ACRS 2022 MONGOLIA

POLE INCLINATION ANGLE DETERMINATION FROM MOBILE LASER SCANNING DATA WITH THE ASSISTANCE OF HIGH-DEFINITION MAP

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KEYWORD: point cloud; tilt angle; CANUPO; RANSAC; DBSCAN

ABSTRACT:

Among all kinds of road infrastructure, pole-like object is one of the common types established along the road. Pole-like objects, e.g., lamp posts and traffic sign poles, provide basic traffic functions that maintain driving order and safety. However, poles may incline due to the strike of external force or accumulative deformation over time, endangering both the drivers and pedestrians. Therefore, this research aims at developing an algorithm to automatically calculate the pole inclination angle with the assistance of High-Definition map (HD map).

In this study, mobile laser scanning data is adopted for the computation of pole-like object inclination. The mobile laser scanners used are two Velodyne VLP-16s, and the point cloud data is stitched through GNSS and IMU. In addition, the proposed method combines the pole locations provided by HD map, so the step of pole detection can be omitted. And the advantage is that it not only reduces data processing time but also avoids the possibility of pole detection failure.

Based on the pole object locations provided by HD map, smaller point sets are cut out from the raw LiDAR point clouds first. By processing these point sets with CANUPO algorithm, the points represent pole-like structure are remained. The next step is to extract the real pole points through Random Sample Consensus (RANSAC) and Density-based spatial clustering of applications with noise (DBSCAN). In the last step, the pole inclination angle can be calculated by fitting the pole points and setting the threshold to determine the effective center of the circle.

The experiment of this research is mainly divided into two parts. The first part collects data for about 30 poles with two 16-line LiDAR Velodyne VLP-16 and terrestrial laser scanner (TLS) RIEGL VZ-400 in experimental area. The TLS data will be processed manually and only the pole point cloud will be left as the reference data. The purpose is to use higher precision instruments and manual processed data to calculate the RMSE between the MLS data and TLS data. And the final calculated RMSE value is 1.0 degrees. In addition, since the point cloud data of the skewed poles are difficult to obtain, we use the Heidelberg LiDAR Operations Simulator (HELIOS++) to simulate the vehicle point cloud data in the second part of the experiment. Three different types of pole models were included in the experiment, lampposts, traffic light poles and street sign poles. And the heights of the three types of poles are 2 meters, 5.5 meters and 10 meters respectively. And we tested the influence of different factors on the calculation results of pole inclination. The final results show that the proposed method can effectively extract the features of poles, and it can be applied to calculate the inclination angles of most poles.

1. INTRODUCTION

Among the various facilities in the road environment, poles provide the important function of indicating route, direction, location, etc. However, due to the impact from external forces or accumulated deformation over a long period of time, these poles may tilt and endanger road users. Therefore, the automatic determination of the pole inclination is one of the important research topics. In the existing research, most of them focus on the extraction and classification of poles. Some researches propose to extract poles from images or videos, but these methods usually rely on the visibility of poles and are susceptible to changes in light and weather (Zaklouta & Stanciulescu, 2012). In order to avoid the above problems, Mobile Laser Scanning (MLS) data began to be widely used in extraction and classification of poles. In 2016, Wu proposed the Ball Falling Algorithm method to extract poles and applied Support Vector Machine (SVM) and Random Forest to classify pole characteristics (Wu et al., 2016). Kang proposed a Circular Model with an Adaptive Radius to identify poles in 2018, and further classify poles according to shape features and spatial topological relationships (Kang et al., 2018). The main challenges faced by the above research are the possibility of failure or error in pole detection and how to robustly segment and identify poles that overlap with trees. The main challenges faced by the above research are the possibility of failure or error in pole detection and how to robustly segment and identify poles that overlap with trees. Therefore, this research aims at developing an algorithm to automatically calculate the inclined angle of poles with the assistance of HD map.

In the following paragraphs, the proposed method will be described in detail in Section 2. Section 3 presents the experimental results and analysis to evaluate the proposed method. Finally, we discuss the conclusions and future work in Section 4.

2. METHODOLOGY

The workflow of the proposed method is shown in Fig. 1, including the following steps: data preprocessing, CANUPO, pole point cloud selection, inclination angle calculation. The detailed algorithms will be described in the following subsections.

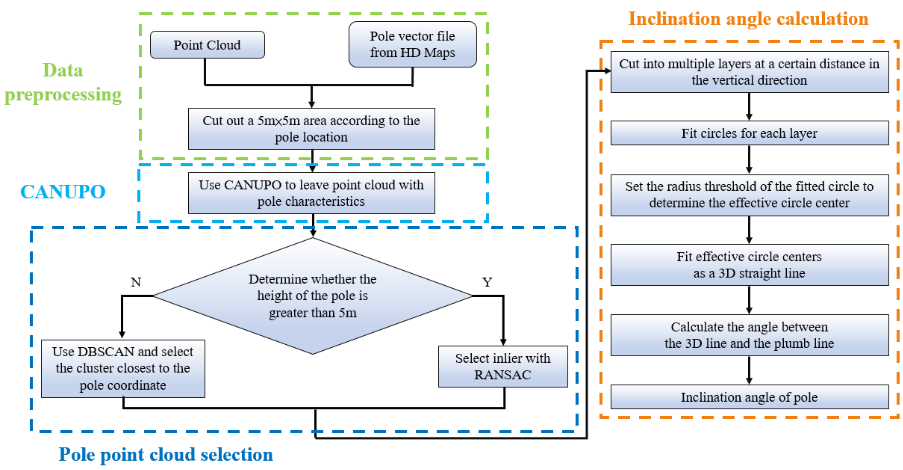


Fig. 1. Workflow of the proposed method

2.1 Data Preprocessing

First, we collect point cloud data through a mobile surveying and mapping system, and stitch the point cloud data using the Normal-Distributions Transform (NDT) matching method according to the trajectory information provided by the inertial navigation system. Fig. 2 shows the point cloud data after splicing. After splicing the point cloud, a point cloud with a range of 5m × 5m for a single pole is cut out according to the location of the pole provided by the HD map. High-Definition map (HD map) is a high-precision map used for autonomous driving, which usually acquire data by using a series of sensors, such as LIDAR, digital cameras and GPS. It contains details that are not usually present on traditional maps. The pole vector file from the HD map used in this research mainly contains information such as the top and bottom coordinates of the poles, and the height of the poles. In this step, we also remove the point within the vertical 30 cm range of the coordinates of the pole bottom to remove the ground point.

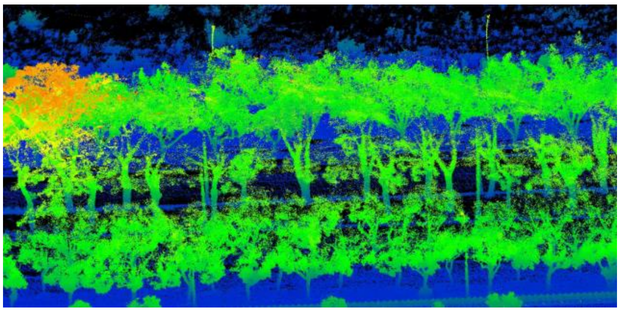


Fig. 2. The stitched point cloud data

2.2 CANUPO

After obtaining the point cloud of a single pole range, the point cloud with pole characteristics is left through CANUPO (Brodu & Lague, 2012). CANUPO is a pulgin provided by CloudCompare. The principle is to cut point cloud data at different scales first, and calculate eigenvalues through principal component analysis (PCA) to obtain point cloud dimension features. Finally, the support vector machine (SVM) is used to achieve the purpose of classifying the point cloud. As shown in Fig. 3 below: Figure 3(a) shows the point cloud of a single pole range, and the green dot at the bottom is the pole coordinate provided by the HD map; Figure 3(b) shows the point cloud after applying CANUPO, the blue point represents the point cloud with the characteristics of the pole, and the red part is the point cloud without the pole characteristic; Whereas in Figure 3(c), only the point cloud with pole features is left.

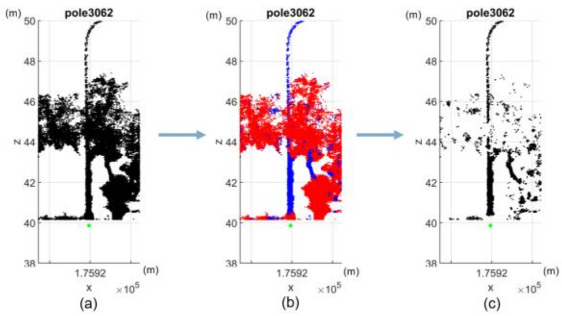


Fig. 3. The schematic of CANUPO

2.3 Pole Point Cloud Selection

Then in the next step, we select the pole point cloud in two ways according to the pole height. For poles higher than five meters, Random Sample Consensus (RANSAC) is applied to fit the point cloud. The main principle is to select the best model with the most inliers within the radius of 20 cm threshold through iteration, and select these inliers as the pole point cloud. In this process, the coordinates of the pole bottom provided by the HD map is also added to the iteration as a reference point to improve the accuracy of the point cloud selection.

For poles below five meters, if the Random Sample Consensus (RANSAC) algorithm is applied, the result is easily affected by other nearby objects, resulting in the failure of the pole point cloud extraction. Therefore, we apply Density-based spatial clustering of applications with noise (DBSCAN) for clustering, and select the cluster closest to the pole bottom as the pole point cloud.

2.4 Inclination Angle Calculation

The last step is to calculate the pole inclination angle. First, we cut the pole point cloud into multiple layers at a certain distance in the vertical direction, fit a circle to each layer, and set a radius of 20 cm as the threshold value to determine the effective center of the circle. Then we fit the effective circle center to a three-dimensional straight line, and the angle between the straight line and the plumb line is inclination angle of the pole, as shown in Fig. 4.

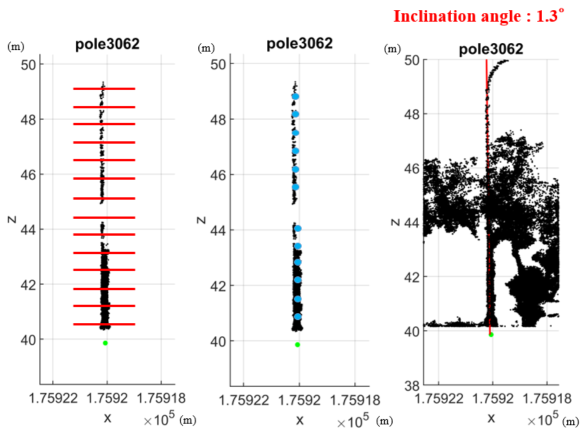


Fig. 3. The schematic of inclination angle calculation

3. EXPERIMENT AND RESULT

The experiment of this study is mainly divided into two parts. In the first part, two 16-line lidar Velodyne VLP-16 and terrestrial laser scanner (TLS) RIEGL VZ-400 are used to collect data in the experimental area respectively. The purpose is to use higher precision instruments and manually processed data to calculate RMSE values to verify the accuracy of the proposed method. In addition, in order to test the applicability of the proposed method, in the second part of the experiment, the Heidelberg Lidar Simulator (HELIOS++) is used to simulate 64-line LIDAR data. And we test the influence of different factors on the calculation results of inclination by simulating point cloud data.

3.1 Experiment 1

3.1.1 Study Area and Materials

The equipment used in the experiment 1 includes the vehicle PEUGEOT 3008, two Velodyne VLP-16 lidars, the iMAR iNAV-RQH inertial navigation system and TLS RIEGL VZ-400, as shown in Fig. 4. The experimental area is located near the Tainan high-speed rail station, and 35 poles were selected as the test targets. The MLS point cloud data is collected at a speed of 20 km/h, and the point cloud density is 2780 points per square meter. And the point cloud density of TLS data is up to one million points per square meter. The measurement range accuracy of MLS and TLS is 3 cm and 5 mm, while the angular resolution is 0.1 degrees and 0.0005 degrees, respectively.

(a)

(b)

(c)

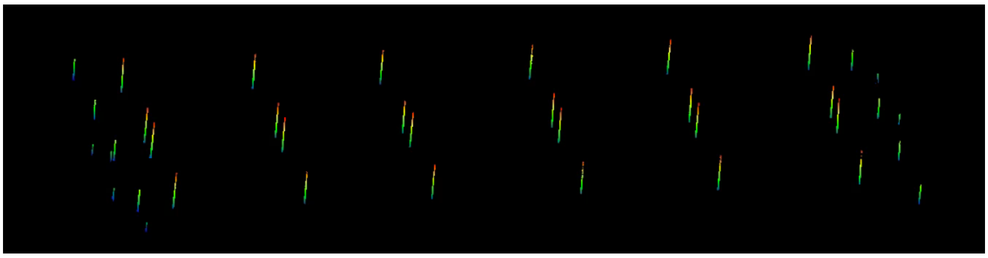
(d)

Fig. 4. Equipment used in experiment 1.

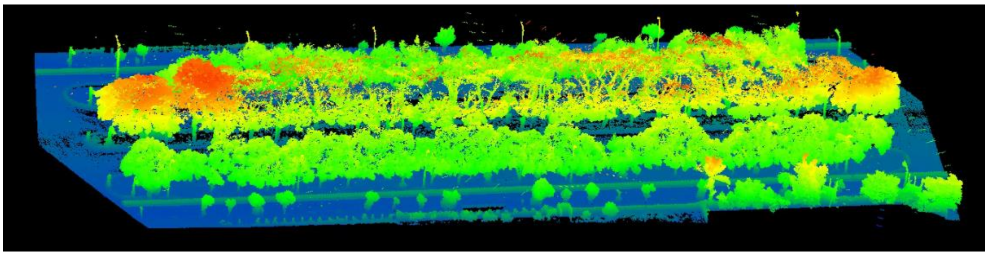
(a) PEUGEOT 3008 (b) Velodyne VLP-16 (c) iMAR iNAV-RQH (d) TLS RIEGL VZ-400

3.1.2 Result of Experiment 1

In experiment 1, we take 35 poles as the test target. The manually processed TLS point cloud is used as the reference data, as shown in Fig. 5(a), only the pole point cloud is left after the TLS data is manually processed. The calculation results of the inclination angle are drawn as a scatter plot as shown in Fig. 6 below. The final RMSE can be obtained as 0.72°.



(a)



(b)

Fig. 5. Point cloud data of the experimental area (a) Manually processed TLS data (b) MLS data

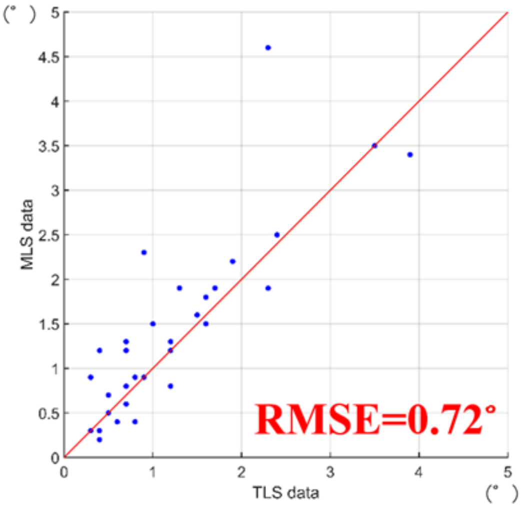


Fig. 6. Scatter plot of inclination angle calculation result

3.2 Experiment 2

3.2.1 Simulation scene settings

In experiment 2, we use the Heidelberg Lidar Simulator (HELIOS++) to simulate Lidar data, and the simulated instrument is Lidar HDL-64E S3. Three different pole models were selected in the simulation, namely lamppost, Traffic light pole and the street sign pole, with heights of 2 meters, 5.5 meters and 10 meters respectively. The three types of poles are inclined in units of 5 degrees, ranging from 0 to 70 degrees, and the inclination directions are divided into four directions, namely forward, reverse, outside, and inside. The vehicle speed ranges from 20 to 60 kilometers per hour, and the lane is assumed to be 3 meters wide, driving in the center of the lane, the pole is fixed on the right side of the driving direction, and the lane is 10 lanes from left to right.

The driving speed of the vehicle are 20, 40, and 60 kilometers per hour respectively, and it is assumed that the lane is 3 meters wide, the vehicle is driving in the center of the lane. The pole is fixed on the left side of the driving direction, and the lane are total 10 lanes from left to right.

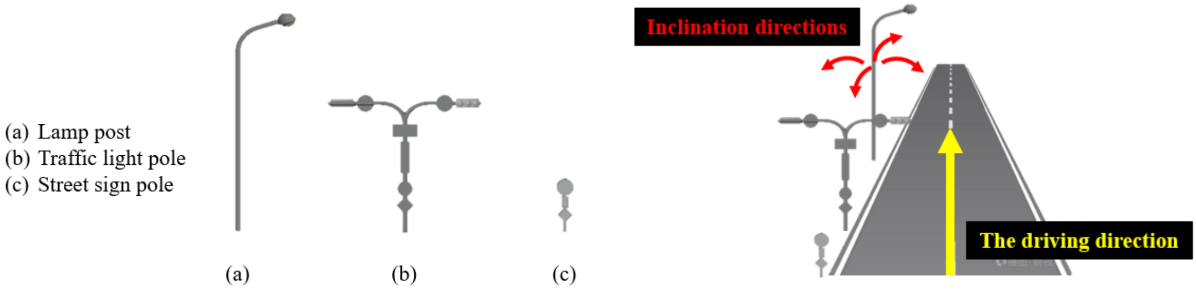
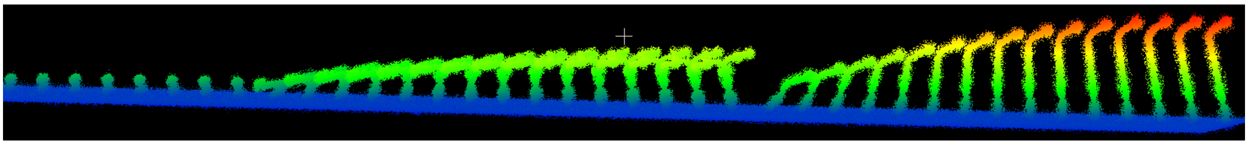
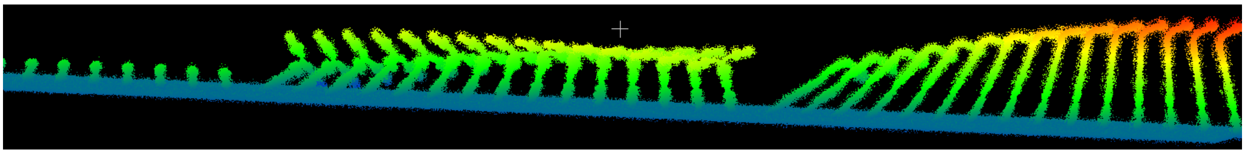


Fig. 7. Simulation scene setup



(a)



(b)

Fig. 8. Simulated point cloud (a) the poles are inclined to the opposite direction (b) the poles are inclined to the outside direction

3.2.2 Result of Experiment 2

The calculation results of the inclination angle of the simulated data are shown in Tables 1 and 2 below. The simulation results show that when the pole is inclined parallel to the forward direction (forward and reverse), the RMSE of the three types of poles is less than 4° under various speed and lane conditions; When the pole is inclined perpendicular to the forward direction (inside and outside), the street sign poles are affected by overlaid signs, and the RMSE value is higher than the other two types of poles, and the accuracy is poor.

		Lanes									
	Speed	1	2	3	4	5	6	7	8	9	10
lamppost	20km/hr	0.89	0.70	0.75	0.69	0.72	0.73	0.73	0.67	0.58	0.62
	40km/hr	0.52	0.53	0.47	0.64	0.69	0.74	0.74	0.73	0.85	0.98
	60km/hr	0.57	0.68	0.57	0.62	0.90	0.67	0.72	0.81	0.68	0.54
Traffic light pole	20km/hr	1.25	2.16	2.93	2.66	2.25	1.01	3.14	3.04	3.49	2.23
	40km/hr	1.28	1.26	2.95	1.42	1.57	2.60	3.33	2.64	2.07	3.52
	60km/hr	1.26	2.45	3.18	2.92	1.99	2.88	3.68	2.22	3.16	2.76
street sign pole	20km/hr	1.15	1.19	1.30	1.27	1.95	0.82	1.93	2.09	2.44	1.99
	40km/hr	0.87	1.23	1.55	0.90	1.01	1.84	2.68	1.64	2.13	2.54
	60km/hr	0.77	1.04	1.28	1.59	1.39	1.42	1.89	1.67	2.35	1.59

Tables 1. RMSE calculated by the inclination of the pole in the opposite direction (unit: °)

		Lanes									
	Speed	1	2	3	4	5	6	7	8	9	10
lamppost	20km/hr	1.35	1.11	1.37	1.07	1.29	1.30	1.11	1.50	1.40	1.51
	40km/hr	1.19	1.43	1.36	1.23	1.32	1.29	1.06	1.35	1.35	1.31
	60km/hr	1.21	1.37	1.26	1.19	1.36	1.18	1.25	1.19	1.32	1.18
Traffic light pole	20km/hr	1.96	2.05	2.10	1.91	2.99	2.72	1.84	2.99	3.18	3.96
	40km/hr	2.05	1.97	1.90	2.10	2.30	2.11	1.79	2.26	2.52	2.47
	60km/hr	1.77	1.74	1.97	2.20	2.71	2.21	2.46	2.78	2.38	2.42
street sign pole	20km/hr	6.94	7.15	6.45	6.80	8.88	7.83	7.10	8.99	7.43	7.11
	40km/hr	6.66	6.97	6.81	7.31	8.14	7.85	6.83	8.46	8.88	7.75
	60km/hr	7.20	6.12	6.77	7.53	8.02	7.30	7.46	6.96	6.64	7.59

Tables 2. RMSE calculated by the inclination of the pole in the outside direction (unit: °)

4. CONCLUSION AND FUTURE WORKS

This study demonstrates the workflow of pole inclination angle determination from mobile laser scanning data with the assistance of high-definition map. Compared with previous studies, the method proposed in this paper combines the pole vector file provided by the HD map, so the step of pole detection can be omitted, which not only reduces the data processing time, but also avoids the extraction failure. The experimental results show that the proposed method can be successfully applied to the calculation of most pole inclination angles. However, the result of calculating the inclination of the street sign pole is affected by the sign surface, which is more unstable than the other two types of poles. And future work includes optimizing the calculation results of the inclination angle of the street sign pole, and increasing the richness of the simulated scene, for example: adding other objects around the pole, testing the influence of the proportion of the street sign pole occluded by the sign on the calculation results, etc...

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