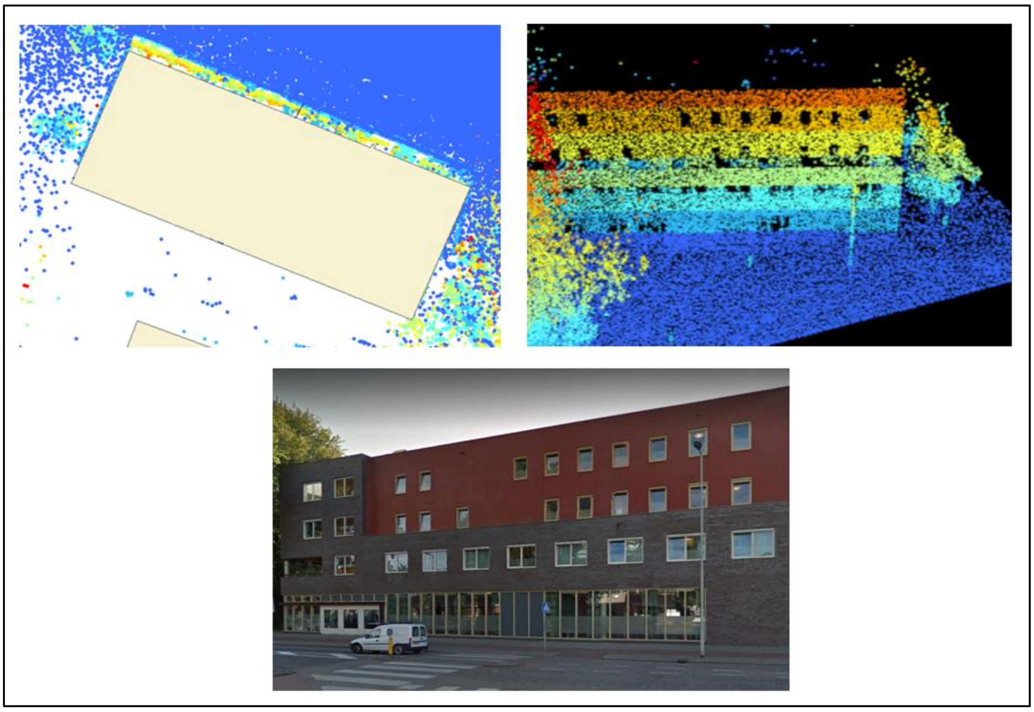

Figure 9: Building feature visualized in 9(a). Map 9(b) LiDAR point cloud 9(c) Image view (Google)

Out of the 34 layers, 19 layers were considered unsuitable to use in the classification process owing to reasons such as the feature not present in the point cloud extents, or the feature being underground, or the feature not being clearly recognizable.

Some examples of layers that remained unrecognizable in the LiDAR dataset include *put* or manhole covers, *wegrichtingselement* or road points. It is not possible to clearly distinguish the LiDAR points belonging to these objects. Figure 10 (Van den Brink, Krijtenburg, Van Eekelen, & Maessen, 2018) gives examples of such layers.

Figure 10: Examples of map elements not considered for classification. Road Markings (left) manhole covers (right)

Some polygon map features such as functional areas or construction work areas were not included in the workflow for polygon matching. Polygons such as functional area consisted of residential areas, agricultural areas etc. For some polygons, the values remained 'unknown'. Hence, such polygons were removed. Figure 11 (Van den Brink et al., 2018) gives an example of functional area and construction work area.

Figure 11: Examples of map elements not considered for classification. Functional area polygon feature (left) and construction area polygon feature (right)

4.2.2. Reviewing map attributes

The map contains additional information of value that can be used for the classification. Generally, the map attributes consisted of IDs such as the object local ID and GML ID, the time stamp information of creation of the map object in the BGT etc. Out of these, there were two important attributes that could be used for the classification purpose

- Relative Height
  Those features that have the relative height of 0 or more indicate that they are at ground or above ground level. This attribute helps determine which points must be considered for matching. For example, if a map feature has a relative height of -1, this indicates that it is an underground feature. Such features are not useful for point cloud classification.
- Type / Class of the polygon map feature
  Every map feature is further elaborated in this field. For example, the road map feature has classes such as cycle path, bus lane, main road, secondary road, footpath, driveway etc. This information can be used to classify the point cloud into many more classes. In addition, this field can also be used to match the correct LiDAR points to a particular class. These details are elaborated in the subsequent sections.

4.2.3. Checking for registration mismatch

The map supported classification makes use of two datasets i.e. the map and the point cloud. This methodology assumes that there exist no glaring registration errors between the two datasets. However, the presence of minor errors if any were checked for. This is performed with a motive to ensure that the LiDAR points are classified correctly. Performing this step also helps to ensure that there is no obvious systematic shift between the two datasets. Hence, a manual check was performed.

The mobile laser scanned point clouds though equipped with positioning and orientation system might not always result in accurate location measurements. The improvement of positioning accuracy can be improved with help of aerial images using techniques such as feature detection, description and matching (Hussnain, Oude Elberink, & Vosselman, 2016). Improving the positional accuracy of LiDAR data is a research in itself and it is not in the scope of this research.

In order to perform the registration check, distinct points of the objects in the map were considered. For example, corners of a building, base location of poles etc. were used. The (x, y) coordinates for both the map objects as well as LiDAR points was recorded for a minimum of 6 points following which the RMSE is calculated. The difference in distance between the (x, y) coordinates of the map as well as the (x, y) coordinates of the point cloud i.e. the dx and dy helped determine the presence of a systematic shift. In case of the presence of a systematic shift, the raw point cloud might be subjected to a simple shifting process to correctly coincide with the map features. The step-by-step process is shown in figure 12.

The manual registration check performed was not extensive. It was challenging to identify suitable points in the LiDAR dataset that corresponded with the map. For the building polygons, most often the base of the façade and the nearby ground had high point densities it was hard to choose and an appropriate point that exactly corresponded with the map. For point map objects such as bins and poles, the point at the base that might was most likely to correspond with the map was chosen. The points for vegetated areas and building installation was extremely hard to ascertain. It was manageable to obtain a minimum of four points. For the other polygon layers such as bare ground, water etc. this attempt was not feasible

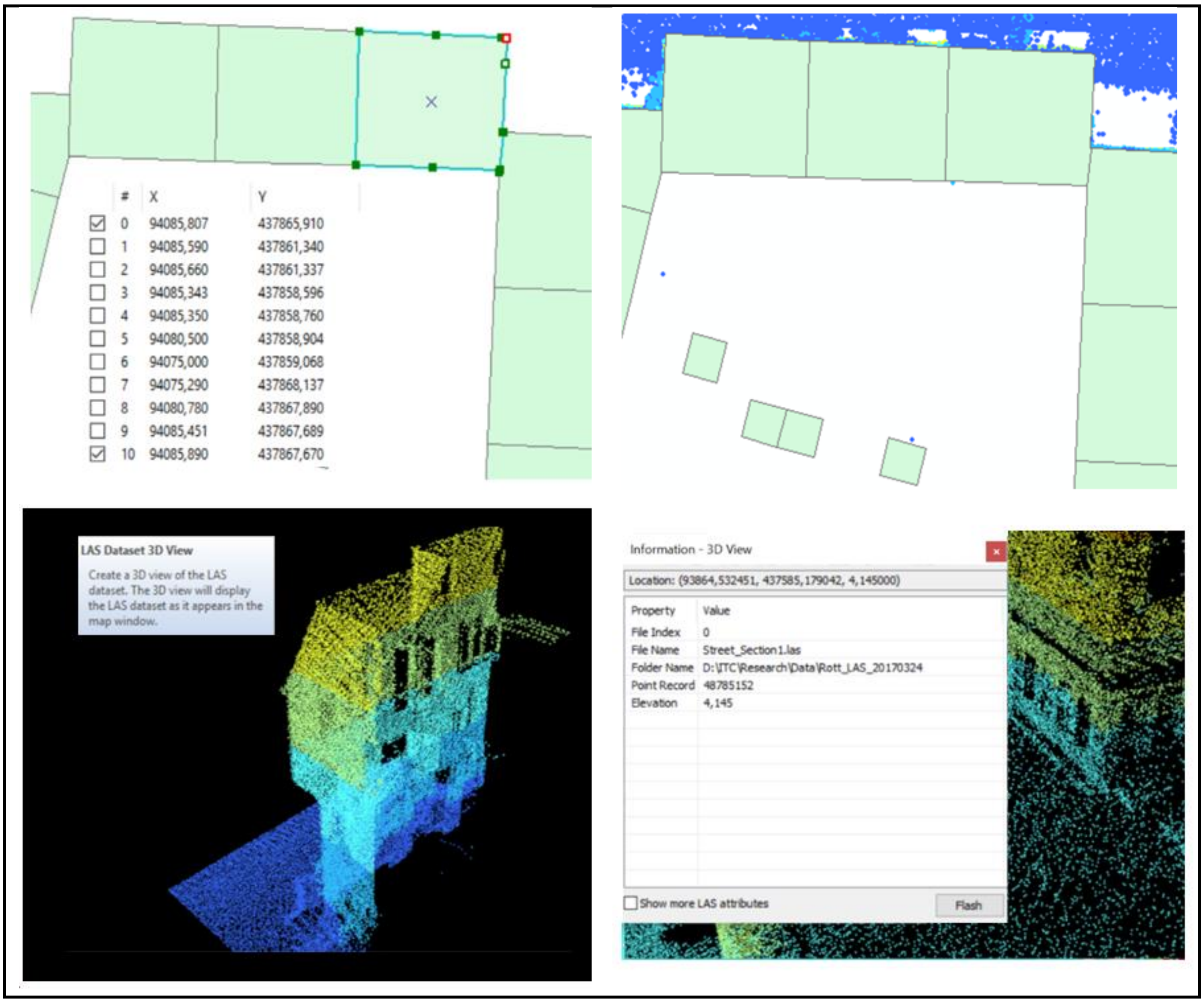

Figure 12: 12(a) The corner vertex of a building polygon is recorded. 12(b) The map overlaid with the LiDAR data. 12(c) The 3D LiDAR view of the chosen building corner is visualized 12(d) The point information of a LiDAR point around the building corner is recorded

The map coordinate and the LiDAR coordinates were thus recorded for a minimum of 6 points for each layer using the 4 steps mentioned above. Table 1 gives the RMSE calculation for the building layer.

	X Coordinate				Y Coordinate			
#	**Map**	**LiDAR**	**dx (m)**	**dx² (m)**	**Map**	**LiDAR**	**dy (m)**	**dy² (m)**
1	93864.75	93864.53	0.217	0.047	437585.19	437585.17	0.010	0.0001
2	93896.22	93896.17	0.047	0.002	437654.08	437654.03	0.044	0.002
3	94054.76	94054.55	0.206	0.042	437869.04	437869.18	-0.146	0.021
4	94085.89	94085.70	0.189	0.035	437867.67	437867.89	-0.229	0.052
5	94170.75	94170.53	0.214	0.046	437864.842	437864.27	0.566	0.320
6	94161.26	94161.06	0.199	0.039	437865.79	437865.83	-0.048	0.002
7	93964.47	93964.37	0.099	0.009	437828.19	437828.26	-0.071	0.005
8	93918.3	93918.56	-0.263	0.0694	437715.76	437715.65	0.106	0.011
		Average dev	0.113			Average dev	0.029	
		Sdx²	0.293			Sdy²	0.415	
		mx	0.191			my	0.227	
	RMSE (m)	**0.297**						

Table 1: RMSE calculation for building layer

It can be seen from table 2 that the RMSE for the building layer is about 0.2m. However, by checking the dx and dy between the map and the LiDAR file, the shift in x direction is not a systematic 0.2m. Similarly, the shift in y direction is also not consistent. However, there exists an overall registration difference between the two datasets. This can be expected.

It is also important to note that since this process is done manually, the points ascertained from the LiDAR point cloud is not accurate. It is subject to errors. Hence, the RMSE in itself cannot be considered completely correct. However, the procedure is sufficient to ascertain that there are no glaring errors.

The RMSE cannot be calculated for each and every layer. This is because layers such as bare ground, water polygons have no distinct points that can considered in the LiDAR dataset. Table 2 gives the RMSE for each of those layers for which it was possible to get a rough approximation. The values cannot be considered concrete however they are useful is setting of a threshold value for point matching process.

Map file	English name	Feature Type	RMSE (m)
gebouwen	Buildings	Polygon	0.297
bak	Bins	Point	1.44
begroeidterreindeel	Vegetated area	Polygon	0.834
gebouwinstallatie	Building installation	Polygon	0.685
kast	Cabinet	Point	0.484
paal	Pole	Point	1.842
vegetatieobject	Tree	Point	0.334

Table 2: RMSE between map and LiDAR datasets

There appeared to be no systematic shift established between the map polygon and the LiDAR dataset for the chosen datasets. Hence, the shifting algorithm was not implemented.

4.2.4. LiDAR data preparation

The information related to the objects into which the point cloud can be classified for is available from the map data. The LiDAR point also includes attributes that can be used for the classification purpose. By leveraging the information in the map and correctly associating with the point cloud information, the classification results can be greatly improved. Height of a laser point is one of the major attributes that was considered to be used for this purpose. Hence, the raw LiDAR file was filtered into ground points, just above ground points and above ground points as shown in figure 13.

Ground points were first filtered. Those points that are between the height of 0.1m and 0.5m above ground level were labelled as just above ground points and the rest were labelled as above ground points. However, here care was taken to ensure that the points belonging to tall objects such as poles, boards, buildings were all labelled as above ground points. These objects do not have the label of just above ground points. The following steps were undertaken to achieve the correct labelling.

1. The ground points were first ascertained. All points with a residual (difference of the height between a point in a neighbourhood to the lowest point in the neighbourhood) of 0.05m were labelled as ground points.

2. For every point that is greater than 0.05m above the ground, it was checked if there existed points in the region of 0.5m height and 1.5m height above that point.
3. If there were points, then the object was considered as a tall object and all the points from ground level onwards were labelled as above ground points.
4. If there were no points i.e. if there was an empty space between the region of 0.5m and 1.5m height, then all the points below 1m height from the ground were labelled as just above ground points.

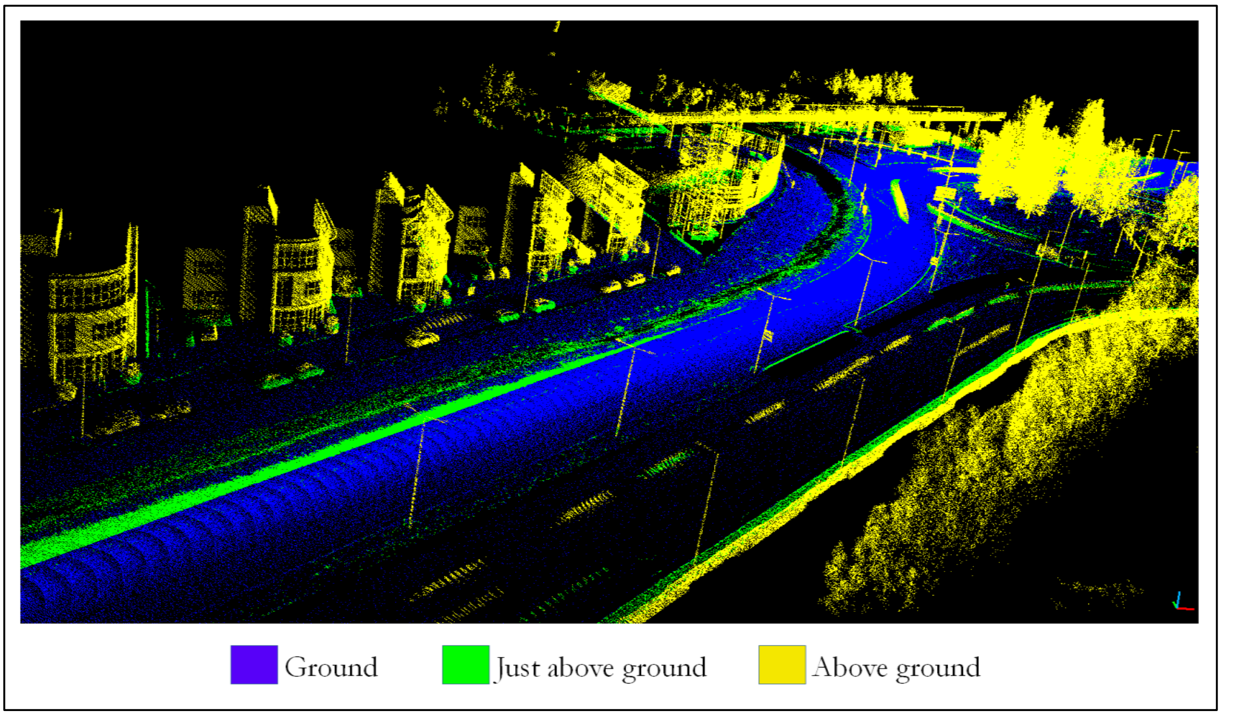

Figure 13: Close-up of LiDAR points labelled by height

Features such as roads and bare ground will contain points only at the ground level. Similarly, features such as low vegetation and road supporting areas such as traffic divider islands will contain points only at ground level and just above ground level. Features such as poles, tress etc., will contain points only above the ground level. Thus, the point cloud was labelled by height to match the correct points to relevant map features.

4.2.5. Final Classes

The data pre-processing step helped finalize 15 out of 34 map features as the final classes for classification. The complete list used for classification purpose is presented in table 3.

One polygon map feature was selected for expansion of the class list. The road layer was selected to show the different types of road classification. Each road function (map attribute) was organized into separate layers and a classification codes was assigned for the same. Table 4 shows the road types.

Therefore, 21 classes were finalized from the 2D topographic map which was used to classify the LiDAR point cloud data.

#	Layer	English Name	Feature Type
1	gebouwen	Buildings	Polygon
2	bak	Bins	Point
3	begroeidterreindeel	Vegetated area	Polygon
4	bord	Board	Point
5	gebouwinstallatie	Building installation	Polygon
6	kast	Cabinet	Point
7	onbegroeidterreindeel	Bare ground	Polygon
8	ondersteunendwaterdeel	Water support	Polygon
9	ondersteunendwegdeel	Road island	Polygon
10	overbruggingsdeel	Bridge	Polygon
11	paal	Pole	Point
12	spoor	Railway	Polyline
13	vegetatieobject	Tree	Point
14	waterdeel	Water	Polygon
15	wegdeel	Road	Polygon

Table 3: Final class list

#	Layer	English Name	Feature Type
1	fietspad	Cycle path	Polygon
3	rijbaan autoweg	Road (motorway)	Polygon
4	rijbaan lokale weg	Road (local)	Polygon
2	parkeervlak	Parking area	Polygon
5	voetpad	Footpath	Polygon
6	OV Baan	Bus lane	Polygon

Table 4: Road class list

4.3. Map based classification

The data pre-processing steps make the datasets ready to use for the classification purpose. The map based classification involves matching the polygon map features and the point map features to the points in the point cloud.

The first step was to match the polygon map features. Polygon map features were arranged in map layers. Each polygon map layer was assigned a class label. A simple point in polygon operation was performed on the entire height labelled point cloud and all the LiDAR points falling inside the polygon map feature was assigned the respective class code. The point in polygon operation resulted in a point cloud matched to polygon map features. Those points that remained unclassified i.e. mostly the above ground points were used for the point matching step.

In the second step, the just above ground and above ground unclassified points were considered underwent a connected component segmentation. As a result, each component was assigned a component ID.

The third step involved the point feature matching. The point features were also arranged in layers per object type. Each layer was assigned a classification code. Those LiDAR point cloud components that were closest to the map point feature was assigned the respective class code.

Following this, a visual check was performed to check if there was scope to improve the classification results. Points belonging to objects such as cars, hedges, pedestrians etc., were left in the 'unclassified' class. The three steps are explained in detail below.

4.3.1. Polygon matching

The polygon map features from the finalized class list was organized in such a way that each class type belonged to a single layer. Thus, polygon map layers for buildings, bare ground, roads were obtained. Each of the map layer was assigned a classification code. Table 5 presents the final classes for polygon map features.

#	Map file	English Name	Feature Type
1	gebouwen	Buildings	Polygon
2	begroeidterreindeel	Vegetated area	Polygon
3	gebouwinstallatie	Building installation	Polygon
4	onbegroeidterreindeel	Bare ground	Polygon
5	ondersteunendwaterdeel	Water support part	Polygon
6	ondersteunendwegdeel	Road support part	Polygon
7	overbruggingsdeel	Bridge	Polygon
8	spoor	Railway	Polyline
9	waterdeel	Water	Polygon
10	wegdeel	Road	Polygon
11	fietspad	Cycle path	Polygon
12	rijbaan autoweg	Road (car)	Polygon
13	rijbaan lokale weg	Road (local)	Polygon
14	parkeervlak	Parking area	Polygon
15	voetpad	Footpath	Polygon
16	OV Baan	Bus lane	Polygon

Table 5: Polygon map features

Not every LiDAR point was clipped with the map polygon feature. Depending on the class of the map polygon, the corresponding height labelled LiDAR point was assigned to it. For example, only the LiDAR points that are above the ground which fall inside the building class polygon map features was assigned the corresponding class label. The map attributes of relative height and class was used to support the correct classification.

- Relative Height - Those polygon features with the relative height of value equal or more than 0 was filtered. For example, if a railway map polygon feature had a relative height of -1, this polygon was not considered for classification. Similarly, if a road feature had a relative height of +1, then the road might be a flyover. Hence only the points that are above the ground (not at ground level) were assigned to this polygon map feature

- Type / Class of the polygon map feature - This attribute also helps in determining with points must be considered for the polygon feature matching. For example, the vegetated area polygon has its physical features defined. They are *bodembedekkers* or ground cover, *bosplantsoen* or forest plantation, *heesters* or shrubs etc. Thus, features such as ground cover can be matched only to ground and just above ground points (to include presence of low vegetation) whereas, forest plantation can be matched to all the points i.e. ground, just above ground and above ground labels that fall inside the polygon.

The overall methodology for polygon map feature classification is presented in figure 14. The technical implementation of this workflow is presented in Appendix II.

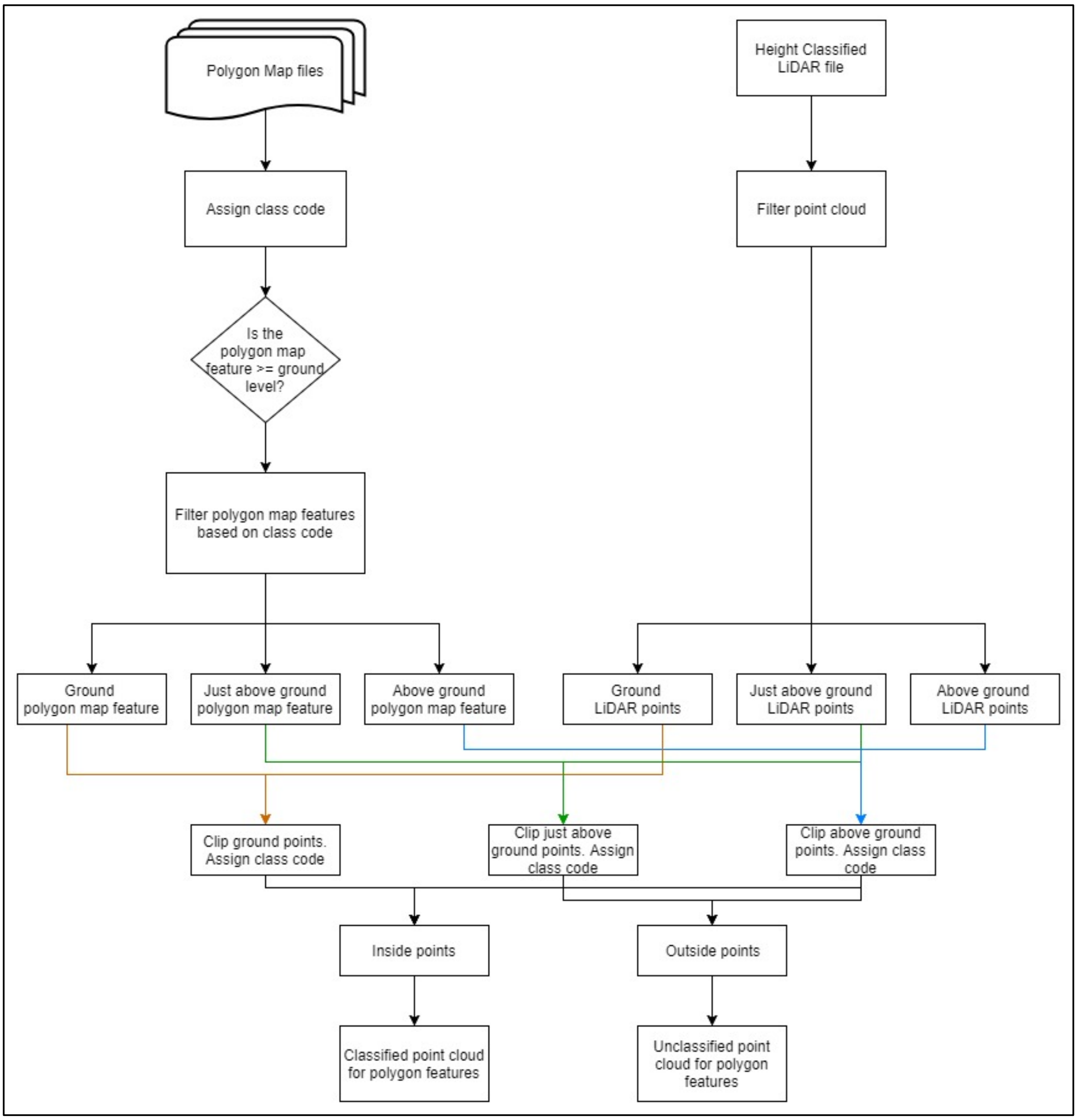

Figure 14: Workflow for Polygon feature matching

Features such as buildings have balconies and supporting structures that fall outside the building map polygon feature. Hence, the polygon files for the building class was buffered by about half a metre so as to include points belonging to these protruding features. This buffer value is user defined and it can be changed to reflect a relevant setting. Figure 15 clearly depicts a scenario where the building façade with balconies is clearly protruding outside the map building polygon boundary.

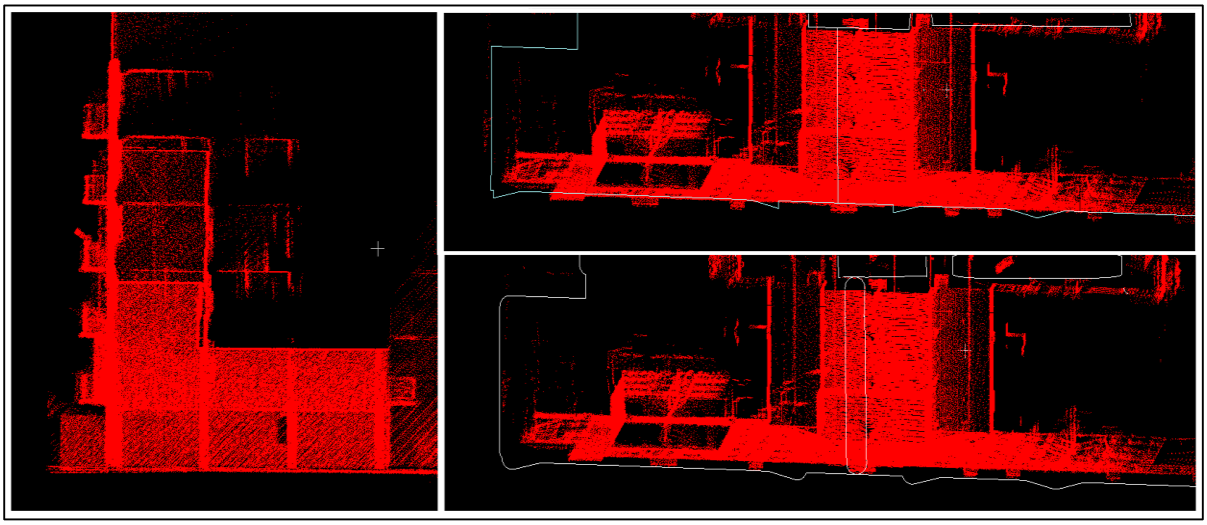

Figure 15: Building polygons that are buffered. 15 (a) Side view showing protruding balconies. 15 (b) Top down view showing actual polygon boundaries. 15 (c) Top down view showing polygon boundaries after buffer

Therefore, the ground LiDAR points are clipped with polygon map features pertaining to ground level such as road, bare ground etc., while the above ground LiDAR points are clipped with polygon map features pertaining to non-ground features such as buildings, over bridges. The LiDAR points clipped from each polygon map feature will then be assigned the class ID of the polygon map feature it is clipped from. Once all the LiDAR points are clipped and their classification field is updated to reflect the polygon map feature class ID, the classified LiDAR points are then combined to form a single point cloud.

The following table 6 summarizes the matching between the map polygon features and the respective LiDAR point features.

#	Map Polygon Feature	Mapped to
1	Buildings	Above ground points
2	Vegetated area	Ground and Just above ground points
3	Building installation	Above ground points
4	Bare ground	Ground points
5	Water support part	Ground points
6	Road support part	Ground and Just above ground points
7	Bridge	Above ground
8	Railway	Ground and Just above ground points
9	Water	Ground points
10	Road	Ground points mostly. (Decided by relative height)

Table 6: Matching between polygon map features and LiDAR points

Those points that fall outside the polygon map feature are used to classify for points above the ground such as poles, tress etc.

4.3.2. Connected Components

The remaining unclassified points after the polygon map feature classification was subjected to connected component segmentation. Performing a simple connected components segmentation does not yield satisfactory results for objects that are close together or for objects that are connected by residual points with a height just above the ground. It can be seen in figure 16 that the individual components that are connected by ground level points have the same component ID.

The point matching algorithm relies on the results from connected component segmentation. Connected components such as those shown in figure 16 might result in poor classification results. It can be seen in figure 16(a) that a pole closer to the tree foliage all get the same component ID. Similarly, in figure 16(b), the grass points seem to be connected to the pole point. In figure 16(c), the tree and a nearby pole are connected by points near the ground (mostly low vegetation points) and thus have the same component ID. All these scenarios lead to incorrect classification.

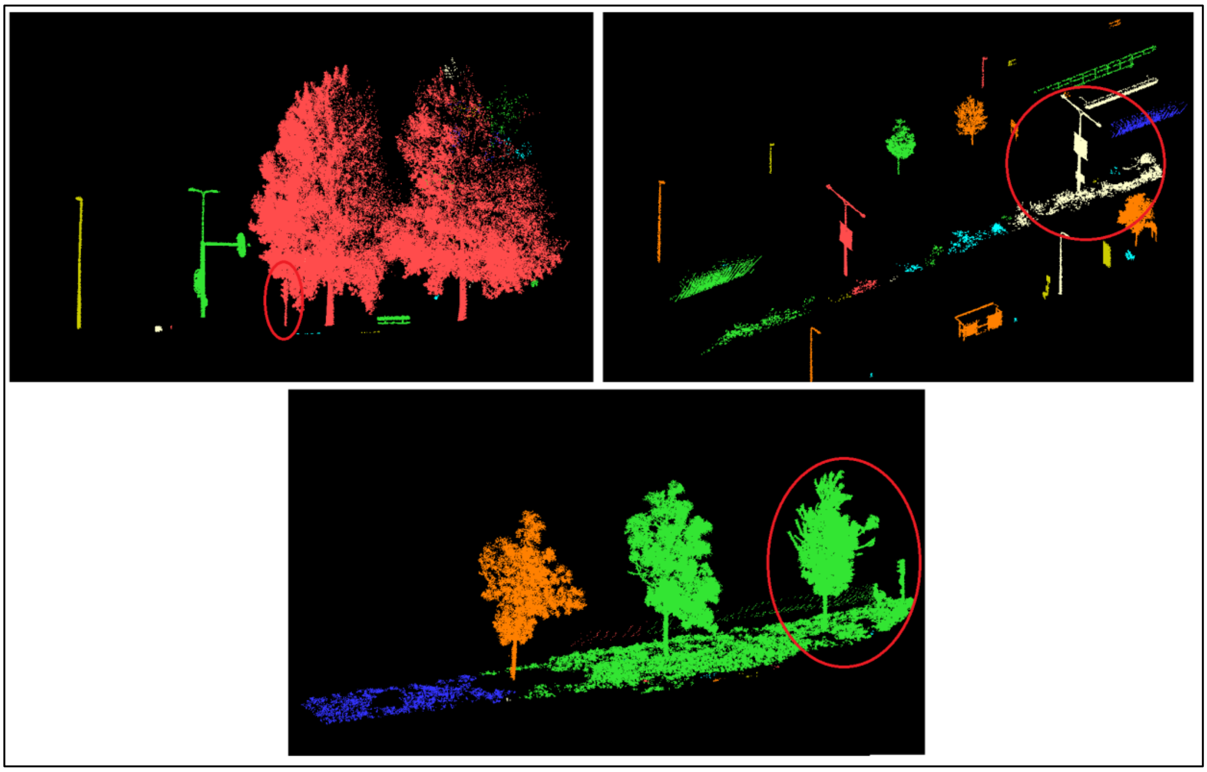

Figure 16: Scenarios that lead to incorrect connected component segmentation
16(a) Tree foliage in touching road traffic signal. 16(b) Pole object connected to many points near the ground.
16(c) Tree and pole object connected by points just above ground

Hence, a modified connected component segmentation is adopted where the segment growing can be applied by first calculating the points at knee height i.e. at a height of 1m (this parameter can be set by the user. For this dataset, 1m was chosen) above the ground. A segment growing was applied for points above and below the points at the knee height. Subsequently, each of the component was given a component ID. The points at the knee height are useful in separating objects that are close together such as a group of trees, poles and boards very close to each other. Table 7 captures the parameters that were used to perform the connected component segmentation.

The points at the knee height are presented in figure 17. For every component, a mean of the knee points is calculated. This point serves as the reference point in the point cloud data to which the map point is matched. The mean point for one of the object is symbolically represented in figure 18.

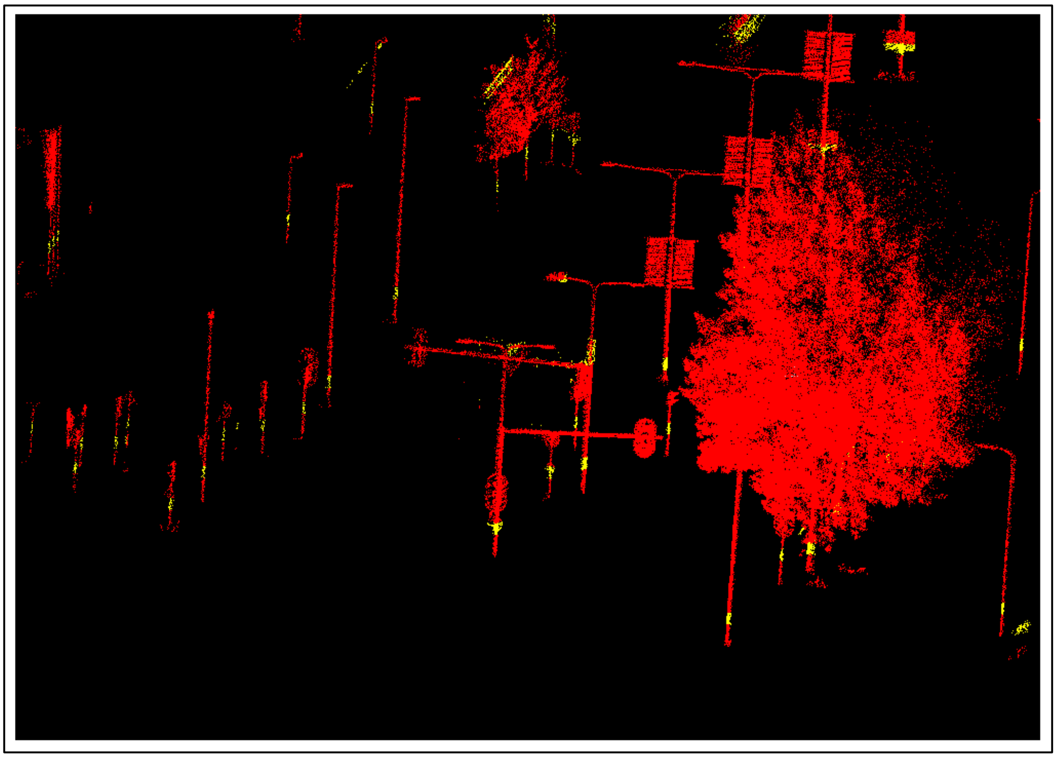

Figure 17: Points at knee height

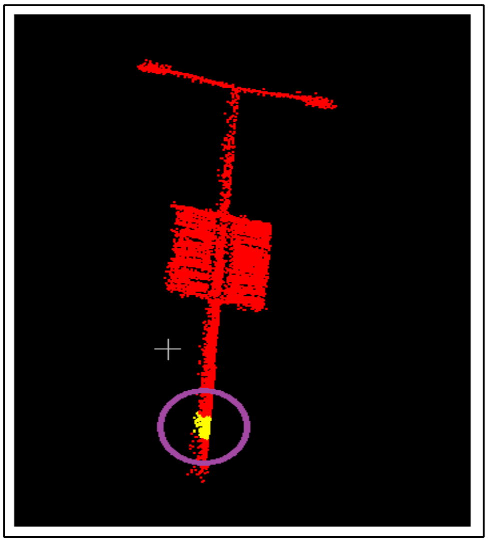

Figure 18: Mean point selected from knee points

Parameter	Value
Number of neighbours	100
Minimum number of components	20
Maximum Distance in Component	1.5
Growing Radius	0.5

Table 7: Parameters for Connected Component Segmentation

Figure 19: Results of improved Connected component segmentation 19(a). Poles separated from tree foliage 19(b). Clear distinction of pole (just above ground points removed) 19(c) Pole and tree separated

In figure 19, the results from the improved connected component segmentation can be visualized. It can be seen from 19(a) that the pole near the trees and the trees in themselves are clearly segmented. Similarly, in figures 19(b) and 19(c), the points just above the ground are not considered for connected component segmentation thus giving better segmentation results.

Hence, the point cloud was segmented such that each point in the component was assigned a component ID. Those components with less than 20 points were ignored. Thus, a mean of all the coordinates at knee height was calculated to get the (x, y) coordinate. The z value of this coordinate was assigned to 0. Hence, a list of one point for each component was generated and this was used for point map feature matching.

4.3.3. Point Matching

The point matching workflow which matches the closest map point to the LiDAR component was carried out in two iterations. In the first iteration, each map point feature was matched with only a single point from each component in the LiDAR point cloud. In the second iteration, each map point feature was matched with all the remaining unclassified points from the result of the first iteration. A more detailed explanation follows.

The point map feature layers were provided as one of the inputs to the point matching workflow. Each of the map point feature was assigned a class ID. The coordinates of the point map files are extracted. These points are then associated with the class labels. Each map coordinate thus carries the spatial information i.e. (x, y) and the ID of the class it belongs to. Table 8 presents the final list of map point features.

#	Layer	English Name	Feature Type
1	bak	Bins	Point
2	bord	Board	Point
3	kast	Cabinet	Point
4	paal	Pole	Point
5	vegetatieobject	Tree	Point

Table 8: Classification codes for point map features

In the first iteration, the LiDAR point cloud which was subjected to connected component segmentation was provided as the second input to the workflow and the single point per component file (the mean of the knee points) of the respective LiDAR file was provided as the third input.

The distance between the each of the map coordinate and each point per component in the LiDAR file was calculated. The 2D Euclidian distance was calculated between each map point and each point in the file containing one point per component. A list was generated which consisted of the component ID of the LiDAR point, the class ID of the map point and the distance between the two points. For a combination of component ID and class ID, the distance was updated if the new calculated distance was smaller than the existing distance of the combination. Thus, a list of component IDs, class IDs and the least distance between the two was generated. Then, the distance was checked against a threshold. This threshold was set as per the RMSE. For each of the dataset used, the threshold was set to 1m. Subsequently, the combination of component ID to the map ID were saved to a final list. Then, all the points in the input LiDAR file which had the same component ID was assigned the class ID as the classification label of the points in the point cloud.

The unclassified points are then used as an input for the second iteration. In this step, the distance between all the unclassified points of a component and the map point feature is calculated. Those components that have a distance of less than or equal to 0.1m are assigned the map class ID. The distance of 0.1m is a user defined threshold which was deemed ideal after some trials. This ensures that the object is correctly classified without additional components being attached to it.

The point matching is a computationally intensive task. Hence, the point matching is divided into two iterations. The unclassified points that remain from the first iteration contains considerably lesser points. Therefore, in the second iteration where the matching takes place by computing distance between every LiDAR point to every map point, it could be ensured that all the components have been correctly matched. The main motive behind this is that the mobile laser scanner data which captures data from ground perspective might not always capture points at knee heights for all the objects. Sometimes, there are occlusions. Hence, the mean point calculated at knee height might not be available for all components. The second iteration ensures that all points of a component are indeed matched with the nearest map point.

The overall methodology for point matching is presented in figure 20. The technical implementation is presented in Appendix III.

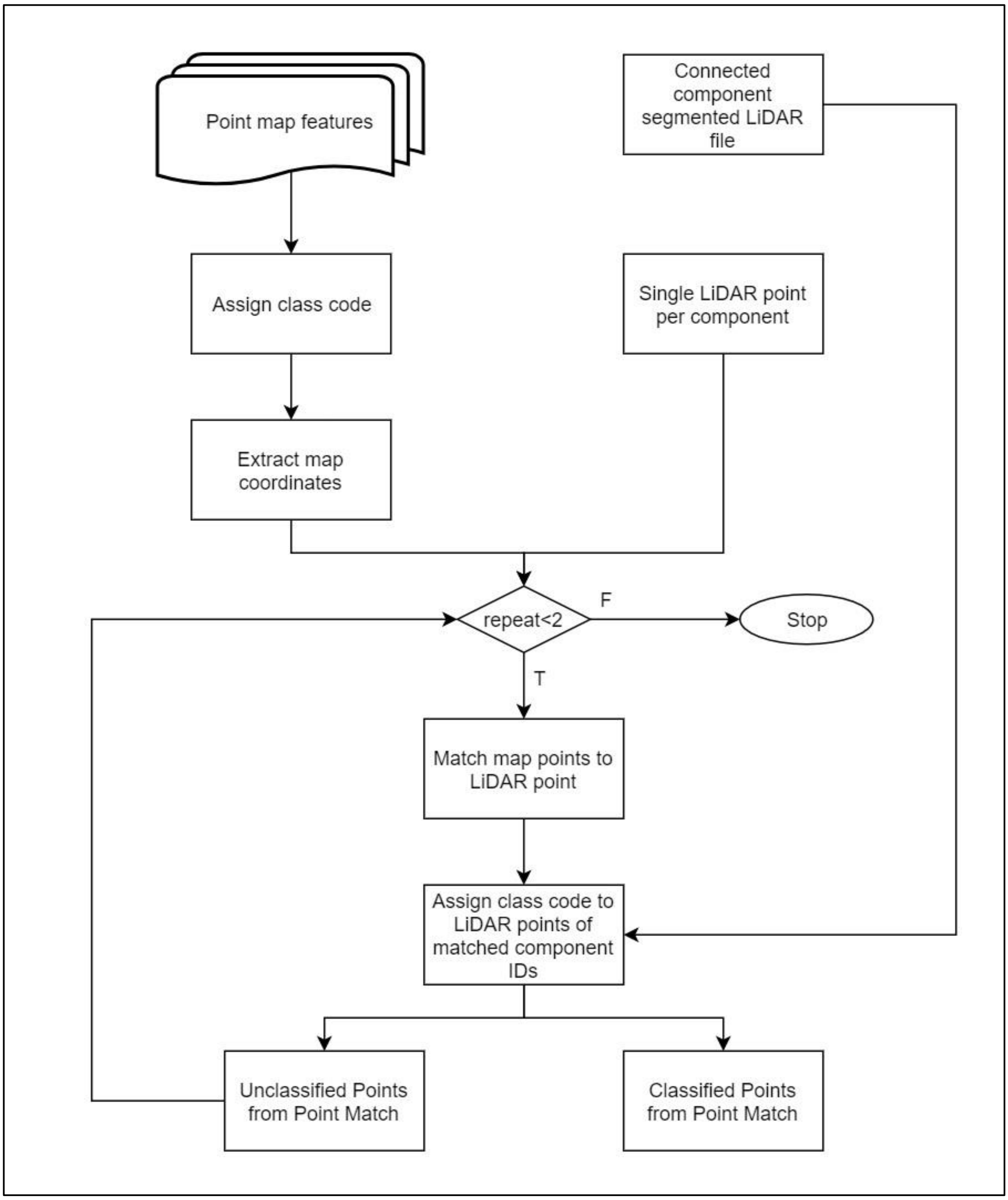

Figure 20: Workflow for point feature matching

4.4. Handling unclassified points

Not all points can be classified in the map based classification. Some of the components in the map might remain unclassified. The points that remain unclassified can be categorized as

- Unclassified points from objects already classified. The objects that contained unclassified points mainly were protruding balconies or other structures from buildings.

- Unclassified points from objects not present in the map. These were mainly the vehicles on the roads or those parked in the parking areas, pedestrians, cyclists, hedges near a building and low vegetation near water polygons.

Generic rules were applied to handle these unclassified points. They are elaborated in the sections below.

4.4.1. Re-assign points belonging to building facades

The building façades do not always conform to the map polygon boundaries owing to protruding features such as support structures or balconies. Though a buffer for the building polygons was used to handle these possibilities, sometimes the buffer proved to be insufficient. Hence, a small correction step was included. All those points that remained unclassified which are present very close to the already classified building polygons were identified and these points were reclassified as building points.

The selection of these small segments near the building was based on height and proximity of the small segments. All the points that were just above ground and above ground with a distance of within 1m were classified as building. The selection of the proximity parameter is user defined and is set based on trial and error.

4.4.2. Remove points belonging to cars

The objects such as cars, trucks, pedestrians and cyclists are not mapped. The LiDAR points belonging to these objects remain in the unclassified category. A large number of points belonging to cars, trucks and cyclists can be removed with the help of common knowledge and information from the map.

The vehicles are usually present in the roads or in the parking areas. Similarly, cyclists most often cycle in the cycle tracks. The average height of a car in the European market is between 1.5m and 2.5m (Automobiledimension, 2012). Hence, a simple rule was set to remove these unclassified points. All the points within the height equal to the average car height in the road polygons of main roads, secondary roads, bus lanes, cycle paths and parking areas were clipped. The footpaths were not considered. This is mainly due to the fact that objects such as bus stops, small boards etc. are present on the footpaths.

4.5. Accuracy Assessment

The final step was to measure the accuracy of the obtained results. The accuracy assessment was carried out by a visual check. The assessment helps in quantifying the quality of the obtained result.

- The count of the number of objects of a particular class in the map within the LiDAR dataset extents are recorded.
- The raw LiDAR dataset is visually analysed to check if the corresponding map feature can be expected.
- The classified LiDAR dataset is visually analysed to count the number of features correctly classified. The percentage of correctly classified features against the expected LiDAR features gives an assessment about the performance of the methodology.
- The misclassified objects, partially classified objects, objects with extra components attached to it and the unclassified components for a particular class type is counted from the classified LiDAR file.
- A confusion matrix is prepared to quantify the overall accuracy assessment.

5. RESULTS

5.1. Polygon Matching

5.1.1. Initial results

The initial results obtained from the polygon matching is shown in figure 21. The LiDAR point cloud is classified into 9 classes.

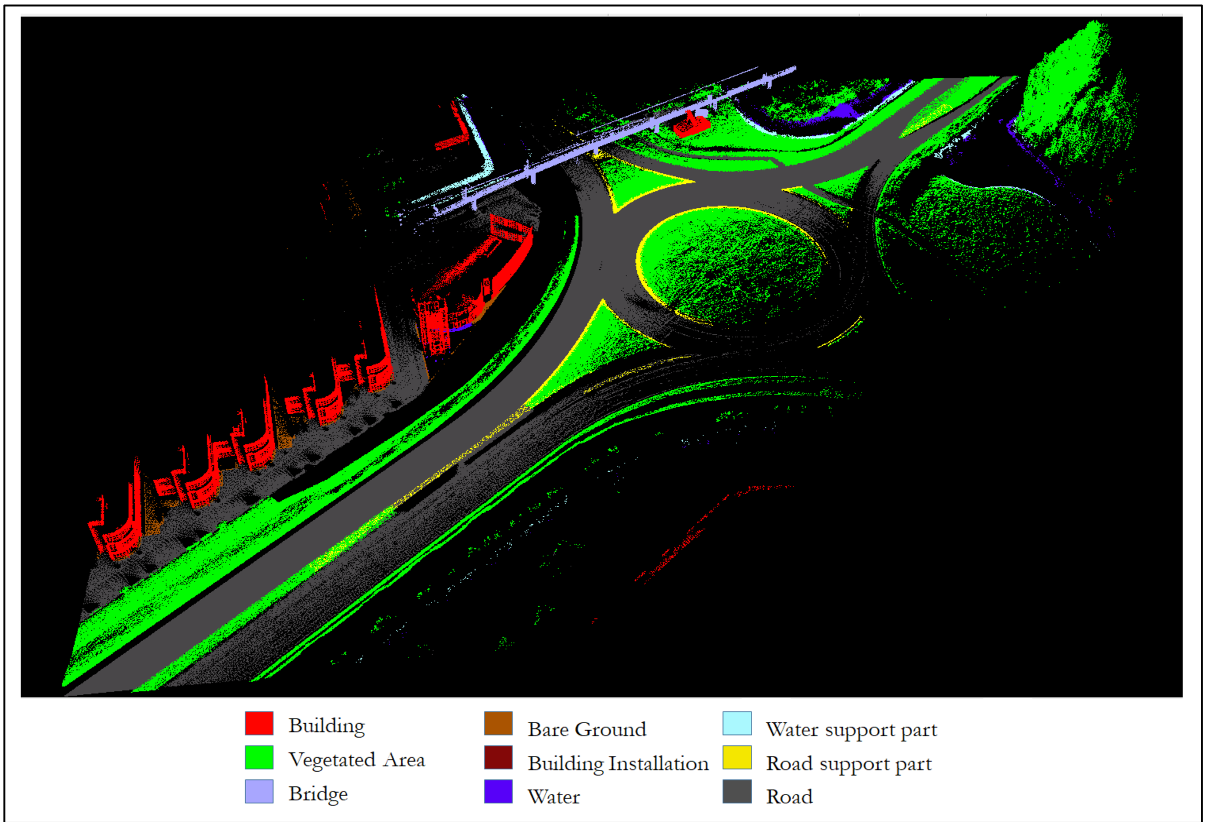

Figure 21: LiDAR classification results from matching polygon map features

It can be seen that the map based classification provides satisfactory results to map objects such as building facades. Various other research involving automatic point cloud classification techniques use the technique of fitting vertical planes to identify building facades (Arachchige, Perera, & Maas, 2012). Though building facades are dominantly planar features, there are buildings that are not necessarily so. In figure 21, the buildings facades are largely curved. In the map based classification, irrespective of the geometry of the building, the facades were correctly classified because the building footprints are retrieved from the building polygons.

The road layer is also mostly planar. Hence, the different classes of roads are not easily distinguishable. The map data serves as a good reference to classify the different road features. The classification of only the road polygons is presented in figure 22. The overall classification of the all the polygon features including the road polygons are shown in figure 23. Since only relevant LiDAR points (based on height class) are classified for the polygon map feature, there is clear distinction between the different object types.

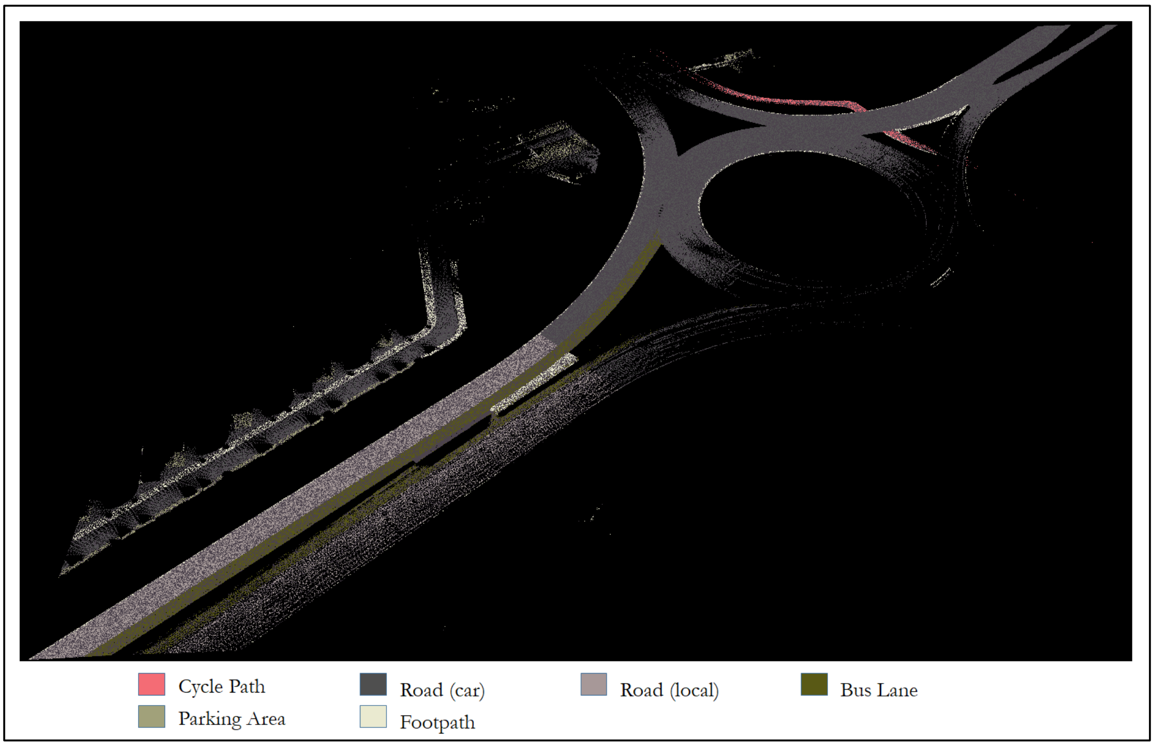

Figure 22: LiDAR classification results from matching different types of road polygon map features

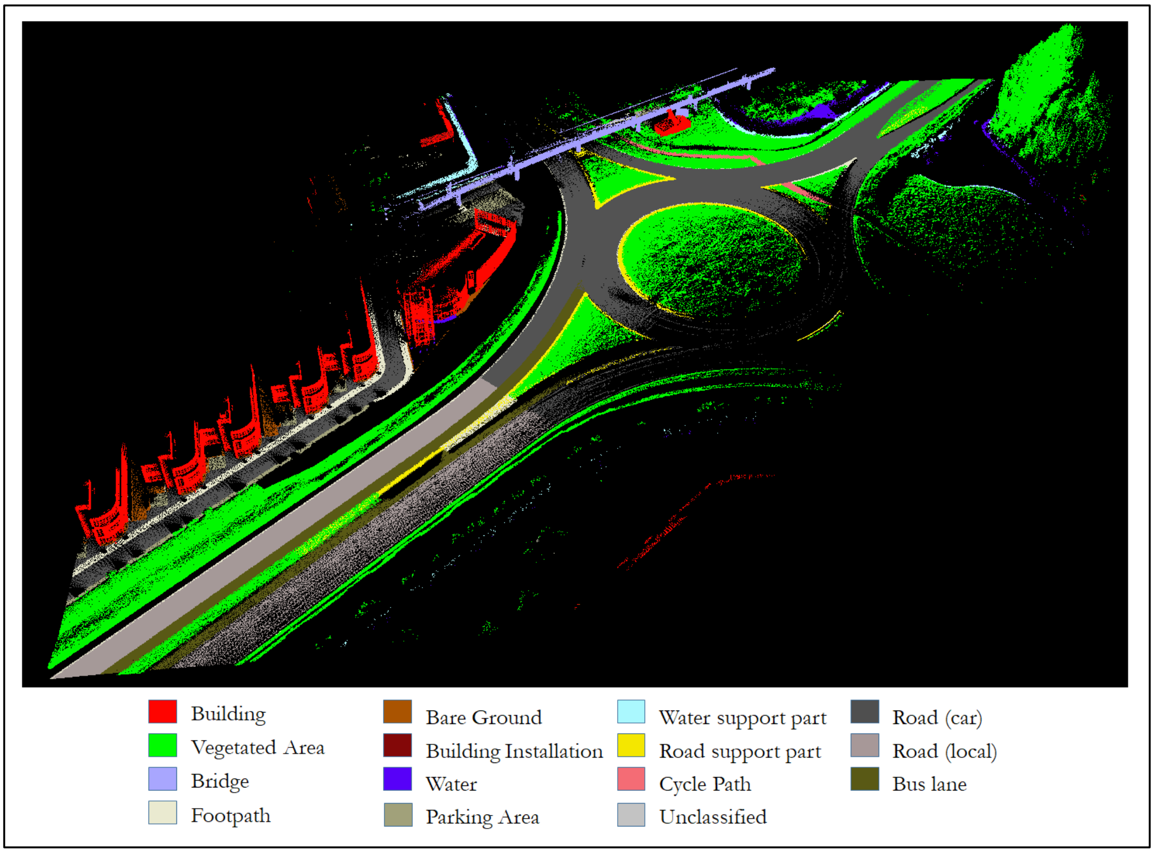

Figure 23: Complete LiDAR classification results from matching polygon map features

5.1.2. Performance

The polygon feature can be used to classify as many classes as present in the map. Pre-classifying the LiDAR points by height greatly improves the result. It can be seen in the two examples that are depicted below. In figure 24, it can be clearly seen that the fly-over bridge on top the road has been clearly classified with the simple operation proposed.

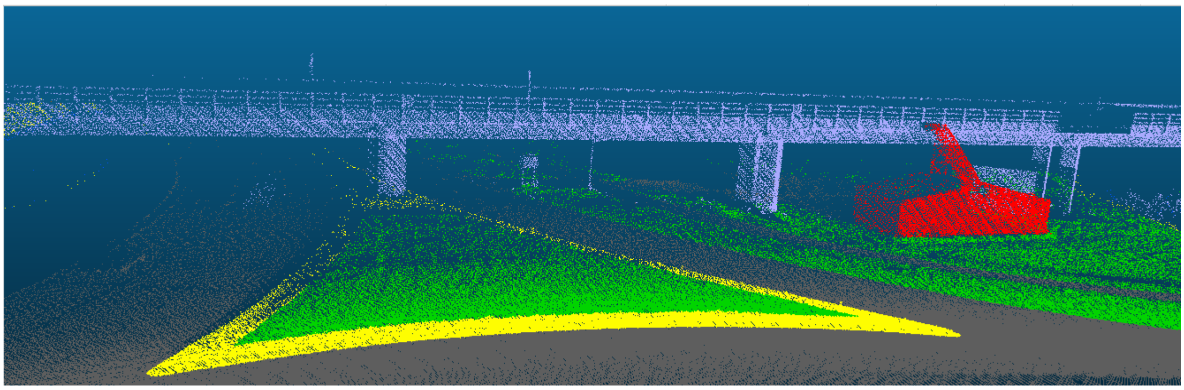

Figure 24: Clear distinction between road and bridge points

Similarly, in figure 25, the building constructed above a road is also clearly classified. In addition, there are additional polygon objects such as road, vegetated area which have all been clearly demarcated.

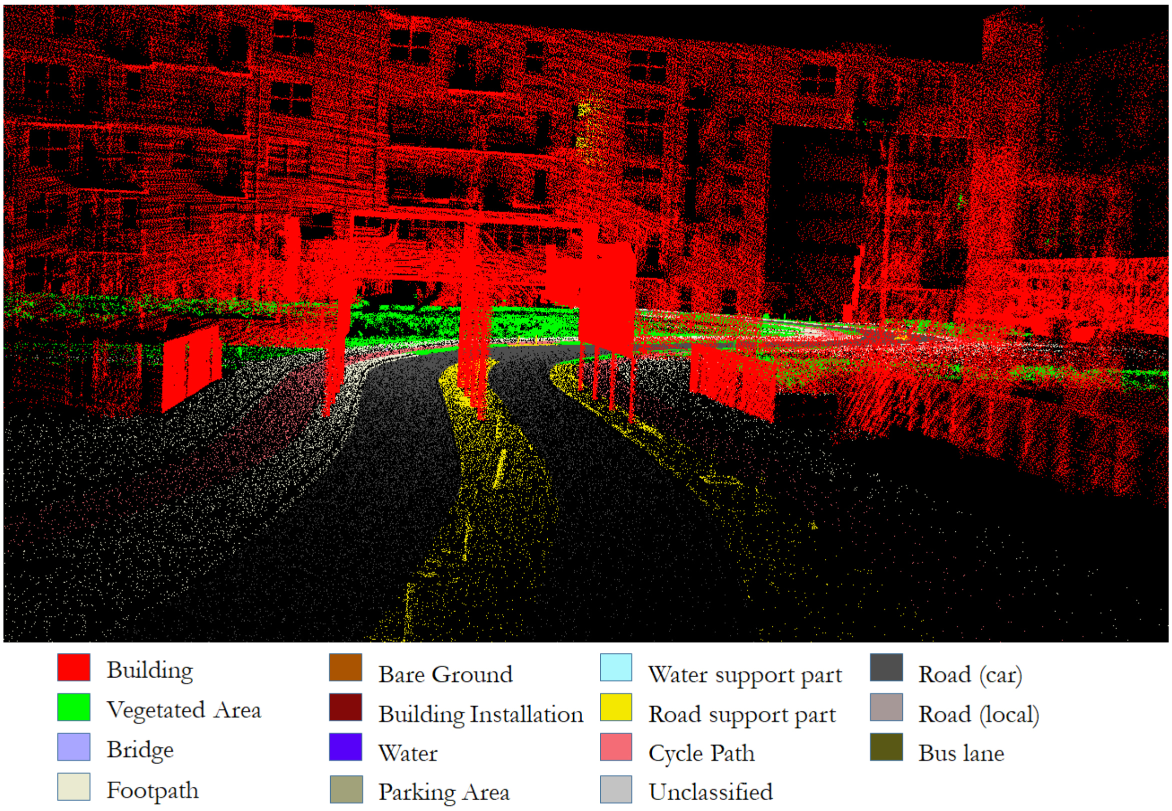

Figure 25: Clear distinction of road from building points

The *begroeidterreindeel* or the vegetated area map polygon feature has classes such as ground cover, grass, forest cover and shrubs. The information in the map and the LiDAR point attribute of height was used to support the classification. Forest cover class mostly contains trees and thus the LiDAR points of all heights was used to classify the same. The classes of ground cover, grass and shrubs have been classified for using the ground LiDAR points and just above ground LiDAR points. Figure 26 shows the map feature of the vegetated area layer with various classes.

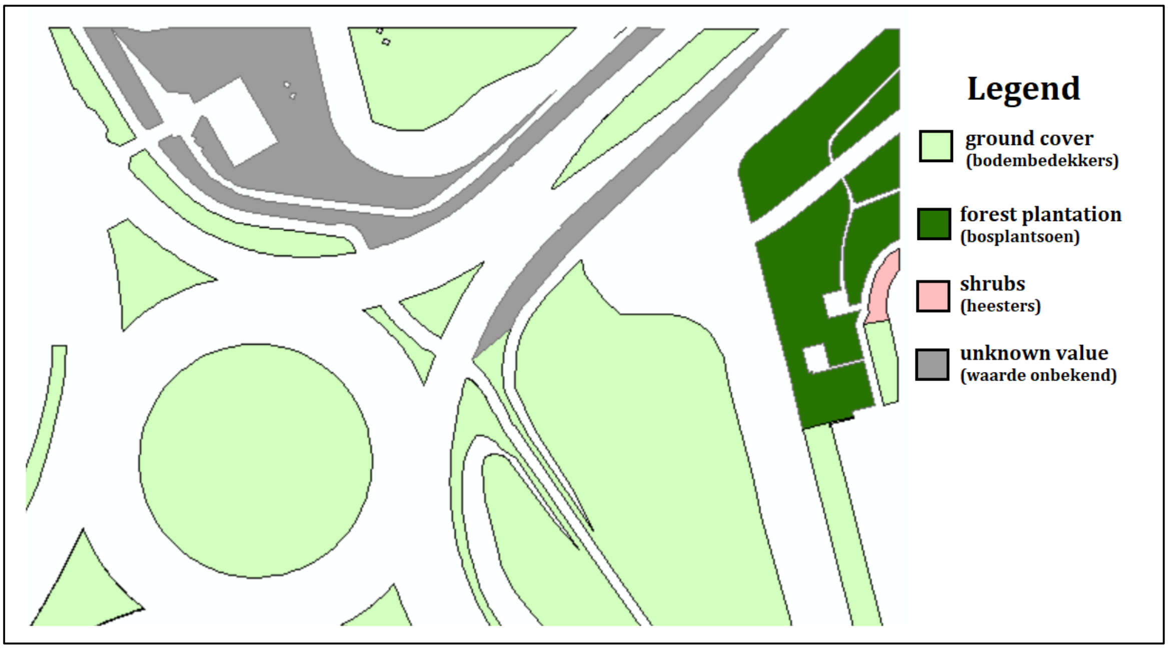

Figure 26: Vegetated area class as shown in the 2D map

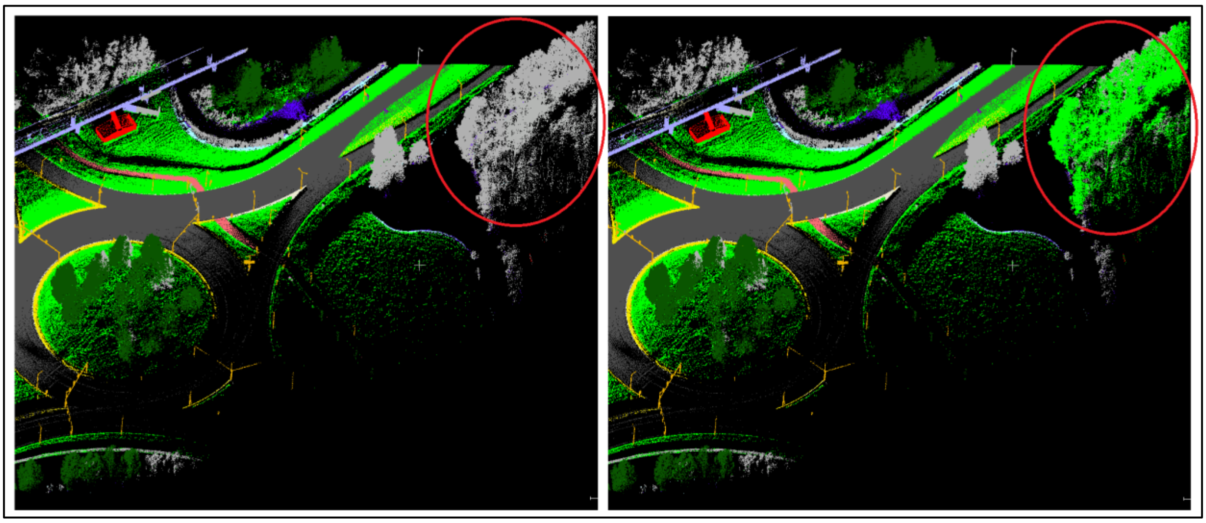

Figure 27: Vegetated area matched to just above ground points (left) Vegetated area matched with above ground points to include trees since the polygon class is *bosplantsoen* or forest plantation

The classification result can be seen for the LiDAR point cloud with and without the application of the value from the map. In figure 27, the point cloud has been classified for just above ground points for vegetated area map polygon. It can be seen that quite a number of points remain unclassified that actually belong to trees. It must be taken into account that the individual tree points of this area has not been captured in the map. However, in the circular ring of the road intersection, the ground cover class of the vegetated area has individual points for the tree objects captured in the BGT. Also, the class of the polygon is grass cover.

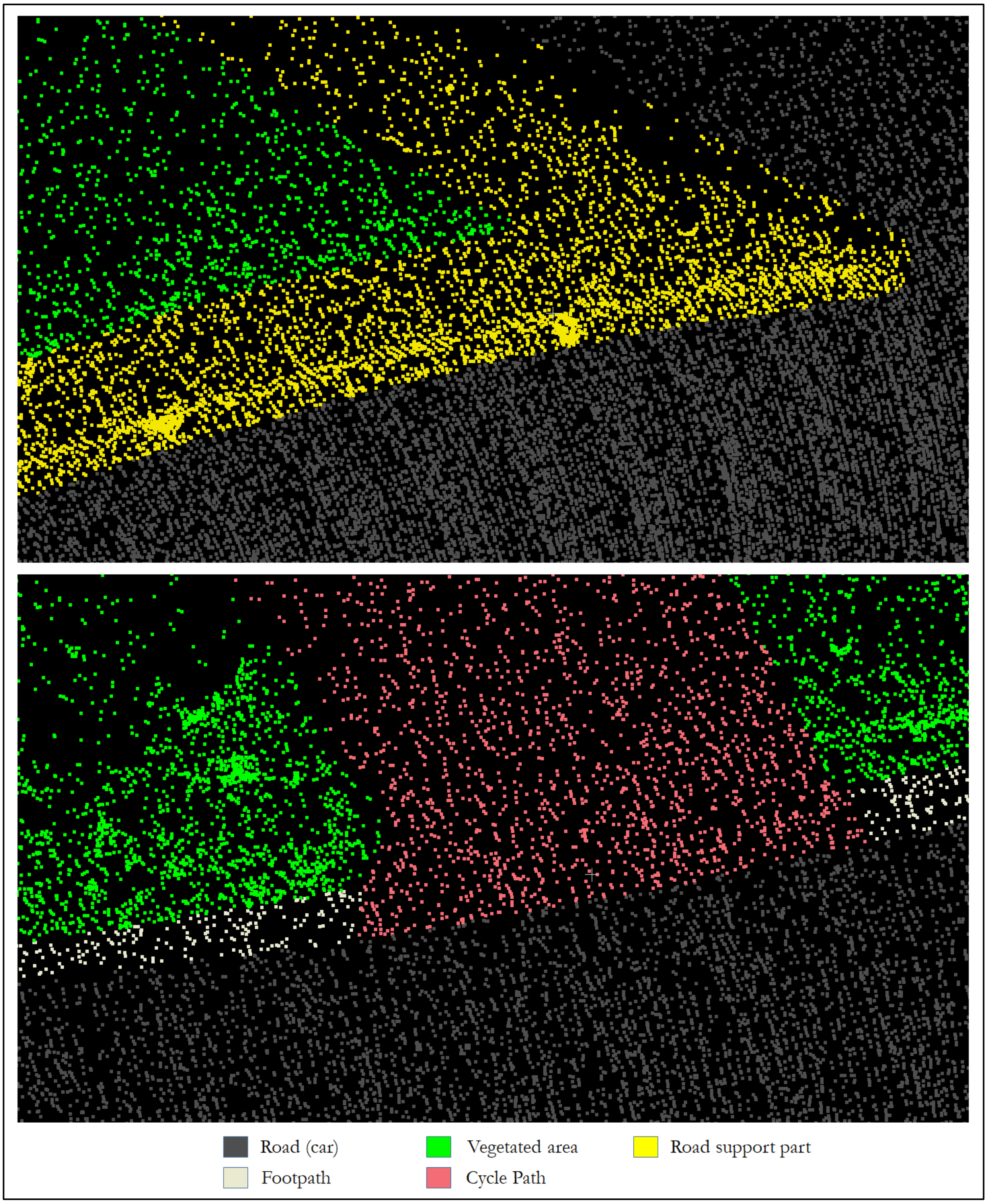

Figure 28: Close up view of points at class transitions of polygon features

Not all LiDAR points are mapped to all polygon map features. Since the class of the object to be classified is known from the map, the points to be considered for classification depend on the height of the laser point. This ensures that wrong points are not classified into a polygon map feature of a certain class. The polygon feature matching was carried out for different road types such as cycle path, bus lane etc. The polygons helped in clear demarcation of the points in these polygons.

However, it is indeed difficult to ascertain the actual classes these points belong to in absence of ground truth. Apart from the well demarcation of objects at same level, even the objects which have a slight height jump such as the road and the road supporting area such as the traffic islands and clearly demarcated. On very close observation, it can be seen that the transitions are well handled as shown in figure 28.

The polygon map features used for point cloud classification generally follows a point in polygon technique. However, this operation was subjected to constraints which helped obtain largely satisfactory results.

5.2. Point Matching

5.2.1. Initial Results

The results obtained from the point matching can be seen in figure 29. The point cloud is classified into trees, cabinets, boards, bins and poles.

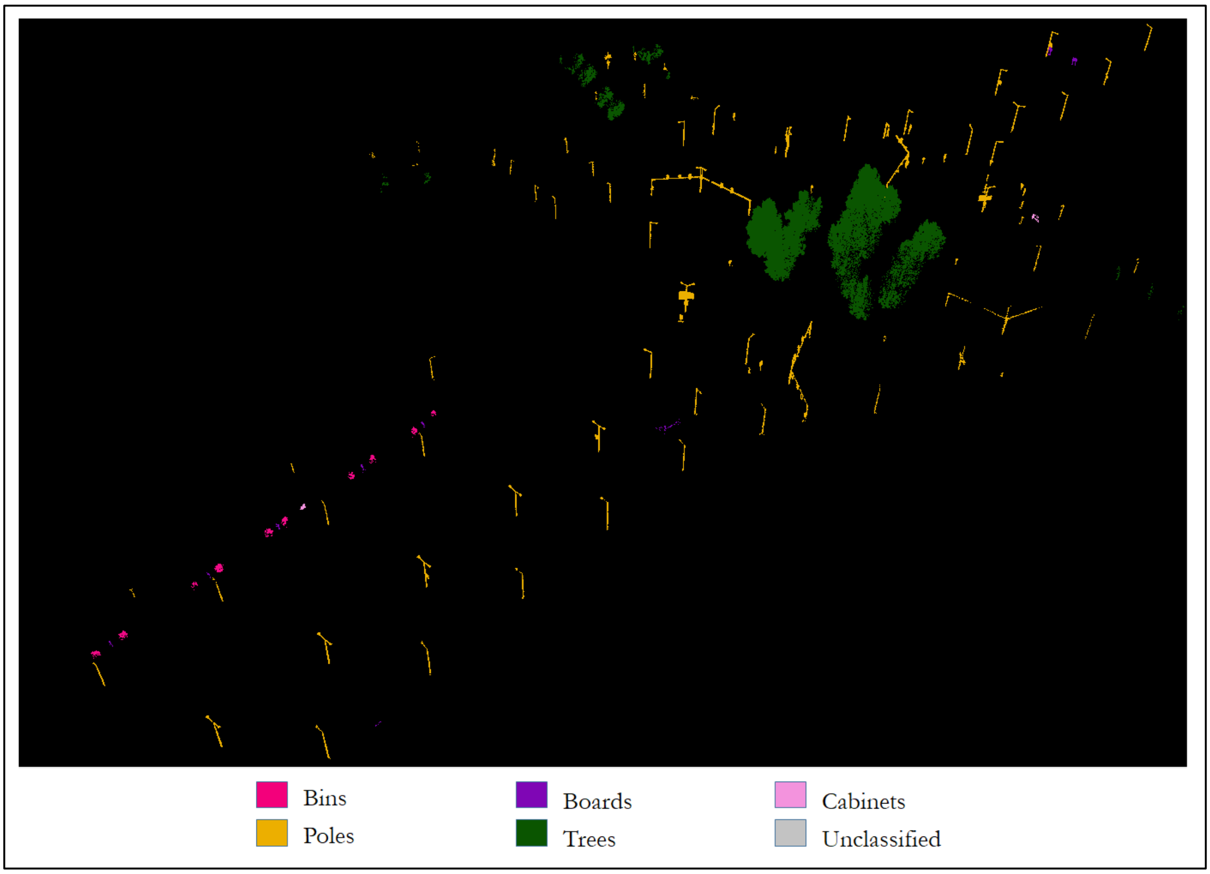

Figure 29: LiDAR classification results from matching point map features

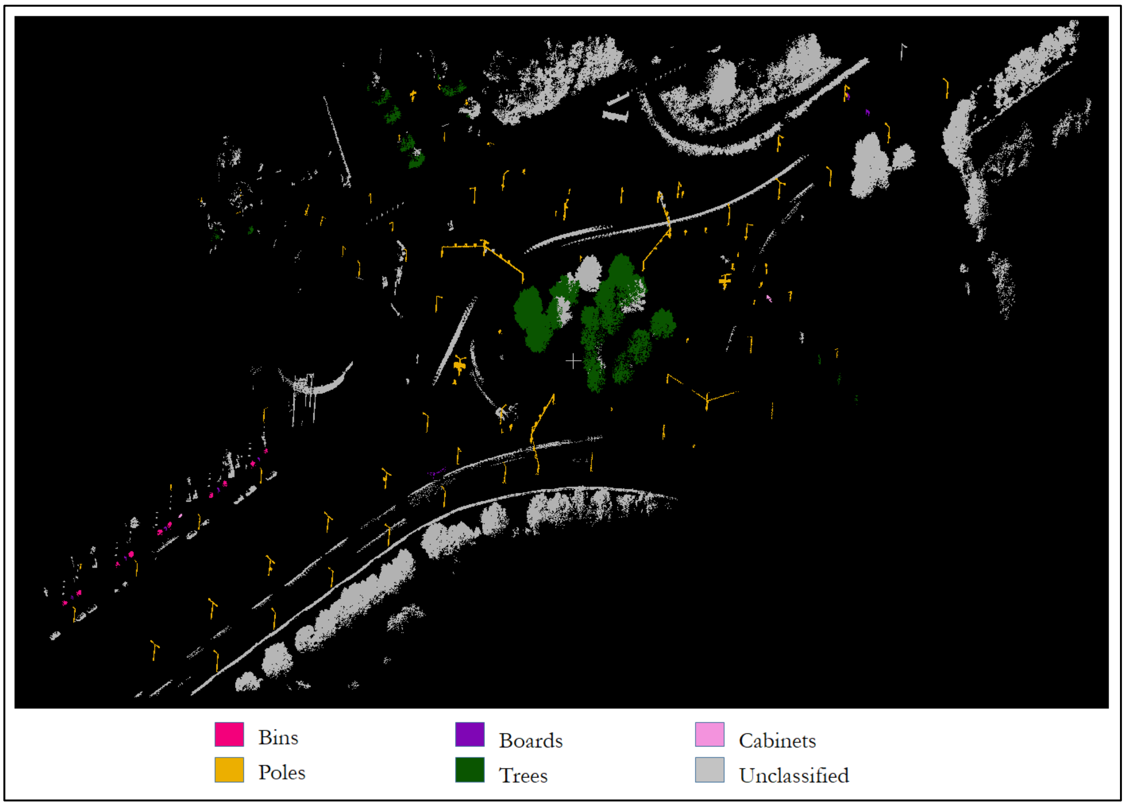

Figure 30: LiDAR classification results from matching point map features – first iteration

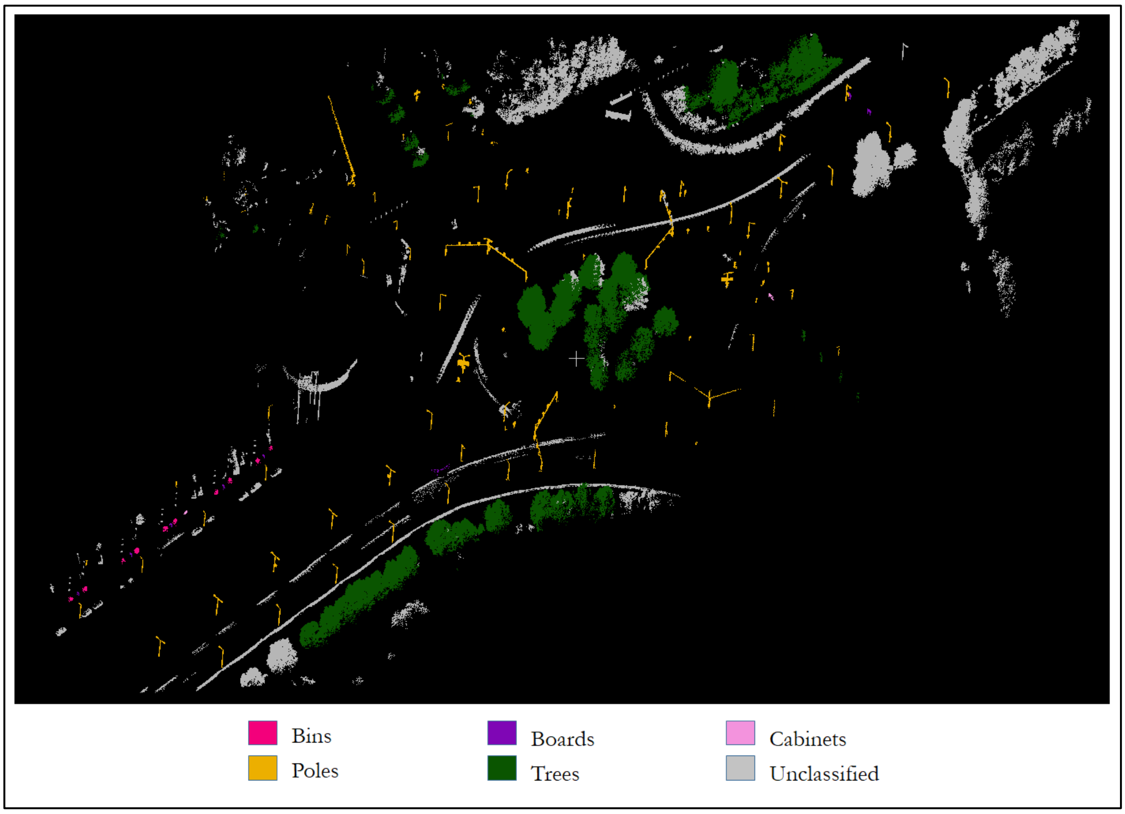

Figure 31: LiDAR classification results from matching polygon map features – second iteration

The result presented in figure 29 is from the first iteration of the point matching algorithm. It can be seen that the point matching algorithm correctly classifies the objects provided they have undergone correct segmentation in the connected component segmentation.

The point matching after the first iteration still contains unclassified points. It can be seen in figure 30 that the trees along the roadside remain unclassified. This is because the knee points of those trees are not present in the LiDAR file since it is occluded by hedges in front of it. The point matching algorithm in the second iteration as shown in figure 31 includes the trees that remained unclassified.

5.2.2. Performance

Close up results of the bin, board and pole objects that are classified are presented in figure 32. The point matching workflow handles intra class variations very well. Provided the component is in a particular class in the map, the size and shape of the object does not hinder the classification accuracy.

In figure 32, the bin objects are of the class 'flower bins' i.e. they contain vegetation. The size and shape of the bins widely vary between the various class types (trash bin, water bin, flower bin). However, since the component is free of clutter, it is clearly distinct in the results of the connected component segmentation and thus, the proposed algorithm gives correct classification results.

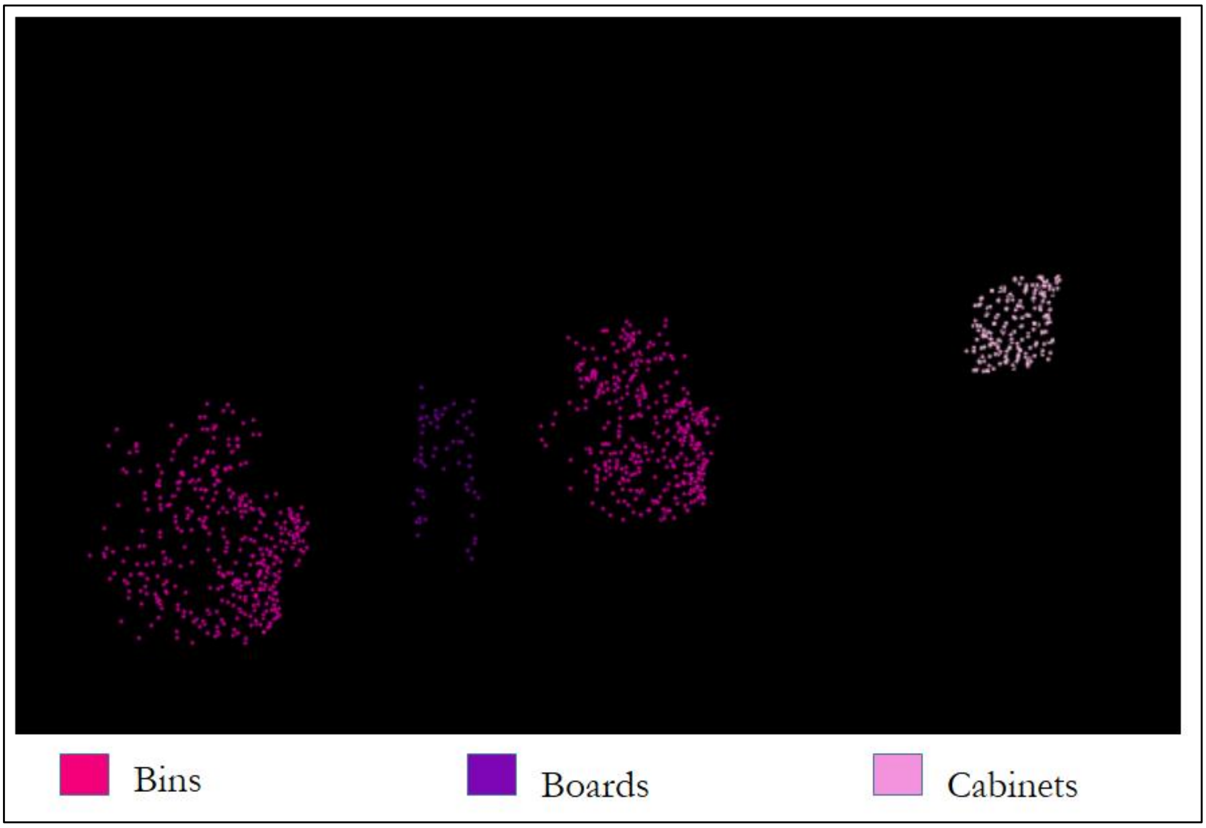

Figure 32: Clear distinction of bin, board and cabinet objects

There are many variations in pole like objects and board objects. They are captured in figures 33 and 34. In a classification technique that does not make use of a map, more than 3 or 4 intra class variations becomes very complex to handle. In figure 33, the third board object is an example of a complex object type. This has been easily classified in the proposed methodology.

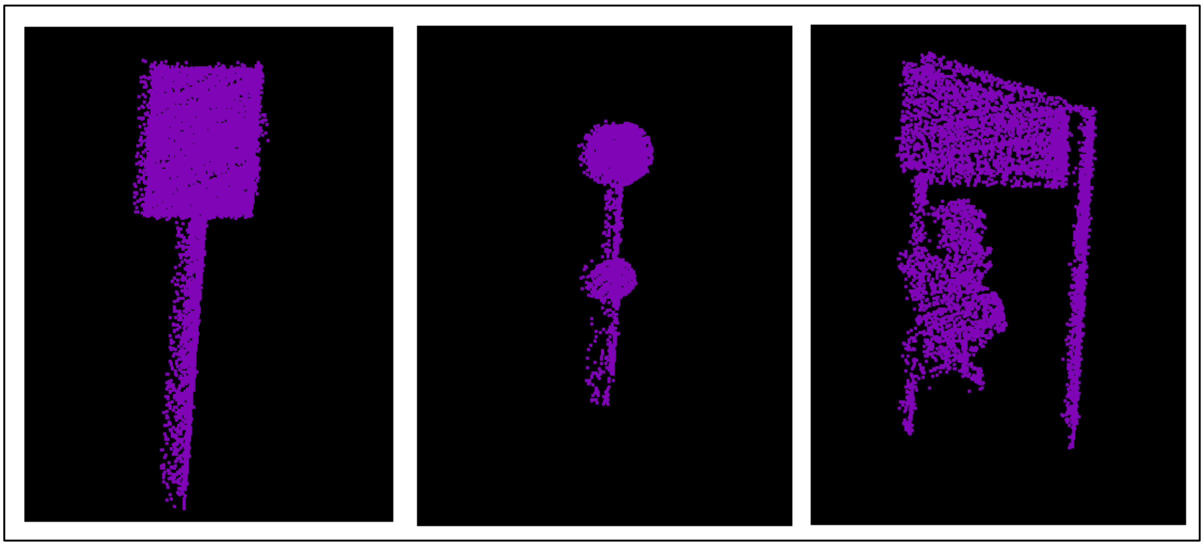

Figure 33: Variations in board objects

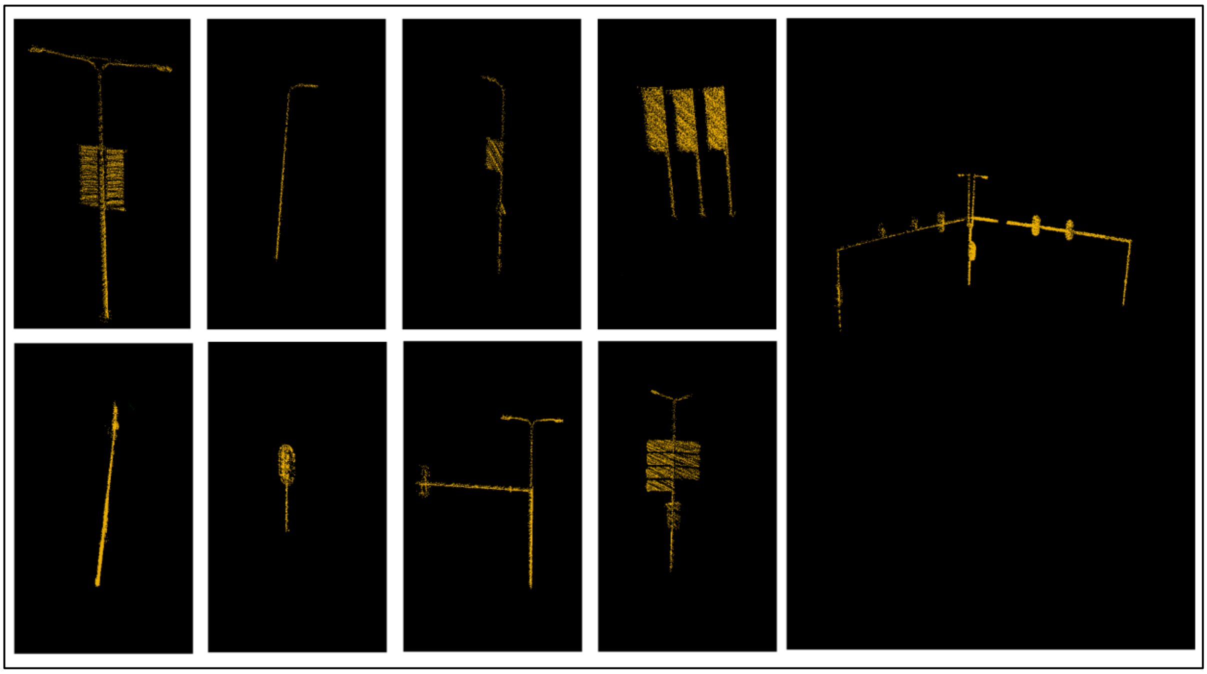

Figure 34: Variations in pole objects

Another advantage of the point matching algorithm is that even in cases of low point density, the objects are correctly identified and are assigned the correct class. In figure 35 it can be seen that the object has very low point density with the reason being its distance from the mobile laser scanner unit. Despite low point density, the object has been correctly classified. However, it is to be noted here that identifying objects with low point density depends on the results of connected component segmentation. Provided the component has points above the threshold set to identify the component (20 points, in this methodology), the components will be correctly classified.

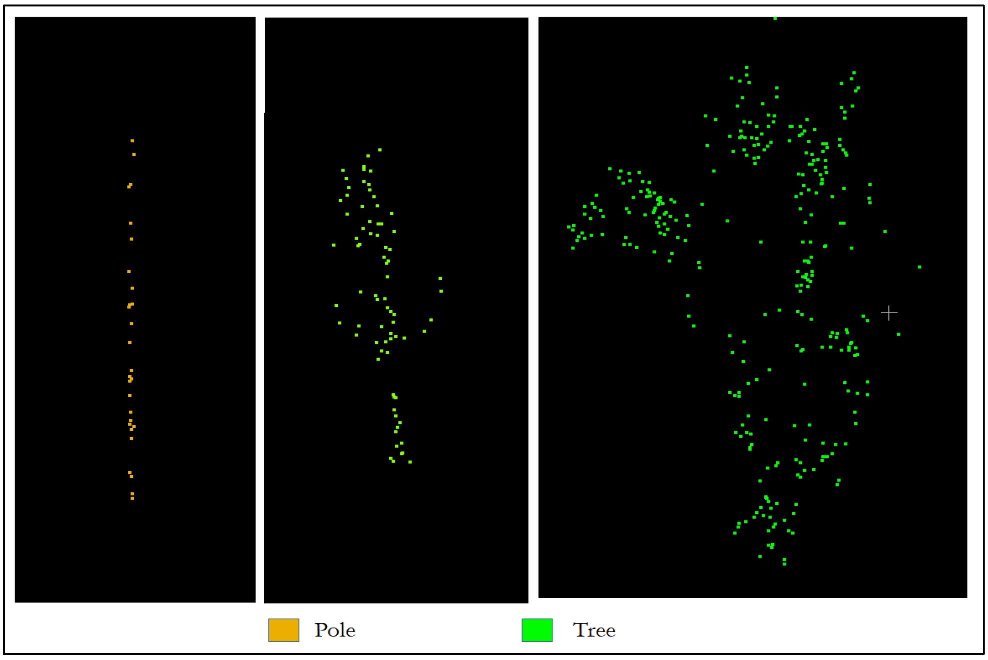

Figure 35: Examples of some objects with low point density

5.3. Handling Unclassified Points

5.3.1. Re-assign points belonging to building facades

In figure 36, we can see small segments that must belong to the building façade. All the points in segments closer to already classified building facades that were within a set threshold of 1m was classified to be a part of the building class. Figure 36 shows all the points that remain unclassified after the polygon and point matching steps and the result obtained after reassigning the points closest to the already classified building points is shown in figure 37.

Figure 36: Segments that remain unclassified

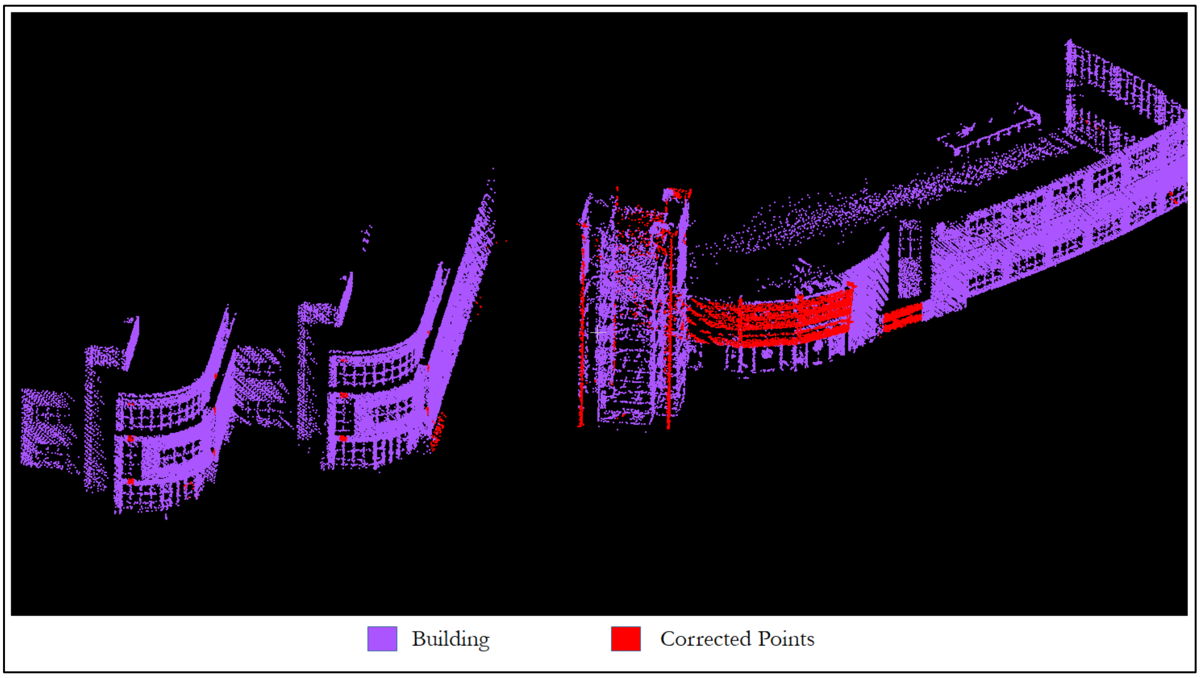

Figure 37: Corrected Building facade segments

5.3.2. Remove points belonging to cars

The results from removing the car points are shown in figure 38. Those points that are on the road are moving cars which are captured by the mobile laser scanner. Also, the cars that are parked near the buildings have been successfully removed. Some cars that have been parked in areas not specified as parking space in map however remain. In figure 38, all points that have remained unclassified are captured with car points being represented in red colour.

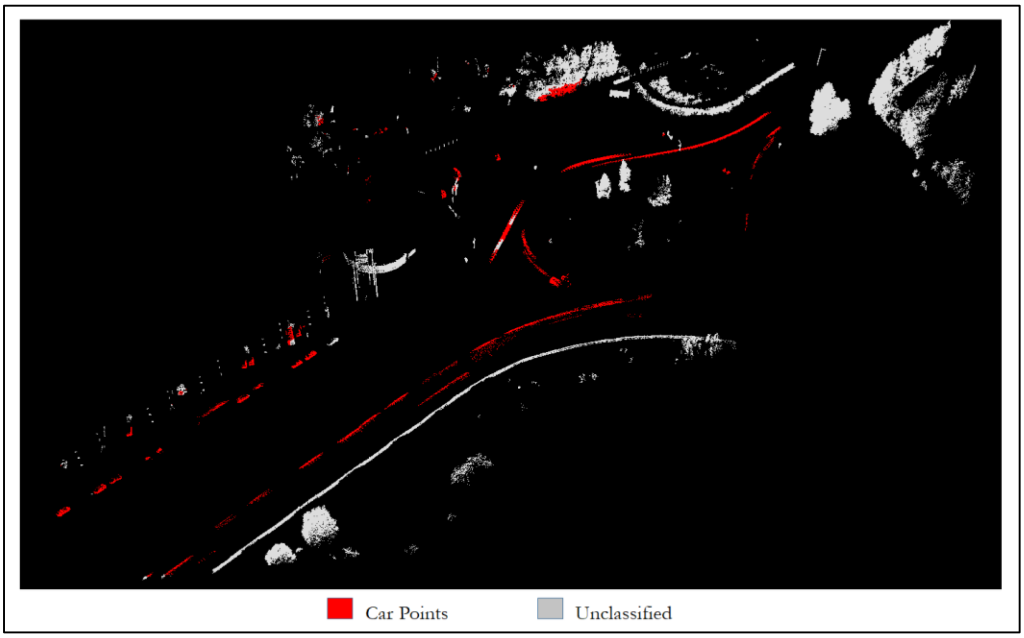

Figure 38: Identification of car points from the set of unclassified points

6. EVALUATION

The point cloud classification has been achieved using the information from a map. This can be seen in figure 39. The map based classification technique has been quite effective.

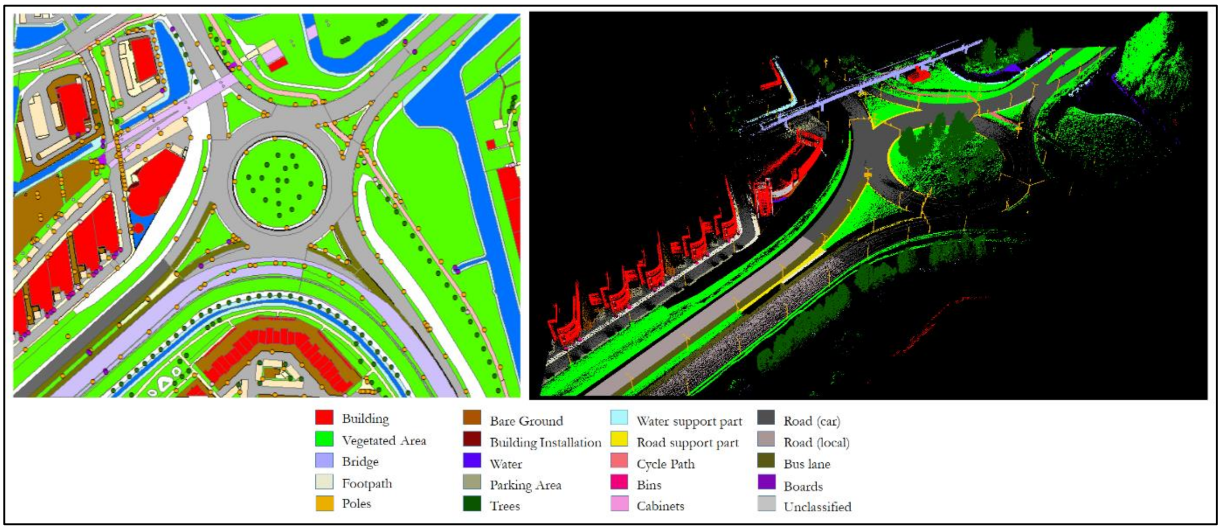

Figure 39: Map to LiDAR classified Point cloud

6.1. Accuracy Assessment

A visual accuracy check is performed to determine the number of objects that have been correctly classified. The map based classification was performed for 3 datasets. The accuracy assessment for each dataset are presented in this section. In order to determine the number of features that have been correctly classified, the obtained results are checked against the number of features present in the map and in the LiDAR file.

Since the map and the LiDAR dataset have different temporal resolutions, the features available on the map might not always be present in the LiDAR dataset. Hence, the number of features present in the map, the number of features present in the LiDAR dataset is first visually ascertained. The classified results are checked to determine if the number of features present in the raw LiDAR data has been correctly classified.

General Setup

In order to capture the number of objects that were correctly classified, the number of objects present in the map on the LiDAR point extent was first determined. The LiDAR file was then checked for the presence of those map objects. There were cases where the LiDAR file had no map object. One such example is shown in figures 40 and 41. The location of board points from the map can be visualised in figure 40. However, the two board points despite existing in reality (as visualized in google street view) are not present in the raw LiDAR file. Objects such as these are recorded as the difference in map data and LiDAR data.

Thus, for each map object, the existence of the object in the raw LiDAR file was recorded and this number was considered for calculating the accuracy. Since this is a map based classification, the wrong map information cannot be considered in the calculation of the accuracy. Subsequently, the number of objects correctly classified was determined by visually checking for every object in the classified LiDAR data.

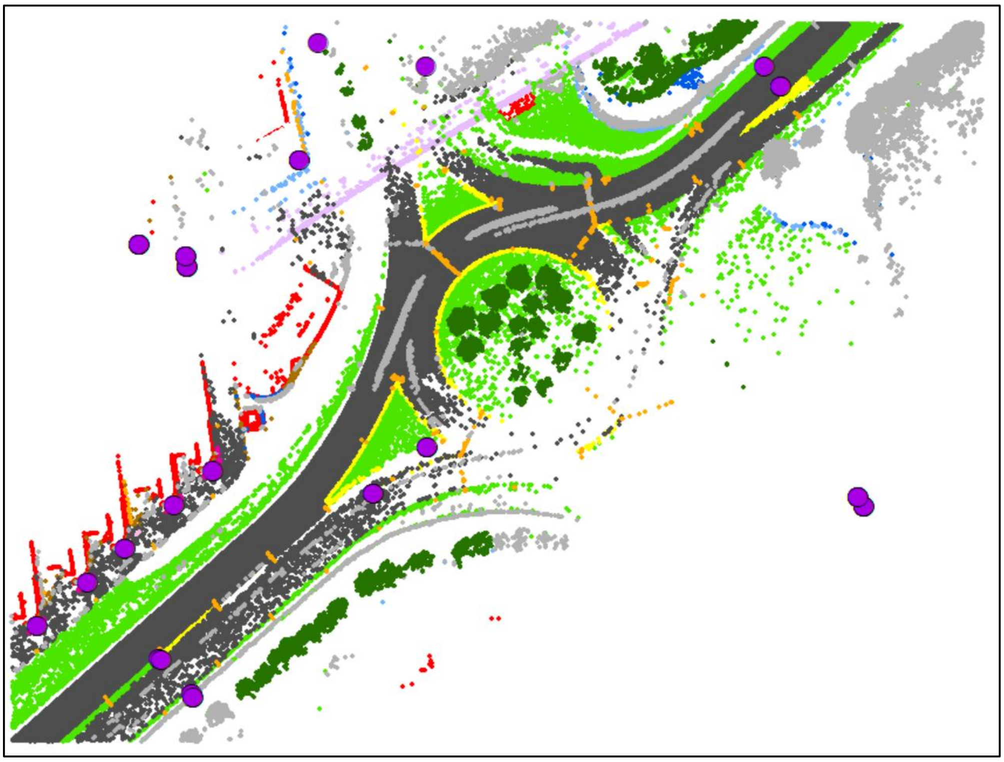

Figure 40: Board points (purple) overlaid on LiDAR dataset

Figure 41: Raw LiDAR file without the boards

Polygon Feature Check

The number of polygon objects for each class that is present in the map is counted. Each of these polygon shape features is visually assessed for the presence of above ground component points such as bins or boards to check if there is any misclassification. The polygon map file is overlaid with the classified polygon LiDAR file to check for point mismatches or wrong assignments near the boundaries. Normally, the polygon objects are usually identified correctly owing to the point in polygon operation.

It can be seen in figure 42 that the presence of even the smallest polygons ensure that a LiDAR point falling within its bounds are captured and classified accordingly. Each polygon feature is carefully assessed for the presence of wrong points. In case there exist a collection of points that are wrong, they are recorded accordingly.

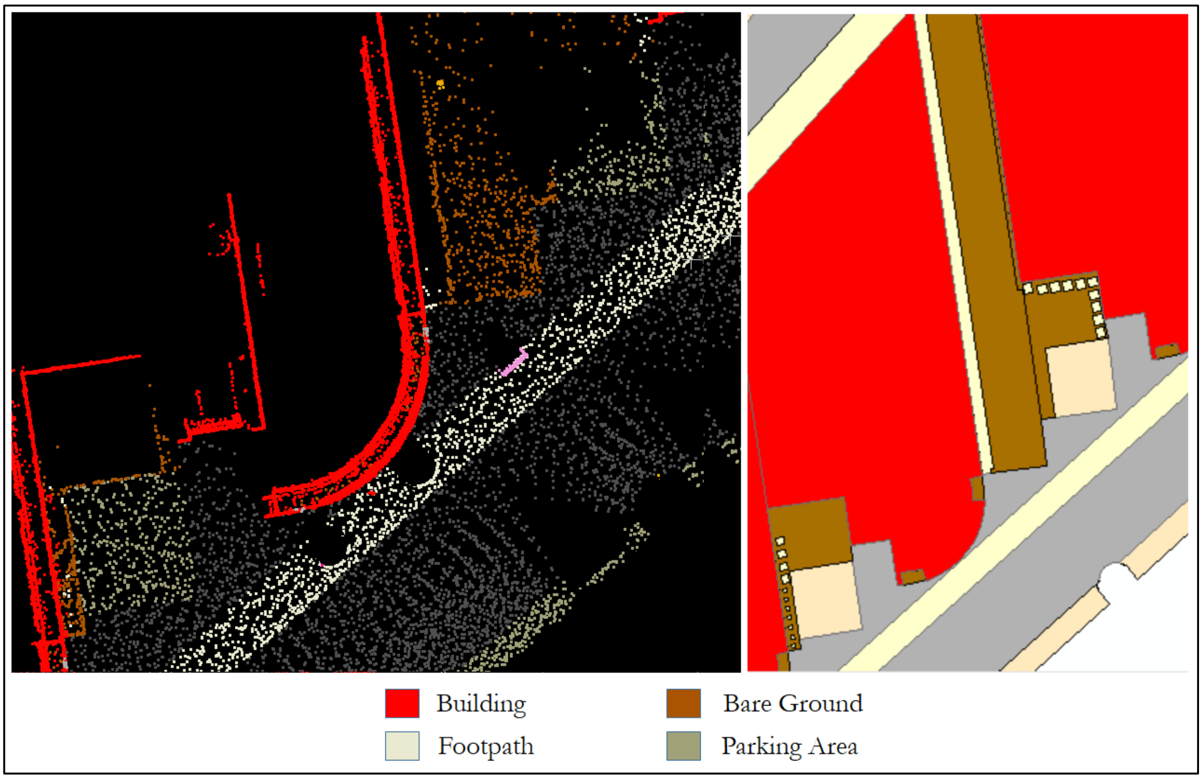

Figure 42: Polygon feature check

Point Feature Check

The number of point objects in the map is counted. The classified LiDAR data is overlaid with the map on the left. There are 3 trees, 1 board and 9 pole points (two board like looking objects have 2 poles each and belong to pole object class) in the map. The same number of features can be visualized in the point cloud.

Figure 43: Point feature check

From figure 43, 7 pole objects, 1 board and 3 trees are expected in the classified point cloud. The number of features expected can be clearly visualized in the classified results. Each component is also checked if it is completely classified. Sometimes, an object for example a tree is not completely classified. There might be some points that belong to the tree but remain unclassified. Similarly, there might be additional points associated with a class object. This is presented in figure 44.

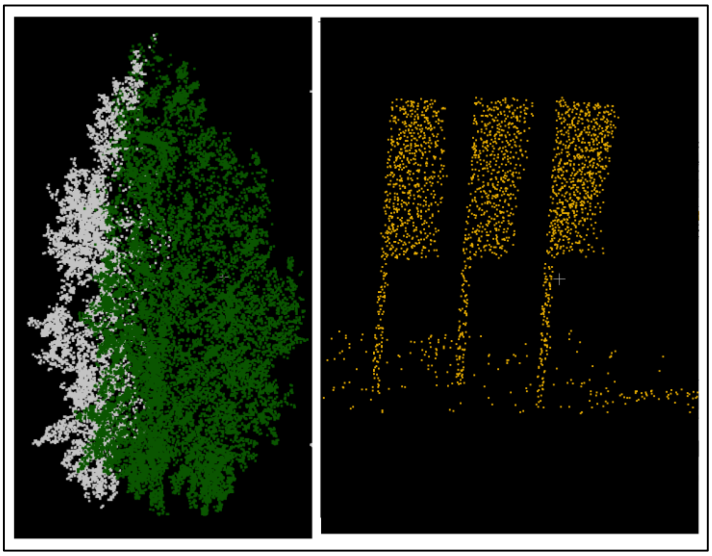

Figure 44: Partially Classified components (left) classified point cloud objects with additional points (right)

Confusion Matrix

Once, an overall information required is captured from the visual accuracy check, a confusion matrix was prepared to get the overall accuracy. Those components that remained unclassified were captured in the unclassified class. Some scenarios presented cases where the components remained partially classified. In certain other scenarios, small unintelligible components were assigned a class. These scenarios were captured in a class called 'other'. Figure 45 gives an example of the unclassified points class where a small component is misclassified as board.

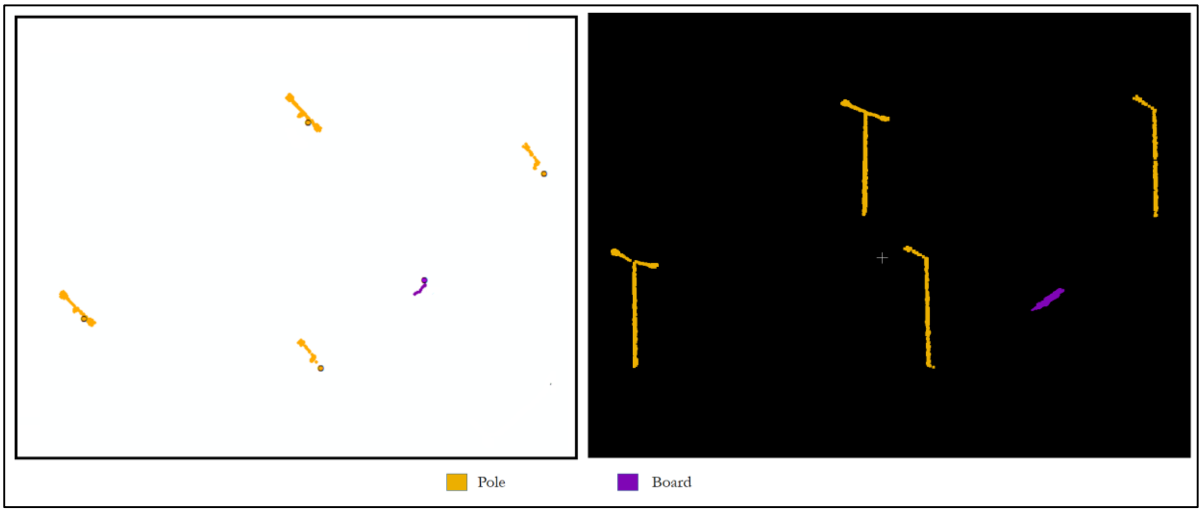

Figure 45: Unintelligible components misclassified

6.1.1. Dataset 1

The results of dataset 1 is presented in figure 46. The point cloud is classified into 21 classes. Table 9 presents the initial assessment after the visual accuracy check.

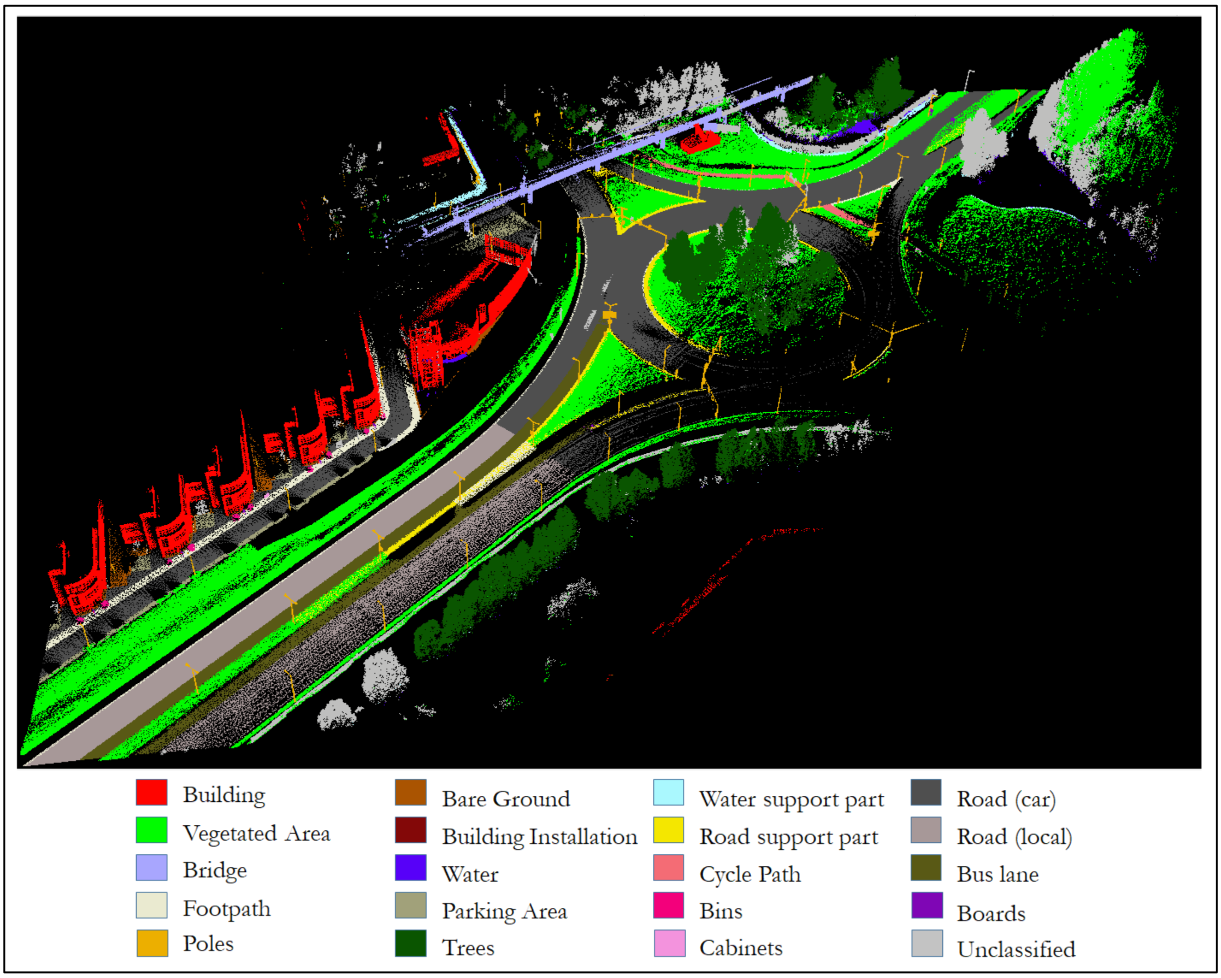

Figure 46: Dataset 1. Fully classified point cloud with unclassified points

The overall accuracy is calculated with the confusion matrix as shown in Table 10. For the dataset 1, the overall accuracy is calculated to be 92.3%. The polygon map features are usually classified correctly owing to the technique for point in polygon operation. There exists no misclassification for polygon shape features.

For the point features however, there exists scope for presence of unclassified points, misclassification, partial classification and the probability of having an additional components attached to the classified object. After careful visual inspection, it was noted that for dataset1, one board, two trees and seven poles remained unclassified. The board had very low point density causing it to be not considered as a separate component from connected component segmentation. For the two pole objects, there was no corresponding map point. For the trees, the distance threshold set to match the component was insufficient.

About 7 small segments were also identified that belonged to pole, tree and board objects. These components were unintelligible and thus they were recorded as points from the 'unclassified' class misclassified as class objects.

SS3Testset1	Map	LiDAR	Fully Classified	Partially Classified	Unclassified	Misclassified	% Accuracy
Buildings	9	9	9	0	0	0	100
Bins	10	10	10	0	0	0	100
Vegetated area	27	27	27	0	0	0	100
Board	16	9	8	0	1	0	88.88
Building installation	1	1	1	0	0	0	100
Cabinet	3	2	2	0	0	0	100
Bare ground	14	14	14	0	0	0	100
Water support part	4	4	4	0	0	0	100
Road support part	7	7	7	0	0	0	100
Bridge	1	1	1	0	0	0	100
Pole	114	90	79	2	7	2	87.78
Tree	72	48	42	4	2	0	87.5
Water	2	2	2	0	0	0	100
Road	17	17	17	0	0	0	100

Table 9: Accuracy assessment for dataset 1

SS3Testset1	Buildings	Bins	Vegetated area	Board	Building installation	Cabinet	Bare ground	Water support part	Road support part	Bridge	Pole	Railway	Tree	Water	Road	Unclassified	Total	User Accuracy	Error of Comission
Buildings	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	100	0
Bins	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	100	0
Vegetated area	0	0	27	0	0	0	0	0	0	0	0	0	0	0	0	0	27	100	0
Board	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	1	9	88.89	11.11
Building installation	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	100	0
Cabinet	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	2	100	0
Bare ground	0	0	0	0	0	0	14	0	0	0	0	0	0	0	0	0	14	100	0
Water support part	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	4	100	0
Road support part	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	7	100	0
Bridge	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	100	0
Pole	0	0	0	0	0	0	0	0	0	2	81	0	0	0	0	7	90	90	10
Railway	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100
Tree	0	0	0	0	0	0	0	0	0	0	0	0	46	0	0	2	48	95.83	4.167
Water	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	2	100	0
Road	0	0	0	0	0	0	0	0	0	0	0	0	0	0	17	0	17	100	0
Unclassified	0	0	0	1	0	0	0	0	0	0	4	0	2	0	0	0	7	0	100
Total	9	10	27	9	1	2	14	4	7	3	85	0	48	2	17	10	**248**		
Producer Accuracy	100	100	100	88.9	100	100	100	100	100	33.3	95.3	0	95.8	100	100	0		**92.34**	
Error of Omission	0	0	0	11.1	0	0	0	0	0	66.7	4.71	100	4.17	0	0	100			

Table 10: Dataset 1 - Confusion matrix

The details have been recorded in the confusion matrix and the producer and user accuracy was calculated. For the polygon map features, the producer accuracy and user accuracy remains at an ideal 100%. The points were inspected closely even at boundaries for any discrepancy. In the visual accuracy assessment, the results seem satisfactory. For point map features, the bins and cabinets were all correctly identified giving an accuracy of 100%. The overall accuracy for board objects is 88.9%. For the pole objects, the producer accuracy is 95.3% while the user accuracy is around 90%. 4 unintelligible objects were classified as pole points thus reducing the producer accuracy. The user accuracy was influenced by misclassification of 2 pole objects as bridge. This is because the pole objects were underneath the bridge. The polygons being classified first, included the pole points in the bridge polygon. 7 pole objects remained unclassified owing to factors such as incorrect map data and insufficient distance threshold.

6.1.2. Dataset 2

The results of dataset 2 is presented in figure 47. The point cloud is classified into 21 classes. Table 11 presents the initial assessment after the visual accuracy check.

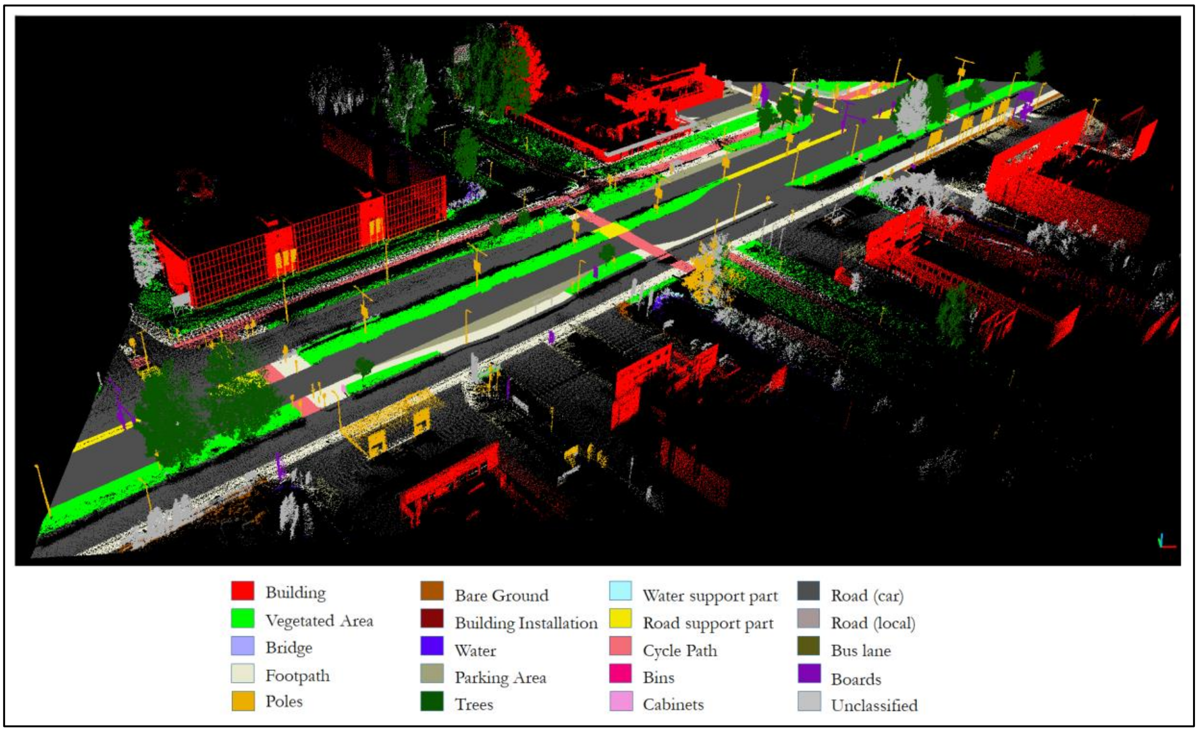

Figure 47: Dataset 2. Fully Classified point cloud with unclassified points

The overall accuracy is calculated with the confusion matrix as shown in Table 12. For the dataset 2, the overall accuracy is calculated to be 95.6%. The polygon map features are usually classified correctly owing to the technique of point in polygon operation. The results of this dataset exhibited situations with misclassification. This misclassification was not between the polygon map features but was present between the polygon object and the nearby points that should have belonged to point map feature (tree object in this situation). The red points belonging to the tree object has been misclassified in figure 48. The point in polygon operation includes all points belonging inside the polygon extents. Thus the tree foliage which is above a building is misclassified. It is to be noted here that the methodology proposed first performs the classification for polygon map features. Thus, all the above ground components within the building polygon are first classified. These classified points are not considered for point matching. This can be rectified by setting rules to handle misclassified points at these transitions (as future work).

SS5Testset1	Map	LiDAR	Fully Classified	Partially Classified	Uncla ssified	Miscla ssified	% Accuracy
Buildings	11	11	11	0	0	0	100.00
Vegetated area	27	27	0	0	0	0	100.00
Board	24	21	19	1	0	1	90.48
Building installation	5	5	5	0	0	0	100.00
Cabinet	3	2	2	0	0	0	100.00
Bare ground	6	6	6	0	0	0	100.00
Water support part	3	2	2	0	0	0	100.00
Road support part	11	11	11	0	0	0	100.00
Bridge	1	1	1	0	0	0	100.00
Pole	162	140	131	0	6	3	93.57
Tree	28	22	19	0	0	3	86.36
Water	3	2	2	0	0	0	100.00
Road	150	150	150	0	0	0	100.00

Table 11: Accuracy assessment for dataset 2

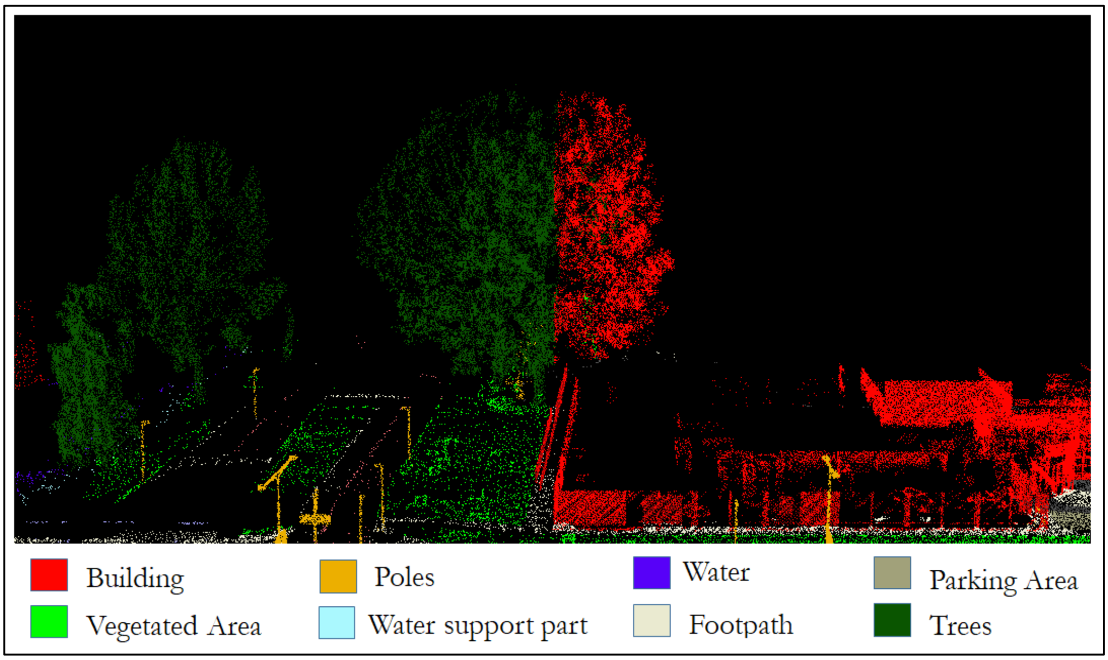

Figure 48: Misclassified tree points

In another situation, there exist small components in the vegetated areas that are misclassified as vegetated objects. It can be seen in figure 49 that small components such as the metal structures are classified as vegetated area points. These objects are not present in the map. The vegetated area takes into account those points that are between 1m and 1.5m high to include the presence of low vegetation. Hence, the accuracy is affected due to the presence of such points.

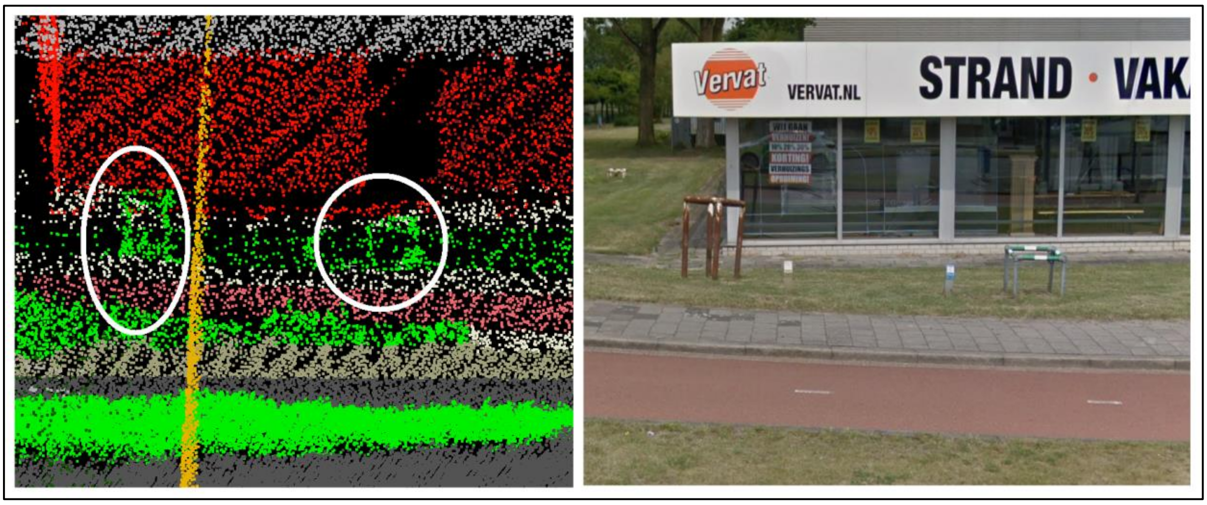

Figure 49: Small components misclassified as vegetated area

SS5Testset1	Buildings	Bins	Vegetated area	Board	Building installation	Cabinet	Bare ground	Water support part	Road support part	Bridge	Pole	Railway	Tree	Water	Road	Unclassified	Total	User Accuracy	Error of Comission
Buildings	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11	100	0
Bins	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100
Vegetated area	0	0	27	0	0	0	0	0	0	0	0	0	0	0	0	0	27	100	0
Board	0	0	0	20	0	0	0	0	0	0	1	0	0	0	0	0	21	95.24	4.762
Building installation	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	5	100	0
Cabinet	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	2	100	0
Bare ground	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0	6	100	0
Water support part	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	3	100	0
Road support part	0	0	0	0	0	0	0	0	11	0	0	0	0	0	0	0	11	100	0
Bridge	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	100	0
Pole	1	0	1	1	0	0	0	0	0	0	131	0	0	0	0	6	140	93.57	6.429
Railway	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100
Tree	1	0	1	0	0	0	0	0	0	0	1	0	19	0	0	0	22	86.36	13.64
Water	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	3	100	0
Road	0	0	0	0	0	0	0	0	0	0	0	0	0	0	150	0	150	100	0
Unclassified	0	0	5	2	0	0	0	0	0	0	4	0	0	0	0	0	11	0	100
Total	13	0	34	23	5	2	6	3	11	1	137	0	19	3	150	6	**407**		
Producer Accuracy	84.6	0	79.4	87	100	100	100	100	100	100	95.6	0	100	100	100	0		**95.58**	
Error of Omission	15.4	100	20.6	13	0	0	0	0	0	0	4.38	100	0	0	0	100			

Table 12: Dataset 2 - Confusion matrix

For the point features, after careful visual inspection, it was noted that for dataset 2, six poles remained unclassified and 3 poles were misclassified. The pole points were mostly left unclassified due to low point density. All the trees were correctly identified. The poles were misclassified as building (due to building buffer), as vegetated area (due to height) and as board (due to same component id as the board). Also, there were 3 trees that were misclassified. One as a building and the other as vegetated area. The third tree had poor connected component segmentation and thus was classified as both tree and pole (different segments). One board object was misclassified as pole since the pole map point was closer to the component in comparison to the board map point.

The details have been recorded in the confusion matrix and the producer and user accuracy was calculated. For the polygon map features, the producer accuracy and user accuracy remains at an ideal 100%. The points were inspected closely even at boundaries for any discrepancy. In the visual accuracy assessment, the results seem satisfactory. For point map features, the cabinets were all correctly identified giving an accuracy of 100%. The overall accuracy for board objects is around 90%. For the pole objects, the producer accuracy is 95.3% while the user accuracy is around 93.5%. 4 unintelligible objects were classified as pole points thus reducing the producer accuracy. The user accuracy was influenced by misclassification of 3 pole objects.

6.1.3. Dataset 3

The results of dataset 3 is presented in figure 50. The point cloud is classified into 9 classes. Table 13 presents the initial assessment after the visual accuracy check.

SS5Testset1	Map	LiDAR	Fully Classified	Partially Classified	Uncla ssified	Miscla ssified	% Accuracy
Buildings	6	6	6	0	0	0	100.00
Bins	14	10	2	0	5	3	20.00
Vegetated area	30	30	30	0	0	6	100.00
Cabinet	5	1	1	0	0	0	100.00
Bare ground	4	3	3	0	0	0	100.00
Pole	27	20	19	0	0	3	95.00
Railway	1	1	1	0	0	0	100.00
Tree	38	38	38	0	0	3	100.00
Road	25	25	25	0	0	0	100.00

Table 13: Accuracy assessment for dataset 3

The overall accuracy is calculated with the confusion matrix as shown in Table 14. For the dataset 3, the overall accuracy is calculated to be 87.4%. The polygon map features are usually classified correctly owing to the technique for point in polygon operation. In dataset 3 as well, there exist small components in the vegetated areas that are misclassified as vegetated objects.

For the point features, after careful visual inspection, it was noted that for dataset 3, the accuracy is mainly affected by bin objects. The bins are all less than 1m in height. Therefore, the connected component segmentation labels those points as just above ground. Thus only 1 bin was correctly identified. Additional components were classified as bins and poles due to the connected component segmentation. The bins are located near bus stops and the connected component segmentation does not clearly separate the component. In dataset 3, most of the trees and poles were correctly identified.

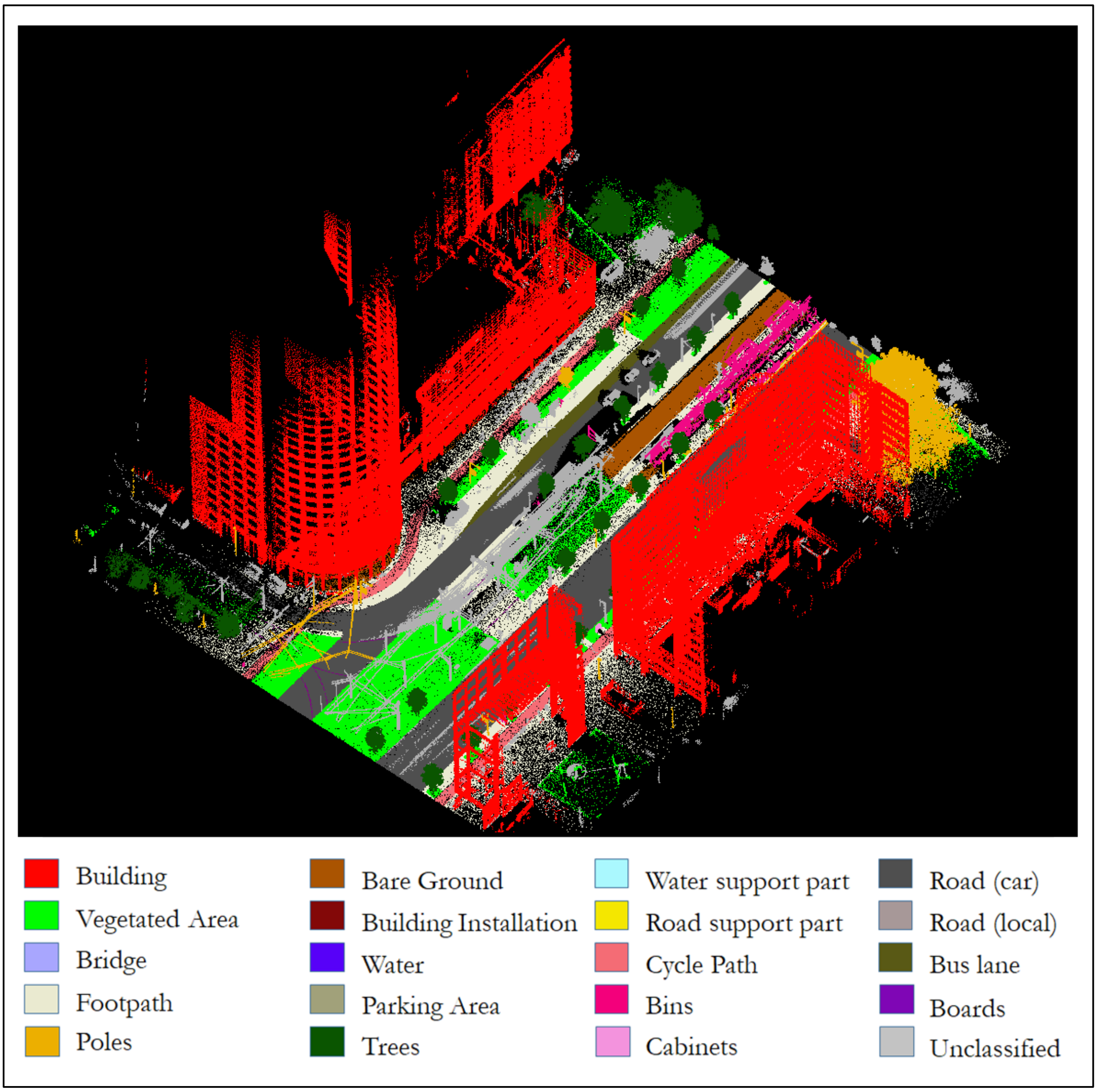

Figure 50: Dataset 3. Fully Classified point cloud with unclassified points

There was a mismatch between the map and the LiDAR for dataset 3. The map contained pole map points where the LiDAR point cloud had trees. Therefore, about 3 trees has been misclassified as poles. This misclassification has not been considered in the accuracy assessment because the focus of this research is map based classification. According to the data in the map, the objects in the LiDAR have been identified accordingly. This type of misclassification can be handled by extending this methodology further to ensure that the object being classified complies with the features defined for each object type.

3 objects that were supposed to remain unclassified were misclassified as building. This is because the overarching arch of the building has a small café underneath it and the tables were misclassified as buildings. Also, very short pole like objects in vegetated areas were also misclassified as vegetated areas since they complied with the height of the 'just above ground' points.

SS4Testset1	Buildings	Bins	Vegetated area	Board	Building installation	Cabinet	Bare ground	Water support part	Road support part	Bridge	Pole	Railway	Tree	Water	Road	Unclassified	Total	User Accuracy	Error of Comission
Buildings	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	100	0
Bins	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	5	7	28.57	71.43
Vegetated area	0	0	30	0	0	0	0	0	0	0	0	0	0	0	0	0	30	100	0
Board	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100
Building installation	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100
Cabinet	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	100	0
Bare ground	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	3	100	0
Water support part	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100
Road support part	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100
Bridge	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100
Pole	0	0	0	0	0	0	0	0	0	0	19	0	0	0	0	0	19	100	0
Railway	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	100	0
Tree	0	0	0	0	0	0	0	0	0	0	0	0	38	0	0	0	38	100	0
Water	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100
Road	0	0	0	0	0	0	0	0	0	0	0	0	0	0	25	0	25	100	0
Unclassified	3	3	6	0	0	0	0	0	0	0	3	0	3	0	0	0	18	0	100
Total	9	5	36	0	0	1	3	0	0	0	22	1	41	0	25	5	**143**		
Producer Accuracy	66.7	0	83.3	0	0	100	100	0	0	0	86.4	0	92.7	0	100	0		**87.41**	
Error of Omission	33.3	100	16.7	100	100	0	0	100	100	100	13.6	100	7.32	100	0	100			

Table 14: Dataset 3 – Confusion Matrix

6.2. Unclassified points

The map based classification proposed in this research gives satisfactory results. However, there still remain points that remain unclassified and misclassified which leads affects the accuracy results. There are several reasons that contribute to the resulting accuracy and they are summarized below.

- Differences in the dataset
- Misclassification
- Partial recognition and/or classification of the object

6.2.1. Differences in the dataset

The usage of two different datasets for this research gives scope for the existence of differences in the dataset. The differences might arise from the reasons being that either the map is not up to date or that the LiDAR dataset does contain the information presented in the map. The LiDAR data might not have the map information owing to temporal differences or occlusions during data capture.

It can be seen from figure 51 that there are two poles have remained unclassified. The map data is presented as an inset. It can be seen that the map contains information about the presence of a pole however it is at a distance away from the LiDAR poles. Also, there are two poles captured in the LiDAR dataset but for the given area, the map contains information of only one pole.

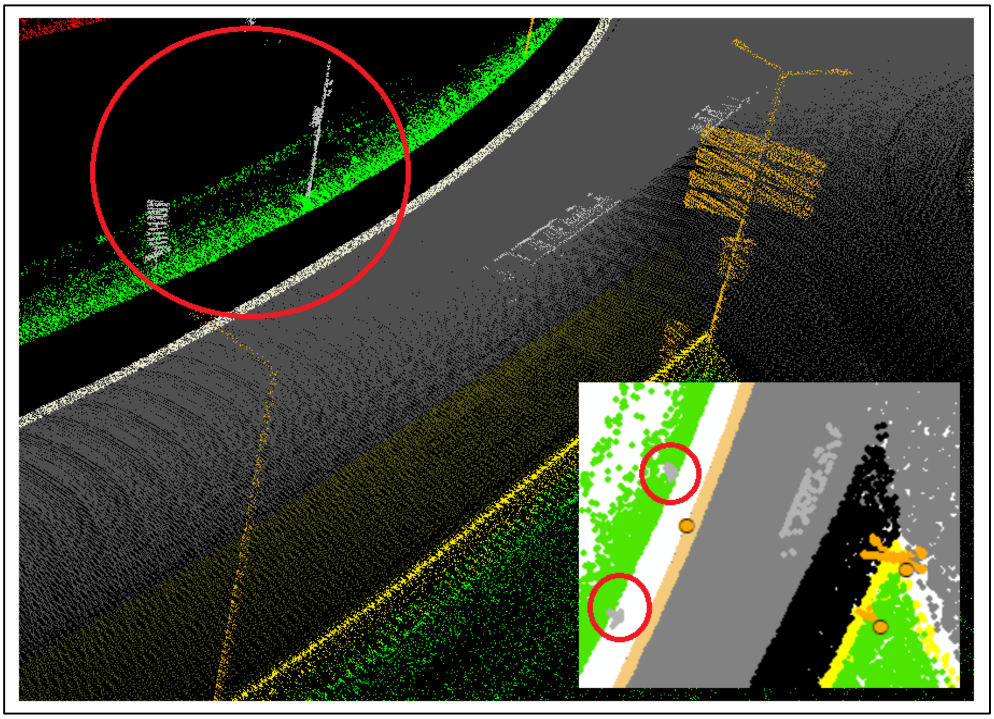

Figure 51: Pole objects not classified due to discrepancy in map. Map shown in inset.

In another example, for the area shown in the map part of figure 53 (right), there exists a number of pole objects. However, the LiDAR dataset contains a structure. On closer inspection and with the help of street view images, it is obvious that the structure is that of a gas station. The discrepancy of information in the map has led to the structure being wrongly misclassified as a pole. Since the point match algorithm takes into account components present close to the point map object, the gas station component is wrongly misclassified. The gas station in google street view is shown in figure 52.

Figure 52: Gas station in street view

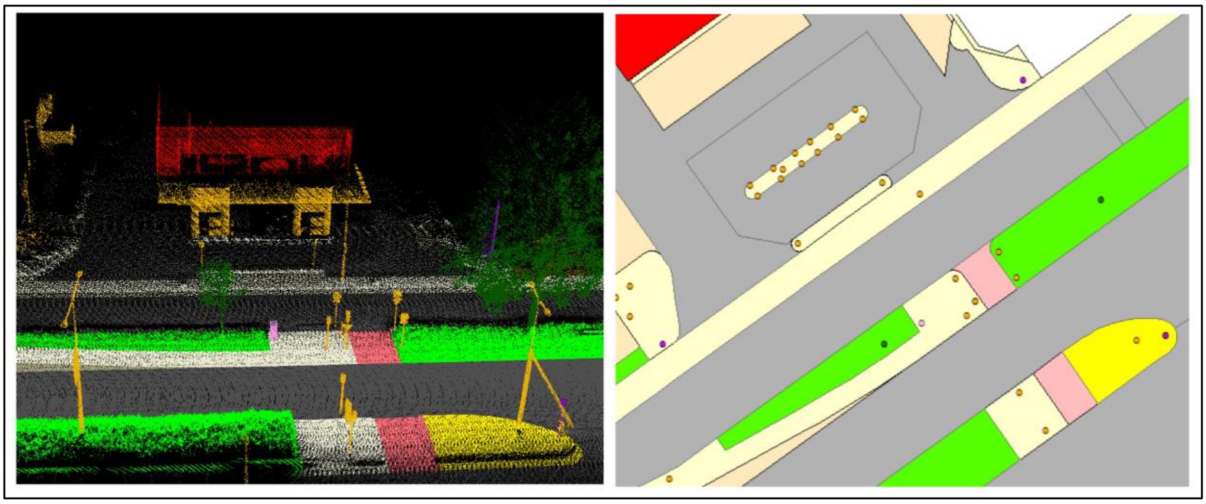

Figure 53: Differences in map and LiDAR data

6.2.1.1. Misclassification

Point cloud classifications are always subject to misclassifications. The proposed methodology is also not free of misclassifications. Though the misclassifications have been minimal, objects that are very close to each other are sometimes misclassified. Misclassification usually occurs between polygon map feature and point map feature. The point in polygon operation simply considers all the points within the extents of the polygon boundary. Despite setting the condition of point height, there exist some discrepancies. Misclassification is almost not present in the point matching phase. This is because the algorithm takes into consideration closeness between objects. This is handled by setting the distance threshold that matches it with map point extremely small.

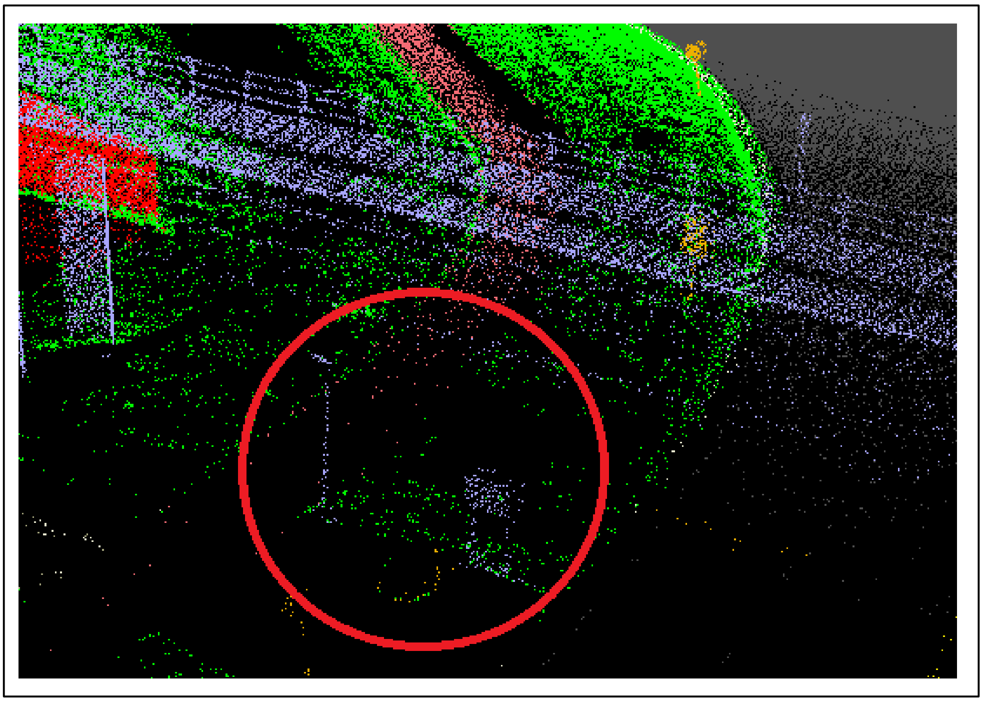

Figure 54: Poles misclassified as bridge

It can be seen in figure 54 that the bridge polygon object is classified. However, two pole objects that are underneath the bridge object is also classified as part of the bridge. This is because the bridge polygon points consist of all the points above ground. The bridge polygon has a relative height of 1 which means that all points above the height of 0.05m and above is part of the bridge.

Due to the setting of buffer for building polygons, poles extremely close to the buildings might be misclassified. One such case was encountered in a situation where the pole was attached to the building. However, in the example depicted in figure 55, pole objects despite being close to the building are not misclassified. It must be noted that a buffer of half a metre was set to classify the building.

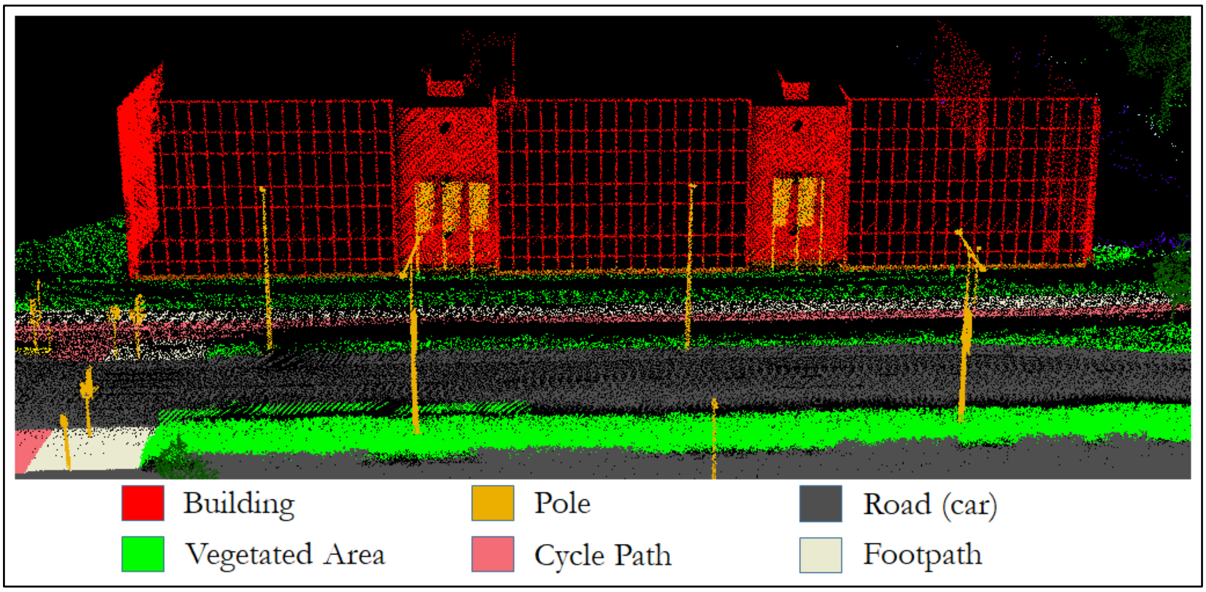

Figure 55: Example of good classification. Buildings and poles despite being very close are correctly classified.

6.2.1.2. Partial classification

The point matching algorithm is tightly coupled to the results from connected component segmentation. Though the proposed methodology takes care of removing as many ground points as possible to ensure good connected component segmentation, often objects such as trees result in poor segmentation. This is mainly because of the irregular structure of the tree.

Partial classification has mainly been encountered for tree objects. The point matching algorithm is run for a second iteration to handle any discrepancies of the set distance threshold. Since the second iteration checks the distance of every component point in the LiDAR file to that of the map object, there exists possibilities of certain components being correctly classified and this has been explained in section 5.3.1. This step is also advantageous in handling classification of objects that were partially classified.

In figure 56, the result of connected component segmentation on tree points are shown. It is clear that some trees have more than one component. Figure 57 shows the results of initial point matching algorithm and the result from the second iteration. It can be seen that by matching all the points of the LiDAR file in the second iteration, the additional tree components have been correctly classified. This of course is specific to this example because the only points present in the vicinity is tree points. In case of other classes of map points, there might be chances of misclassification but this is very minimal owing to the setting of a very small distance threshold. Despite the efforts, there still exist objects that remain partially classified.

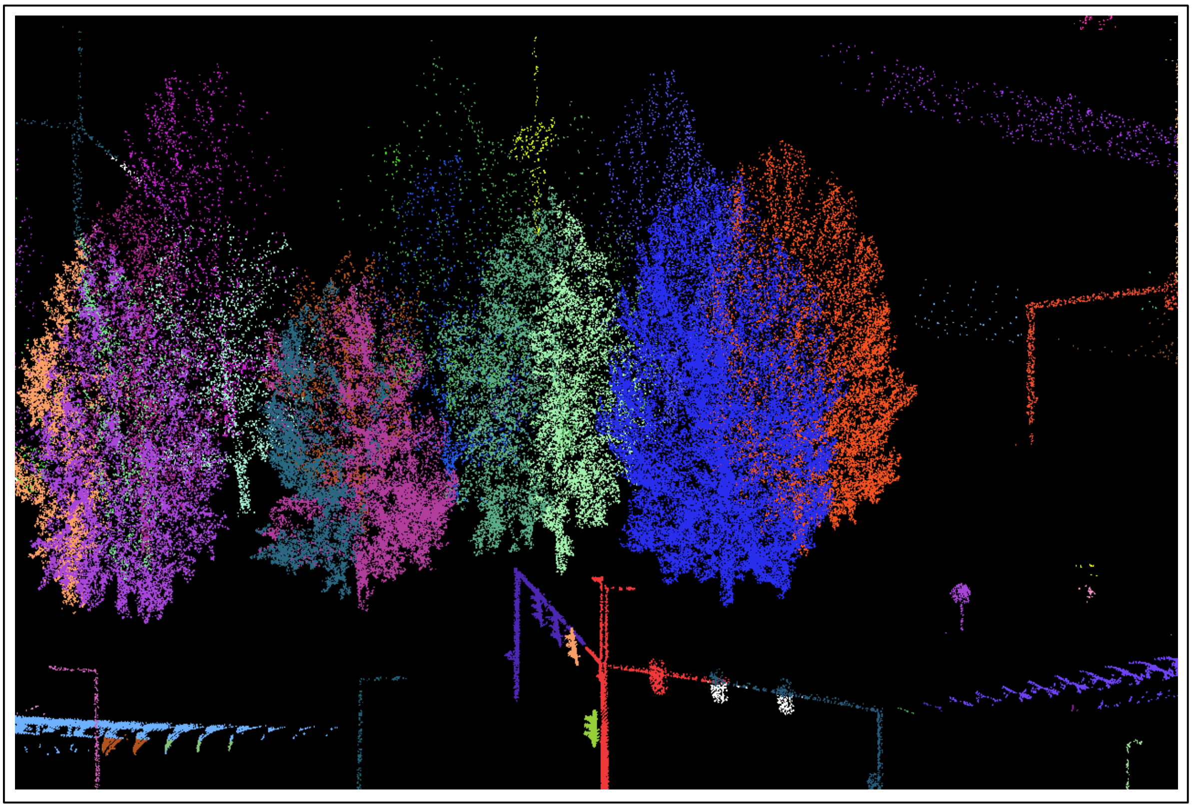

Figure 56: Connected Component segmentation on tree points

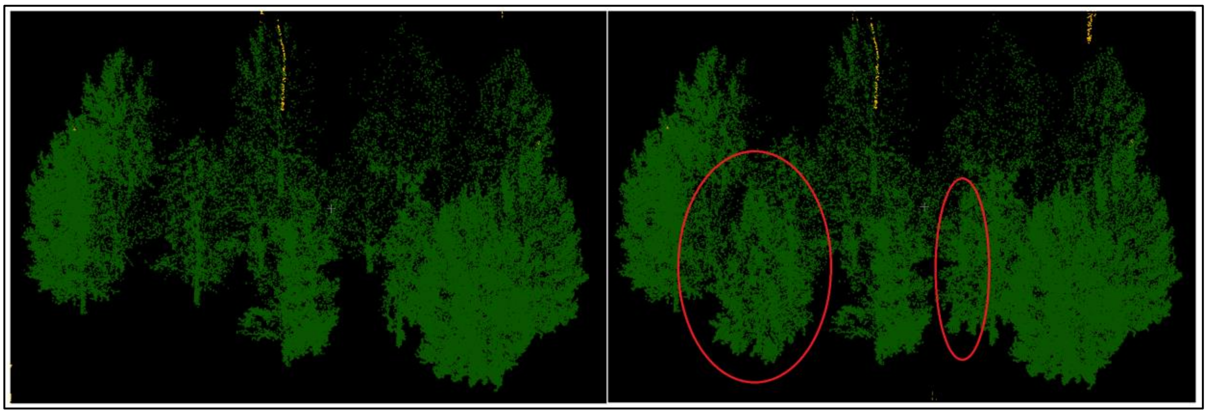

Figure 57: Tree points classified in first iteration (left) improved classification in second iteration (right)

There still exist unclassified points. These points majorly include cars, hedges and in this particular dataset, some trees.

The dataset captured by the mobile laser scanning system is subject to some positional errors. In the evaluation of the methodology it was noticed that some errors in objects remaining unclassified was due to the fact that the set distance threshold was not sufficient to match the map point with that of the LiDAR component. While the point matching algorithm is robust to handle a slight registration mismatch up to 1.5m, anything beyond that must be handled prior to implementing this methodology.

In other situations, points with very low densities though classified might not remain intelligible. In figure 58, we can see the raw point cloud with low point density. The figure on the right shows trees and pole points. However, they cannot be ascertained. Despite the map serving as a good reference point for classifying objects with low density, there might be situations wherein unintelligible components are classified as map objects. In the circle highlighted, there exists 2 pole points and 2 tree points in the map. Thus the closest components to those point map features are classified. It is a challenge to ascertain their accuracy in the visual check.

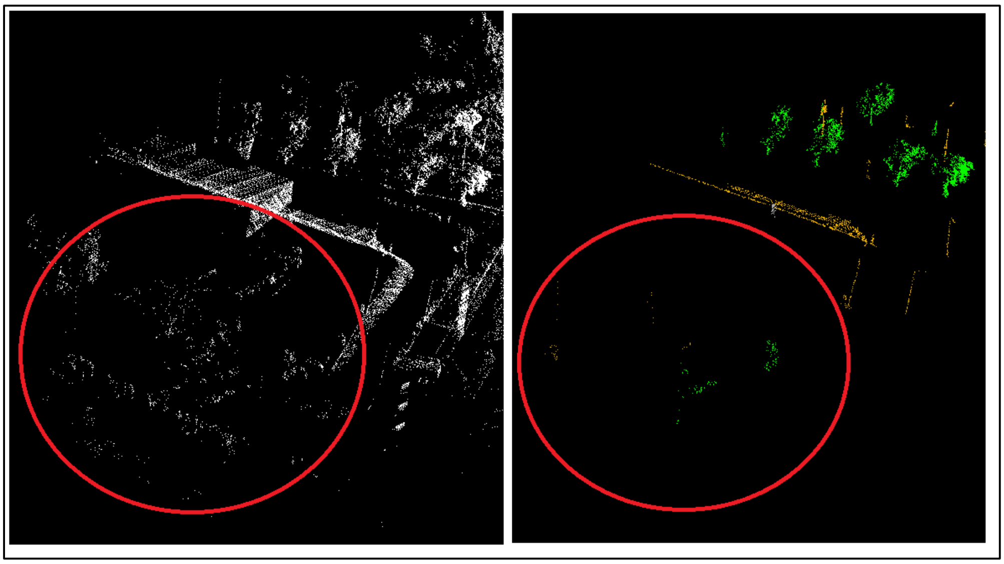

Figure 58: Classification of unintelligible components

7. DISCUSSION

7.1. Data Pre-processing

7.1.1. Additional Classes

The data pre-processing is an important step that shaped the classification methodology. The information already available in the map and the LiDAR datasets served as good starting points. The map datasets can be further scrutinized for additional information that can be utilized for the classification purpose.

For example, objects such as bus stops, children playthings (see-saws, slides), picnic tables, telephone booths, parking meters etc. could also be classified with the map data. Even road markings can be mapped with help of map data. The example of road marking is shown in figure 59 (Van den Brink et al., 2018). The road marking is visualized in point cloud data. Intensity is used to visualize the same. Thus point cloud attributes such as these can be used to extract them easily. Research to extract road markings involve the combination differential grayscale of RGB colour, laser pulse reflection intensity, and the differential intensity of RGB colour to identify the same (Gao, Zhong, Tang, Wang, & Liu, 2017). The process can be made simpler with the use of map information.

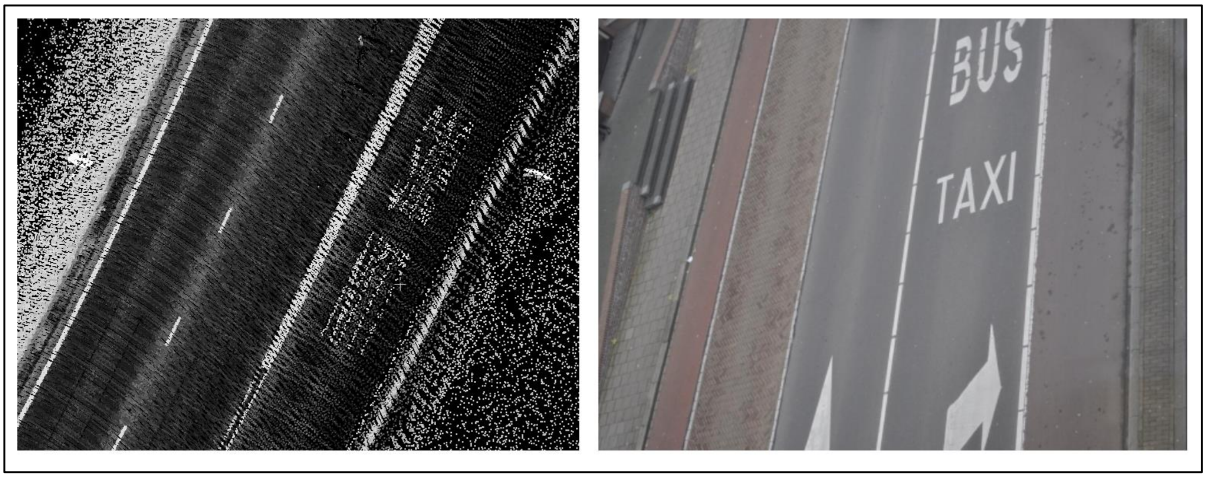

Figure 59: Road markings in point cloud (left) and in image (right)

7.1.2. LiDAR Height attribute

A mobile laser scanned point cloud does not include many attributes. It contains the 3D coordinates and the intensity. It is often augmented with RGB values and neighbourhood information for further processing (Zheng, Lemmens, & Van Oosterom, 2017). However, the attribute of the point cloud height proved to be very useful for the point cloud classification. The methodology adopted in this research relies mostly on the success of connected component segmentation to correctly classify the above ground features such as poles and trees. Most often, these objects are present on road dividers or vegetation covered areas or areas with grass cover. The grass points are not always at ground level. Hence, filtering the point cloud into only ground and non-ground often interferes with the performance of connected component segmentation. This is because most often point belong to low vegetation hinder the performance of connected component segmentation. This can be seen in figure 60.

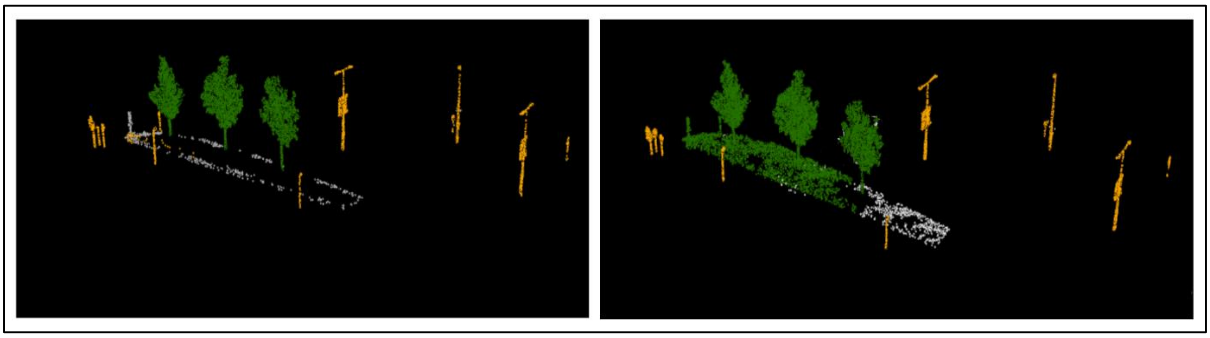

Figure 60: Advantage of classifying LiDAR by height removes points just above ground thus helping better connected component segmentation

Figure 60 shows the classified point cloud in two scenarios. The scenario on the left shows the point cloud classification after filtering the points into ground, just above ground (low vegetation) and above ground points. The scenario on the right shows the point cloud classification by just filtering the point cloud to ground and non-ground points. It is obvious that in the scenario on the right, the pole object behind the tree has been misclassified. The results are better depicted in the scenario on the left.

The setting of the height levels for labelling the point cloud by height are user defined parameters. The possibilities of filtering the point cloud into more height levels than just the 3 levels demonstrated in this research could be explored. The height of the just above ground components could be reduced further and a new height filter for low urban scene objects such as bins and cabinets could be introduced to reduce the errors obtained in dataset 3.

Another important aspect in data pre-processing included the registration check between the two datasets. A manual technique was adopted in this research. For effective matching of map features to the point cloud, it is essential that the two datasets have almost no registration errors. The most important information a map can provide is the location details i.e. the (x, y) coordinates for a specific object. The methodology adopted in this research has limited scope to handle minor registration mismatches. In situations of greater registration differences, it is advised to rectify the differences prior to adopting the methodology proposed in this research.

7.2. Map based classification

The connected component segmentation is one of the crucial pieces of the proposed methodology. In order to perform the point matching, the accuracy of the results largely depend on the results from this procedure. The segmentation procedure proposed here handles the cases of objects that are extremely close to one another. This is clearly demonstrated in figure 55. However, there still are situations where the segmentation of point clouds depends on factors such as occlusions and clutter.

In figure 61, it can be seen that the bin component highlighted in yellow has many other components such as tram stop and a moving tram in the same component segment. In the current methodology, the classification occurs based on the connected component segmentation. However, the map data can also be utilised to improve the segmentation process. This means that, from the map data we can expect the points to be belonging to a certain classes of objects. The segmentation process can therefore be performed by setting the parameters such that the points get segmented into the correct classes.

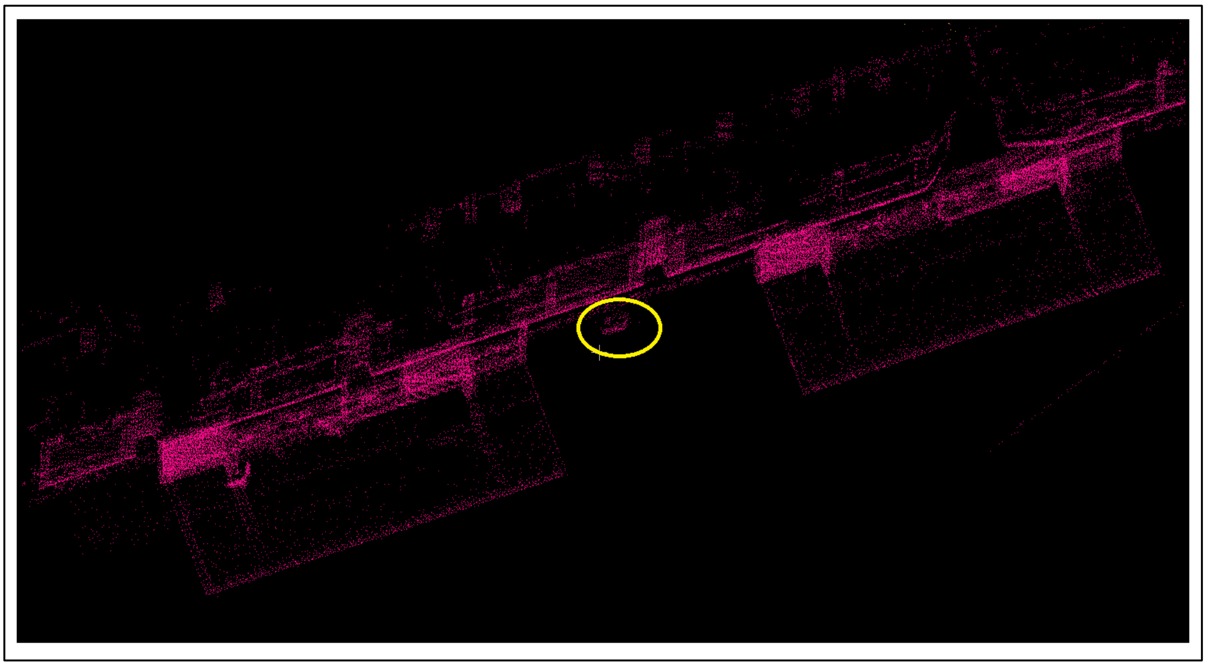

Figure 61: The bin object highlighted in the yellow circle. The other points are misclassified due to connected component segmentation yielding same component number for the entire point cloud subset highlighted here

One such example was demonstrated for reassigning the points belonging to the building façade. From the map data, it was expected that the small unclassified points closest to the already classified building points were part of the building. Hence, the simple rule of height and proximity was used to segment and classify them correctly. Thus, the connected component segmentation can be supported with the information in the map.

For example, in figure 61, the segmentation could be improved to obtain only the bin component. This can be done by constructing a minimum bounding box around the location of the map point feature of the bin and assigning only those points to the bin segment. The bounding box size can by the type of bin (from the map) and the standard bin type dimensions (from the municipality documents).

7.2.1. Low point density

Though the map based classification performs well even for objects with low point density, the results are influenced by the connected component segmentation. Usually components below 20 points are ignored in the connected component segmentation. The presence of a map object at these locations lead to the object not being classified. Therefore, the segmentation can also be modified to fit these situations.

7.3. Handling Unclassified points

The methodology proposed here tries to improve the initial classification results based on the insight gathered after the initial visual check. The unclassified points are mostly

- Points from objects not present in the map i.e. cars, pedestrians etc.
- Points misclassified as 'unclassified' points.
- Points from partially segmented components.

The points remaining unclassified due to its information not available in the map could only be handled and removed for car objects. Points belonging to pedestrians and other larger vehicles remain a challenge to handle.

The explanation that could be provided for the presence of unclassified points pertains to the setting of distance threshold for point matching algorithm. Most often, the single point chosen per component of the LiDAR dataset was not sufficient to recognize the component correctly. Thus, the second iteration was implemented. Despite the obtained improvement in the classification, components that were captured farther away from the MLS device usually remained unclassified. This could be attributed to lower positional accuracy of objects captured father away from the scanning device.

The third reason was the points that remained unclassified resulted from partially segmented components such as points from the building façade. In the methodology proposed, the correction is aimed only for the building façade parameters. Several other objects also have points that remain unclassified and one of the most obvious class is trees. The reason for this is the performance of the connected component segmentation. In order to correct for these points, more rules need to be set. This research explores the potential of using the map to set segmentation parameters to improve the classification results and it is demonstrated for one class. The same can be performed for other classes as well.

8. CONCLUSIONS AND RECOMMENDATIONS

8.1. Answers to Research Questions

The main objective of this research was to perform the classification of a dense mobile laser scanned point cloud from the information available in the map. This research has successfully achieved its objective. The methodology proposed in this research has given good accuracy results between 87 and 96%.

Sub-objective 1 - To correctly assign the classes defined in the map to the point cloud data

Q. Which set of points belong to the objects in the topographic map?
A. The points captured by the mobile laser scanned data includes that of a road scenery. The large scale 2D topographic map is also obtained of the same area. The details on the map is quite extensive with as many as 15 classes that could be used for classification. The points belonging to the map objects of buildings, vegetated areas, roads, water polygons, road support part, poles, trees, cabinets, boards and bins belonged to the objects in the topographic map.

Q. How does the appearance of objects in the map vary from the point cloud?
A. Objects in the map is represented in vector data format of point, line or polygon. The polygon objects are generally planar segments in the point cloud with most of the polygon map features being ground points. The building facades are also obtained from polygon map features. The point map feature differed greatly in appearance in the point cloud depending upon the class of the object. Each class also had a good amount of intra-class variations ranging from simple structures to complex structures.

Q. What are characteristics that should be assigned to the map objects?
A. The map objects were classified according to height of the point cloud. Map objects such as roads and bare ground polygons do not contain non ground points. Similarly, map objects of buildings, poles, trees etc. captured in mobile laser scanner point clouds contain only points above the ground as a part of the building façade, pole or tree. Thus, only above ground points were considered to map the same. Similarly, map objects of vegetated area or road divider polygons contain points that are at ground level and just above ground level and thus only those points were used to classify for these classes.

Sub-objective 2: To account for differences in the dataset

Q. Which objects appear in the point cloud but do not appear in the map?
A. The map does not contain information about vehicles and pedestrians. Thus, these points remained unclassified in the point cloud. The methodology was extended to remove points belonging to these objects from the point cloud. This was done by setting a generic rule i.e. those points between the height of 0.05m and 2.5m from the ground (i.e. from ground level to the average height of a car) in areas belonging to roads and parking spots were removed. This largely helped remove car points.

Sub-objective 3: To assess the quality of the classification

Q. What is the accuracy achieved in the classification?

A. The map based classification resulted in generally a high accuracy between 87% and 96%. The point cloud classification was performed on 3 datasets which consisted of different types of road scenes. One of the dataset was a highway which had many vehicles on the road but consisted of objects far apart which could be distinguished well. An overall accuracy of 91.6% was achieved for this dataset with. The second dataset consisted of many point map features in an area consisting of business establishments. An accuracy of 96.2% was achieved for this dataset. The third dataset used consisted of a busy area near the city centre with lots of pedestrians and vehicles. An accuracy of 87.4% was achieved for this dataset.

Q. What are the factors influencing the achieved accuracy?

A. Misclassification and unclassified results due to point matching, though minimal, influenced the achieved accuracy. Unclassified results mainly resulted from mismatch in map data, low point density and due to the setting of the distance threshold for point matching. In addition, the connected component segmentation also influenced the achieved accuracy. Misclassification generally occurred between polygon map objects and point map objects. The point in polygon operation though controlled by height of LiDAR points gave room for errors.

Q. What is the influence of registration errors between the datasets?

A. The registration errors majorly influenced the setting of the distance threshold to match the map points with the LiDAR component. The distance threshold was set between 1m and 1.5m for the point matching depending upon the RMSE obtained from the data pre-processing stage. Datasets with extremely minimal registration errors could result in achieving higher accuracy.

8.2. Conclusions

The point cloud has been classified into 21 classes uses the information available in the map. Generally, point cloud classification is performed for classes such as buildings, vegetation, roads, pole like objects, wires etc. When dealing with large intra class variability, the point cloud classification is performed for a certain type of object. The map based classification is advantageous in the sense that it can deal with large number of classes as well as large number of intra-class variations i.e. different types of pole structures, different types of boards, bins etc. The datasets used each contained roughly about 9 to 12 million points. After the classification, only about 5% of the points remained unclassified.

The data pre-processing steps proposed has strengthened the classification process by reducing the scope for large misclassification of the point cloud objects. The height parameter thus taken into consideration has proved advantageous to ensure that only relevant points are mapped to a particular class object.

The map has not only been used as a starting point to identify laser points belonging to a particular class. The metadata available in the map has also been utilized to improve the classification results. This is particularly well evident in areas which have a bridge above a road or a building constructed above a road. The map attributes have sufficiently helped in classifying the LiDAR points correctly.

Since the classification is map supported, there exists small chances of an object class being misclassified as another. Also, there are chances where smaller components that are present near a map object that might also be wrongly misclassified. From the assessment, misclassification contributes to only 2% of the results while unclassified objects contribute to about 8% of the classification results.

A huge advantage of map based classification is that it gives quick results. These results can be used in a large number of applications. Some of the examples include the usage of these results as samples for machine learning algorithms to train the classifiers. They can also be used for change detection.

8.3. Recommendations

The map based classification gives good results of quick point cloud classification. It is also efficient in classifying the point cloud into a large number of classes. However, there still is scope for further improvement.

- The classification of objects is performed by directly assigning the class information from the map. However, an additional check can be performed to test if the object being classified is indeed the correct object. This will reduce the components from being misclassified especially at class transitions. Rules can be set as a post processing step to achieve this.

- The map also contains many more classes into which the point cloud can be classified. For example, road markings can also be classified with the help of the map. However, it will prove to be difficult with just coordinate information. Similar to using height information of the points in the LiDAR, other point cloud attributes such as intensity etc. can be used to classify these objects.

- Currently, the accuracy assessment is done manually. In areas where there is low point cloud density, the map still performs satisfactorily to provide good results. However, a manual check might not be feasible to determine the accuracy appropriately because it is impossible to clearly understand the point cloud component. Hence, other methods such as using a reference dataset can be explored.

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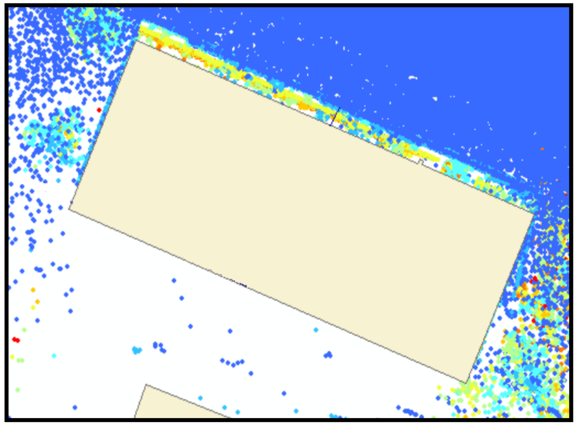
APPENDIX I: VISUAL CATALOGUE

This catalogue consists of the layers that were finalized to be used in the classification process. The objects can be categorized as

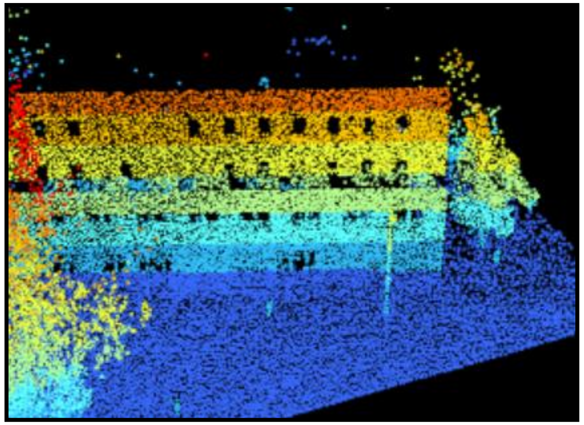
1. Objects clearly recognizable
    a. Buildings
    b. Bins
    c. Board
    d. Cabinet
    e. Pole
    f. Tree
2. Objects not clearly recognizable in LiDAR but used for classification
    a. Vegetated area
    b. Bare ground
    c. Water support part
    d. Road support part
    e. Bridge
    f. Railway
    g. Road
    h. Building Installation

The visual catalogue also consists of brief description of the object and how certain properties might be used to better distinguish them from other nearby objects.

BUILDING



Building polygon in map overlaid on 2D LiDAR data



3D LiDAR visualization of building

Image of the building polygon*

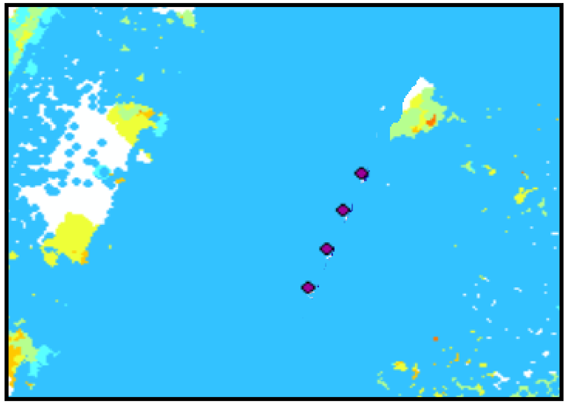
Map feature type Polygon

Description The building is a polygon feature in the map. It is clearly distinguishable in the LiDAR point cloud as building facades. The above screenshot shows the building feature in the map and in the MLS point cloud and in the image.

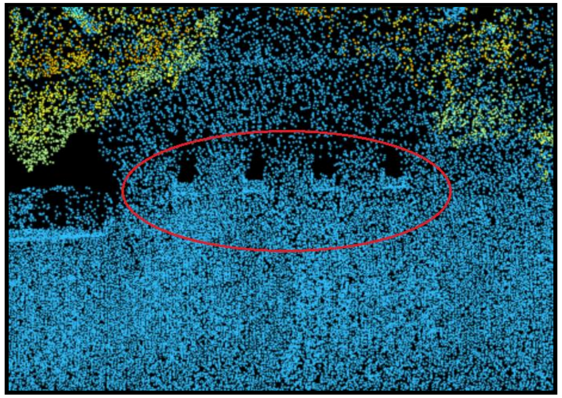
Fitting a vertical plane to the facades, computing surface normal and getting the maximum height of the vertical planar segments are the checks that might be used to help distinguish the building.

*Google, "Streetview," digital images, *Google Maps* (http://maps.google.com), taken February 2018.

BIN



Bin point in map overlaid on 2D LiDAR data



3D LiDAR visualization of bin

Image of the bin points*

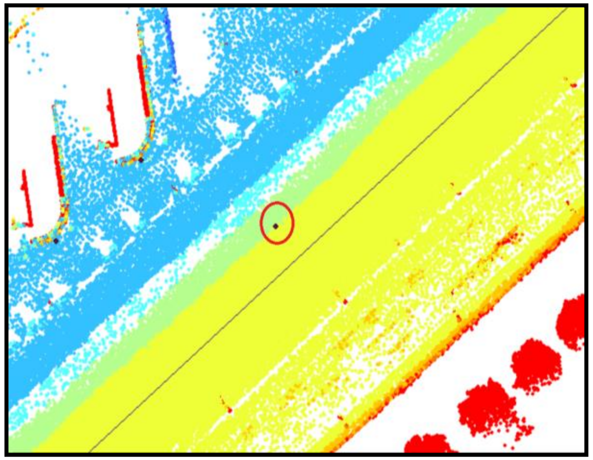
Map feature type Point

Description The bin is a point feature in the map. It is not always clearly distinguishable in the LiDAR point cloud due to its size and shape. The above screenshot shows the bin feature of a trash bin and in the MLS point cloud and in the image. The other types of bin present in the map include street side trash bin, large containers to dispose construction waste, flower bins and water bins.

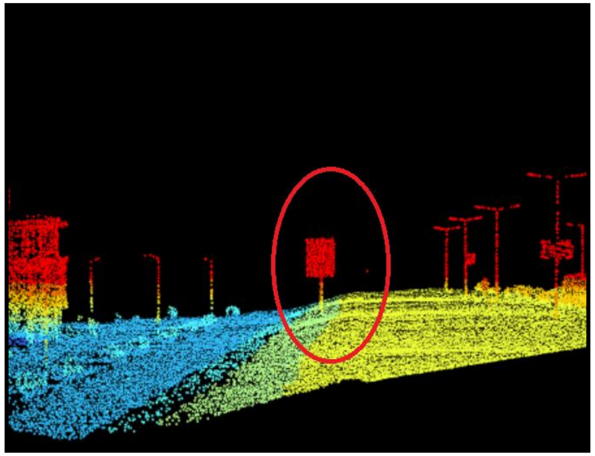
It is challenging to fit a geometry for the different types of bins. However, minimum bounding box for each bin type might be used to distinguish bins from nearby features.

*Google, "Streetview," digital images, *Google Maps* (http://maps.google.com), taken February 2018.

BOARD



Board point map overlaid on 2D LiDAR data



3D LiDAR visualization of board

Image of the board*

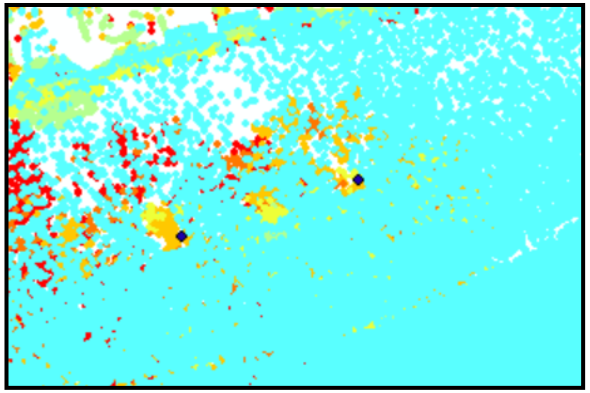
Map feature type Point

Description The board is a point feature in the map. It is clearly distinguishable in the LiDAR point cloud. The above screenshot shows the board feature in the MLS point cloud and in the image. The other types of boards present in the map include information board, street name board, billboard and traffic sign board.

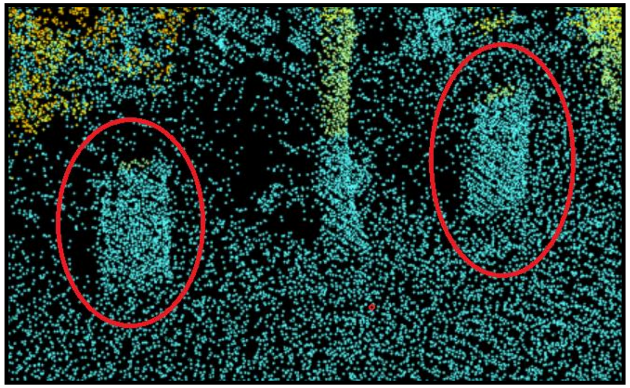
Boards usually have a single pole like object or two pole like objects that support the board. There are a lot of intra class variations in the map board object. The presence of pole like feature supporting a vertical plane might be checked for to establish the object as a board.

*Google, "Streetview," digital images, *Google Maps* (http://maps.google.com), taken February 2018.

CABINET



Cabinet points in map overlaid on 2D LiDAR data



3D LiDAR visualization of Cabinets

Image of the Cabinet point*

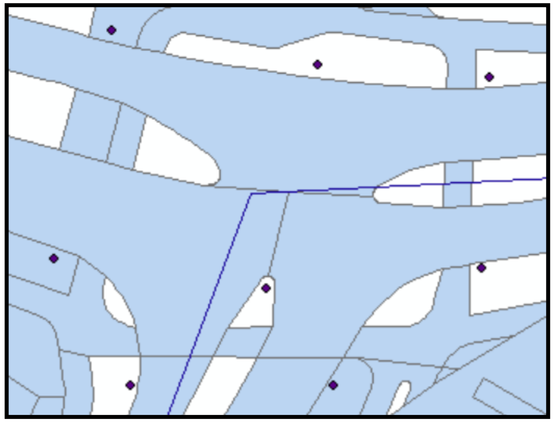
Map feature type Point

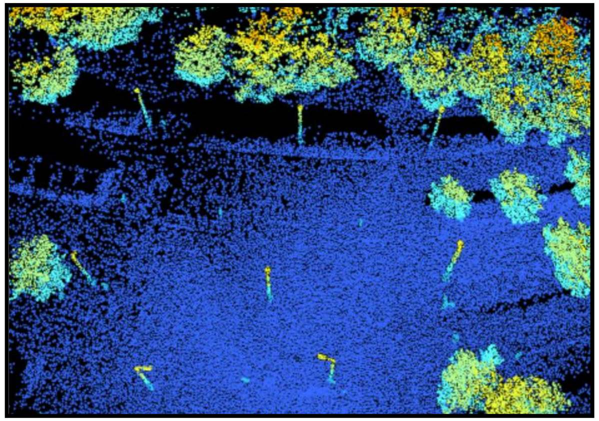
Description The cabinet is a point feature in the map. It is mostly clearly distinguishable in the LiDAR point cloud. The above screenshot shows the cabinet feature in the MLS point cloud and in the image. Cabinets are objects that house access points to public services such as electric cabinet, gas cabinet, public lighting cabinet, sewer cabinet and telephone cabinet.

Cabinets are of cuboidal shapes. The map can be used to leverage the specific type of the cabinet feature. Minimum bounding box, fitting vertical planes and height jumps might be used to distinguish them.

*Google, "Streetview," digital images, *Google Maps* (http://maps.google.com), taken February 2018.

POLE





Pole points in map overlaid on 2D LiDAR data

3D LiDAR visualization of Poles

Image of the Poles*

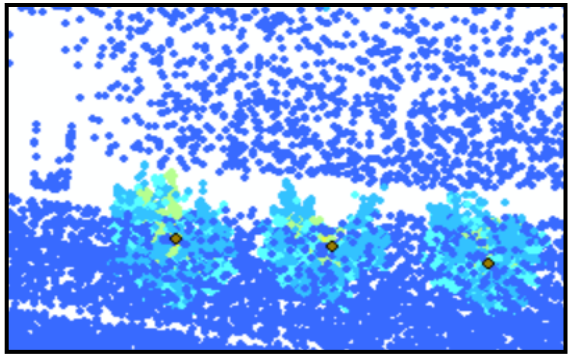
Map feature type Point

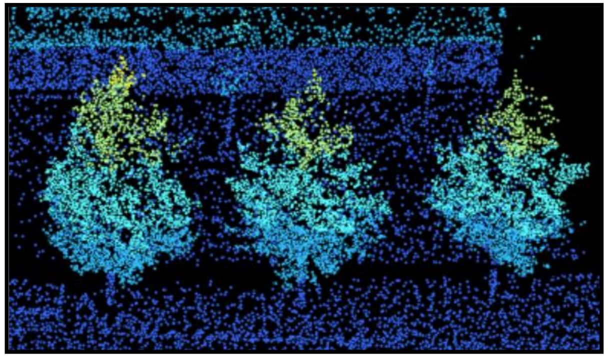
Description The pole is a point feature in the map. It is clearly distinguishable in the LiDAR point cloud. The above screenshot shows the pole feature in the MLS point cloud and in the image. There are different types of poles in the map such as light pole, traffic light pole, flag poles and poles at start and end of pedestrian areas (called stop poles).

A number of pole detection algorithms are researched upon. Poles can be identified also by height and bounding box parameters.

*Google, "Streetview," digital images, *Google Maps* (http://maps.google.com), taken February 2018.

TREE





Tree points in map overlaid on 2D LiDAR data

3D LiDAR visualization of trees

Image of the tree point*

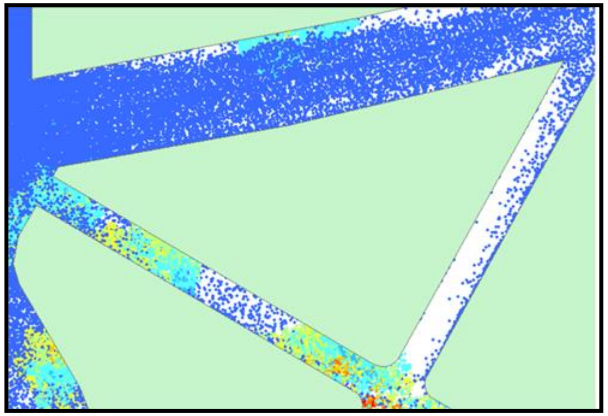
Map feature type Point

Description The tree is a point feature in the map. It is mostly distinguishable in the LiDAR point cloud. The above screenshot shows the tree feature in the MLS point cloud and in the image.

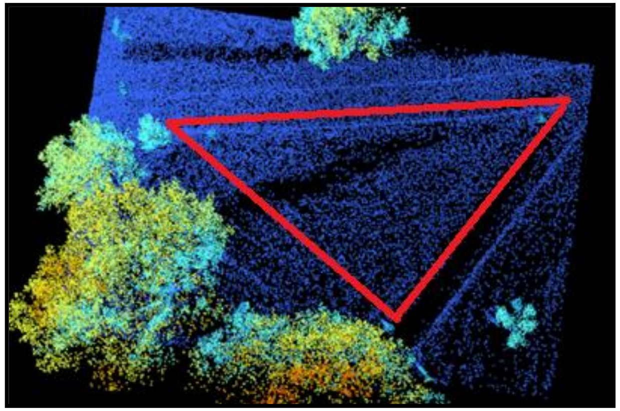
Trees are one of the challenging objects to clearly distinguish owing to their irregular shape. Trees that are far apart can be easily distinguished however, tress close together are not that easy to distinguish. The methodology suggested in this research identifies individual tree barks and performs a region growing from that seed point. Other features such as surface normals and point density can be used to distinguish trees.

*Google, "Streetview," digital images, *Google Maps* (http://maps.google.com), taken February 2018.

VEGETATED AREA



Vegetated area polygon in map overlaid on 2D LiDAR data



3D LiDAR visualization of vegetated area

Image of the vegetated area polygon*

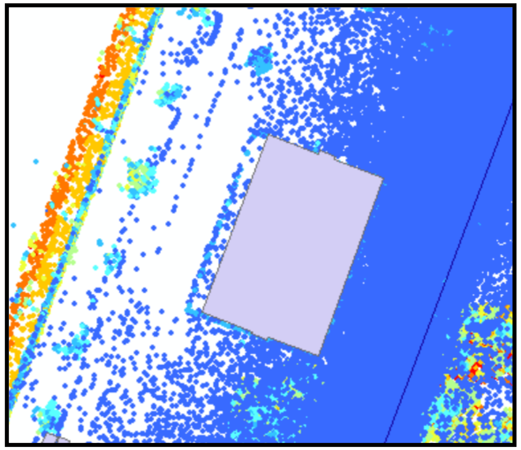
Map feature type Polygon

Description The vegetated area is a polygon feature in the map. It is not distinguishable in the LiDAR point cloud. The above screenshot shows the vegetated area feature in the MLS point cloud and in the image. The red triangle is an approximation of the LiDAR points belonging to the vegetated area. The vegetated areas are distinguished into classes such as bushes, grass and forest plantation depending on the type of vegetation in these polygons.

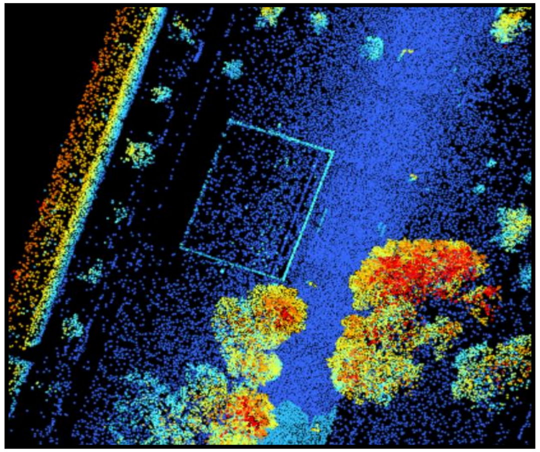
The map information can be leveraged to set a height check for the LiDAR points belonging to vegetated areas.

*Google, "Streetview," digital images, *Google Maps* (http://maps.google.com), taken February 2018.

BARE GROUND



Bare ground polygon in map overlaid on 2D LiDAR data



3D LiDAR visualization of bare ground

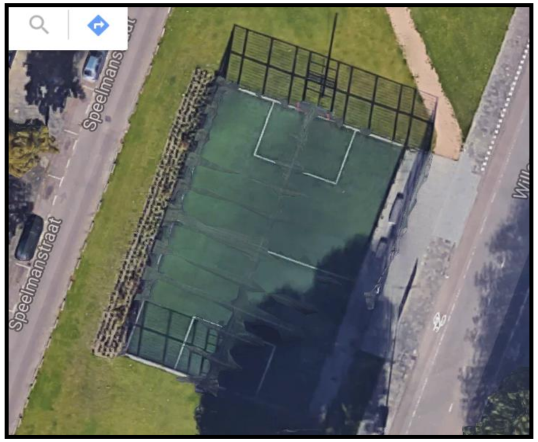


Image of the bare ground point*

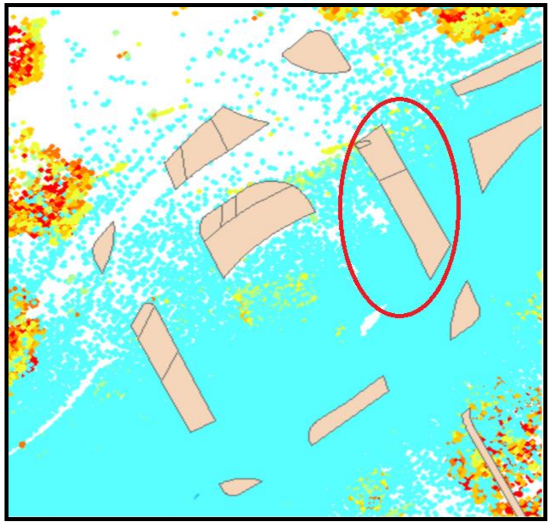
Map feature type Polygon

Description The bare ground is a polygon feature in the map. It is not distinguishable in the LiDAR point cloud. The above screenshot shows the bare ground feature in the MLS point cloud and in the image. The screenshot shown here is that of a tennis court and can be approximately distinguished in the LiDAR points. The bare ground has classes such as courtyard, concrete and sand.

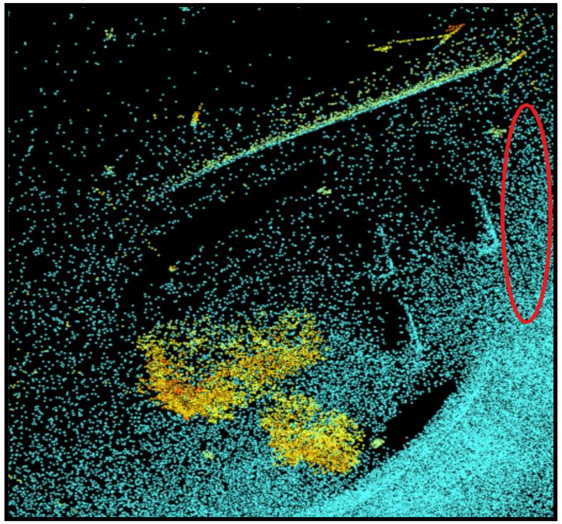
The bare ground features must contain points only at the ground level. Hence, the height attribute can be used to distinguish this object. In cases of its proximity to other features at ground level such as road, it remains quite challenging to distinguish the same. Other point cloud attributes such as intensity can also be used for distinguishing these features.

*Google, "Streetview," digital images, *Google Maps* (http://maps.google.com), taken February 2018.

ROAD SUPPORT PART



Road support parts in map overlaid on 2D LiDAR data



3D LiDAR visualization of road support part

Image of the road support areas*

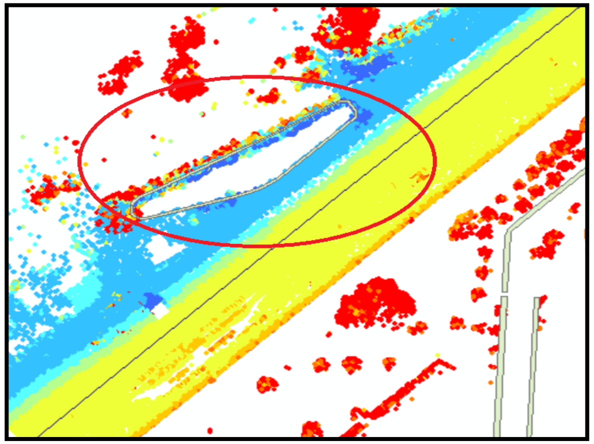
Map feature type Polygon

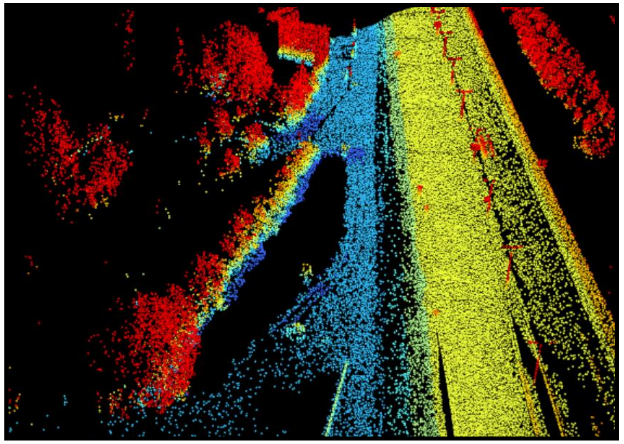
Description The road support is a polygon feature in the map. It is not distinguishable in the LiDAR point cloud. The above screenshot shows the approximation of the road support feature in the MLS point cloud and the feature in the image. The screenshot shown here is that of a road dividers and they cannot be distinguished in the LiDAR points.

The road support features must contain points only at the ground level and just above ground level. Hence, the height attribute can be used to distinguish this object. In cases of its proximity to other features at ground level such as road, the height jump can be used to distinguish the same.

*Google, "Streetview," digital images, *Google Maps* (http://maps.google.com), taken February 2018.

WATER SUPPORT PART





Water support polygon in map overlaid on 2D LiDAR data

3D LiDAR visualization of Water support polygon

Image of the Water support area*

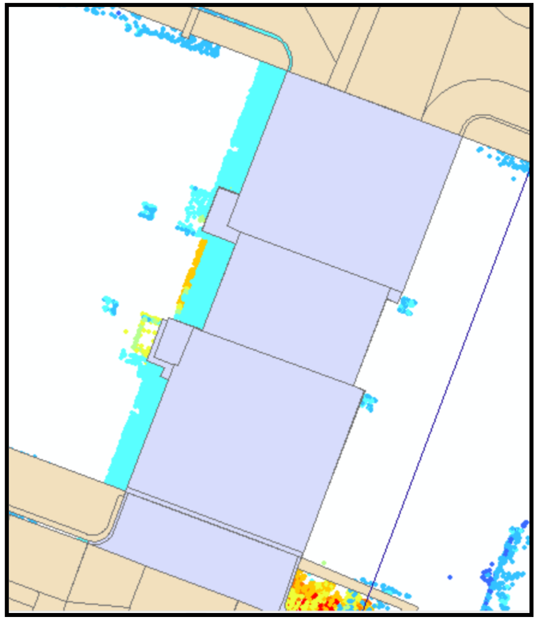
Map feature type Polygon

Description The water support is a polygon feature in the map. It is not distinguishable in the LiDAR point cloud. The above screenshot shows the approximation of the water support feature in the MLS point cloud and the feature in the image. The screenshot shown here is that of a manmade structure at the edge of the water body. It is also not distinguishable in the image.

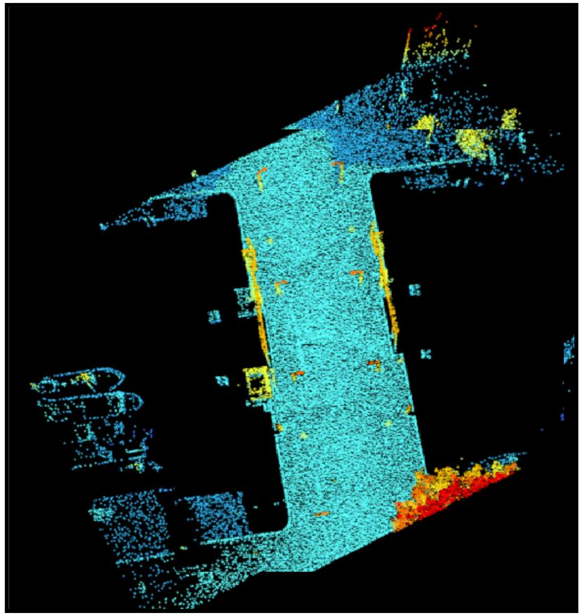
The water support features are complex to ascertain. These features might be distinguished with the help of a map by testing its proximity to water features and height attribute.

*Google, "Streetview," digital images, *Google Maps* (http://maps.google.com), taken February 2018.

BRIDGE



Bridge points in map overlaid on 2D LiDAR data



3D LiDAR visualization of Bridge

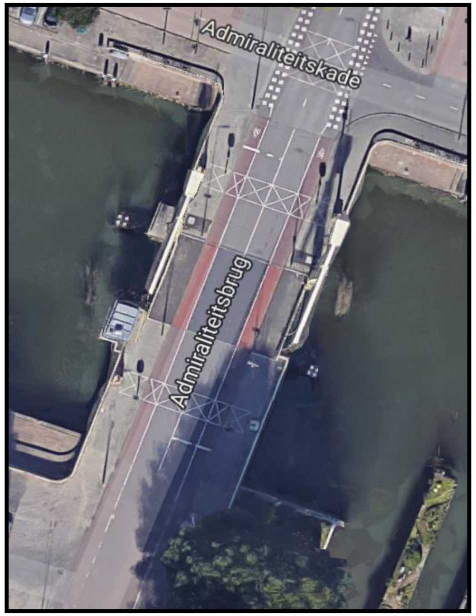


Image of the Bridge*

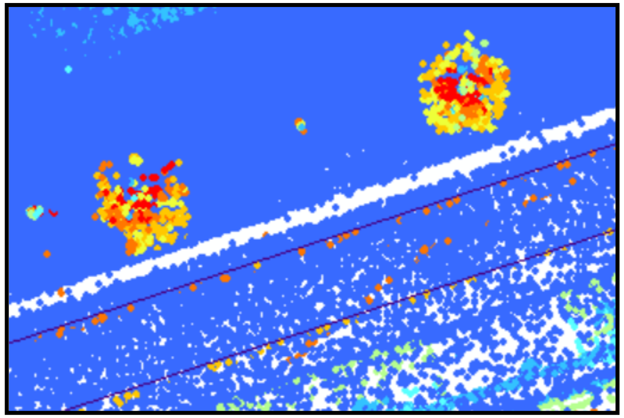
Map feature type Polygon

Description The bridge is a polygon feature in the map. It is not distinguishable in the LiDAR point cloud. The above screenshot shows the approximation of the bridge feature in the MLS point cloud and the feature in the image. Bridges are sometimes part of the road features as shown in the image above.

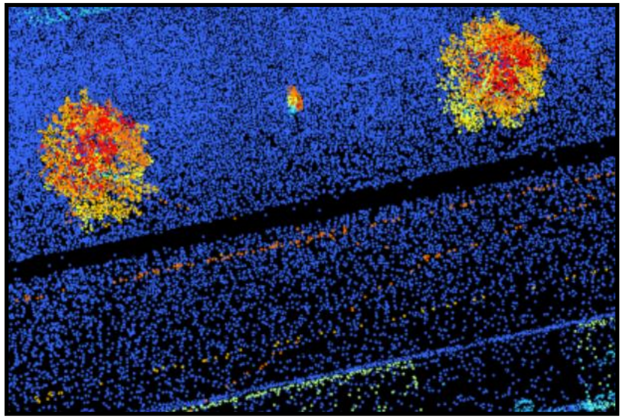
The bridges can be identified by fitting planar surfaces. The information from the relative height attribute in the map can be leveraged to ascertain if the bridge is at ground level or higher. For higher bridges, the presence of empty space underneath the bridge points can be ascertained. For a bridge at ground level, the height jump with its nearby ground features can be check for.

*Google, "Streetview," digital images, *Google Maps* (http://maps.google.com), taken February 2018.

RAILWAY



Railway line in map overlaid on 2D LiDAR data



3D LiDAR visualization of railway points

Image of the railway line*

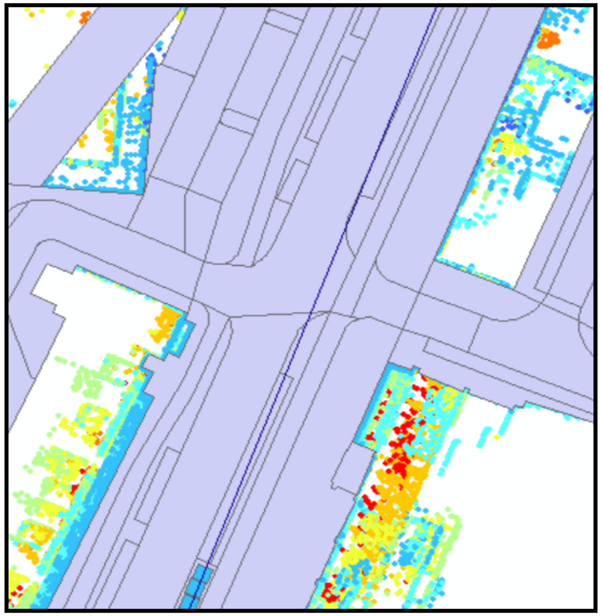
Map feature type Polyline

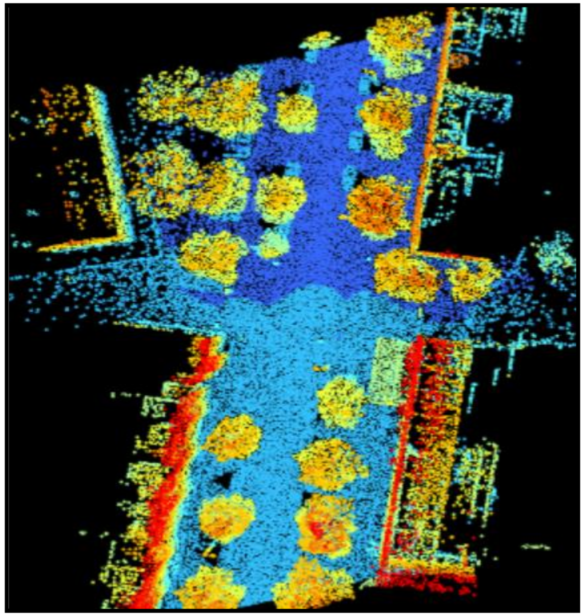
Description The railway is a polyline feature in the map. It is not distinguishable in the LiDAR point cloud. The above screenshot shows the approximation of the railway line feature in the MLS point cloud and the feature in the image. The map contains information about the railway line such as tram line, fast tram line and train line.

The polyline features are buffered to convert it to a polygon object. The buffer width is set based on the object type. Here, the gauge width for the trains and trams in the Netherlands can be used to set the width. Height jumps can be checked to distinguish the rail track from its nearby ground level features.

*Google, "Streetview," digital images, *Google Maps* (http://maps.google.com), taken February 2018.

ROAD





Road polygon in map overlaid on 2D LiDAR data

3D LiDAR visualization of road

Image of the road feature*

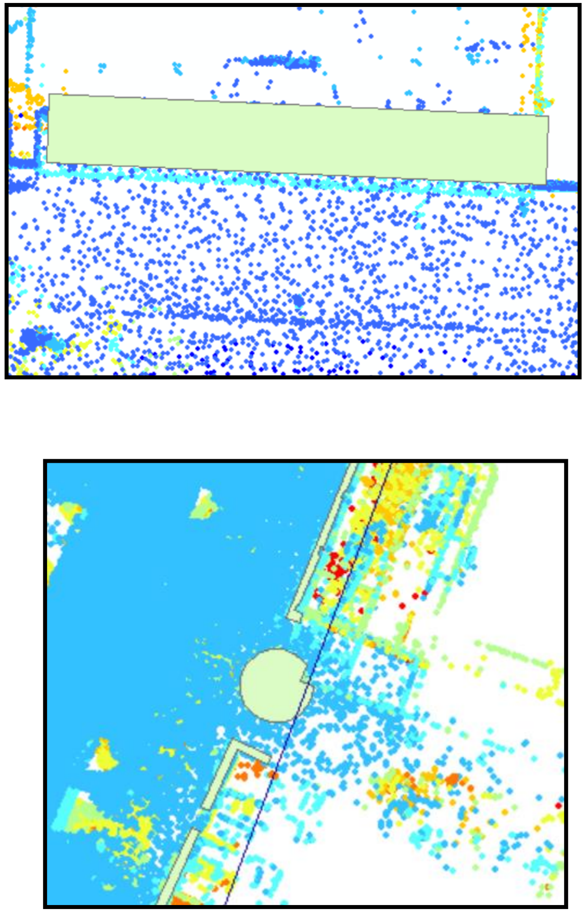
Map feature type Polygon

Description The road is a polygon feature in the map. It is not distinguishable in the LiDAR point cloud. The above screenshot shows the approximation of the road feature in the MLS point cloud and the feature in the image. The road features have many classes such as cycle path, motorway, secondary roads, driveways, footpaths and bus lanes

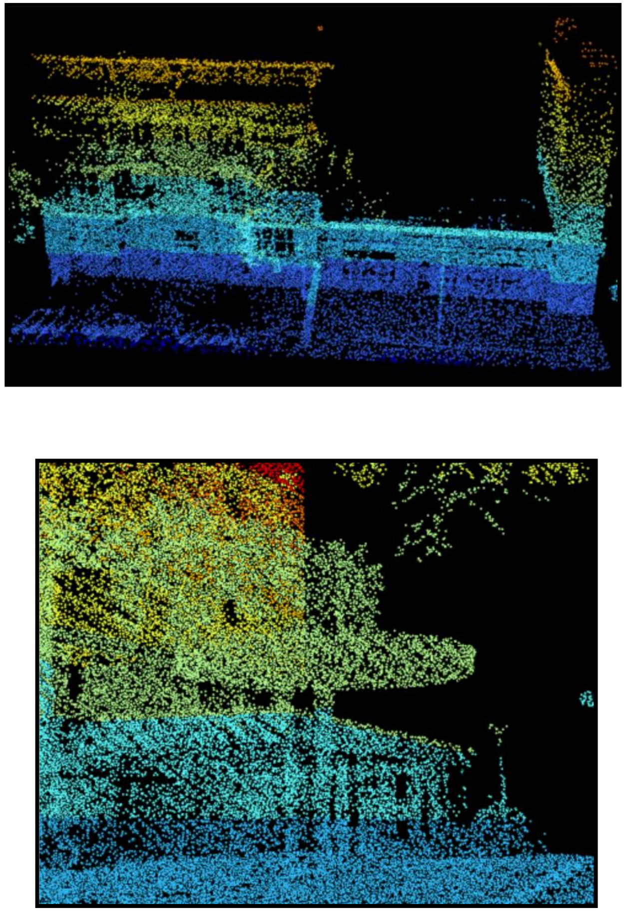
The road features are mostly at ground level. In case of fly-overs, the relative height attribute from the map can be used to identify them. For ground features, they might be distinguished with the planar surfaces and height jump at the edges.

*Google, "Streetview," digital images, *Google Maps* (http://maps.google.com), taken February 2018.

BUILDING INSTALLATION



Building Installation polygon in map overlaid on 2D LiDAR data



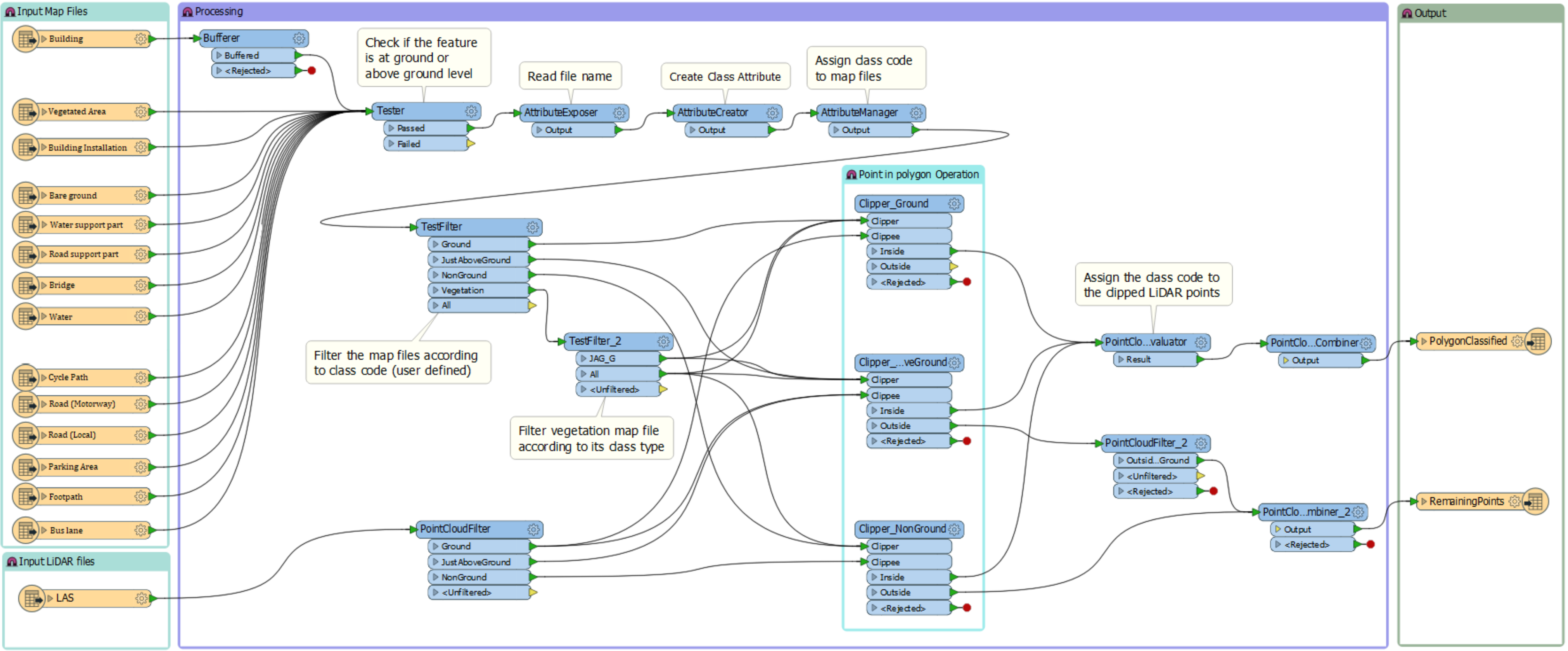
3D LiDAR visualization of Building Installation

Image of the Building Installation polygon*

Map feature type	Polygon
Description	The building installation is a polygon feature in the map. It is not always clearly distinguishable in the LiDAR point cloud. The above screenshot shows the building installation feature in the MLS point cloud and in the image. Building installations are normally awnings (as shown in the first row) or staircases in front of the building. The properties to distinguish building installation features can be quite complex. The map can be used to leverage the specific type of the building installation feature to check for planarity and height jumps.

*Google, "Streetview," digital images, *Google Maps* (http://maps.google.com), taken February 2018.

APPENDIX II: POLYGON MATCHING WORKFLOW



APPENDIX III: POINT MATCHING WORKFLOW