

A Moving Window Search Method for Detection of Pole Like Objects Using Mobile Laser Scanner Data

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Abstract— Pole-Like Objects (PLOs) in the road environment located nearby the road boundary are important roadway assets. They play vital role in the road safety inspection and road planning. In present study a novel automated method for the detection of PLOs from Mobile Laser Scanner (MLS) point cloud data has been proposed. Proposed method includes four basic steps. Initially ground points are roughly filtered out from the input dataset to reduce the processing of un-necessary points; formerly local window search is performed at non-ground points to find out the concentrated point distribution. Principal Component Analysis (PCA) has been implemented at such concentrated distributed points for the identification of PLOs. In last step of proposed method knowledge based information are used for suppressing the false positives and rectifying the output. Proposed method has been tested on a MLS point cloud data of complex road environment and corresponding PLOs are detected having completeness and correctness of 91.48 % and 86.00 % respectively.

Keywords— LiDAR, Pole Like Objects, PCA

I. INTRODUCTION

PLOs play an important role in road environment. Road safety inspection, road planning, traffic management and future driver assistance consider the pole-like objects and its location along the corridor. Collection of pole-like structures information manually or using total station and GPS on a large scale is very time consuming, labor intensive, and costly.

Laser scanning or Light Detection And Ranging (LiDAR) systems use lasers to capture three-dimensional (3D) data from a tripod, a mobile vehicle, or an aircraft. Terrestrial laser scanners provide highly accurate (cm level) 3D point clouds, which are a set of vertices representing the surface of the object. These 3D vertices enable designers to experience and work directly with real-world conditions by viewing and manipulating point clouds in computer-aided design softwares. MLS technology is seeing increasing adoption in use for traditional surveying and photogrammetric applications. This increase is due to the continuous development in terms of data capture speed, accuracy and density of point data obtained from these systems. There is a rapid growth in the utilization of MLS systems in many road corridor applications. These systems capture huge point clouds that describe very highly detailed road scenes. Mobile LiDAR system has been designed to collect geo referenced dense point cloud information of objects along the highway

or rural roads. Mobile LiDAR system captures the highly accurate point cloud data at highway speed without interfering with traffic stream [1]. They greatly increase the safety for the surveyors and operators by removing them from the traffic stream. They can also capture the data in the evening or overnight, when there is less traffic, as the LiDAR sensors operate day and night. It is important to automate the detection of different road furniture such as road poles, the curb and the street floor from the point cloud captured by the MLS. This automatically extracted information could be used in many applications such as volume and quantity surveys, right-of-way asset inventory compilation and GIS applications.

Extraction of PLOs from MLS data plays key role in various important applications such as reconstruction and modeling of road environment, Automatic Driver Assessment (ADA) which incorporate the road safety problems and traffic management. PLOs are also useful to optimize the road planning having less destruction overhead and city management.

Much research has tried to detect the road poles from MLS point clouds. Typically two different approaches based on the format of the input point cloud are present in available literature. The first approach utilizes the cross section information of the point cloud, where the scanning system operates in a profile mode. The second approach utilizes the unorganized point clouds that result from registering multiple

drivelines. In the later approach there is no neighborhood structure present in the point cloud because it is lost after merging multiple drivelines together.

PCA was used for the extraction of different types of road poles [2]. Proposed method was divided in two phases, first phase, examines the effect of the point cloud density and the neighborhood size of segmented linear features. The second phase focuses on the extraction of different types of road poles and how to define their position and radius.

Investigation at the local pole pattern was used for the extraction of pole-like structures [3]. Proposed method was based on the characteristic of the pole, where the pole is an upright object and it has a Z extension. Therefore there is a kernel region of specific radius where laser scan points are required to be present and a hollow cylinder where no points are allowed to be present. An assumption that ground points are already removed from input point cloud was established [4]. Proposed algorithm consists of four steps. First, the input point clouds were segmented, as the result; points estimated on each object were grouped. Second, smoothing was applied to each segment. Third, each point was classified into the points of the PLOs, planar objects, and other objects. Finally, the degree of the PLOs of each segment was evaluated, and the segments of the PLO were extracted by thresholding.

A percentile based pole recognition algorithm was proposed [5]. Algorithm states that the vertical poles are very common in road area. Instead of the analyzing the whole candidate, segmentation of the data on the basis of height percentile was performed. After dividing the candidate into height percentiles, a certain percentile was divided into horizontal slices. For each slice a two-dimensional enclosing rectangle was fitted to the points represented in the XY plane. Based on the existing algorithm a method for the extraction of pole like objects was proposed [6]. Method was divided in five phases; rough classification, rule-based tree detection, percentile-based pole extraction, and knowledge-based further classification; at last, quantitative assessment works cyclically to check the performance of proposed algorithm, which includes two parts: an automatic quality assessment based on point wise and a visual examination based on object wise. If the classified result is not satisfied enough, the optimization would start again from the beginning and continue to loop till getting the optimal result.

A method to extract traffic signs/signals by using position of road boundary was proposed [7]. Road boundary was detected by identifying longest straight line from each profile scan and it was assumed that traffic signs/signals were lies in close proximity of the road boundary. Further, regular mesh grids with a unique hash value was designed using proximity points of the road boundary followed by clustering, object segmentation and feature extraction of traffic signs/signals from other objects.

Generally there is tradeoff between the accuracy and the processing time of algorithms. Algorithms typically depends the on the application for which the pole like objects

extraction has been performed. In the case of ADA the processing time of algorithm must be fast as well accurate, but in the case of reconstruction and modeling of road environment the accuracy of algorithm should be at acceptable level but the processing time of an algorithm (secondary concern) also be the satisfactory level because the data of MLS is in huge amount (bulky data size).

In present study a novel method for the detection of PLOs using MLS data is proposed. Method based on simple geometric principles such as local window search and PCA. Proposed method has been tested on MLS data of a test site. Test site contains different common features in urban environments (i.e. large buildings, junctions, roundabouts, small parks, parked vehicles or bins).

Section II of the manuscript describes the proposed method for PLOs detection. Result and corresponding discussion are shown in Section III and section IV respectively. Conclusions are deliberated in Section V.

II. METHODOLOGY

The proposed method for the detection of PLOs from MLS data consists four consecutive steps (Figure 1). Method uses raw unstructured mobile LiDAR data in XYZ format as input.

- Rough ground point elimination from raw input point cloud having X, Y, and Z coordinate values, using height variance.
 - Local moving window search at non-ground point cloud space. This step allows to basically find the candidate PLOs using point density.
- Tri-dimensional analysis at candidate PLOs. Eigen value and Eigen vector (PCA) are used in order to identify the PLOs.
- Refinement of false positives from identified PLOs using knowledge base information.

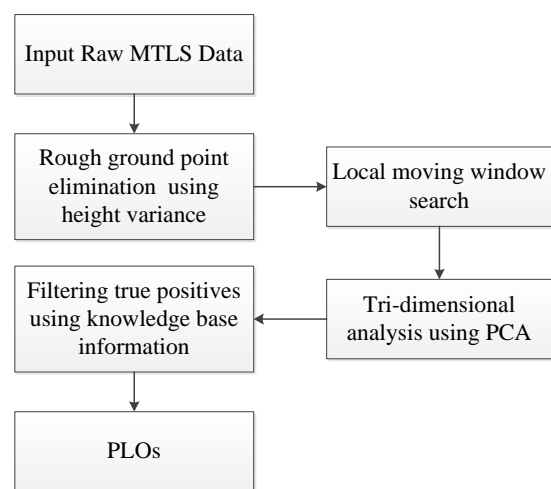


Figure 1. Process sequence of proposed method.

A. Rough Ground Point Elimination

Initially, each LiDAR points are selected as seed point sequentially and their neighboring points are identified based on two-dimensional (2D) K-d tree. Neighbors of seed points are identified within user defined circle, XY coordinate of seed point is used as center of the circle with a user defined radius OR_1 . Height variance $\delta z(i)$ is calculated using seed point and its earlier determined neighbor points (1).

$$\delta z(i) = \sum_{k=1}^n \frac{[Z(k) - \bar{Z}]^2}{n} \quad (1)$$

Where i represents seed point at the center of user defined circle, Z is height value of LiDAR point, n is the total number of points within circular neighborhood of seed point i , \bar{Z} is mean of the height of all n points .

$$\forall C_i : \begin{cases} \text{if } \delta z(i) < \delta z(i)^{th} & \text{Ground points (G)} \\ \text{else} & \text{Non-ground points (NG)} \end{cases} \quad (2)$$

Input LiDAR data points are divided into ground points (G) and non-ground points (NG) using (2) (Figure 2), where $\delta z(i)^{th}$ is height variance threshold value and C_i is selected i^{th} circle.

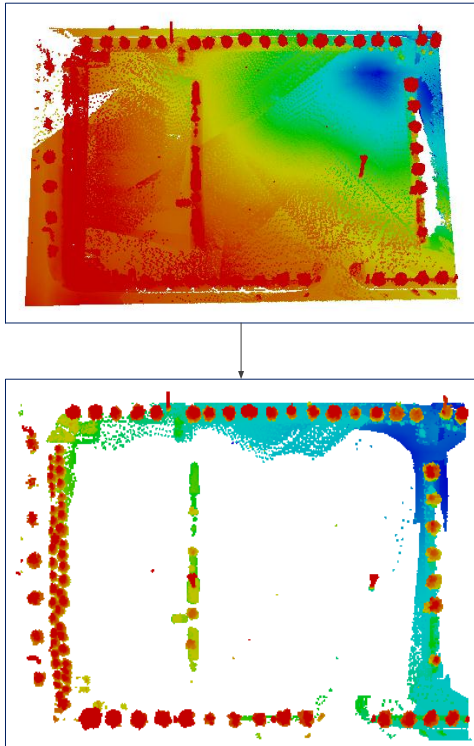


Figure 2. Eliminated ground points.

B. Local Moving Window Search

After filtering the ground points all the non-ground points are projected at XY plane and local window search operation is performed. For doing so, a user defined window is defined (W_s) and top left corner of projected dataset (non-ground points) is selected as seed point (point p , Figure 3). All the points lying under the local window are extracted and their variation in X and Y direction is calculated (3, 4). If the calculated variance ($\delta x(i), \delta y(i)$) is less than a predefined threshold ($\delta x(i)^{th}, \delta y(i)^{th}$) then tridimensional analysis using PCA is performed at these points (5) otherwise, window points are skipped. Further, window is moved in X direction and again similar procedure is applied. Process is stopped after window is reached at the bottom right corner of projected dataset (point r , Figure 3).

$$\delta x(i) = \sum_{p=1}^n \frac{[X(p) - \bar{X}]^2}{n} \quad (3)$$

$$\delta y(i) = \sum_{p=1}^n \frac{[Y(p) - \bar{Y}]^2}{n} \quad (4)$$

$$\forall W_i : \begin{cases} \text{if } [(\delta x(i) < \delta x(i)^{th}) \ \&\& \ (\delta y(i) < \delta y(i)^{th})] & \text{Processed in next step} \\ \text{else} & \text{Skipped} \end{cases} \quad (5)$$

Where, n is the total number of points are present in search window and W_i shows the selected i^{th} window.

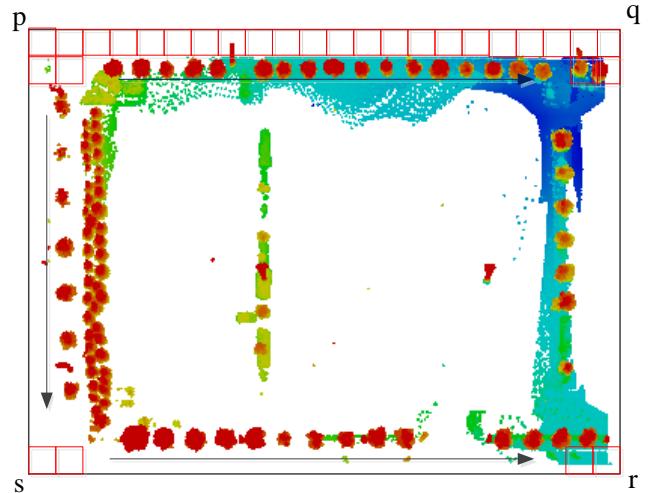


Figure 3. Moving window search.

C. Tri-dimensional Analysis using PCA

The objective of this step is to identify the PLOs from the eligible window points. For doing so, tri-dimensional analysis is carried out using Principal Components Analysis (PCA). Initially all the points of each eligible window are

taken sequentially and their variance co-variance matrix is calculated (6). Further, eigen values and corresponding eigen vector of variance co-variance matrix is calculated (7). The eigen values are normalized (9, 10) and the angle (θ) between the eigen vector ($E_{\alpha_{\max}}$) corresponding the maximum normalized eigen value (α_{\max}) and Z axis is calculated (12). If the value of maximum normalized eigen value and the calculated angle is greater than a particular threshold ($\alpha_{\max}^{\text{th}}$, θ^{th}) then the window points are classified as a PLOs (13).

$$C = \begin{bmatrix} \delta_x^2 & \delta_{xy} & \delta_{xz} \\ \delta_{xy} & \delta_y^2 & \delta_{yz} \\ \delta_{xz} & \delta_{yz} & \delta_z^2 \end{bmatrix} \quad (6)$$

$$|C - \lambda * I| = 0 \quad (7)$$

$$\lambda = \begin{pmatrix} \lambda_1 \\ \lambda_2 \\ \lambda_3 \end{pmatrix} \quad (8)$$

$$N\lambda_i = \frac{\lambda_i}{(\lambda_1 + \lambda_2 + \lambda_3)} \quad (9)$$

$$N\lambda_1 + N\lambda_2 + N\lambda_3 = 1 \quad (10)$$

$$E_{\alpha_{\max}} = a\hat{X} + b\hat{Y} + c\hat{Z} \quad (11)$$

$$\theta = \cos^{-1} \left(\frac{c}{\sqrt{(a^2 + b^2 + c^2)}} \right) \quad (12)$$

$$\forall We_i : \begin{cases} \text{if } [(\alpha_{\max} > \alpha_{\max}^{\text{th}}) \ \&\& \ (\theta > \theta^{\text{th}})] & \text{Classified as PLOs} \\ \text{else} & \text{Skipped} \end{cases} \quad (13)$$

Where, We_i is selected i^{th} eligible window.

D. Refinement

In this step, on the basis of knowledge base information some false positives which are misclassified as PLOs in previous step (Tri-dimensional Analysis using PCA) are removed. In order to carry out this, information like average height of PLOs and average number of LiDAR points for each PLO is used. Difference (ΔH) between average of few (n) LiDAR points close to maximum Z and minimum Z values are computed. By taking the average, effect of outlier or noise is avoided. Number of LiDAR points (Δn) for each PLO is also calculated. If difference, ΔH and number of LiDAR

points, Δn satisfy: $\Delta H > \Delta H^{\text{th}}$ and $\Delta n > \Delta n^{\text{th}}$; then only points belong to PLO.

III. RESULT

A. Study Area and Dataset

The proposed algorithm is tested on the mobile LiDAR data captured by Lynx Mobile Mapper, at Canada (Figure 4, Figure 5). Data is freely available for self-training at Terrsolid official website.

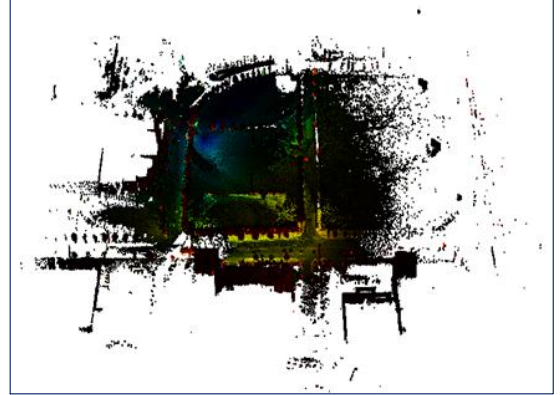


Figure 4. Perspective view of input point cloud dataset.

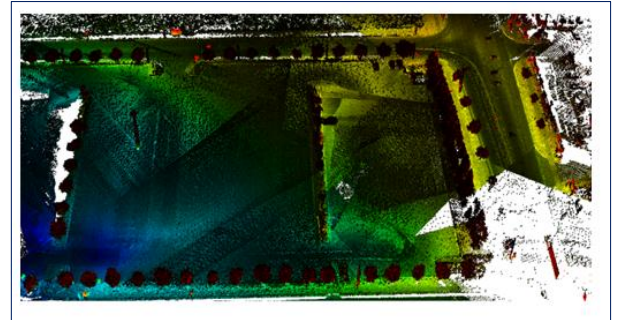


Figure 5. Zoomed view of input point cloud dataset.

Point cloud of test site has low 2D point cloud density (Table 1) having mainly ground objects including road section, trees with short trunk, street lights, low vegetation and buildings both sides of the road. Boundary of the road is not clearly defined but marked based on the location of different street furniture. Data characteristics for test site are shown in Table 1.

Table 1. Test site data characteristics

Name	Number of points	File Size	Average point density* (points/m ²)	Maximum height difference** (m)
Test site	2,830,444	2.59 GB	114	3.8

* 2D point density is calculated by projecting the 3D point cloud on XY plane.

** The biggest height difference on the ground surface.

B. Output Dataset

Detected PLOs of test site are shown in Figure 6. These query poles are important feature of road environment and have large impact on road safety problems. Therefore, their locations from road boundary, separation between them are important information, which could be easily measured through modest geo statistical calculation applied on detected geo referenced point cloud (Figure 6).

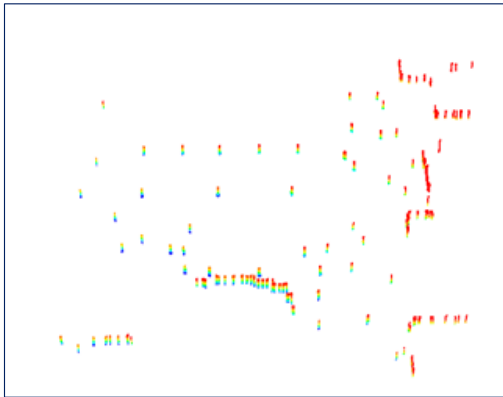


Figure 6. Detected PLOs of Test Site.

IV. DISCUSSION

Only the XYZ coordinates of input point cloud are only used by the proposed method, it does not required on the scanning geometry and neighborhood structure data. Therefore, dependency of algorithm on the scanning geometry [7-9] is removed. There is no training data is required in the proposed method, several existing algorithms [10, 11] need training data for the detection of pole structures. No initial assumption on the poles location is used. Non-ground points including all the PLOs are extracted in first step. Existing methods typically fails to detect many pole-like objects due to rough classification approach used to separate out ground, on-ground and off-ground points [12]. Due to incorrect initial point cloud segmentation several methods [4] are unable to detect many pole-like objects. Proposed method is not sensitive at point cloud density.

Performance of proposed method for PLOs detection is shown in Table 3. The completeness of 91.48% and correctness of 86.00% (Table 3) are achieved at parameter values given in Table 2. All the PLOs including partially occluded poles (only middle segment), tilted poles, poles situated very close to other objects and vertical pole attached with tilted pole are easily extracted. Completely occluded poles, top or bottom or both segment occluded pole, poles located far away from road boundary having quite less LiDAR points are few exceptions and they are not detected. Building columns having similar geometrical features as pole-like structures are also classified as pole.

Table 2. Number and type of poles detected test site

Parameters	Threshold Values
W_s	0.2 meter * 0.2 meter
OR_1	0.3 meter
α_{max}^{th}	0.8
θ^{th}	15°
ΔH^{th}	6 meter
Δn^{th}	70
$\delta z(\mathbf{i})^{th}$	0.3 meter
$\delta x(\mathbf{i})^{th}$	0.1 meter
$\delta y(\mathbf{i})^{th}$	0.1 meter
n	10
ΔH^{th}	6 meter
Δn^{th}	70

Table 3. Statistics of detected PLOs

Test site	PLOs detected/PLOs reference	False Positives	Completeness	Correctness
1	43/47	7	91.48 (%)	86.00 (%)

$$Completeness(\%) = \frac{\text{Number of PLOs detected}}{\text{Total number of PLOs}} \times 100$$

$$Correctness(\%) = \frac{\text{Number of PLOs detected}}{\text{Number of PLOs detected} + \text{Number of False Postives}} \times 100$$

V. CONCLUSIONS

A new method is proposed in this research for detecting the pole-like objects from mobile LiDAR data. Knowledge based approach is adapted for designing this four steps method. Point cloud data from one test site is used for testing the proposed method. Initial step is used for removing the unnecessary ground points from input dataset and all the non-ground points, which have all the PLOs are retained. Second and third steps are used for PLOs detection from non-ground data points. At last refinement is applied using knowledge base information to filter out the false positives from the detected PLOs. The completeness of 91.48% and correctness of 86.00% are achieved after applying proposed

method at the point cloud data of test site. PLOs completely occluded by the tree are not detected. Building columns geometrically similar to the query pole are classified as pole-like structure. Proposed method uses only XYZ coordinates of point cloud and does not depend on the additional information such as scanning geometry, neighborhood structure, intensity, etc. and it also does not use any initial assumption on poles location and training data. Proposed method is not sensitive to the point density. Poles situated very close to non-pole object and tilted poles are also easily detected. Vertical pole connected with tilted pole is also detected. Therefore, proposed method removes the limitations of existing methods. From the results obtained in the test site and the thorough analysis of the methods, it can be concluded that proposed method is more general and improves the performance of the existing methods by: (i) detecting PLOs joined to other features or connected to other poles, (ii) it is fully automatic and does not require the use of training data, (iii) no initial assumptions about the relative location of the poles are needed, and (iv) it is independent of the scanning geometry and it only needs the XYZ coordinates of the original points.

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