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Transportation Infrastructure Asset Management using LiDAR Remote Sensing Technology

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Abstract: Light Detection and Ranging (LiDAR) scanning systems integrate laser scanners, Global Positioning Systems, and inertial navigation technologies into one system that can acquire positional data and intensity information about surrounding objects. In Mobile Laser Scanning, data collection equipment is mounted on a truck that travels through a highway creating a 3D point cloud image of the entire road segment. The high point density of such datasets enables automated extraction of multiple roadway features, which are typically collected manually during long site visits. In addition, LiDAR datasets could also be used to assess geometric elements of highways such as available stopping sight distance. If used to their full potential, LiDAR datasets could create a paradigm shift in how geometric assessments and safety audits on highways are conducted. To highlight the full potential of LiDAR data in transportation engineering and to address doubts about the feasibility of extracting information from LiDAR, this research effort provides a thorough review existing and future applications in this area. Unlike previous research, this effort includes a thorough review of the previous attempts of data extraction from LiDAR while highlighting limitations in existing algorithms and areas where more research is required.

Keywords: *Transportation Engineering; Highway Design; Infrastructure Management; LiDAR; Remote Sensing*

I. INTRODUCTION

Light Detection and Ranging (LiDAR) is a remote sensing technology that uses light rays to collect information about objects without making physical contact with those objects. LiDAR data could be airborne (data collected using airplanes), spaceborne (collected using satellites) or terrestrial (collected form the ground). More so, ground based LiDAR data can either be static or mobile. In Mobile Laser Scanning (MLS) scanning equipment is mounted on vehicles, which travel along the highway of interest capturing 360^0 imagery of the roadway. MLS is the most common approach to collect data for transportation applications since road features can be captured with a high level of detail.

In addition to the laser sensors, data collection vehicles are mounted with Global Navigation Satellite System (GNSS) receivers and inertial measurement unit (IMU) which provide information about the exact position of the sensor. LiDAR data is collected using scanning equipment reflecting light beams off objects. The light pulse emitted from the sensor bounces off the target object and is reflected backto the sensor; given the properties of the reflected beam, the distance between the scanner and the scanned object can be computed. Position information of the scanned object can then be determined based on the distance between the scanner and the object and the positional information of the scanner obtained from the GNSS equipment. During the scanning process, thousands of beams per second are transmitted from the laser scanner, this results in millions or, in some cases, billions of distance measurements to surrounding surfaces. Constant scanning of objects around the sensor creates a 3D point cloud of known positional attributes as seen in Fig 1. Unlike traditional surveying of roadways, using LiDAR data produces highly accurate images of roads while travelling at highway speed, which causes minimal disruption to road traffic.

Realizing the potential of having LiDAR data and its value to highway data collection efforts, many transportation agencies across North America, including Departments of Transport (DOT) at Oregon, Washington and North Carolina, started collecting this type of data. In Canada, Alberta Transportation (AT) started collecting LiDAR point cloud data at multiple highways across the province of Alberta in 2012. Despite many agencies collecting LiDAR data, the efforts to explore the potential usage of the data have been somewhat limited. This could be a matter of researchers not realizing the full potential of such data or not having the expertise required to extract more information from those datasets. This has led most DOTs which have collected LiDAR data to limit its usage to asset management applications such as traffic sign inventory. According to a former director of asset management at Utah's DOT, the key to maximize the benefits from LiDAR data is sharing data among different divisions at an agency [1].

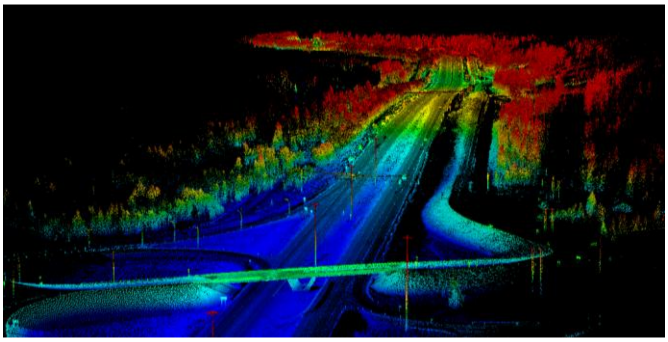

Fig 1: LiDAR point cloud highway

To highlight the full potential of LiDAR data in transportation and in an attempt to address doubts about the feasibility of extracting information from LiDAR images, this paper provides a thorough review of the potential applications of LiDAR in the field of transportation. The review provides information about the applications and algorithms that have been developed in previous research to extract valuable information from LiDAR data. Finally, the paper discusses potential gaps and areas where more research might be required to use LiDAR data to its full potential.

II. LIDAR IN TRANSPORTATION INFRASTRUCTURE MANAGEMENT

Departments of Transports (DOTs) have been collecting LiDAR data due to its value in traffic sign inventory and other asset management applications, however, research shows that LiDAR applications in transportation extend beyond asset management. In fact, a report by the National Highway Cooperate Research Program (NCHRP) in the United States highlighted several different applications of LiDAR in transportation illustrated in Fig. 2[2]. The research found that current and emerging applications for MLS in transportation cover a wide range of topics. This paper reviews previous research that explored using LiDAR data in extracting on-road information, roadside information and in conducting assessment of highways.

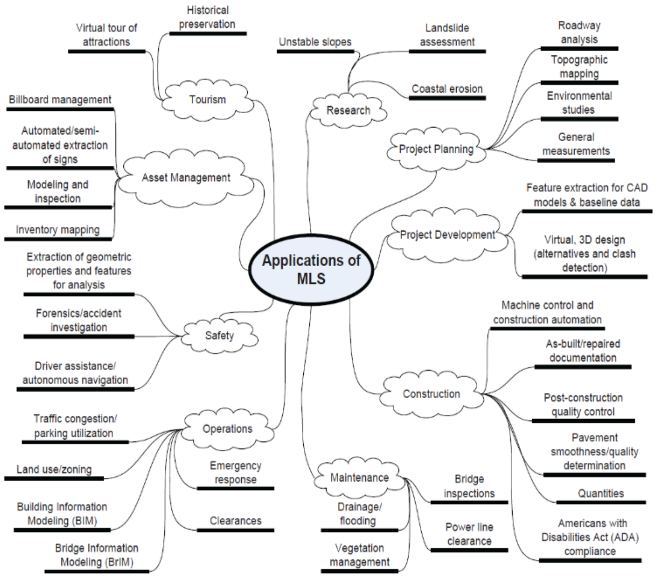

Fig 2: Applications of MLS in Transportation[2]

III. REVIEW

3.1 Lane Marking and Road Edge Extraction.

Extracting lane markings and road edges from LiDAR data has been heavily explored in previous research. The high reflectivity of lane markings makes extracting such information from LiDAR images feasible. The algorithms and tools used in the extraction vary among the different studies, as does the accuracy achieved.

Zhou and Deng [3] used airborne LiDAR in the detection of curbstones. The authors propose a three-step algorithm to extract curb information. The first step involves identifying points where there is an abrupt change in height. Once that is done, the maximum height difference (MHD) within the neighborhood is computed between midpoints of high and low points on either ends of the height jump. These points are arranged into a sequence to obtain a polygonal chain describing the approximate curbstone location and all points near the chain are then fitted to a sigmoidal function to increase the accuracy. The final step involves closing gaps between nearby and collinear line segments. To assess the performance of the proposed algorithm, the authors compared their results obtained from Aerial Laser Scanning (ALS) to information obtained using GPS and MLS. The results revealed that completeness varied between 53% and 92% from ALS which was higher than that of mobile laser scanning (MLS) (54% to 83%). The failure to achieve 100% rates was attributed partially to parked cars that blocked the curbstones. Further, the authors report that when comparing the Root Mean Square (RMS) value between GPS points and points obtained through laser scanning values of 0.11 m and 0.06 m were obtained for ALS and MLS data, respectively.

Zhang [4] attempted real time extraction of a roads surface and road edges from LiDAR data during the data collection stage. LiDAR range data is decomposed into elevation signals and signals projected on the ground plane. The algorithm performs elevation based filtering to identify a road candidate region and pattern recognition techniques are used to determine whether the candidate region is a road segment. After that, line representation of the projected signals on the ground plane is identified and compared to a simple road model in the top-down view to determine whether the candidate region is a road segment with its road edges. According to the authors, the proposed algorithm was validated under various urban scenarios and was successful. The authors state that the algorithm detects most road points, road-curb points, and road-edge points correctly with a false alarm rate and a miss rate of 0.83% and 0.55% respectively.

Jaakkola, et al. [5] attempted detecting road markings and curbstone information from LiDAR data with the aid of image processing techniques. The authors attempted classifying the data into road markings and curbstone points while modelling the roads surface as a triangulated irregular network (TIN). The classification involved segmentation of road markings and curbstones by using thresholding and through the application of morphological operations to elevation and intensity images. Success rates in the region of 80% were reported in the study for the classification of curbstones, zebra crossings, and parking space lines.

In a paper by Kumar, et al. [6] the extraction of road edges was attempted using image segmentation techniques. The authors used a combination of Gradient Vector Flow (GVF) and Balloon Parametric Active Contour models to perform the extraction. The algorithm involves converting the LiDAR images into 2D raster surfaces based on elevation, reflectance, and pulse width attributes. Edge boundaries of the raster surfaces are then formed by using hierarchical thresholding (limits noise) and canny edge detection (determines boundaries). A snake curve is then used to construct road segments that would intersect with LiDAR road data points. The developed technique was tested on three 50m road sections, one with a grass-soil boundary, one with curbstones and one with a shoulder prior to the grass-soil boundary. The road sections were segmented into multiple sub-sections and the edge extraction was accurate in all but two instances. Inaccuracy was attributed to a low point density on one edge of the road compared to the other.

In another study Kumar, et al. [7] extended their work on road edge extraction to extract lane marking information from mobile LiDAR data. In this study the authors perform range dependent thresholding to the LiDAR intensity values and use binary morphological operations to obtain lane marking information. As in the case of the road edge extraction, the authors start by converting the data into 2D range and intensity raster surfaces before applying the thresholding and the morphological operations. For incomplete road markings (i.e. locations where markings had rubbed off), linear dilation was used to fill in the gaps. Moreover, assuming prior knowledge of road marking dimension, an erosion process is carried out to remove any outlying points and any artificial noise added by dilation. Markings were extracted over seven road sections covering 150m. Of 93 road markings, 80 markings were correctly detected. The undetected markings were attributed to low point density and low intensity.

Guan, et al. [8], also develop an algorithm to extract lane markings using range dependent thresholding and the application of morphological operations. The authors first propose a curb based procedure to extract the roads surface. This is done by slicing the LiDAR data into blocks perpendicular to the roads trajectory. Within each block, differences in elevation are used to classify points into layers and to identify road edges (curbs) which represent the boundaries of the road surface. Once the road surface is extracted, the geo-referenced intensity images of the LiDAR points are generated using Inverse-Distance-Weighted interpolation (IDW). The IDW rasterizes the road surface based on the reflectivity of points and their proximity to the central point on the road. The final step of the extraction procedure involves using density-dependent multi-threshold segmentation to filter out lane markings and the application of closing morphological operations to remove noise and fill in gaps within extracted lane markings. The algorithm was applied on two datasets covering 168m of roadway length. Three sub-segments of those two roadways were used to assess the accuracy of the algorithms. This was done by manually comparing the results of the sub-segments to the ground truth. The authors measured how complete the extracted road markings were (completeness) and the percentage of the extracted road markings are valid (correctness) achieving success rates of 0.96 and 0.83 for completeness and correctness, respectively.

In Thuy and León [9], the lane detection process starts by plotting the probability density function (pdf) for the reflectivity observations of all data points. Since most the points fell on the road's surface, the maximum observation in pdf is assumed to correspond to the reflectivity of the roadway. Once that is identified, a dynamic threshold is calculated based on the maximum of the reflectivity pdf to distinguish and improve the contrast between the road surface points and lane markings. A threshold value is then chosen based on the standard deviation. Values estimated for the road surface are subtracted from the histogram within a one-sigma interval. The mean value is recalculated and used as the threshold for image binarization. A Canny filter (edge detection algorithm) is applied to the binary image for better lane detection. Although the developed algorithm was tested, not much discussion is provided on the results of the lane detection results. It is worth noting that paper also proposed a method for lane tracking using Kalman filters, however, this is out of the scope of this review.

Yan, et al. [10] proposed a scan line based method to extract road markings from mobile LiDAR point clouds. After processing the data and removing outlying observations, the proposed algorithm involves ordering LiDAR points sequentially by timestamp. Points are then organised into scan lines based on scanner angle. According to the authors, such an arrangement increases the efficiency of data processing. Seed road points are extracted based on the Height Difference (HD) between trajectory data and the road surface. Seed points are then used to extract the full road points. This is done by fitting a line through the seed point and all other points along the scan line using moving least squares and only retaining points which fall within a certain threshold of the line. Road points are then classified based on intensity into asphalt points and road marking points. Intensity values are then smoothed by a dynamic window median filter to reduce noise and road markings are extracted using the Edge Detection and Edge Constraints (EDEC) method, which measures abrupt changes in intensity along a scan line. Data from Jincheng highway in Beijing (China) was used to test the proposed algorithm. The authors applied their procedure on 3 segments ranging in length from 70 to 100m. Average completeness and correctness rates of 0.96 and 0.93, respectively were achieved.

3.2 Traffic Signs

Traffic sign extraction has been the most common application for LiDAR data. Extraction of traffic sign inventory from LiDAR images has been attempted in many studies using both airborne and mobile laser data. Extraction results and procedures vary among different studies, however, in general, high success rates have been achieved.

In one of the earliest studies to attempt automatic road sign extraction from LiDAR data, Chen, et al. [11] 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. [12], 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 [3]. 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. [13] 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 [14], 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 [15] 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 point density.

Wu, et al. [16] 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. [17]removed 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 were removed from the data and intensity filtering was applied to remaining points. A Gaussian mixture model was 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. [18] followed a similar procedure to Soilán, et al. [17] by filtering points by intensity and 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). 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.

Ai and Tsai [2] used computer vision techniques to detect traffic signs. The primary aim of the study was not to detect traffic signs, instead the authors attempted automatic assessment of traffic sign reflectivity conditions. The authors proposed a four-stage procedure by which traffic signs are first extracted and color segmented from video log images. The next step involves linking the LiDAR point cloud points to image pixels to make use of the intensity information of those points. Since intensity is affected by many factors including incidence angle and range (i.e. the distance from the scanner to the object), the next stage involves normalization of the intensity values. The authors develop empirical equations to correct for confounding factors. The final stage involves relating the intensity values to the reflectivity standards, which is done through experimental lab tests. Field tests of the developed algorithm showed that the retroreflectivity from the handheld retroreflectometer are highly consistent with the values obtained from the LiDAR data. The inconsistencies found were attributed to the handheld retro-reflectometer accuracy. As for the traffic sign detection, the authors state that their technique was able to detect 85% of traffic sign data.

3.3 Roadside Objects

Road side objects including lamp posts, trees and utility poles can have huge effects on the severity of runoff the road crashes. Roadside objects such as culverts, trees, utility and light poles, are associated with the highest percent of severe accidents [19]. Thus, their existence and proximity to the road must be identified for effective roadside management. The feasibility of extracting such objects from LiDAR data has been explored in previous research.

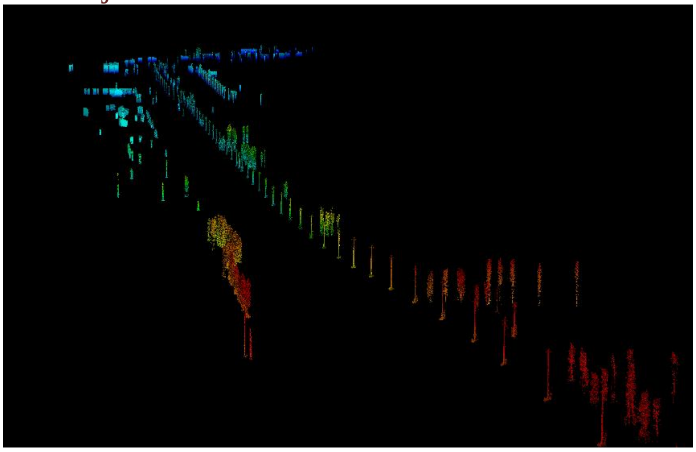

Fig 3: Roadside poles and trees

Recent work byZheng, et al. [20] proposed a technique to automatically extract street lighting poles from mobile LiDAR data. The proposed method involved segmentation and recognition approach. The authors first used a piecewise elevation histogram segmentation method to remove ground points. Then, a new graph-cut-based segmentation method was introduced to extract the street lighting poles from each cluster obtained through a Euclidean distance clustering algorithm. In addition to the spatial information, the street lighting pole’s shape and the point’s intensity information were also considered to formulate the energy function. Finally, a Gaussian-mixture-model-based method was introduced to recognize the street lighting poles from the candidate clusters. The proposed approach was tested on several point clouds collected by different mobile LiDAR systems. Experimental results showed that the proposed method achieved an overall performance of 90% in terms of true positive rate.

Lehtomäki, et al. [21] develop a MATLAB algorithm which can be used to extract and classify road side objects such as poles and trees from LiDAR data. First roadside objects are segmented into homogenous clusters based on proximity. After that principle component analysis is used to define two primary axes for each of the clustered objects. The ratio of the two primary axes was computed to classify the clustered object. If the ratio is large, the object is classified as a potential pole. For further classification, a mask is used to determine if the data is accepted as a pole or, instead, classified as a tree trunk. The mask is made of two cylinders with the same axis, with the smaller one located inside the other. The cluster is then fitted to the smaller cylinder, and the number of data points in each cylinder is compared. If the number of points in both cylinders is equivalent, this increases the likelihood of the cluster taking a pole-like shape. This mask is moved from the bottom to the top of the cluster to minimise the impacts of obstructions such as branches or posted signs on the verification process. Testing showed that 69-78% of roadside objects were detected successfully using the proposed algorithm. The authors also found that objects within 12.5m of the scanner resulted in higher detection rate and accuracy. For objects that were not detected, the authors attributed this to an insufficient number of data points or objects being obstructed from the view of the scanner.

Extracting road side objects from LiDAR was also studied in a paper by Pu, et al. [22]. The objective of this paper was to automatically classify a LiDAR dataset into different objects. The algorithm used a hierarchical classification method of the LiDAR dataset where the data points are first classified into three large categories: ground surface, objects on-ground, and objects off-ground. Prior knowledge of the size, shape, orientation along with topological relationships is used to further classify on-ground objects into categories such as traffic signs, trees, building walls and barriers. Testing showed that the algorithms were successful in detecting certain objects such as poles with an 86% accuracy. Other features such as traffic signs (61%) and trees (64%) had lower success rates.

In work by Lin and Hyyppa [23] the authors attempted extracting information about pedestrian culverts from mobile LiDAR data. The study developed an algorithm to perform the detection, however, it was found that the complete coverage (exact dimensions) of pedestrian culverts cannot be obtained from mobile scans. Therefore, it is recommended that scanning is performed in a “stop-go” fashion in order increase the density of the scans. Although pedestrian culverts could not be detected accurately, the study highlights the feasibility of detecting storm drainage culverts since water is detected easily by LiDAR.

3.4 Road Cross Section Information

Cross sectional slopes are important in ensuring speedy water drainage off roads to minimize the risks of hazards such as aquaplaning. Similarly, superelevation (tilting) on horizontal curves ensures that the effects of centrifugal forces are minimized, which minimizes the risk of overturning or lateral skidding. Moreover, slopes also play an important role in designing a highways lateral clearance. Despite that, a limited amount of studies attempted extracting such features from LiDAR data.

Tsai, et al. [24] developed an algorithm that can be used to extract cross slopes of roads from mobile LiDAR data. The laser scanner is oriented to a specific beam angle and beam distance. Cross section information is then extracted for region of intersect perpendicular to the roads trajectory. The length of the region of interest is user defined and bounded by lane markings on the edges. The authors recommend that lane markings are extracted from the LiDAR dataset but based on an algorithm proposed in a different study. Once the desired ROI is extracted, its cross slopes are estimated using linear regression. To identify the appropriate depth for the ROI, the authors run a sensitivity analysis. The analysis revealed that length of ROI should be 2ft to achieve adequate cross slope measurements. In addition to the sensitivity analysis, the authors tested the proposed algorithm in a controlled environment to assess its accuracy and repeatability. The authors found that the proposed algorithm yielded results within 0.28% of the digital level measurements.

In another recent paper which considered extracting road cross sectional inventory, Holgado- Barco, et al. [25] propose an algorithm which can be used to determine slopes, lane widths and number of lanes on a segment from mobile LiDAR images. The algorithm involves road segmentation where the road surfaces is extracted using an adaptive height threshold and scanner angle. After extracting the road surface, the procedure involves intensitybased filtering of the data to obtain lane markings. A geometric filter is applied to lane markings to remove false positives. Once this is done, Principal Component Analysis is used to connect discontinuous lines. Distances between lines are then used to identify lane width, shoulder widths and slope differences. The proposed technique was tested on two motorways (400m and 1km) in Spain. Comparing multiple extractions on each motorway, the authors found that only slight variations in the extracted information existed. Variations in shoulder width along the same segment was attributed to the existence of vehicles that obstructed the view of the scanner.

3.5 Vertical Alignment Information

One application for LiDAR in transportation is to facilitate the production of as-built drawings without the need for extended site visits. Accordingly, a number studies have attempted the extraction of geometric details of road segments, road grades, road slopes and vertical and horizontal profiles from LiDAR data.

One of the most relevant studies which worked on the collection of vertical alignment information from LiDAR data was the project led by Iowa’s DOT [26]. To estimate highway grade, the authors used least squares regression analysis to estimate the elevation of points along the centerline of a highway. The boundaries of the 100ft road segments (road edges) were first manually defined in ArcGIS by drawing polygons around the location of interest. The midpoints of the edges were used as the centerlines of the road segments and multiple linear regression was used to estimate the elevation of points along the proposed centerline. The predictors of the regression model were: (i) the lateral distance of a LiDAR point from the centerline and (ii) the longitudinal distance along the segment from its origin. The regression coefficients of the two independent variables (lateral distance to the centerline and longitudinal distance to the centerline) represented the cross slope and the grade of the segment, respectively. The study found that the estimated grade and slope attributes both deviated significantly from field survey measurements, particularly for cross slopes. This led the authors to conclude that collecting LiDAR data for those purposes alone was not cost effective.

In other work estimating highway grade, Zhang and Frey [27], used a similar technique to that in [26] except that in this study the authors used road width information to define road edges and a map of the road to estimate the location of the centerline. The paper also used regression analysis to estimate the grade of the road with the authors reporting a level of accuracy of up to 5%. One major limitation of this study and the one by Souleyrette, et al. [26] is that the segments for which grade estimation is attempted need to be straight segments (i.e. estimation was not possible for segments with great deviations in the horizontal alignment of the road). This led authors to select segments which were short enough so that the curvature was not significant. The segments, however, had to be long to have enough points for the regression analysis and meet the normality assumption. Hence, the authors were faced with a segmentation issues.

In more recent work, Dawkins [28] used LiDAR data to validate road profile extracted using a vehicle suspension model, although the author does not provide much details on how the profile was estimated using LiDAR data. It is likely that the paper traced the path of the data collection vehicle and used the elevations of the point cloud points along that line to produce the profile. However, this is not explicitly discussed in the paper.

Wu, et al. [29] used LiDAR data to compute the elevation of the road surface. In the process, 3D cloud point data were projected onto vertical planes defined by the trajectory of the vehicle collecting the LiDAR data. The points along the profile were segmented using the Douglas-Peucker algorithm, which connects points within the vertical planes to produce a line segment representing one portion of roads profile. Since the aim of the analysis was not to extract the vertical profile of the road segment, the authors do not provide any discussion of the level of accuracy achieved.

Unlike other studies, Han, et al. [30] used a photogrammetric approach to analyze road profile. The authors used a laser module to measure the distance between the sensors on board the data collection vehicle and the road surface. This information was linked to the image coordinates. To identify the profile at a certain location, image coordinates corresponding to the real space coordinates of that location were identified along with the elevation information.

Kim, et al. [31] explored the measurement of several geometric features from LiDAR data. The paper does not provide details of the extraction procedure; however, it is claimed that the extraction of horizontal and vertical alignments as well as cross sectional slopes was achievable. According to the authors, horizontal alignment extraction involves splitting the data into straight and curved segments using the Douglas and Peucker simplification algorithm while cross sectional information was estimated using the least squares method. Test data was collected on 1km long highway in China. When comparing between finally extracted elements and ground truth the authors claim that the extraction procedure yielded almost the same values as ground truth when considering construction errors. The paper concludes that the extraction of road information from LiDAR images is more efficient than traditional manual methods.

In summary, although there have been several attempts to utilize LiDAR data in extracting vertical alignment attributes of roads, more research is clearly required in this area.

3.6 Pavement Condition Assessment and Monitoring

A common application for LiDAR data in highway engineering is pavement condition assessment and rehabilitation. LiDAR images produces closely spaced points with accurate positional details, this enables the creation of surfaces and meshes which represent the roads surface. Deviations in those surfaces can be analyzed to assess the pavement conditions. Several studies explored pavement condition assessment using laser data.

For example, Gräfe [32] developed a model which uses LiDAR to perform guided roadway milling. The model works by creating a digital surface model of the road and analyzing the roads cross section at regular intervals. The study reported accuracy of up to 0.004m in height.

Tang, et al. [33], developed three different algorithms to assess the flatness of concrete from LiDAR images. According to the authors, the algorithms were able to detect surface flatness defects as small as 3cm across the road surface and 1mm thick. This level of accuracy was achieved using LiDAR scans which were made 20m away from the assessed location.

Tsai and Li [34] attempted the detection of pavement cracks from 3D laser scans. The authors proposed a technique by which cracks can be segmented using a dynamic optimization-based method. The performance of the detected cracks using the crack segmentation procedure were compared to manually established ground truth using a linear-buffered Hausdorff scoring method. The authors conclude that cracks with widths of 2mm and thicker can be efficiently detected using the 3D laser system under a controlled laboratory environment. The performance of the proposed technique was also satisfactory under different lighting conditions and different intensity contrast.

Lato, et al. [35]used mobile LiDAR to detect hazard of falling rocks along transportation corridors. The study involves differential monitoring of rock movement and failure by performing real-time measurements of the road side. Multiple mobile laser scans are compared to identify potential rock movement. The measurements were extracted using 3D metrology software PolyWorks. The authors conclude that multiple scans using a mobile LiDAR system are useful in the detection of small rock block release (sub 15cm).

Embankment slope instability was also assessed by Miller, et al. [36]. The authors used terrestrial laser scans to test for slope failure and extract slope features in transportation corridors. The slope deformation and failure is examined at two locations. The study found that, for both sites, the detection of minor changes, such as soil creep and surface runoff was possible using the laser scans, however, vegetation was found to be a confounding factor to the detection. The authors used a least squares surface matching algorithm to filter out the vegetation, whichresulted in detection of change at a centimetric precision level.

3.7 Sight Distance Assessment

In recent years, research has turned to using LiDAR data in sight distance assessments. Although, in theory, designing curves based on the minimum stopping sight distance requirements ensures that this distance is available at any point along the curve, the assumptions associated with the estimation procedure and certain project constraints (financial or practical) mean that there may be locations along a highway where minimum requirements are not met. Moreover, highway features may change after construction with maintenance activities and pavement operations often affecting the original design of highways. Similarly, the addition of roadside structures such as buildings or trees may limit the available sight distance in the post construction stage.

Khattak and Shamayleh [37]used aerial LiDAR data to assess highway stopping and passing sight distances. Aerial LiDAR data was collected along Iowa Highway 1 (also known as Solon Bypass). The data was used in ArcGIS to create a Triangulated Irregular Network (TIN) surface. The created surface was inspected visually and any potential problematic locations (in terms of stopping and passing sight distance) were marked. Furthermore, the Line of Sight tool (in ArcView) was used to further narrow down and identify problematic locations. The authors found ten locations where sight distance was limited. Later, a field validation was conducted and the results were validated.

Castro, et al. [38] also used ArcGIS to develop a method to obtain available sight distances. The method involved the creation of a Digital Terrain Model (DTM) raster, which, along with an observer input, allows for the computation of Viewsheds. Viewsheds denote areas on the raster that are visible for the observer. All visible areas are converted into polygons and then intersected with a vehicle trajectory obtained from GPS. The distance between the observer and the closest intersection is taken as the available sight distance. The sight distances obtained were compared to values given by highway design software, Trivium. Although, statistical analysis showed no significant difference between the obtained and design data, there were several locations where the design software reported shorter sight distances, as it can better detect vertical curve obstructions.

A few years later,Castro, et al. [39] developed an automated method for sight distance detection using ArcGIS tools. The method uses aerial LiDAR data to create a Digital Terrain Model (DTM). The visibility of multiple target points from a single observer are then assessed using ArcGIS tools until an obstruction is detected. At that point the available sight distance is noted as the distance between the observer point and the last visible point. The obtained sight distances are compared to those found in [38] using Kolmogorov-Smirnov and Wilcoxon tests revealed no significant differences.

In a different study, Castro, et al. [40] attempted to show differences in accuracy between DTM (bare ground) and the Digital Surface Model (DSM) also known as Triangulated Irregular Network (TIN) surfaces when extracting sight distance information. The paper used both mobile and aerial data for two DSMs. Kolmogorov–Smirnov and Mann–Whitney–Wilcoxon tests were used to measure any differences in sight distance outputs using the two surface models. The results showed a significant difference between all three surfaces. Specifically, DSMs were found to have shorter sight distances than DTMs, which means that more obstructions can be picked up. Comparisons between the aerial and mobile DSMs showed that mobile DSMs had a greater density which allows for a higher DSM resolution, leading to a more accurate representation of the environment.

Tsai, et al. [41], was one of few studies which attempted analyzing sight distance at intersections from LiDAR data. Although the authors do not assess sight distance in particular, they propose a manual method which can be used to detect obstructions at an intersection by analyzing aerial LiDAR data. The first step in the procedure involves offsetting GPS points representing the road's centreline so that they trace the centerlines of the travel lanes on the major and minor roads instead. Based on the type of control and posted speeds at the analyzed intersection, the authors determine the dimensions and the edges sight triangle which must be kept clear of any obstruction. The triangle is overlayed onto a digital surface model created using the LiDAR data and LiDAR market software is used to perform a plane of sight analysis between the observer and all target points. This process yields a raster grid of visible and nonvisible cells which are overlayed on the sight triangle. Sight distance was computed based on the outcomes. Before assessing the proposed method, the authors highlighted the importance of removing overhanging objects such as cables from the LiDAR data before performing the assessment since those objects result in false obstructions when creating surface models. The obstruction information obtained using the proposed method was compared to field data collected at an intersection, The authors conclude that the proposed technique was effective in determining 92% of obstructions. This outperformed normal on-site line of sight assessment which was only effective in detecting 64% of obstructions. Missed obstructions were often objects which were present between consecutive lines of sight.

As evident from the review, only a handful of studies have attempted using mobile LiDAR data in assessing sight distance along highways. In general, the review shows that not many studies were able to test the repeatability of the developed algorithms since testing was mostly conducted on a single segment, in addition, some of the algorithms developed required manual user input at some stages of the implementation. Moreover, although stopping sight distance has been assessed in a few papers, to the best of our knowledge, no previous studies have attempted assessing passing sight distance and only a single study has attempted the assessment of intersection sight distance.

3.8 Vertical Clearance Assessment

Various techniques have been used to conduct vertical clearance assessment on highways, one of which is through using LiDAR data. 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 [42], similarly, clearance assessment using photolog data has also been previously attempted [43].

Terrestrial LiDAR scanning has also been used to assess clearance with the aim of minimizing human error associated with conventional surveying tools. In a paper by Liu, et al. [44], 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. Although, this technique increases the likelihood of determining the actual minimum clearance beneath a bridge, static LiDAR scanning means that disruptions to traffic and safety concerns still exist. Moreover, network level analysis is still not possible since the technique involves conducting site visits and scanning each bridge on the network individually.

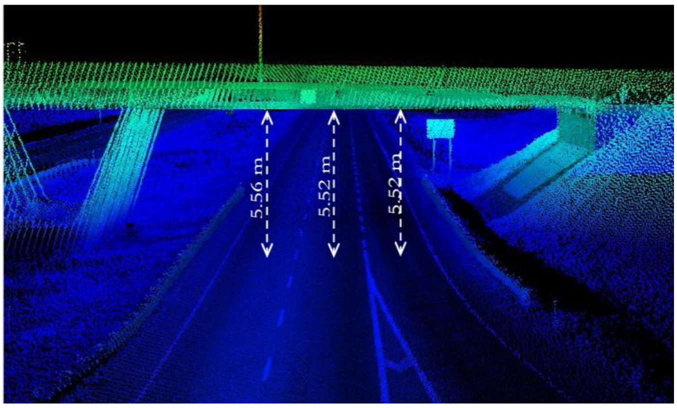

Fig 4: Clearance Using Mobile LiDAR

Puente, et al. [45] used mobile LiDAR data in the assessment of vertical clearance in tunnels. The authors propose a semi-automated algorithm where cross sections along the trajectory of the tunnel are first extracted and used to measure the 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 and the cross section of the of the tunnel is defined using convex hull before measuring the clearance. Although the results were encouraging, with relative error between ground truth and detected clearance not exceeding 1% for most cross sections, the algorithm was only used to assess a portion of the point cloud data. As to why the full point cloud was not used to test the algorithm in their study, the authors cited loading time as the main issue.

It is worth noting that a few studies have also attempted utilizing LiDAR point cloud data for structural assessment of bridges, see, for example, [46-49].

IV. RESULTS AND DISCUSSIONS

As evident from the review, there seems to be a general appreciation for the potential value of LiDAR in transportation applications. However, there is still a need for more research and efforts even in areas where there has been a significant amount of works.

It is clear from the review that a large portion of pervious research has concentrated on extraction of traffic sign inventory and lane markings from LiDAR data. The main reason such features have attracted more interest than others is because filtering such features is less complicated due to their reflective properties. Traffic signs and lane markings typically have high reflective properties. Consequently, LiDAR points representing those objects have higher intensity values. This unique range of intensity facilitates the isolation of those features from the rest of the point cloud.

While many studies have attempted extracting lane markings and traffic sign information from LiDAR, more research is still required in these areas. As for lane marking extraction, most studies which exist in the literature todayonly tested their algorithms on short segments, this raises concerns about the processing times associated with the proposed extraction procedures, particularly if they were to be replicated on longer segments. Moreover, the fact that most of the algorithms developed were only tested on straight segments also raises concerns about the applicability of the proposed techniques to segments where horizontal curves exist.

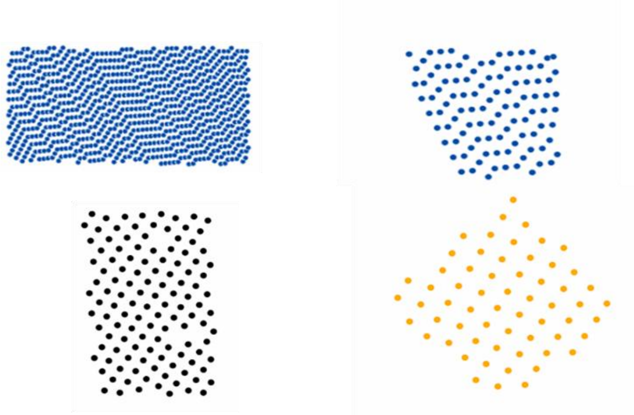

Fig 5: LiDAR Clusters of Traffic Signs

As in the case of lane markings more work is needed in the areas of traffic sign extraction. The clear majority of existing studies in this area have been limited to inventorying traffic signs only. More research is clearly required in areas related to classifying traffic signs into different types of signs where possible (i.e. warning signs, route guidance signs, etc.). As seen in Fig 3, point cloud data extracted for individual signs takes well defined shapes. Hence, automated classification of signs based on shape is achievable. Similarly, more research is needed in areas related to the assessment of traffic sign refelectivity using mobile LiDAR. Although the variety of factors affecting the retro-intensity values and accounting for those factors make such assessments extremely challenging [50], the few attempts which exist in the literature show that such assessments are possible [2].

The review also highlights the need for more research in the extraction of road geometric elements from LiDAR data.

In summary, despite the huge effort that has been put in by researchers in recent years, this paper shows that more research is still required and warranted. While some areas have been researched more than others, the paper shows that potential for more research exists regardless of the application. Future research can extend in four different streams (i) researching the extraction of new features (ii) improving the processing time required to extract features and performing assessments (iii) developing new algorithms which can be used to achieve higher success rates compared to existing algorithms and (iv) increasing the level of automation in extracting different features.

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References

[1] S. Higgins, 3D data is your asset. SPAR 3D's weekly newsletters for 3D-scanning professionals, Vol. 2016, 2016.

[2] C. Ai, Y.J. Tsai, An automated sign retroreflectivity condition evaluation methodology using mobile LIDAR and computer vision, Transportation Research Part C: Emerging Technologies 63 (2016) 96-113.

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

[4] W. Zhang, LIDAR-based road and road-edge detection, Intelligent Vehicles Symposium (IV), 2010 IEEE, IEEE, 2010, pp. 845-848.

[5] A. Jaakkola, J. Hyyppä, H. Hyyppä, A. Kukko, Retrieval algorithms for road surface modelling using laser-based mobile mapping, Sensors 8 (9) (2008) 5238-5249.

[6] P. Kumar, C.P. McElhinney, P. Lewis, T. McCarthy, An automated algorithm for extracting road edges from terrestrial mobile LiDAR data, ISPRS Journal of Photogrammetry and Remote Sensing 85 (2013) 44-55.

[7] P. Kumar, C.P. McElhinney, P. Lewis, T. McCarthy, Automated road markings extraction from mobile laser scanning data, International Journal of Applied Earth Observation and Geoinformation 32 (2014) 125-137.

[8] H. Guan, J. Li, Y. Yu, C. Wang, M. Chapman, B. Yang, Using mobile laser scanning data for automated extraction of road markings, ISPRS Journal of Photogrammetry and Remote Sensing 87 (2014) 93-107.

[9] M. Thuy, F. León, Lane detection and tracking based on lidar data, Metrology and Measurement Systems 17 (3) (2010) 311-321.

[10] L. Yan, H. Liu, J. Tan, Z. Li, H. Xie, C. Chen, Scan line based road marking extraction from mobile LiDAR point clouds, Sensors 16 (6) (2016) 903.

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

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

[13] S. Weng, J. Li, Y. Chen, C. Wang, Road traffic sign detection and classification from mobile LiDAR point clouds, 2015 ISPRS International Conference on Computer Vision in Remote Sensing, International

Society for Optics and Photonics, 2016, pp. 99010A-99010A-99017.

[14] C. Ai, Y.-C.J. Tsai, Critical assessment of an enhanced traffic sign detection method using mobile LiDAR and INS technologies, Journal of Transportation Engineering 141 (5) (2014) 04014096.

[15] J. Landa, D. Prochazka, Automatic road inventory using LiDAR, Procedia Economics and Finance 12 (2014) 363-370.

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

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

[18] B. Riveiro, L. Díaz-Vilariño, B. Conde-Carnero, M. Soilán, 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 9 (1) (2016) 295-303.

[19] C.V. Zegeer, D.W. Reinfurt, W.W. Hunter, J. Hummer, R. Stewart, L. Herf, Accident effects of sideslope and other roadside features on two-lane roads, Transportation Research Record (1195) (1988).

[20] H. Zheng, R. Wang, S. Xu, Recognizing Street Lighting Poles From Mobile LiDAR Data, IEEE Transactions on Geoscience and Remote Sensing 55 (1) (2017) 407.

[21] M. Lehtomäki, A. Jaakkola, J. Hyyppä, A. Kukko, H. Kaartinen, Performance analysis of a pole and tree trunk detection method for mobile laser scanning data.

[22] S. Pu, M. Rutzinger, G. Vosselman, S.O. Elberink, Recognizing basic structures from mobile laser scanning data for road inventory studies, ISPRS Journal of Photogrammetry and Remote Sensing 66 (6) (2011) S28-S39.

[23] Y. Lin, J. Hyyppa, Geometry and intensity based culvert detection in mobile laser scanning point clouds, Journal of Applied Remote Sensing 4 (1) (2010) 043553-043553-043515.

[24] Y. Tsai, C. Ai, Z. Wang, E. Pitts, Mobile cross-slope measurement method using lidar technology, Transportation Research Record: Journal of the Transportation Research Board (2367) (2013) 53-59.

[25] A. Holgado- Barco, B. Riveiro, D. González- Aguilera, P. Arias, Automatic Inventory of Road Cross- Sections from Mobile Laser Scanning System, Computer- Aided Civil and Infrastructure Engineering 32 (1) (2017) 3-17.

[26] R. Souleyrette, S. Hallmark, S. Pattnaik, M. O'Brien, D. Veneziano, Grade and cross slope estimation from LiDAR-based surface models, 2003.

[27] K. Zhang, H.C. Frey, Road grade estimation for on-road vehicle emissions modeling using light detection and ranging data, Journal of the Air & Waste Management Association 56 (6) (2006) 777-788.

[28] J.J. Dawkins, Model based off-road terrain profile estimation, 2014 American Control Conference, IEEE, 2014, pp. 2792-2797.

[29] C.-W. Wu, S.-H. Chio, 吳志文, 邱式鴻, Road surface modeling from vehicle-borne point cloud by profile analysis, 33rd Asian Conference on Remote Sensing 2012, ACRS 2012, Vol. 2, 2012, pp. 1031-1040.

[30] J.-Y. Han, A. Chen, Y.-T. Lin, Image-Based Approach for Road Profile Analyses, Journal of Surveying Engineering 142 (1) (2015) 06015003.

[31] J. Kim, J.-C. Lee, I.-J. Kang, S.-Y. Cha, H. Choi, T.-G. Lee, Extraction of geometric information on highway using terrestrial laser scanning technology, Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci 37 (2008) 539-544.

[32] G. Gräfe, Kinematic 3D laser scanning for road or railway construction surveys, Proceedings of the International Conference on Machine Control & Guidance, 2008, pp. 24-26.

[33] P. Tang, D. Huber, B. Akinci, Characterization of laser scanners and algorithms for detecting flatness defects on concrete surfaces, Journal of Computing in Civil Engineering 25 (1) (2010) 31-42.

[34] Y.-C.J. Tsai, F. Li, Critical assessment of detecting asphalt pavement cracks under different lighting and low intensity contrast conditions using emerging 3D laser technology, Journal of Transportation Engineering 138 (5) (2012) 649-656.

[35] M. Lato, J. Hutchinson, M. Diederichs, D. Ball, R. Harrap, Engineering monitoring of rockfall hazards along transportation corridors: using mobile terrestrial LiDAR, Nat. Hazards Earth Syst. Sci 9 (3) (2009) 935-946.

[36] P. Miller, J. Mills, S. Barr, M. Lim, D. Barber, G. Parkin, B. Clarke, S. Glendinning, J. Hall, Terrestrial laser scanning for assessing the risk of slope instability along transport corridors, (2008).

[37] A.J. Khattak, H. Shamayleh, Highway safety assessment through geographic information system-based data visualization, Journal of Computing in Civil Engineering 19 (4) (2005) 407-411.

[38] M. Castro, L. Iglesias, J.A. Sánchez, L. Ambrosio, Sight distance analysis of highways using GIS tools, Transportation Research Part C: Emerging Technologies 19 (6) (2011) 997-1005.

[39] M. Castro, J.A. Anta, L. Iglesias, J.A. Sánchez, GIS-based system for sight distance analysis of highways, Journal of Computing in Civil Engineering 28 (3) (2013) 04014005.

[40] M. Castro, S. Lopez-Cuervo, M. Paréns-González, C. de Santos-Berbel, LIDAR-based roadway and roadside modelling for sight distance studies, Survey Review (2016) 1-7.

[41] Y. Tsai, Q. Yang, Y. Wu, Use of Light Detection and Ranging Data to Identify and Quantify Intersection Obstruction and Its Severity, Transportation Research Record: Journal of the Transportation Research Board (2241) (2011) 99-108.

[42] Alberta Transportation, Vertical Clearance Measurements (VCL2), Alberta Infrastructure and Transportation 2014, p. 13.

[43] R.G. Lauzon, Automated vertical clearance measurement during photolog operations, 2000.

[44] W. Liu, S.-e. Chen, E. Hasuer, Bridge Clearance Evaluation Based on Terrestrial LIDAR Scan, Journal of Performance of Constructed Facilities 26 (4) (2012).

[45] I. Puente, B. Akinci, H. González-Jorge, L. Díaz-Vilariño, P. Arias, A semi-automated method for extracting vertical clearance and cross sections in

tunnels using mobile LiDAR data, Tunnelling and Underground Space Technology 59 (2016) 48-54.

[46] S.-E. Chen, W. Liu, H. Bian, B. Smith, 3D LiDAR scans for bridge damage evaluations, Bridges (2014).

[47] H. Bian, L. Bai, S.-E. Chen, S.-G. Wang, Lidar based edge-detection for bridge defect identification, SPIE Smart Structures and Materials+ Nondestructive Evaluation and Health Monitoring, International Society for Optics and Photonics, 2012, pp. 83470X-83470X-83410.

[48] B. Guldur, J.F. Hajjar, Laser-based structural sensing and surface damage detection, Department of Civil and Environmental Engineering Reports. Report No. NEU-CEE-2014-03. Department of Civil and Environmental Engineering, Northeastern University, Boston, Massachusetts. http://hdl. handle. net/2047/d20015559 (2014).

[49] B. Jafari, A. Khaloo, D. Lattanzi, Long-term monitoring of structures through point cloud analysis, SPIE Smart Structures and Materials+ Nondestructive Evaluation and Health Monitoring, International Society for Optics and Photonics, 2016, pp. 98052K-98052K-98058.

[50] A.G. Kashani, M.J. Olsen, C.E. Parrish, N. Wilson, A Review of LiDAR radiometric processing: From Ad Hoc intensity correction to rigorous radiometric calibration, Sensors 15 (11) (2015) 28099-28128.