Automated Inventory of Overhead Assets on Highways using Mobile LiDAR Data

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Abstract:

Assessment of vertical clearance on highways is an integral step to ensuring that design standards are met throughout the service life of the highway. The assessment enables timely intervention, in case clearance requirements are not met, thereby extending the service life of structures and avoiding prohibitive maintenance costs due to damage which could occur to those overhead objects in case of collisions. That being said, before clearance can be assessed at overhead objects, these objects must first be detected, inventoried and classified. Unfortunately, manual procedures to collect such information on highways are unsafe, time consuming, labour intensive and, in some cases, impractical. This is particularly true when information is required on a network-level. This paper proposes a novel technique by which overhead objects could be automatically detected, classified and inventoried using mobile LiDAR data. Moreover, the proposed algorithm also provides an estimate of the clearance at those objects. The technique involves defining the road trajectory of the highway and then using search algorithms to detect overhead structures. Further, the algorithm employs clustering tools to classify the detected structures into different objects (eg: bridges vs power lines). The algorithm also yields an estimate of the clearance all detected overhead objects. The algorithm is tested on two different highway segments at the province of Alberta and was successful in detecting all overhead structures on those highways, and in providing a decent estimate of the clearance at all those structures.

1. Introduction

Network-level assessment of vertical clearance, particularly at bridges, is an essential step to effectively manage existing highway infrastructure. In bridge inspection and asset management programs, departments of transport (DOT) must keep inventory of all bridges on highways. Vertical clearance information at bridges is then obtained as part of the bridge assessment process to ensure minimum clearance requirements are met. In fact, clearance assessment must be conducted periodically, since structural degradation might cause changes to minimum clearance.

Identifying deficiencies in structures such as bridges in time to undertake proactive maintenance action is also a critical step to an efficient bridge management program. This involves identifying problems and performing preventive maintenance before structural damage is irreversible and before safety problems arise. If properly implemented, such procedures could help extend the service life of existing highway assets. In contrast, if changes in minimum clearance are not addressed, they could result in substantial losses to DOTs.

Unfortunately, in current surveying practice inventorying overhead objects and conducting clearance assessment is a time consuming, labour intensive and financially demanding exercise. This means that network-level assessments of all structures is impractical, particularly in places like Alberta where a large highway network exists with approximately 4,500 bridges (Alberta Transportation 2016). In order to manage infrastructure on a network of this size, road authorities often set priorities in their infrastructure management programs. Although all provincial structures require inspection, frequency of inspections may vary depending on class of highway and the condition of the structure.

Considering the fact that around 40% of the bridges currently in use in Canada were built over 50 years ago (Hammad *et al.* 2007), it is obvious that a significant number of these structures are approaching critical conditions and require strengthening, rehabilitation, or replacement. However, given the limitations of existing data collection techniques and the limited maintenance budgets due to high transportation infrastructure deficits(Mullin 2014), assessing clearances on all those structures and taking proactive action to address any deficiencies is not feasible.

To overcome such issues and facilitate more effective assessment of vertical clearances, DOTs have been considering using technology for such assessment. This includes attempts to use digital rods and static Light Detection and Ranging (LiDAR) equipment to obtain clearance measurements (Liu *et al.* 2012). Although such techniques increase the accuracy of the measurements by minimizing human error, road closure are still required to perform such assessments, hence, they are still time consuming.

This paper proposes a novel algorithm by which overhead assets on a highway could be automatically detected, inventoried, and classified using mobile LiDAR data. Moreover, the algorithm also provides an estimate of the clearance at those objects. Mobile LiDAR data consists of closely spaced points collected through mobile laser scanning (MLS) of highways. In MLS scanning equipment is mounted on a vehicle which collects data while travelling at highway speeds. This causes minimal disruption to traffic and increases the efficiency of the data collection process. The data is collected through sensors reflecting light beams off objects. Using information on reflection time and energy, intensity and positional information of points can be computed. The scanning process creates a 360^0-virtual point cloud data of the highway such as that seen in Figure 1. Such data can be used to extract traffic sign inventory and lane markings (Guan *et al.* 2014, Ai and Tsai 2016, Soilán *et al.* 2016, Gargoum *et al.* 2017) as well as several geometric features of highways (Park *et al.* 2007, Kumar *et al.* 2013, Holgado-Barco *et al.* 2015, Holgado-Barco *et al.* 2017). MLS has also been used in sight distance assessments (Castro *et al.* 2011). MLS provides a high level of detailed data which makes it the most common approach to collect LiDAR data for transportation applications (Williams *et al.* 2013).

The algorithm proposed in this paper involves fully automated detection of overhead objects on a highway segment and provides a rough estimate of clearance information for each object. The accuracy and repeatability of the algorithms was tested on two different highway segments. Testing revealed that the algorithm was successful in detecting and classifying all overhead structures, including bridges, moreover, the algorithm was also able to provide satisfactory estimates of clearance. The simplicity of the extraction procedure makes accurate information readily available to highway agencies issuing overheight permits. Furthermore, the availability of network-level information on overhead assets could also help in more efficient re-routing of vehicles which exceed clearance requirements.

2. Previous Work

Various techniques have been used to conduct vertical clearance assessments on highways. Although some municipalities still use manual methods, such as theodolites and total stations, other digitized devices have recently been adopted. For instance, many DOTs use digital measuring rods and electronic measuring devices (Alberta

Transportation 2014), similarly, clearance assessment using photolog data has also been previously attempted (Lauzon 2000).

Terrestrial LiDAR scanning is another technique which has been used to assess clearance. The aim here is to minimize human error associated with conventional surveying tools. In a paper by Liu *et al.* (2012), static terrestrial LiDAR scans of a bridge deck and the ground points beneath the deck were used to assess vertical clearance. The authors developed an algorithm where scanned ground points are automatically matched to bridge deck points which fall within a certain margin of the vertical plane, perpendicular to the ground surface. The algorithm loops through all points until all points on the ground surface are matched to points on the bridge deck. Despite their potential in increasing the accuracy of clearance measurements, the static nature of such tools means that disruptions to traffic and safety concerns still exist. Moreover, network level analysis is not possible since conducting site visits and scanning each bridge individually is still required.

In a recent paper, Puente *et al.* (2016), used mobile LiDAR data in the assessment of vertical clearance in tunnels. The authors propose a semi-automated algorithm where cross sections of the tunnel are first extracted and then used to measure clearance. The method involves using lane markings to define the edges of the travel lanes at which the clearance must be evaluated. The edges are then matched with the points at the roof of the tunnel. The results revealed a maximum relative error between ground truth and detected clearance of 1% for most cross sections. However, the algorithm was only used to assess a portion of the point cloud data available with the authors citing loading time as the main reason why the full point cloud was not used. Although out of the scope of this paper, it is worth noting that a few studies have attempted utilizing LiDAR point cloud data for structural assessment of bridges, see, for example, (Bian *et al.* 2012, Chen *et al.* 2014, Guldur and Hajjar 2014, Jafari *et al.* 2016).

In summary, not many studies have attempted measuring vertical clearance of bridges using mobile LiDAR data. In fact, to the best of the authors' knowledge, no studies to date have attempted the automated detection of bridges on highways. Moreover, previous research seems limited to using LiDAR data in assessing clearance of bridges only with no attention given to other overhead objects such as the power lines and overhead signs. In an attempt to address those limitations, this paper develops an automated algorithm which can detect, classify and provide a clearance estimate for all overhead objects on a highway using mobile LiDAR data.

3. Extraction Procedure

The algorithm proposed in this paper works on detecting overhead structures and providing an estimate of their clearance. This is essential when network-level assessment of vertical clearance is desired or when agencies are interested in inventorying overhead structures that exist on a certain highway. The aim is to minimize the need for user input and provide end-users with a tool where they can import the data for a highway segment and automatically detect locations where overhead structures exist, classify them and obtain an estimate of their clearance. The next few paragraphs provide a description of the steps required to extract the information.

3.1.1 Trajectory Definition

The first step of the detection process involves defining points parallel to the roads centreline which trace the roads trajectory and cover the entire road segment. These could be GPS points collected in a separate survey or points representing the centreline of the highway. In case of this study, the set of points tracing the path of the data collection truck were used. These points were obtained by filtering the LiDAR point cloud based on the scanner angle in MATLAB.

3.1.2 Non-ground point extraction

Once the trajectory points were defined, the next step is to filter out the non-ground points from the LiDAR road segment. For this step the LiDAR point cloud data is imported into ArcGIS and classified to ground and non-ground points. The ground points are then omitted leaving the user with non-ground data only.

3.1.3 Object detection

The third and final stage of the detection process involves matching the trajectory data with the non-ground points to locate the overhead structures. At every point along the defined trajectory, the K-Nearest Neighbor search algorithm (Altman 1992) was employed to search for overhead structures within a frame of certain dimensions around the trajectory point. As displayed in Figure 2, the aim here is to search the nearest overhead point to the trajectory point on the ground. The MATLAB algorithm loops through all trajectory points (black pins shown in Figure 2) and returns a list of points for which an overhead match was found. For instance, for the first two frames in Figure 2, no overhead points exist above the trajectory points, therefore, no overhead object is detected. However, for the third frame overhead points do exist and hence, the code detects that this is a location where an overhead structure does exist.

For points where a match is detected, the algorithm also returns a clearance measurement at the point of detection. Although this measurement does not cover the entire span of the overhead object, it gives the user an estimate of the vertical clearance of the object in question. Moreover, this measurement eliminates the likelihood of human error associated with traditional surveying practice, thus, resulting in a more accurate measurement.

3.1.4 Clustering

To identify the number of overhead structures determined on a particular segment, trajectory points along the roads surface for which a match was found are clustered. In this study, the DBSCAN (Density-Based Spatial Clustering of Applications with Noise) clustering algorithm was used (Ester *et al.* 1996). The DBSCAN algorithm is a density based algorithm that works by regrouping points based on proximity (ε) and hit count. The proximity measure defines how close multiple points within a cluster are to one another. Hit count is a measure of the number of points within a certain cluster. If points are further away from one another or if only few points are within close proximity, it is likely that these points do not represent a cluster.

Clustering identifies groups of points which are potential candidates for being a cluster or, in this case, an overhead object. This is done by defining certain thresholds for the proximity and the hit count variables. In this paper a hit count of 4 and an Ɛ of 1m were used. Once objects are classified into different clusters, the number of points per cluster are used to classify clusters into different objects (above average points per cluster means the cluster is a bridge)

4. Case Study

The LiDAR data used in this study was collected by Alberta Transportation (AT) using REIGL VMX 450 laser scanning system, the system is mounted of a data collection vehicle which travels along highways of interest. Surveys are conducted within normal traffic flows at speeds of up to 100 km/h, at a rate of 1.1million points per second. Data collected along a given highway is processed and saved in multiple LAS files. The data considered in this paper was collected on the two different highways.

The developed algorithm was tested on two highways at the Province of Alberta, Canada. The segments were both 4km divided segments which included a variety of overhead structures including bridges and cables. The segments had differing levels of vegetation and tree density as well as different horizontal and vertical alignments. The segment of Highway 1 analysed (Figure 3a) is located west of the city of Calgary, while the Highway 14 segment (Figure 3b) is located southeast of the city of Edmonton.

5. Results and Discussion

5.1 Overhead Object Detection and Classification

Figure 4 shows the results of the overhead structure detection performed on both Highways. For each highway, two different figures are displayed. Figure 4a represents a plot of the detected clusters and Figure 4b represents a plan view of the LiDAR data. The horizontal axis on the plots represents the UTM easting coordinates while the vertical axis represents the UTM northings coordinates. Each diamond on the plots represents a cluster of points which, in turn, represent an overhead object. For clusters where the hit count was large relative to other clusters on the segment (i.e. hit count > mean hit count on the segment), the cluster is classified as a bridge otherwise the object is a cable. If the cluster on Figure 4a are traced down to Figures 4b the overhead object can be seen on the plan view of the LiDAR highway.

Tables 1 and 2 show the overhead structure detection results for highways 1 and 14, respectively. For each clusters, the tables show the cluster ID, the overhead object each cluster represents, the coordinates of the object, the minimum elevation and the points per cluster.

On the analyzed segment of Highway 1, two bridges and two powerlines were detected. On Highway 14, seven different objects were detected including two pairs of bridges, two powerlines and a false positive.

As expected the density of points in each cluster are higher for bridges due to the lateral span on those structures. In case of the false positive on Highway 14, the cluster for this object included 4 points. Although this satisfies the threshold for the minimum points per cluster set in DBSCAN clustering algorithm, it is not a true object. While reducing the threshold to 3 points will remove the false positive, it would also remove the cable represented by cluster 7. However, since the primary aim of the analysis is to detect bridge structures this is not a major issue.

5.2 Clearance Estimate

The clearances estimated in the detection process are presented in Tables 1 and 2. For Highway 1, the minimum bridge clearance based on the detection results is 5.57 meters and 5.63 meters for bridges A and B, respectively. On Highway 14, the minimum clearance was 5.77 meters and 5.86 meters for Bridges A1 and A2 and 6.66 meters and 6.04 meters for the two bridges B1 and B2.

The posted minimum clearance at the analyzed bridges, as shown in Table 3 ranges from 5.2 meters to 6.5 meters. It is worth noting here that AT require that the posted minimum clearance is 0.1-m less than the minimum height measured between the lowest point on the overhead structure and the surface of the roadway. After subtracting the 0.1-m tolerance, the number is also rounded down to the nearest 0.1-m. This means that if the minimum clearance measured at a bridge is 5.32 meters, the posted minimum clearance beneath the bridge should be 5.2m. Comparing the posted minimum clearance to that obtained from the detection, the results reveal that the percentage difference ranges from 0.47% to 4% with an average difference of 1.68% for all bridges. These results indicate that, in addition to the capabilities of the proposed algorithm to detect, classify and inventory overhead objects, the algorithm is also effective in providing a decent estimate of clearance at those objects.

It is worth noting here that, based on the clearance estimates, the posted clearance values are conservative except in the case of Highway 14 Bridge A2. In case of this bridge the clearance is less than that posted by 60cm.

With regards to the power lines, the minimum clearances are also summarized in Tables 1 and 2. Clearance information about those objects is not known and not posted, however, clearance at those objects typically ranges from 6 meters to 20 meters depending on the voltage being carried in the cable (OPSD, 2011).

5.3 Value of Proposed Algorithm

Although the difference between the estimate and posted clearance on Highway 14 Bridge A2 might not seem significant, it shows that DOTs must be extra-cautions when posting minimum clearance signs. This finding also demonstrates the importance of performing a detailed clearance assessment before posting signs. Considering the height of trucks (figure 5), a difference of 60cm in the posted clearance might be the difference between a truck driving smoothly beneath a bridge and a collision costing hundreds of thousands of dollars in repair.

The assessment also shows that DOT's might need to revise the margin of error used when posting minimum clearance signs. In Alberta, a 10cm factor of safety is used when posting a minimum clearance. Depending on the measurement tool used to assess clearance, it might be safer for agencies, particularly those using manual clearance assessment tools, to increase their margin of safety when posting signs because it is highly likely that the clearance was not assessed at the 'true' minimum location. While the estimate obtained from the proposed algorithm is satisfactory, performing a detailed clearance assessment where multiple points across the span of each bridge is performed using LiDAR is still necessary and could be explored in future research.

The value of the algorithm in identifying the absolute minimum clearance at bridges makes accurate information readily available to highway agencies responsible for issuing overheight permits. In many parts across Canada permits are mandatory when height of a vehicle or load exceeds 4.15 m (Ontario MOT 2009, Manitoba Infrastructure 2017).

Despite DOT issuing permits, the risk of damage to overhead objects still exists due to potential inaccuracies in measurements. Therefore, permit holders are asked to accept responsibility for any and all damage that may be caused (Ontario MOT 2009).

The proposed algorithm could also reduce processing times required to issue permits. Processing times usually vary with the variation of the permit type and the issuing agency. In Ontario, for instance, permits can be Annual, Project, Single Trip and Special Vehicle Configuration with processing times for Annual permit reaching up to 15 business days (Ontario MOT 2009). Using a more efficient vertical clearance assessment procedure might reduce those times significantly. The availability of network-level information on clearances could also help in more efficient re-routing of vehicles which exceed clearance requirements assisting in more efficient network operation and better level of service.

6. Conclusions and Recommendations

This study provides a novel algorithm which can be used to automatically detect and inventory overhead objects on a highway network using LiDAR data point cloud data. The algorithm involves automatically detecting all overhead objects on a highway and while also providing a clearance estimate at each of those objects including bridges. The algorithm was tested using data collected on two highways in Alberta, Canada. The algorithm was successful in detecting all overhead objects on both highways. This included the detection of powerline cables and bridges.

The developed algorithm is of great value for DOTs looking to automatically inventory overhead objects on an entire highway network, with minimal effort. Moreover, the algorithm also provides an estimate of clearance at those objects which can be used to ensure that those objects meet clearance requirements throughout their service life. Furthermore, the simplicity of the extraction procedure makes information typically collected in long site visits readily available to highway agencies issuing overheight permits. The availability of network-level information on overhead objects, their locations and types could also help in more efficient re-routing of vehicles which exceed clearance requirements. Bridge inspection agencies can also use the extracted information to manage their rehabilitation and maintenance programs by prioritizing structures with potential clearance problems addressing those concerns in a timely manner before irreversible damage occurs or safety problems arise. Although the proposed algorithm provides a decent estimate of clearance at overhead objects, detailed clearance assessment of objects, particularly objects of large span such as bridges, using LiDAR is an opportunity for future research. Moreover, LiDAR data can also be used to assess the structural integrity of bridges in future work.

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Table 1: Overhead Object Detection Results (Highway 1)

Cluster ID	Object	Eastings	Northings	Min Clearance	Points Per Cluster
1	Bridge A	5665281	612324.3	5.57	19
3	Cable A	5664144	613526.5	8.06	5
4	Cable B	5663579	613972.6	9.85	5
5	Bridge B	5663332	614171.5	5.63	26

Table 2: Overhead Object Detection Results (Highway 14)

Cluster ID	Object	Eastings	Northings	Min Clearance	Points Per Cluster
1	Cable	344291.6	5926148	15.80	11
2	Bridge A1	344345.6	5925679	5.77	103
3	Bridge A2	344380.2	5925623	5.86	100
4	False Positive	344820.8	5924901	6.29	4
5	Bridge B1	344869.3	5924822	6.66	107
6	Bridge B2	344895.9	5924779	6.04	117
7	Cable	346752.7	5924438	14.47	4

Table 3: Estimated Clearance

	Conventional Measure (m)		Min Clearance Estimate (m)
	Posted	Calculated	
HWY 1 Bridge A	5.3	5.4	5.57
HWY 1 Bridge B	5.3	5.4	5.63
HWY 14 Bridge A1	5.9	6	5.77
HWY 14 Bridge A2	6.5	6.6	5.86
HWY 14 Bridge B1	5.7	5.8	6.66
HWY 14 Bridge B2	5.7	5.8	6.04

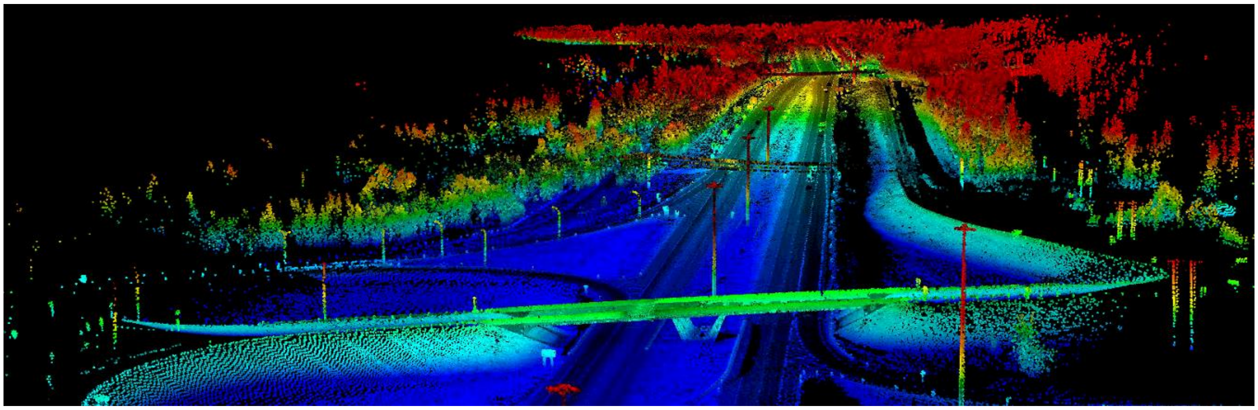


Figure 1: Point Cloud Highway

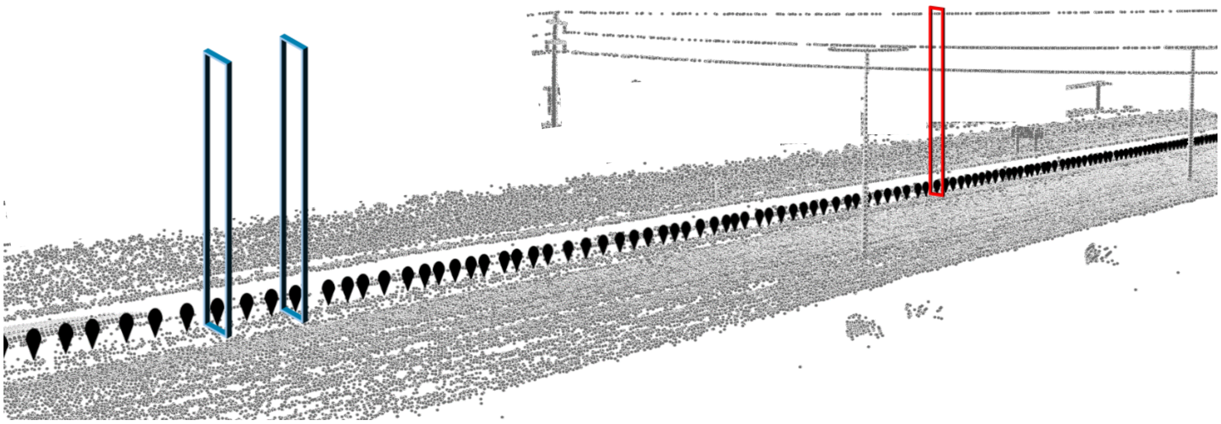
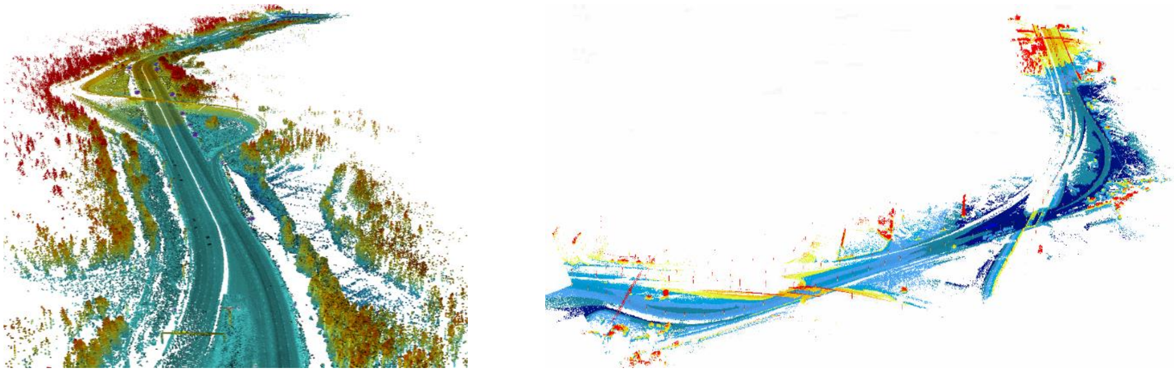
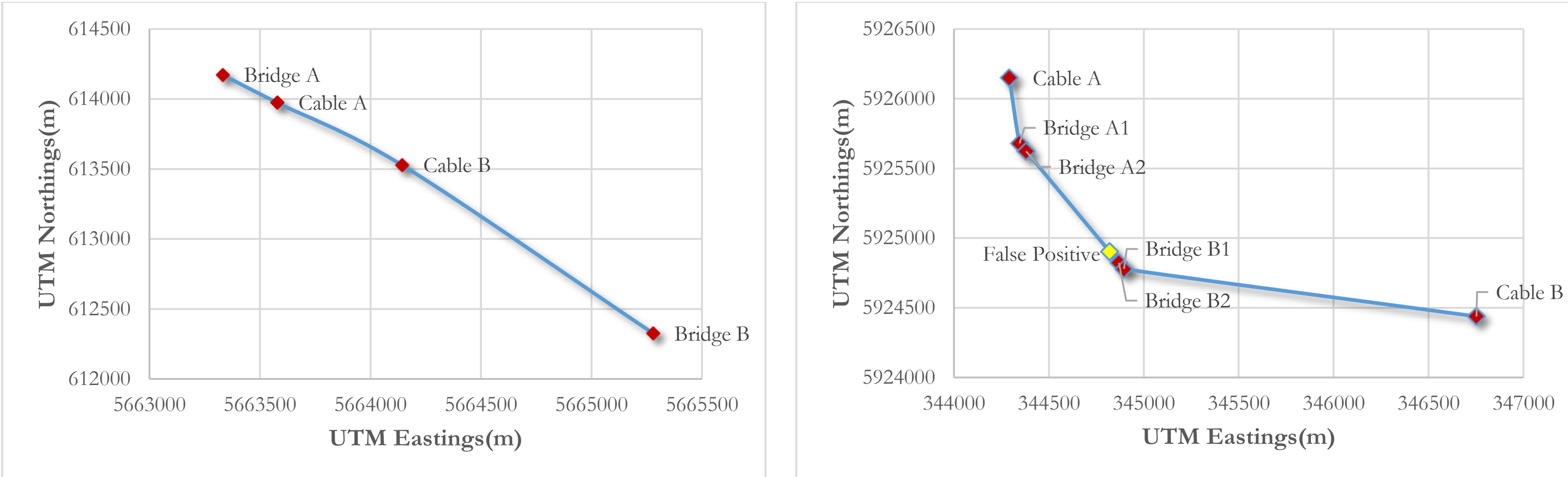


Figure 2: Overhead Object Detection

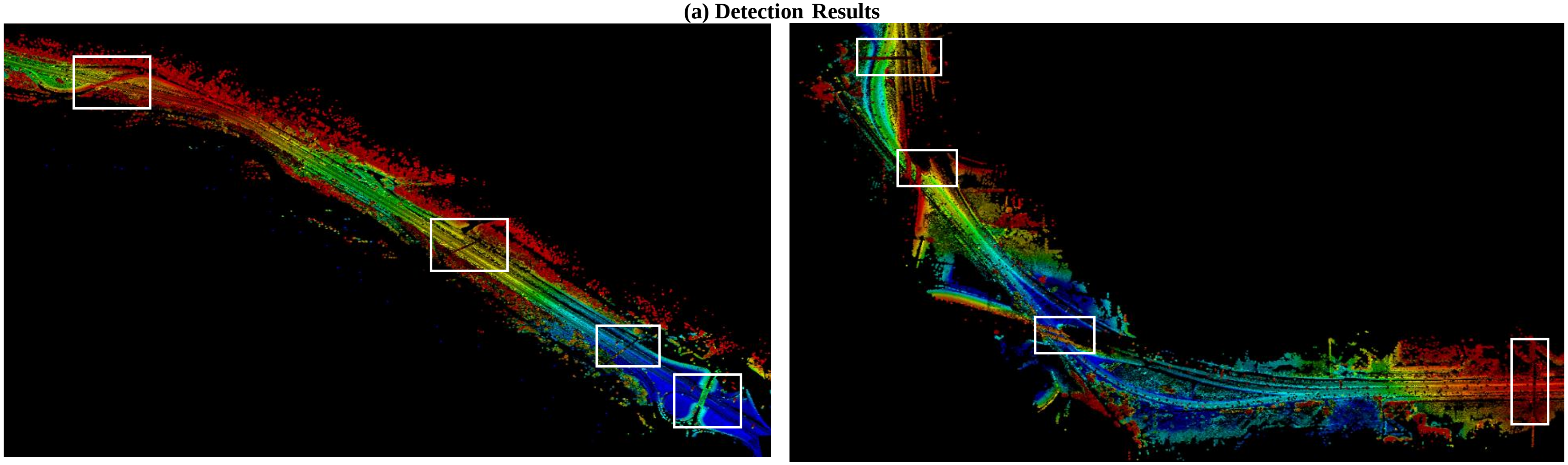


(a) Highway 1 **(b) Highway 14**

Figure 3: Point Cloud Data at Test Highways



(a) Detection Results



(b) Plan view of LiDAR segment

Figure 4: Overhead Structures Detected (Highway 1 Left, Highway 14 Right)

Figure 5: Truck Passing Beneath Bridge A (Highway 1)