Critical Assessment of Automatic Traffic Sign Detection Using 3D LiDAR Point Cloud Data

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ABSTRACT

Traffic signs are important roadside appurtenances that provide critical guidance to road users including regulations, destinations, and safety related information. Traffic signs need to be inventoried by transportation agencies for asset management and maintenance purposes. However, the traditional method of manually inventorying signs is dangerous, labor-intensive, and time-consuming. There is a need for a safer and more effective traffic sign inventory method. This paper is the first that critically assesses the use of an automatic method for traffic sign detection using 3D LiDAR point cloud data in support of traffic sign inventory. The contribution of this paper is three-fold: 1) it presents an automatic method for traffic sign inventory using 3D LiDAR point cloud data; 2) it critically assesses the performance of the presented method in terms of detection rate and false negative (FN)/false positive (FP); 3) it suggests the adequate parameter values to achieve a good traffic sign detection rate. Actual data, collected on Interstate 95 (major arterial) and 37th Street in Savannah, Georgia (local road), is used to assess the performance. Results show that the presented method can correctly detect 94.0% and 91.4% of the traffic signs on both roadways, respectively, with less than 7 FP cases. The results demonstrate that the presented method using 3D LiDAR point cloud data is promising for providing an alternative for traffic sign inventory. Future research directions are recommended.

INTRODUCTION

Traffic signs are essential appurtenances in the transportation system. Traffic signs provide vital guidance to road users regarding traffic regulations, adequate warnings, destinations and traveling information, and temporary road conditions. It is essential for transportation agencies to inventory the traffic signs under their jurisdiction, so they know the locations and conditions of their signs. Manual traffic sign inventory methods are commonly used by most of transportation agencies, e.g. state departments of transportation (DOTs). It requires engineers to physically approach to traffic signs and collect corresponding attribute data. Spreadsheets *(1)* and handheld computers *(2)* are widely used for a manual inventory. This method is dangerous, labor-intensive, and time-consuming. There is a need to explore alternatives for a safer and more effective traffic sign inventory.

With the advancement of light detection and ranging (LiDAR) technology, terrestrial LiDAR has become popular in asset data collections *(3-5)*. In recent years, mobile LiDAR data has been increasingly used for roadside inventory *(6, 7)*. With accurate geo-referenced 3D point cloud data and the embedded unique retro-intensity information from the collected object, the LiDAR technology has the potential to achieve a safer and more effective traffic sign inventory. Although some researchers have attempted to use the LiDAR technology to collect traffic signs, a complete introduction of the method and the critical assessment on its performance is lacking. The objective of this study is to present an complete automatic traffic sign detection method using 3D LiDAR point cloud data and to conduct a critical assessment of its performance by using the actual data collected on Interstate 95 (I-95) and 37th Street in Savannah, Georgia (37th Street). Based on test outcomes, this study also suggests the adequate parameter values to achieve a good traffic sign detection performance.

This paper is organized as follows. The first section identifies the research need and objective. The second section presents an automatic traffic sign detection method using 3D LiDAR point cloud data. The third section presents the experimental test using actual data. Finally, conclusions and recommendations for the future research are discussed.

AN AUTOMATIC TRAFFIC SIGN DETECTION METHOD USING 3D LIDAR POINT CLOUD DATA

An automatic traffic sign detection method using 3D LiDAR point cloud data is presented in this section. Although there are some preliminary presentations on the use of 3D LiDAR data to collect traffic signs, this paper is the first to present a complete traffic sign detection method for traffic sign inventory.

The 3D LiDAR point cloud data is acquired using Georgia Tech's mobile sensing system that can collect the data at highway speed. The integrated system includes the emerging mobile LiDAR system (i.e. Riegl LMS-Q120i), high resolution video cameras (i.e. Point Grey Gras-50S5C), and an accurate positioning system (i.e. Applanix LV 210PP) composed of a global positioning system (GPS), an inertial moment unit (IMU) and a distance measurement instrument (DMI), as shown in Figure 1.

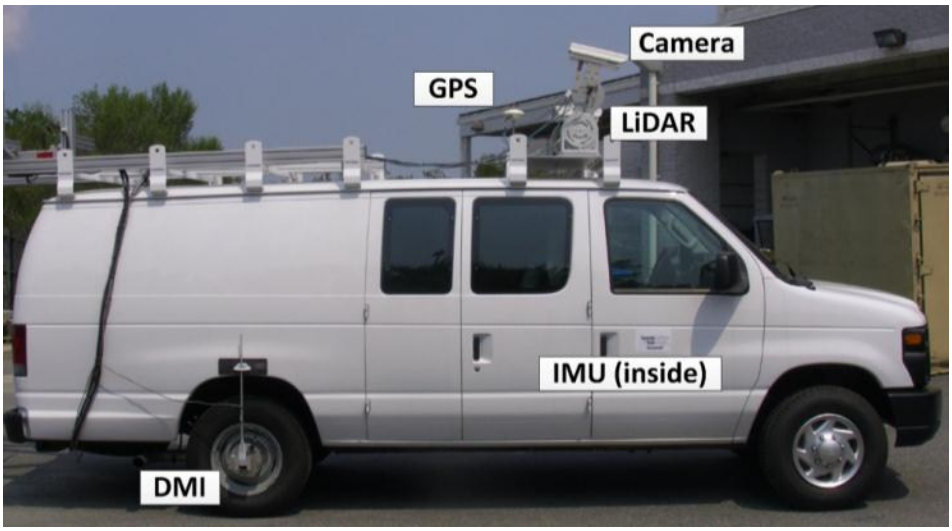


Figure 1 Georgia Tech's mobile sensing system for collecting 3D LiDAR point cloud data

The mobile LiDAR system in this study is a line-scanning laser device that produces 10,000 laser points per second. As the vehicle moves in the longitudinal direction of the road, the scanning line of the LiDAR system is aligned perpendicularly to the ground. The scanning range is ±40° to the horizontal direction, which produces an 80° fan covering the roadside. Currently, the frequency of the LiDAR system is configured at 100 Hz and 100 points within each scan, while the LiDAR heading angle is configured at 20°. Figure 2 shows an illustration of data acquisition. For example, if a standard 48×60 speed limit sign is mounted on the roadside with a lateral offset of 12 ft. (3.6 m) to the edge of the road, the current configuration will be able to acquire a point cloud containing approximately 12×8 points at 60 mph (100 km/h). The configuration can be adjusted to accommodate different data collection scenarios.

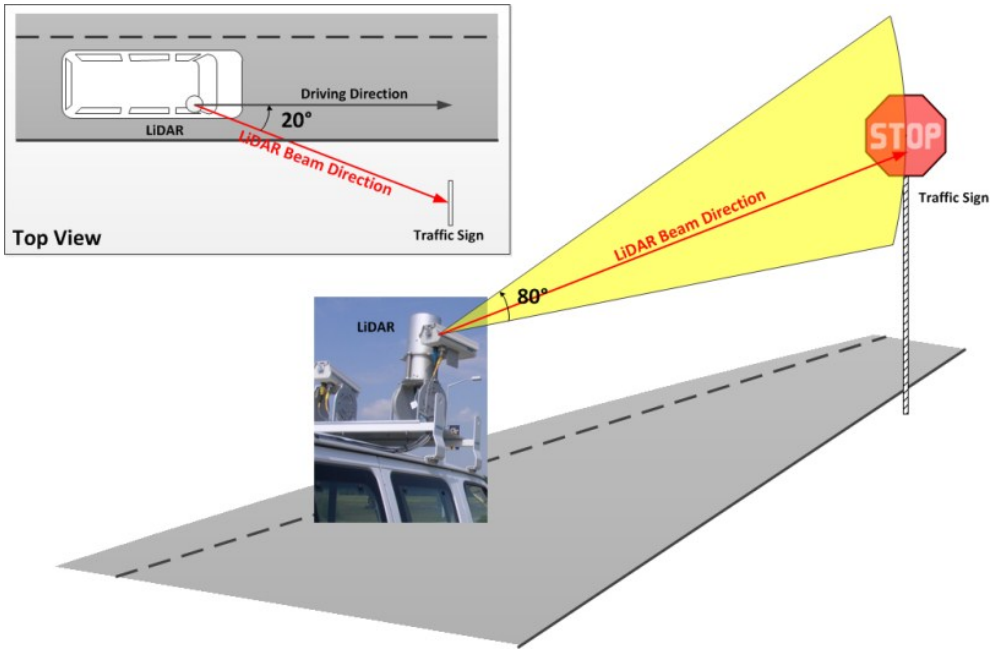


Figure 2 Illustration for data acquisition using LiDAR

The new detection method contains five primary steps, including sensor calibration, data acquisition, point cloud data computation, point cloud data processing, and coordinate generation for the detected traffic signs. Figure 3 shows the flow of the traffic sign detection method using 3D LiDAR point cloud data.

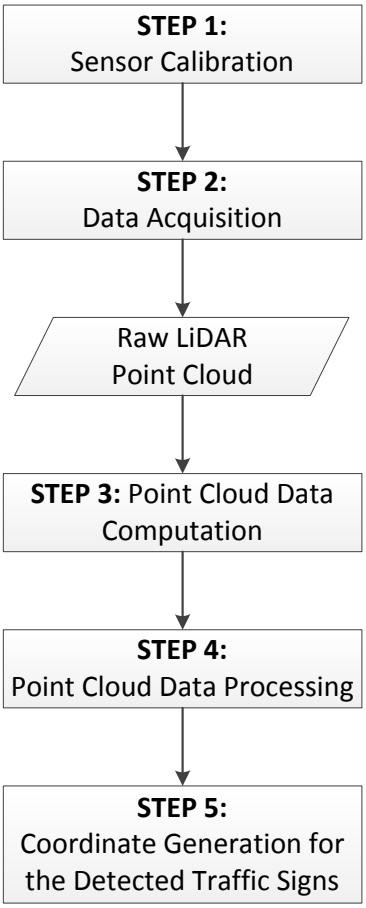
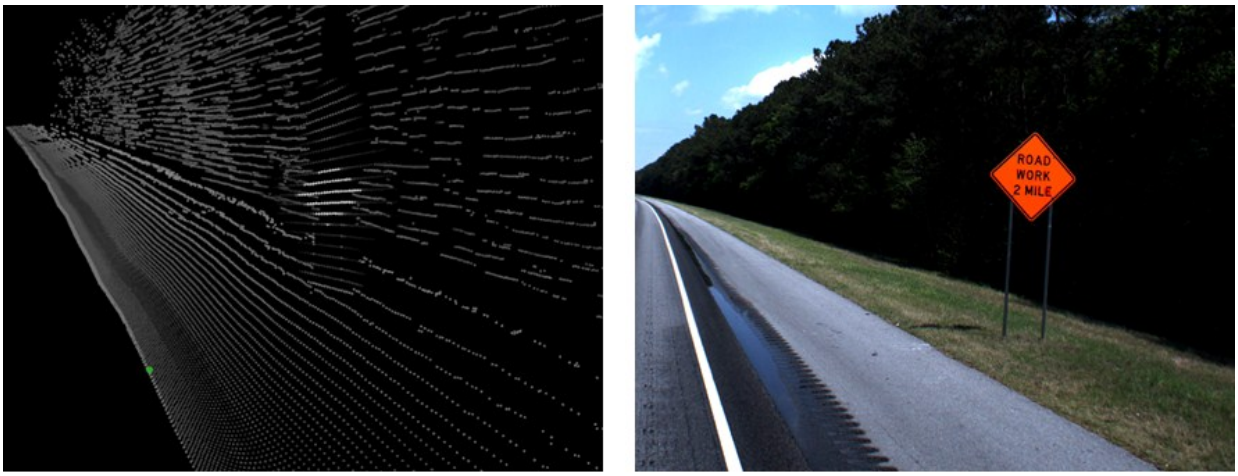


Figure 3 Flowchart of the traffic sign detection method using 3D LiDAR point cloud data

STEP 1: Sensor calibration. For different sensor configurations, the system requires calibration of the LiDAR sensor to determine the positions (i.e. offsets in x, y, and z directions) and the actual poses (i.e. heading, rolling, and pitching angles) relative to the data collection system. The calibration results will be used for point cloud data computation. Sensor calibration needs to be conducted only when the sensor configuration is changed. In this study, the offsets of -6.0 inch (-15.3 cm), 16.1 inch (40.9 cm) and 21.8 inch (55.3 cm) for the x, y, and z directions, and the poses of 20°, 0°, and 1.2° for the heading, rolling, and pitching angles, are calibrated and used.

STEP 2: Data acquisition. Once the sensors are calibrated, the data collection system can be driven on roadway for data collection. The 3D LiDAR point data can be collected and synchronized with the corresponding high resolution video log images (i.e. 2,448×2,048). Figure 4 shows an example of the acquired data. Figure 4(a) shows the 3D LiDAR point cloud data. Figure 4(b) shows the corresponding video log image.



(a) 3D LiDAR point cloud data **(b) Video log image data**

Figure 4 Example of the collected data on I-95

STEP 3: Point cloud data computation. After the data is acquired, the raw 3D LiDAR point cloud data and the corresponding raw GPS data are synchronized. The raw GPS data must be adjusted using the real-time IMU data, and it must be corrected using the differential base stations to obtain better accuracy. Using the sensor calibration results and the post-processed GPS data, the global coordinates for each point in the 3D point cloud can be accurately derived.

STEP 4: Point cloud data processing. The point cloud data are processed in three sub-steps for automatic traffic sign detection.

STEP 4.1: Point cloud filtering using retro-intensity. The retro-intensity is defined as the ratio of the energy returned from the object to the energy emitted from the LiDAR sensor. A higher retro-intensity indicates a better object reflectance. Since most of the traffic signs are designed to be retro-reflective, most of the traffic signs have a relatively high retro-intensity value in the LiDAR point cloud data compared to other objects. Using the retro-intensity parameter, only the clusters from the objects with high retroreflectivity will be filtered as the candidates for detected traffic signs.

STEP 4.2: Validate the clusters using geometrical constraints. Since traffic sign are standardized in the manual on uniform traffic control devices (MUTCD) for their locations and dimensions *(8)*, these standards can be used for validating the clusters from STEP 4.1 to further remove the non-traffic sign clusters. In this study, the elevation, the lateral offset, and the hit count are used. The elevation parameter corresponds to the height of the traffic sign. The lateral offset parameter corresponds to the lateral location relative to the edge of the road. The hit count parameter is the number of LiDAR points that hit the cluster, which corresponds to the dimension of the traffic sign. A detailed analysis of how to determine the parameter values is presented in Section 3.

STEP 4.3: Determine the representative point. After the detected clusters are validated, the centroid of each cluster is used to represent the corresponding traffic sign. Within the centroid, the extracted attributes, e.g. the coordinates, the elevation, etc., corresponding to the detected traffic sign are embedded; other attributes, e.g. the MUTCD code, traffic sign dimension, etc., required for traffic sign inventory *(9)* can be filled in later.

STEP 5: Coordinate generation for the detected traffic signs. After the point cloud data is processed, the detected traffic signs are represented by a sequence of geo-referenced points (i.e.

the centroids for each detected traffic sign). A database can be generated containing the GPS coordinates with the corresponding traffic signs and attributes. Figure 5 shows an example of the detected traffic signs and the corresponding attributes on a geographic information system (GIS) map. This step summarizes the complete automatic traffic sign detection method using 3D LiDAR point cloud data.

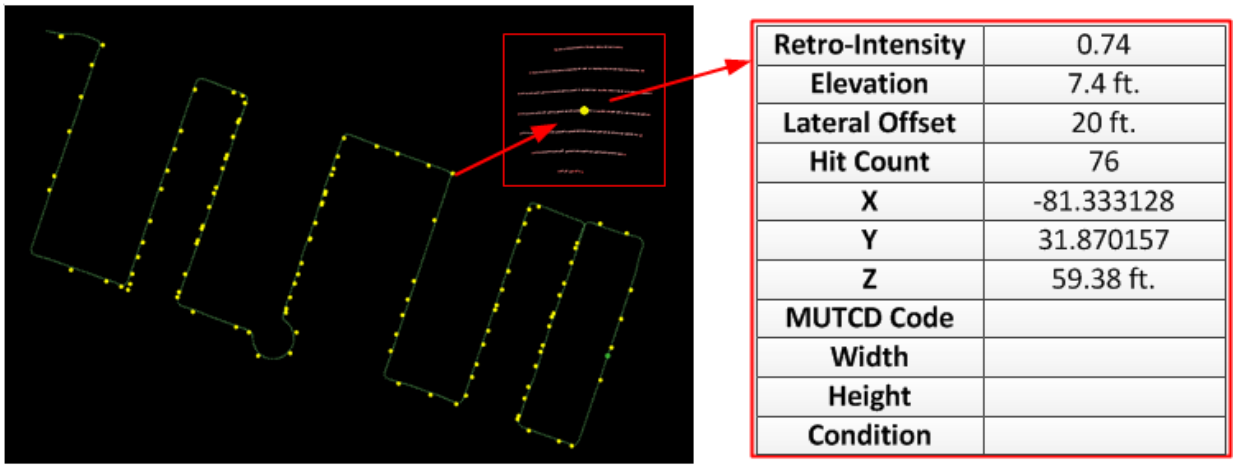


Figure 5 Example of the detected traffic sign and the corresponding attributes on GIS map

Although the transportation agencies can use other commercially available software or code their own application to implement the present method following similar steps, in our study, functions from Trimble® Trident Analyst software are used to detect traffic signs.

EXPERIMENTAL TEST

The objective of the experimental test is to assess the performance of the presented automatic traffic sign detection method using 3D LiDAR point cloud data. Actual data collected on I-95 and 37th Street is used to critically assess the performance of the presented method in terms of detection rates and the FN and the FP. The adequate parameter values for a good detection rate are also suggested.

The dataset collected on I-95 covers 17.5 miles of roadway containing 127 traffic signs with different attributes. The data is collected on the outer lane of the three-lane road at the speed of 60 mph (100 km/h). The dataset collected on 37th Street covers 2.9 miles of roadway containing 115 traffic signs with different attributes. The data is collected at the speed of 30 mph (50 km/h). Both of the datasets are collected using the same LiDAR heading angle of 20° and scanning frequency of 100 Hz. The ground truth is manually extracted using the video log images that are synchronized with the LiDAR data. Figure 6 shows the map of the road sections for the data collection.

Figure 6 The selected data collection sections for experimental test

Determination of Adequate Parameter Values

As presented in Section 2, the key parameters used for the presented method are related to the basic traffic sign characteristics, such as the retroreflectivity, the elevation, etc. Therefore, the initial parameter values can be set based on the MUTCD standard defining the traffic sign characteristics. To adapt the traffic sign characteristics on different roadways, we have selected the first 10 traffic signs on different roadway types to calibrate the parameter values. Once these parameter values are calibrated, they can be applied to the same types of roadway. The following rules are used to determine the adequate parameter values:

- Retro-intensity. The retro-intensity value selected for I-95 should be greater than that for 37th Street. It indicates that the traffic sign retroreflectivity condition on the major arterials is generally better than the local roads. On one hand, the retro-intensity value should be kept low enough to prevent FN (i.e. missing signs). On the other hand, a higher retro-intensity value is used to be selective on sign detection for minimizing the FP (i.e. false detection). From the observation of the selected 10 traffic signs for calibration, the minimum retro-intensity values of 0.73 are identified for I-95 and 0.67 for 37th Street. Therefore, values of 0.7 and 0.65 are used for I-95 and 37th Street, respectively.
- Elevation. The elevation value selected for I-95 should be slightly smaller than that for 37th Street. It is consistent with the traffic sign installation standard defined in the MUTCD *(8)*. For example, although the traffic sign should be typically mounted at a minimum of 7 ft. (2.1 m) in height, many secondary signs can be mounted at a minimum of 5 ft. (1.5 m) on freeway or expressway. Therefore, values of 4 ft. (1.2 m) and 6 ft. (1.8 m) are used for I-95 and for 37th Street, respectively. It is also suggested that the elevation value should not be smaller than 3 ft. (0.9 m) to avoid the false detection of vehicle license plates and temporary traffic control drums.
- Lateral Offset. The lateral offset value selected for I-95 should be greater than that for 37th Street. It is consistent with the traffic sign installation standard defined in the MUTCD and the observation in the calibration set. Based on the MUTCD, the traffic sign should be

mounted at a minimum of 12 ft. (3.6 m) lateral offset on freeway or expressway, whereas a minimum of 2 ft. (0.6 m) lateral offset in residential area *(8)*. However, as observed in the calibration set, many specific service signs on the freeway or expressway are mounted as far as 48 ft. off the road, while some of the traffic signs are mounted as far as 12 ft. (3.6 m) off the road when the region is not confined. Therefore, values of 60 ft. (18.3 m) and 20 ft. (6.1 m) are used for I-95 and 37th Street respectively.

- Hit Count. The hit count value selected for I-95 should be smaller than that for 37th Street. As presented in Section 2, the LiDAR point cloud data is collected using consecutive scanning lines crossing the roadside objects. When the scanning frequency is fixed (i.e. 100 Hz), the distance between the consecutive scanning lines is determined by the driving speed and the distance between the consecutive points within the same line is determined by the distance between the LiDAR sensor and the object. Therefore, a traffic sign with the same dimension contains less hit points on I-95 than on 37th Street, because the vehicle speed for data collection is greater, while the distance from the LiDAR to the traffic sign is also larger on I-95 than on 37th Street. By exploring the smallest signs collected in the datasets on I-95 (i.e. milepost sign) and on 37th, Street (i.e. no-parking sign) and based on the data collection speeds, values of 10 and 20 are used for I-95 and for 37th Street, respectively.

The rules for determining adequate parameter values for the presented detection method are based on the characteristics of traffic signs defined in the MUTCD and the calibration from a fraction of the testing datasets. In this paper, the first 10 traffic signs are used for the calibration. However, transportation agencies can define their fractions for better parameter values. Table 1 presents the selected parameter values used for the experimental test in this study.

Table 1 The parameter values applied for the tests on I-95 and 37th Street

I-95		37th Street	
Retro-Intensity	0.70	Retro-Intensity	0.65
Min Elevation (ft.)	4	Min Elevation (ft.)	6
Max Lateral Distance (ft.)	60	Max Lateral Distance (ft.)	20
Min Hit Count	10	Min Hit Count	20

Testing Results

With the determined parameter values, the datasets collected on I-95 and 37th Street are tested using the presented method. Table 2 shows the automatic detection results.

Table 2 Traffic sign detection results for the tests on I-95 and 37th Street

I-95		37th Street	
Distance	17.5 miles	Distance	2.9 miles
# of Signs Tested	117	# of Signs Tested	105
Detection Rate	94.0%	Detection Rate	91.4%
False Negative	7	False Negative	9
False Positive	6	False Positive	7

For the data collected on I-95, the detection rate is 94.0% with only 6 FP cases. For the data collected on 37th Street, the detection rate is 91.4% with only 7 FP cases. The results have

demonstrated that the presented method using 3D LiDAR point cloud data is promising for providing an alternative for traffic sign inventory.

The detailed analysis of the FN cases and FP cases are conducted. There are four types of FN cases: traffic signs with poor retroreflectivity condition, traffic signs with insufficient height, occluded traffic signs, and overhead traffic signs.

- Traffic sign with poor retroreflectivity condition. Several such FN cases are identified on 37th Street, where the retroreflectivity condition of the traffic signs is relatively poor. In contrast, this FN case is not identified on I-95, where the traffic signs are maintained in a timely manner. Figure 7 shows an example of a FN case containing a traffic sign with poor retroreflectivity condition on the 37th Street. It can be observed in the video log image that the no-parking sign has severely deteriorated. In the corresponding LiDAR point cloud data, the retro-intensity values of the points within the no-parking sign region are much smaller than the set parameter value of minimum retro-intensity as 0.65. Therefore, the traffic sign region will not be detected from the background. The further investigation finds that the average of the retro-intensity values in the traffic sign regions is approximately 0.45. By further reducing the parameter value of retro-intensity to below 0.45, this traffic sign can be correctly detected. However, many FP cases are detected using such a small retro-intensity parameter value.

Figure 7 Example of FN case with a traffic sign with poor retroreflectivity on 37th Street

- Traffic sign with insufficient height. Several such FN cases are identified on 37th Street, where some of the traffic signs fail to meet the height requirements defined in the MUTCD. In contrast, this FN case is not identified on I-95, where the traffic signs have better compliance. Figure 8 shows an example of a FN case containing a traffic sign with insufficient height on 37th Street. The height of the traffic sign is measured as 5.1 ft. (1.6 m), which is smaller than the set parameter value of minimum elevation as 6 ft. (1.8 m). Therefore, the traffic sign region is rejected. By further reducing the parameter value of elevation to below 5 ft. (1.5 m), this traffic sign can be correctly detected. However, several additional FP cases are detected, such as the reflective stickers on the mailbox, etc.

Figure 8 Example of a FN case with a traffic sign with insufficient height on 37th Street

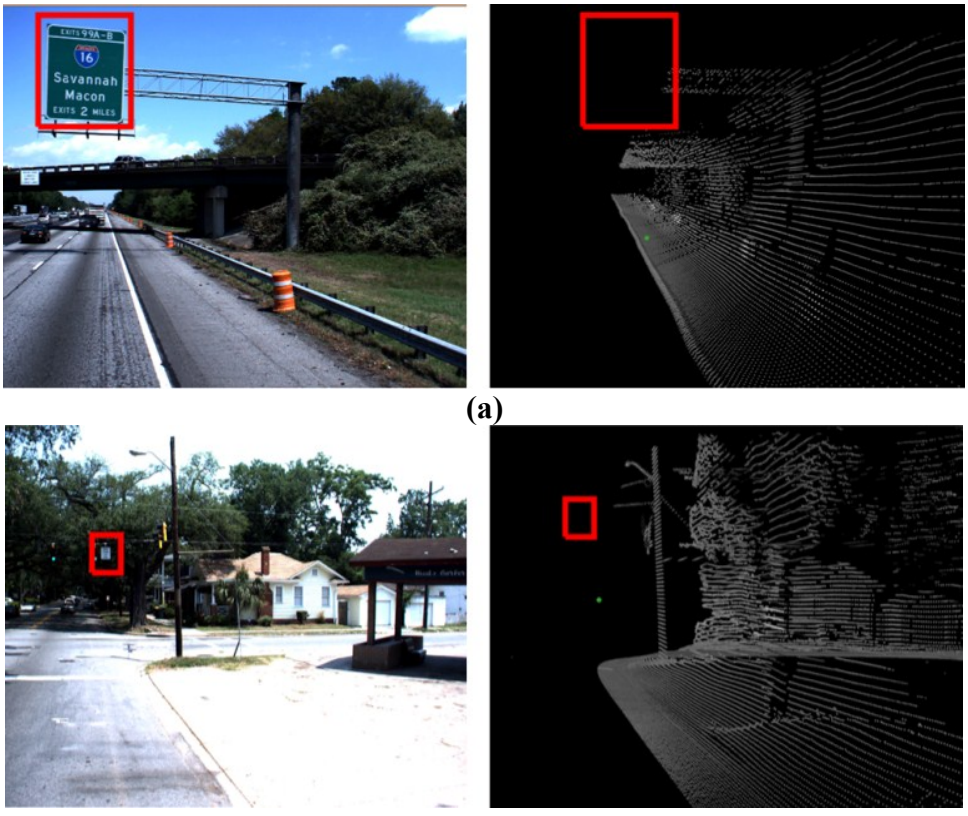
- Occluded traffic sign. One of the drawbacks of the LiDAR point cloud data collection is that only the object in the line of sight of the LiDAR sensor can be collected. Therefore, when the heading of the LiDAR sensor is configured at a fixed angle (e.g. 20° in this study), the line of sight is fixed. If the object closer to the LiDAR sensor is collected, the occluded object will not be detected. Figure 9(a) shows an example of a FN case containing an occluded traffic sign on I-95. The merge sign is occluded by the temporary work zone warning sign. Although in the video log image, the merge sign is still visible, it cannot be detected using LiDAR point cloud data due to the occlusion. Similar cases are identified in the local road, where traffic signs are occluded by the tree branches, as shown in Figure 9(b).

(a)

(b)

Figure 9 Example of FN cases containing occluded signs on (a) I-95 and (b) 37th Street

- Overhead traffic sign. The coverage of the LiDAR data along the road is dependent on the path of the data collection vehicle and the heading angle of the LiDAR sensor (e.g. 20° in this study). For the purpose of traffic sign inventory, the LiDAR sensor is typically scanning vertically to the roadside and the data collection vehicle is driving on the outer lane of the road. Under such configuration, it is likely that many overhead signs are not detected. In contrast, the overhead signs can still be collected in the video log images. Figure 10 shows examples of such FN cases on I-95 and 37th Street.



(a)

(b)

Figure 10 Example of FN cases containing overhead signs on (a) I-95 and (b) 37th Street

There are three types of FP cases in which objects with high retroreflectivity are mistakenly detected as traffic signs. Although the constraint of traffic sign elevation effectively rejects many of the objects with high retroreflectivity, such as vehicle license plate, temporary traffic control drums, etc., there are still several types of FP cases that are difficult to be eliminated, including reflective commercial signs, changeable message boards, gates with reflective strips, etc. Figure 11 shows the examples of the identified FP cases. It is observed that although these FP cases are mistakenly detected using 3D LiDAR point cloud data, they can be easily eliminated using the 2D video log images.

(a) **(b)** **(c)**

Figure 11 Examples of the identified FP cases

In summary, the results from the data collection on I-95 and 37th Street have demonstrated the presented method using 3D LiDAR point cloud data is promising for providing an alternative for traffic sign inventory. The suggested rules for determining the adequate parameter values show its effectiveness for the presented method. The FN and FP cases are critically assessed to assist in exploring the potential improvements. Two of the identified FN cases can be further eliminated by adjusting the parameter values, e.g. the traffic signs with poor retroreflectivity condition and insufficient height, while the other two identified FN cases can be further eliminated by changing the LiDAR configuration, changing the data collection path, or integrating the presented method with the image-based method. The integration of the presented method with the image-based method can also help to eliminate the identified FP cases.

CONCLUSIONS AND RECOMMENDATIONS

Traffic signs are important appurtenances for the transportation system and provide vital guidance for the road users. It is essential for transportation agencies to inventory the traffic signs. Traditionally, manual traffic sign inventory methods, which are dangerous, labor-intensive and time-consuming, are used. This study presents an automatic traffic sign detection method using 3D LiDAR point cloud data. The performance of the presented method is critically assessed using the actual data collected on I-95 and 37th Street. The detection rate is presented, and the FN cases / FP cases are analyzed in detail. The results have demonstrated that it is a promising alternative for traffic sign inventory.

The followings summarize the major findings of this study.

- Based on the test results, it has demonstrated that the presented traffic sign detection method using 3D LiDAR point cloud data has a good traffic sign detection rate. The result from the data collected on I-95 shows a slightly better detection rate than the one on 37th Street because the traffic signs on major arterials are likely to have better retroreflectivity conditions and are mounted in much better compliance with the MUTCD standard, comparing with the ones on local roads.
    - Based on the test conducted on I-95, the detection rate is 94.0% (110 correctly detected signs) with only 6 FP cases. The occluded traffic signs and overhead traffic signs are identified as the primary FN cases in this dataset.
    - Based on the test conducted on 37th Street, the detection rate is 91.4% (96 correctly detected signs), with only 7 FP cases. The traffic signs with poor retroreflectivity

condition and traffic signs with insufficient height are identified as the primary FN cases in this dataset.

- Based on the results, the current selections of parameter values, including the retro-intensity, the elevation, the lateral offset and the hit count, are adequate for the presented automatic traffic sign detection method. The rules for determining these parameter values show its effectiveness.
- Based on the results, the current LiDAR configuration (i.e. 20° heading angle and 100 Hz scanning frequency) and the data collection driving speed (i.e. 60 mph (100 km/h) for I-95 and 30 mph (50 km/h) for 37th Street) are adequate for the presented automatic traffic sign detection method.

The followings are recommended for future research.

- Additional datasets for roadways with traffic signs having different attributes, e.g. condition, type, dimension, location, etc., are recommended to further assess the performance of the presented method.
- Further adjustments of parameter values are recommended to eliminate the FN cases, including the traffic signs with poor retroreflectivity condition or insufficient height, without introducing excessive FP cases.
- The integration of 2D video log image and 3D LiDAR point cloud data is recommended to further eliminate the FN cases, including the occluded signs and the overhead signs, and the FP cases, including the changeable message board, the reflective strip, etc.

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