AUTOMATED HIGHWAY SIGN EXTRACTION USING LIDAR DATA

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ABSTRACT

Traffic signs are an integral element of any transportation network; however, keeping records of those signs and their conditions is a tedious process, which is both time consuming and labour intensive. As a result, many agencies around the world have been working towards automating the process of sign collection. One form of automation is using remote sensing techniques to extract traffic sign information. This paper proposes an algorithm, which can be used to automatically extract traffic signs from mobile Light Detection and Ranging (LiDAR) data. The number of signs on a road segment is identified and the coordinates of those signs are used to map the data onto the road segment. The sign extraction procedure involves applying multiple filters to the point cloud data and clustering the data into traffic signs. The proposed algorithm is tested on three different highways located at different regions around the province of Alberta, Canada. The segments on which the algorithm was tested included two-lane undivided rural road and four-lane divided highways. Geometry on the different highways varied as did the vegetation and tree density. Success rates ranged from 93-to-100% with the algorithm performing better on highways where overhead signs did not exist. The results show that the proposed method is simple yet effective in collecting inventories of traffic signs at high precision rates.

KEYWORDS

Remote Sensing; Light Detection and Ranging; LiDAR data; Traffic Sign Detection Algorithms; Traffic Sign Mapping; Image Analysis; Point Cloud Data.

1. INTRODUCTION

Traffic signs represent the means of communication between road users and engineers who design roads and regulate traffic flow along those roads. Transportation Agencies around the world spend remarkable efforts in creating inventories of traffic signs along roadways (*1*). The manual process to enumerate traffic signs on roads are tedious, time consuming, and labour intensive. As a result, Departments of Transport (DOT's) around the world have, for long, considered automating the process. Many DOTs currently use video logs to collect road sign inventory data, nevertheless, those videos are often manually processed by trained individuals, which means that, although effort associated with site visits has been reduced since video log data is collected using vehicles travelling at highway speeds, the process is still inefficient and highly time consuming due to the post processing efforts required (*2*).

Many researchers have considered moving the process into full automation by using techniques that would enable automatic extraction of data off the video images. Efforts in that regard include using computer vision techniques and image processing tools which could recognize traffic signs from the video logs automatically, see, for example, (*3; 4*). While extraction is possible using those techniques, quality of some frames within the video logs is sometimes poor, significantly affecting the degree of accuracy achievable during the extraction (*5*).

The recent increase in computing power and the popularity of remote sensing techniques in transportation has led highway agencies to consider extracting road sign data from Light Detection and Ranging (LiDAR) point cloud images. In fact, with studies predicting processing time savings of up to 76% compared to conventional sign data collection techniques (*6*) and given the high accuracy of LiDAR images, many researchers have been studying means by which such data can be used in the automated traffic sign inventory extraction. This is particularly true in regions where LiDAR data is frequently collected and available.

LiDAR data could be airborne (data collected using airplanes), spaceborne (collected using satellites) or terrestrial (collected from the ground). Ground based LiDAR data can either be collected in either a static or mobile form. Mobile laser scanning is the most common approach to collect data for transportation applications due to the high level of detail provided (*7*). LiDAR data is collected through a laser reflecting light beams off objects. The light pulse emitted from the sensor is reflected back allowing the elevation and intensity information of the object to be collected and calculated. Elevation information is then matched with position information obtained using GPS sensors to identify the location of the reflected beam.

The FHWA's (Federal Highway Administration) Manual on Uniform Traffic Control Devices (MUTCD) requires that traffic signs be painted with high retro-reflective material so that they are visible to road users in poor lighting conditions when headlights of vehicles are reflected against them. These retro-reflectivity requirements mean that intensity of the signs is unique compared to other road features. Therefore, filtering out road sign information from LiDAR point cloud data is both feasible and viable options to create inventories of these signs.

In this study a technique is proposed to automatically extract traffic signs information from LiDAR images by applying multiple filters to the point cloud data. Filtered data is then clustered into sign groups with the aid of a clustering algorithm. Once that is done, coordinates of the developed clusters are plotted on Google Maps to verify the accuracy of the extracted information.

The proposed technique is tested on three different highway segments in the province of Alberta, Canada and a high degree of accuracy is achieved in all three cases. This study contributes to the existing literature in that a) it proposes a novel automated sign extraction technique which does not assume prior knowledge of sensor location or road surface elevation b) the method does not make use of LiDAR market software; c) the proposed technique is fairly simple and requires limited processing time d) traffic signs can be extracted with a high level of accuracy ranging from 93.4% to 100 % using the proposed technique.

2. PREVIOUS WORK

As already noted, there has been a recent shift towards automatic road sign extraction using LiDAR data. In one of the earliest studies to attempt such extraction, Chen et al. (*8)* used mobile LiDAR point cloud data to obtain traffic sign inventory along a 600m road segment in Chicago. The technique used in the study involved filtering the data based on a user defined distance from the sensor, a certain sensor angle interval and intensity. Data clustering was then performed through which points were placed into a grid, and a threshold was defined to keep grids that a higher point density only before geometric filtering was applied. Although the study claims to have produced satisfactory results, no information is provided about the percentage of signs accurately extracted.

In a more recent study, Vu et al. (*9)*, attempted real time identification and classification of traffic sign (i.e. detection and classification occurs while the probe vehicle travels along the road collecting LiDAR data). The authors used onboard sensors including a sensor platform equipped with GPS/IMU, 3D LIDAR, and a vision sensor. Data points were first filtered by intensity using a virtual scan image and the range is checked between each high intensity plane and only planes of a spacing of more than 1m are retained. Principle Component Analysis (PCA) was then used to determine alignment of planes, and only planes aligned along the road are retained. The main limitation of this study was that the extraction procedure was only applied on a test track; hence, its performance in a dynamic environment is unknown. Real time traffic sign detection was also attempted (*10*). LIDAR point cloud data was converted to camera coordinates and the regions of interest were then identified and classified using colour characteristics of the images. Success rates ranging from 84 to 96% were reported depending on whether the sign was in the range of the data collection vehicle.

Weng et al. (*11)* used mobile LIDAR data collected on Huandao road in Xiamen, China to detect and classify traffic signs. Approximately 6.7 million points were collected and a C++ algorithm was used to detect signs. The detection phase involved filtering by intensity, hit count, elevation, and height filtering. A minimum of 70 points is chosen as a threshold for hit count, a minimum elevation of 2m, and a minimum sign height of 0.4m. The success rate of detection is not discussed, but it is mentioned that some false positives such as billboard signs are detected.

Ai and Tsai (*6)*, filtered their data based on intensity, hit count, and MUTCD elevation and offset values. To find the optimal threshold value for each parameter, an initial value is chosen for each parameter, then a sensitivity sweeping procedure is used to optimize the thresholds for each parameter minimizing false-negatives and false-positives. Trimble T3D analyst software is used for automatic sign detection. The algorithm was tested on road segments in Indiana with a 94% detection rate achieved with 6 false-positives for I-95 highway and a 91.4% of success rate with 7 false-positives achieved on 37th street. There were also four cases of false-negatives which were attributed to either poor retro-reflectivity, insufficient height, or being obstructed by other objects.

Landa and Prochazka (*12)* also filtered the data by intensity, however, Euclidean distance was used for clustering. The clusters were then filtered based on density, elevation and height. A 93% success rate was reported in the study with the authors attributing missed signs to low density.

In their paper, Wu et al. (*13)* used PCA and intensity filters to detect vertical planes where traffic signs exist in LiDAR point cloud data. On-image sign area detection is then implemented by projecting the 3D points of each traffic sign onto a 2D image region that represents the traffic sign. Success rates are not discussed in the study.

Soilán et al. (*14)*, started by removing points more than 20m from scanner. The ground surface was then converted to a raster grid and a raster coordinate system is created. Ground points are then removed from the data and intensity filtering is applied to remaining points. A Gaussian mixture model is used to further remove low intensity points. Density based cluster algorithm was used for clustering and PCA was used to distinguish signs from posts. The method was applied to an urban road and a highway segment in Spain achieving success rates of 86.1% and 92.8% for the urban road and highway respectively. The study attributed false positives to planar metallic surfaces and pedestrians dressed in reflective clothing.

Riveiro et al. (*15)* followed a similar procedure to Soilán et al. (*14)* by filtering points by intensity and then using Gaussian mixture models to further filter the data points. A similar procedure was also used for the clustering and PCA was used to remove false positive clusters (clusters with curvature). In this study the methodology was tested in Brazil, Spain and Portugal with success rates ranging from 80% to 90% depending on the road type and the type of sign extracted.

As evident from the review, recent years have seen a rise in the attempts to utilize LiDAR data in extracting road sign information. Different algorithms are proposed with satisfactory success rates in most studies, however, there is still need for more research in this area.

3. EXTRACTION METHOD

The aim of this paper is to extract road traffic signs from LiDAR point cloud data. As already noted, the proposed extraction process involves three main stages. The data is first filtered by intensity, and after that, a clustering algorithm is used to classify filtered points into clusters. Further filtering within clusters is then performed to remove false positives from the data set.

3.1 Retro-intensity Filtering

The first stage of the extraction process involved filtering out the data based on intensity. LiDAR data is collected using laser beams which emit light pulses against objects and, depending on the reflectivity of the object, the pulses are reflected at different strengths. Based on the strength of the reflected pulse, different intensity values are assigned to LiDAR points. In more technical terms, retrointensity is a ratio of the percentage of energy redirected from the target object to that emitted from the LiDAR scanner. This is consistent with the definition of retroreflectivity defined by the Federal Highway Administration (*16*). As mentioned earlier, the MUTCD requires that traffic signs are painted with retroreflective material to ensure that these signs are visible during poor lighting conditions. Therefore, if LiDAR points are filtered based on intensity it is possible to retain points with high reflectivity such as traffic signs and lane markings.

Since data is collected in the LAS point cloud format it was first necessary to convert the data into ASCII text format. This conversion makes it more convenient to filter out certain portions of the data. A heuristic approach was followed to identify the threshold at which intensity filtering should be applied. The threshold is decreased until the majority of traffic signs are captured. This may result in other objects being retained along with the traffic signs, however, further filtering enables isolating traffic sign information.

3.2 Clustering

Once the data was filtered based on intensity, LiDAR points with high retroreflectivity were retained. Each group of points within close proximity and with a high density represented a cluster and each cluster represents a certain high intensity object as seen in Figure 1. The majority of those objects are traffic signs, however, clusters could also represent other high intensity objects such as licence plates of vehicles. In order to identify the number of homogenous groups (clusters) that exist, which is a proxy of the number of signs on the road, the DBSCAN (Density-Based Spatial Clustering of Applications with Noise) clustering algorithm was used (*17*).

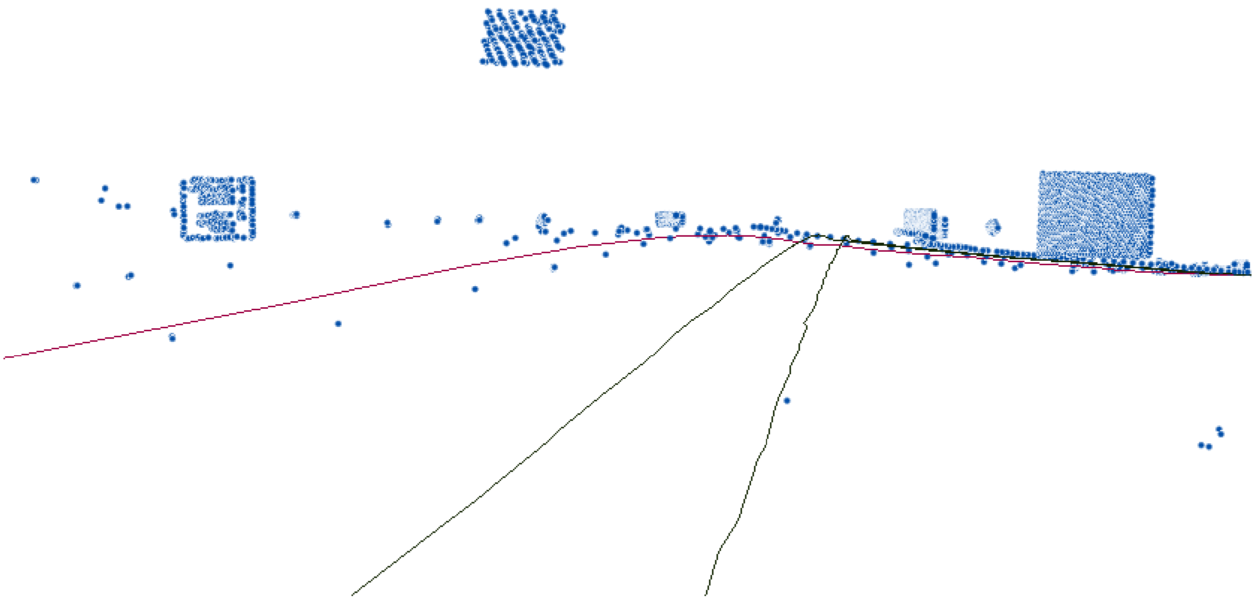


FIGURE 1: Point Cloud Clusters

The DBSCAN algorithm is a density based algorithm that works by regrouping points based on proximity (Ɛ) and hit count (*18*). 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, a traffic sign, by defining certain thresholds for the proximity and the hit count variables. It is worth noting here that the MATLAB DBSCAN clustering algorithm had to be modified to cluster in a 3-dimensional environment rather than 2-dimensions.

In this paper, a minimum hit count threshold of 17 was used (i.e. if the number of points in a group was less than 17 it was not considered as a cluster) and the proximity parameter threshold was 1.0m (i.e. if the spacing between adjacent points within a group was more than 1m they were considered as points belonging to the same cluster). These thresholds were selected since they were the most effective in identifying traffic sign clusters only (i.e. other objects with high intensity such as road markings and licence plate were minimized using these thresholds). The optimum clustering parameters were identified using data from only two of the three highways considered in the case study. Data from the third highway was used for validation purposes.

3.3 Lateral and Elevation Geometric Filtering

Although intensity based filters and clustering produce satisfactory results in terms of the sign extraction accuracy, further filtering is recommended to reduce the number of false positives in the data. A false positive is defined as an object which was identified by the algorithm as a sign even though ground truth shows that it is not. Examples of this include licence plates of vehicles or other reflective roadside objects.

Two techniques were used for further filtering. The first was to filter based on the height range within a certain cluster. This was done by identifying the points of minimum and maximum elevation within the cluster and ensuring that the range did not fall below a certain threshold. A threshold of 0.25m was used, which is 10cm less than the minimum vertical height of a traffic sign in Alberta(*19*). Here it is recommended that local sign dimensions are used if the algorithm were to be applied in a different region.

The second technique was to create a buffer zone of areas where it is impossible for a road signs to exist and filter out those areas. Buffer zones were created in ArcGIS and points that lie inside and outside the buffer could be separated. One buffer zone removed points within the travel lanes of the road while the other was used to delete areas with large offset from the road's centerline.

Once all the different filters are applied, the extracted road sign information is saved as a .csv file which contains the exact position of the sign (latitude and longitude coordinates), elevation information and retro-intensity values for each point within a sign cluster. Since traffic sign inventory involves obtaining the number of signs on a road segment and the exact position of those signs, coordinate information is then imported into Google Earth to verify the position of the signs along the highway.

4. CASE STUDY

The developed algorithm was tested on three different highways in the province of Alberta. The three segments were chosen so that the geometric features on the segments varied. This included variation in the number of lanes, whether a median was present or not and the type of the median, the horizontal alignment along the road, and the type of intersections that exist on the segment (if any). Different segments had differing levels of vegetation and tree density as well. The next few paragraphs provide information about the data collection process along with some details about the three highways on which the algorithm was tested.

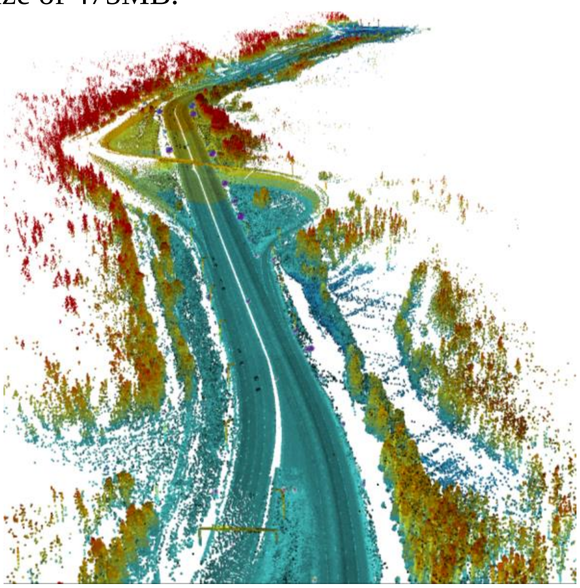
4.1 LiDAR Data Collection

In 2012, Alberta Transportation started using Tetra Tech's PSP-7000 Multi-Function Pavement Surface Profiling vehicle to collect 360˚ LiDAR point cloud of road corridors. The vehicle, seen in Figure 2, was used to collect data on multiple highways around the province using Trimble's MX-8 LiDAR system. Surveys are conducted within normal traffic flows at posted speeds up to 100 km/h. Provincial surveys conducted at 90 km/h result in LiDAR point densities on the pavement surface of 150-1000 points/m^2 (*20*). Data collected along a given highway is saved in multiple *.LAS* files with each file representing a certain segment along the highway. Due to the high point density of the data, the size of the 4km segment file could reach 500MB. The data considered in this paper was collected on the three different highways shown in Figure 3. Moreover, ground truth information about traffic signs on the three highways was collected using Google Street View images. The images were manually observed and the total number of signs on each segment was recorded.

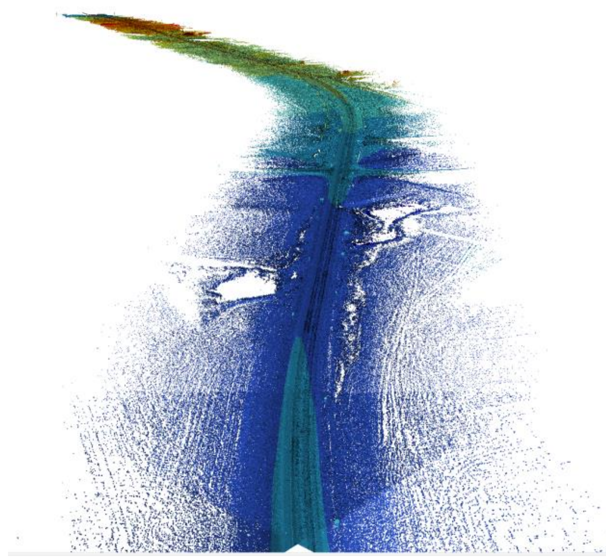
FIGURE 2: PSP-7000 Multi-Function Pavement Surface Profiling Vehicle

4.2 Highway 1

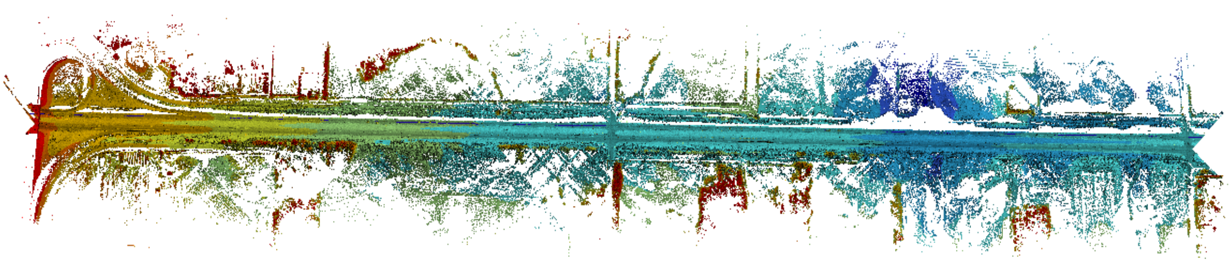
The portion of Highway 1 considered in the analysis extended for a length of 4km and lies in the western part of the province of Alberta. The segment is part of a four-lane divided highway located west of the city of Calgary. The speed limit on the segment is 110 km/h and it is highly travelled highway due to its proximity to Banff's National Park. The segment also has a high density of trees and vegetation on either sides of the road. In addition, there is physical separation of the two travel approaches. The type of median varies along the segment (depressed vs raised) as does the horizontal alignment of the segment. An interchange exists at the midpoint of the segment as seen in Figure 3a. The point cloud file of this segment consisted of over 17million points with a file size of 475MB.



(a) Highway 1



(b) Highway 36



(c) Highway 14

FIGURE 3: Point Cloud Data at Highways of Interest

4.3 Highway 36

The Highway 36 segment also extended for a length of 4km. The segment was a two-lane undivided rural road located in the southern region of Alberta, southeast of the city of Lethbridge. Unlike Highway 1, vegetation is extremely low on this portion of Highway 36 with the roadside area relatively clear. The *.LAS* point files for this segment consisted of 28.9 million points. The speed limit on the road is 100 km/h and there is an at-grade stop controlled intersection at one point along the segment. There is also a horizontal curve on the segment as seen in Figure 3b.

4.4 Highway 14

The Highway 14 segment extended for a length of 3.3km. The segment is a four-lane divided rural road located southeast of the City of Edmonton. The travel approaches are separated by a depressed median with moderate vegetation and tree density on the side of the road. The *.LAS* point files for this segment consisted of 24.2 million points. The speed limit on the road is 100 km/h. Three intersections exist on the segment with two at-grade two-way stop-controlled intersections and a grade separated intersection at one end of the segment. Unlike the other two highways, where the horizontal alignment of the road changed, Highway 14 is a straight segment.

5. RESULTS AND DISCUSSION

Table 1 shows the outcomes of applying the proposed algorithm to each of the three highway segments. As evident in the table, high success rates were recorded on all three highways. The following is a discussion of results and the main challenges encountered during the extraction process on all three highways.

5.1 Extraction Reliability

As already discussed, the extraction process involved multiple steps. In order to achieve the highest success rates with minimal processing effort, the results extracted at each stage were compared to the ground truth where it was decided whether further filtering was required.

TABLE 1: Extraction Results

Road Segment	Highway 1	Highway 36	Highway 14
Length	4 km	4 km	3.3 km
Actual number of signs	76	29	50
False Positives	0 (all off-road signs and vehicles removed by filters)	0 (2 guide posts removed by height filtering, 2 potential vehicles and 4 off-road signs removed by road buffer, and metal shed removed by road buffer)	0 (all off road signs and vehicles removed by filters)
False Negatives	5 overhead signs (detected but removed once road buffer is applied)	0	2 signs (not picked up due to low point density)
Height Filtering	No height filtering done	2 guide-post clusters with heights below 0.25m were removed	4 vehicle clusters removed by height filtering (clusters below 0.25m height removed)
Road Buffer	5 overhead signs removed, 3 cars, 2 exit speed signs (which by our criteria are not true signs on our segments)	Metal shed removed off road and one vehicle removed on road.	1 car removed by road buffer
Detection rate	71/76=93.4% 76/76 = 100% (after applying elevated buffer zone filtering)	29/29= 100%	48/50=96%

On Highway 36, only intensity filtering and clustering were required for the algorithm to detect all traffic signs on the road. However, the algorithm also picked up nine false positives. This included highway guide posts and some signs from the minor road at stop controlled intersection. The algorithm also detected a reflective side of a truck and a portion of a metal shed seen in Figure 4 as false positives. Therefore, simply filtering the data at certain intensity levels and running the density based clustering algorithm resulted in an overestimation of traffic signs on the segment by 27%. Applying the sign height filter removed both guide posts on the segment bringing the number of false positives to only 6, which corresponded to a 20% overestimation rate. After running the final step of the extraction process, "buffer zone filtering", all remaining false positives were omitted leading to 100% success rate on the Highway 36 segment.

FIGURE 4: Metal Shed Highway 36 (False Positive)

As in the case of Highway 36, intensity filtering and clustering were also effective in detecting all signs on Highway 1. However, again, three vehicle clusters, including the two of which belong to the same truck (as seen in Figure 5) and two exit speed signs that were also detected as false positives. This resulted in a 6% overestimation rate of signs on the segment. Although buffer zone filtering would be effective in removing those false positives, it would also filter out 5 overhead signs, hence, the 5 false positives would be replaced by 5 false negatives. Therefore, buffer zone filtering reduced the success rates on Highway 1 to 93.4%. This dilemma was resolved using elevated buffer zone filtering which is discussed in section 5.2.

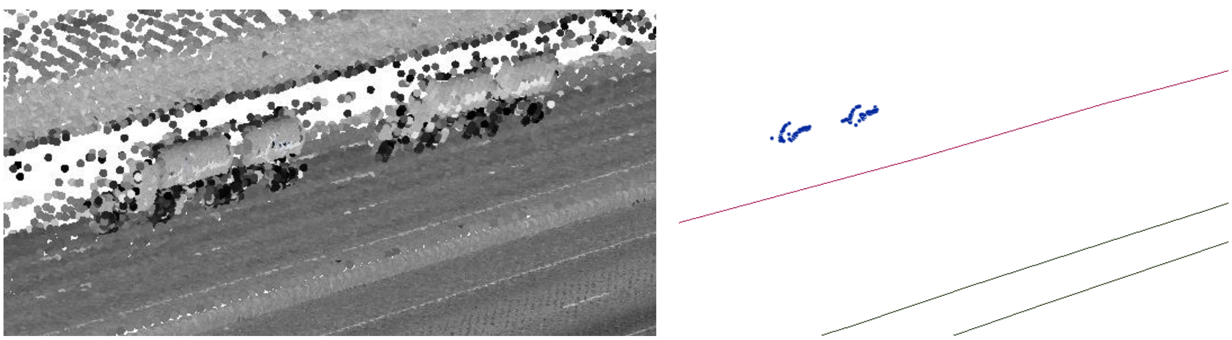


Figure 5: Truck Highway 1 Cluster (False Positive)

On Highway 14, intensity filtering and clustering resulted in 53 clusters. 48 of those were true signs and 5 were false positives. Ground truth showed that the segment had 50 signs, hence the algorithm failed to detect two true signs (i.e. there were two false negatives). The reason these signs were not detected is because the point density for those signs was relatively low. This could be due to the poor condition of the reflective material on those signs. In the case of the false positives, height filtering was applied to remove those clusters, and this removed 4 out of the 5 vehicle clusters. The remaining cluster was removed using buffer zone filtering on the road, resulting in a detection rate of 96.5%.

As in the case of the detection rates, the positions of the extracted road signs are also highly accurate. Figures 6 and 7 show the traffic sign clusters detected on Highway 36 and Highway 14 respectively. As evident from the figures, all signs seem perfectly aligned along the edges of the road. In fact, observing the street view of each cluster provides an image of the sign at the exact position of each pin. Positioning accuracy is useful when sign replacement or maintenance is required. Knowing this information is also an asset to Intelligent Transportation Systems (ITS) where the information can be imported into connected and autonomous vehicle applications. For instance, consider a vehicle approaching a curve in a connected vehicle environment where the position information of vehicle is known. Assuming knowledge of the exact position of the curve warning sign, an advisory message can be communicated to the driver based on the relative position of the vehicle to the traffic sign. In autonomous vehicles, having prior knowledge of the exact positions of road side objects would help avoid fixed object collisions.

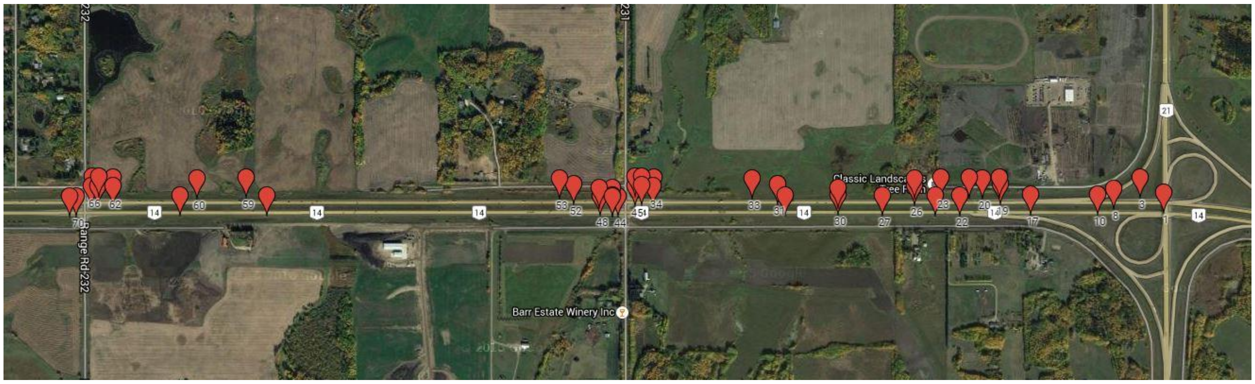


FIGURE 6: Sign Cluster Map (Highway 14)

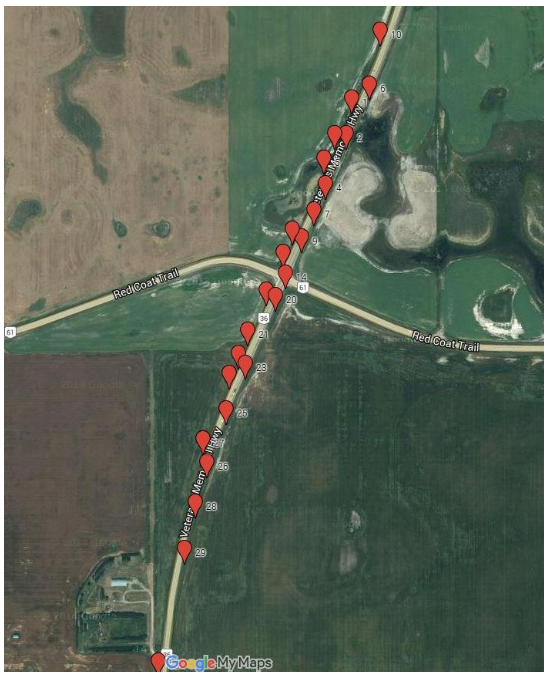


FIGURE 7: Sign Cluster Map (Highway 36)

5.2 Challenges

In general, relatively high sign detection accuracy is achieved on all three highways, however, it is evident that false positives create a challenge particularly when dealing with vehicles on roads where overhead signs exist. Ten out of the nineteen false positives detected on the three segments were vehicles. Four of the ten were removed using height filters, while road buffers were required for the remainder. The issues with filtering using a road buffer on segments where overhead signs exist is that all points within the road are filtered out, including those signs. Therefore, although the proposed algorithm did produce fairly accurate results on highways where overhead signs exist (Highway 1), its efficiency is relatively higher on segments where those signs do not exist. In order to overcome this issue, point cloud data of Highway 1 was filtered by elevation (i.e. only points having an elevation of more than 4m were kept). The proposed algorithm was then applied on the elevated segment alone in order to isolate overhead sign clusters from false positives on the road. This technique was effective in keeping overhead sign information while removing false positives on the road leading to 100% success rates on the highway segment.

Unlike the presence of vehicles on a road segment, the variation in the geometry and vegetation levels between the different segments did not have any negative impacts on the sign detection accuracy. With that being said, it is worth pointing out that the signs on service roads, ramps and minor roads if present adjacent to a road segment, might add some false positives to the data. This was an issue on Highway 36 where almost 50% of the false positives detected on the segment were signs on the minor approach at a stop controlled intersection.

Finally, it is worth noting that other methods for removing false positives were also attempted but proved unsuccessful. The coefficient of determination of clusters was calculated but no consistent relationship between low R^2-values and false positives was observed. Further, the average cluster intensity was calculated assuming that low average intensity would correspond to a false positive, however, this also proved not so effective in filtering out the false positives. Finally, an attempt was made to buffer clusters by vertical scan angles but the results were not reliable because of unexpected angle returns for points.

6. CONCLUSIONS AND FUTURE RESEARCH

In this paper an algorithm for automated sign extraction is proposed. The proposed method was tested on three different highways located in various parts of the province of Alberta. The three segments were chosen so that the geometric features on the segments varied. This included variation in the horizontal alignments, medians, and number of lanes along the road. Different segments also had different levels of vegetation and tree density. Despite these variations, success rates were fairly consistent ranging from 93.4% to 100% amongst the three segments. Higher success rates are observed on the two segments where overhead signs did not exist.

This paper demonstrates the feasibility of automatically extracting traffic signs from LiDAR point cloud images at high accuracy levels. The extracted information is extremely valuable to transportation agencies keeping traffic sign inventory by significantly reducing the efforts associated with manual data collection. The developed algorithms provide a list of traffic signs along a road segment. This list contains information about the exact position of the signs, the intensity information and the elevation of each point within a sign cluster. This information could be used to assess the conditions of signs based on intensity. In fact, automatically assessing the conditions of different signs and classifying signs based on their shapes using the extracted data are opportunities for future research. The extracted information also enables mapping signs along a highway. This is useful when sign replacement or maintenance is required. Knowing this information is also an asset in ITS applications where the information can be imported into connected and autonomous vehicles.

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REFERENCES

[1] Larson, C., and O. Skrypczuk. Comprehensive data collection to support asset management at Virginia Department of Transportation. *Transportation Research Record: Journal of the Transportation Research Board*, No. 1885, 2004, pp. 96-103.

[2] Ai, C. A Sensing Methodology for an Intelligent Traffic Sign Inventory and Condition Assessment Using GPS/GIS, Computer Vision and Mobile LiDAR Technologies. 2013.

[3] Tsai, Y., P. Kim, and Z. Wang. Generalized traffic sign detection model for developing a sign inventory. *Journal of Computing in Civil Engineering,* Vol. 23, No. 5, 2009, pp. 266-276.

[4] Ruta, A., Y. Li, and X. Liu. Real-time traffic sign recognition from video by class-specific discriminative features. *Pattern Recognition,* Vol. 43, No. 1, 2010, pp. 416-430.

[5] Tsai, Y., and Y. Huang. Automatic detection of deficient video log images using a histogram equity index and an adaptive gaussian mixture model. *Computer-Aided Civil and Infrastructure Engineering*, Vol. 25, No. 7, 2010, pp. 479-493.

[6] Ai, C., and Y.-C. J. Tsai. Critical assessment of an enhanced traffic sign detection method using mobile LiDAR and INS technologies. *Journal of Transportation Engineering,* Vol. 141, No. 5, 2014, p. 04014096.

[7] Williams, K., M. J. Olsen, G. V. Roe, and C. Glennie. Synthesis of transportation applications of mobile LiDAR. *Remote Sensing,* Vol. 5, No. 9, 2013, pp. 4652-4692.

[8] Chen, X., B. Kohlmeyer, M. Stroila, N. Alwar, R. Wang, and J. Bach. Next generation map making: geo-referenced ground-level LIDAR point clouds for automatic retro-reflective road feature extraction.In *Proceedings of the 17th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*, ACM, 2009. pp. 488-491.

[9] Vu, A., Q. Yang, J. A. Farrell, and M. Barth. Traffic sign detection, state estimation, and identification using onboard sensors.In *16th International IEEE Conference on Intelligent Transportation Systems (ITSC 2013)*, IEEE, 2013. pp. 875-880.

[10] Zhou, L., and Z. Deng. LIDAR and vision-based real-time traffic sign detection and recognition algorithm for intelligent vehicle.In *17th International IEEE Conference on Intelligent Transportation Systems (ITSC),* IEEE, 2014. pp. 578-583.

[11] Weng, S., J. Li, Y. Chen, and C. Wang. Road traffic sign detection and classification from mobile LiDAR point clouds.In *2015 ISPRS International Conference on Computer Vision in Remote Sensing*, International Society for Optics and Photonics, 2016. pp. 99010A-99010A-99017.

[12] Landa, J., and D. Prochazka. Automatic road inventory using LiDAR. *Procedia Economics and Finance,* Vol. 12, 2014, pp. 363-370.

[13] Wu, S., C. Wen, H. Luo, Y. Chen, C. Wang, and J. Li. Using mobile LiDAR point clouds for traffic sign detection and sign visibility estimation.In *2015 IEEE International Geoscience and Remote Sensing Symposium (IGARSS),* IEEE, 2015. pp. 565-568.

[14] Soilán, M., B. Riveiro, J. Martínez-Sánchez, and P. Arias. Traffic sign detection in MLS acquired point clouds for geometric and image-based semantic inventory. *ISPRS Journal of Photogrammetry and Remote Sensing,* Vol. 114, 2016, pp. 92-101.

[15] Riveiro, B., L. Díaz-Vilariño, B. Conde-Carnero, M. Soilán, and P. Arias. Automatic Segmentation and Shape-Based Classification of Retro-Reflective Traffic Signs from Mobile LiDAR Data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing,* Vol. 9, No. 1, 2016, pp. 295-303.

[16] Carlson, P. J., and M. S. Lupes. Methods for maintaining traffic sign retroreflectivity.In, 2007.

[17] Ester, M., H.-P. Kriegel, J. Sander, and X. Xu. A density-based algorithm for discovering clusters in large spatial databases with noise.In *Kdd, No. 96*, 1996. pp. 226-231.

[18] Yarpiz. Density-Based Spatial Clustering of Applications with Noise (DBSCAN) in MATLAB.In, 2015.

[19] Alberta Transportation. *Sign Catalogue and Images*, 2013.

[20] STEEL, P., D. Mesher, and J. Adamson. Development of a Road Safety Audit Network Screening Tool.In *Twenty-Fourth Canadian Multidisciplinary Road Safety Conference*, 2014.