INVENTORY OF 3D STREET LIGHTING POLES USING MOBILE LASER SCANNING POINT CLOUDS

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ABSTRACT

This paper presents a novel approach for extracting street lighting poles directly from MLS point clouds. The approach includes four stages: 1) elevation filtering to remove ground points, 2) Euclidean distance clustering to cluster points, 3) voxel-based normalized cut (Ncut) segmentation to separate overlapping objects, and 4) statistical analysis of geometric properties to extract 3D street lighting poles. A Dataset acquired by *a* RIEGL VMX-450 MLS system are tested with the proposed approach. The results demonstrate the efficiency and reliability of the proposed approach to extract 3D street lighting poles.

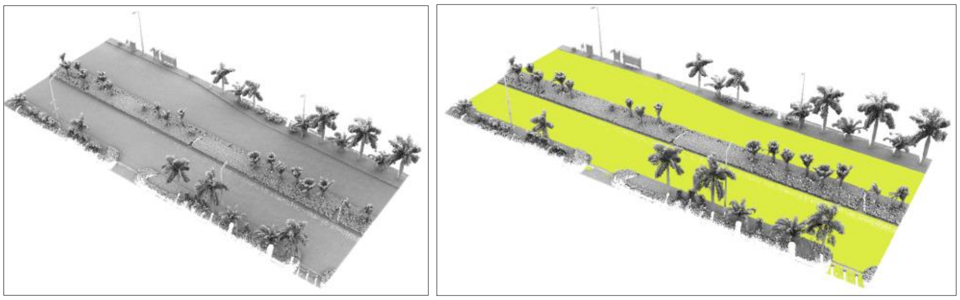
Index Terms— Lighting pole extraction, mobile laser scanning, point clouds.

1. INTRODUCTION

In Global Status Report on Road Safety 2013, the UN World Health Organization (WHO) indicates that, worldwide, the total number of road traffic deaths remains unacceptably high at 1.24 million per year [1]. To reduce the number of deaths, transportation departments need to implement more effective road safety policies. In these polices, detection and maintenance of road infrastructure on a regular basis plays an important role. As one of road infrastructure, street lighting poles, which can be found everywhere on the roads, are usually used to furnish illumination for assisting the pedestrians and drivers at night. On the other hand, poles serve as holders for other objects such as advertising boards, traffic lights, and traffic signs. Cost-effectively monitoring and managing street lighting poles are essential to enhance road safety. Identifying poles is very important and will make the detection of the attached objects easier. Usually rounded and long, poles are made of different materials and they have different heights and radii. However, in the same scene, the type of poles is usually identical.

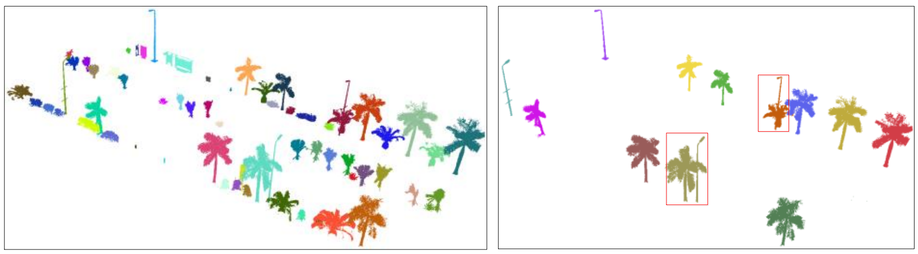
The average density of the point clouds collected by a mobile laser scanning (MLS) system can reach up to 4000 points/m^2 with a moving speed of approximately 50 km/h. Therefore, MLS systems provide a promising way to extract street lighting poles. In fact, automated extraction of street lighting poles from MLS point clouds has been an active research topic in recent years. A framework based on a collection of characteristics of point cloud segments was presented in [2] for poles structure recognition. A novel pairwise 3D shape-context method was proposed in [3] to extract street lighting poles from MLS point clouds. In [4], the proposed method firstly generated supervoxel segments from point clouds, and then defined a set of rules for merging these segments into meaningful units. Finally, the semantic knowledge of urban objects was formed and used for object classification. A hierarchical strategy including segmentation, principal component analysis (PCA)-based orthogonal regression, filtering, and parameter extraction procedures was presented in [5] to extract the geometric parameters of the vertical profiles and cross-sections of roads. In [6], by using local neighborhoods and based on the analysis of the relative sizes of the eigenvalues, poles were extracted.

In this paper, we propose a novel approach to extract street lighting poles directly from MLS point clouds. The approach includes four stages: 1) elevation filtering to remove ground points, 2) Euclidean distance clustering to cluster points, 3) voxel-based normalized cut (Ncut) segmentation to separate overlapping objects, and 4) statistical analysis of geometric properties to extract 3D street lighting poles. The proposed approach has been tested on a set of 3D point clouds acquired by a RIEGL VMX-450 MLS system. The results demonstrate the efficiency and reliability of the proposed approach to extract 3D street lighting poles.



(a) (b)

Fig .1. (a) Raw point cloud. (b) Road surface segmentation results (yellow part).



(a) (b)

Fig. 2. (a) Clustering result using the Euclidean distance clustering approach (different colors mean different clusters). (b) Filtering result using prior knowledge.

2. METHOD

The proposed algorithm contains four steps: ground point removal, Euclidean distance clustering, Ncut segmentation, and 3D lighting pole extraction.

2.1. Ground Point Removal

It is a big challenge to deal with the whole point clouds because of the huge amount of data. Instead of processing overall point clouds, it is necessary to partition the whole data into a number of blocks and remove the uninterested parts (ground points) to reduce the spatial and computational complexities.

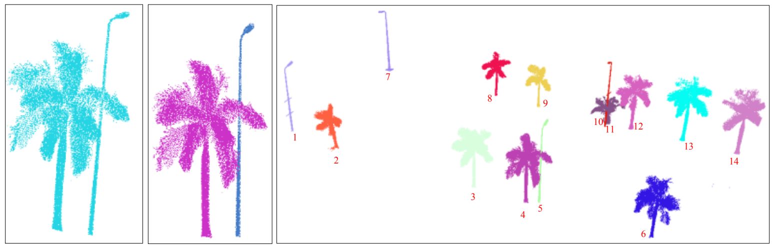
In this paper, we first use the trajectory data to partition the raw point clouds into a number of blocks. Within each block, ground points are segmented with a surface growing algorithm [2] [7] according to their coplanarity and connectivity. The implemented approach is based on planar seed surface detection in 3D Hough space. Further the neighboring points are added to the seed surface if they are below a threshold distance to this plane. After adding a point, the plane is determined anew by adjustment of all accepted points. Points are added to segments until defined growing criteria are exceeded. Leveraging the prior knowledge that the area of ground is large and the geometric centers are below the trajectory, we can segment the ground points. And then, by given an elevation threshold, we can remove the ground points. Fig. 1 shows the ground removal result.

2.2. Euclidean Distance Clustering

After removing the ground points, on-ground objects are isolated. Because of the discrete and unorganized characteristics of point clouds, we need to organize points into clusters that represent individual objects before extracting lighting poles. Here, we introduce a Euclidean distance clustering approach, which clusters points based on their Euclidean distances to their neighbors. Theoretically, an unclustered point is grouped into a specific cluster if and only if its shortest Euclidean distance to the points within this cluster lies below a predefined threshold. Finally, we leverage the knowledge that lighting poles always have some geometric constrains, like height, to eliminate those low-height clusters. In Fig. 2 shows different clusters with different colors.

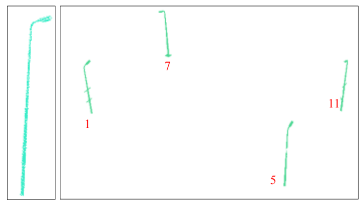
2.3. Normalized Cut Segmentation

Some clusters contain more than one object as shown in the red rectangle in Fig. 2(b). Thus, we use an Ncut segmentation method [8] to segment these clusters in order to obtain separated objects. First, the cluster is divided into a voxel structure with a voxel spacing v_e. Second, the nonempty voxels are used to construct a weighted graph $\boldsymbol{G} = \{\boldsymbol{V}, \boldsymbol{E}\}$, where $\boldsymbol{V}$ takes the nonempty voxels as nodes and $\boldsymbol{E}$ is formed between every pair of nodes. The similarity between a pair of nodes is represented by the weight w_{ij} which is computed as follows:



(a) (b) (c)

Fig. 3. (a) Raw point clouds. (b) Illustration of bipartition. (c) Ncut segmentation result (different colors mean different clusters).



(a) (b)

Fig. 4 (a) Lighting pole prototype. (b) Extracted lighting poles

Table 1

Bhattacharya distances between the lighting pole prototype and the different objects

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
$\|d_{bhati}\|$	4.16e -4	4.18e -1	4.38e -1	3.99e -1	4.52e -4	2.79e -1	1.67e -3	2.35e -1	1.33e -1	2.87e -1	5.94e -4	4.18e -1	3.99e -1	2.36e -1

$$w_{ij} = \begin{cases} \exp\left(-\dfrac{\left\|p_i^{XY} - p_j^{XY}\right\|_2^2}{\sigma_{XY}^2}\right) \cdot \exp\left(-\dfrac{\left|p_i^Z - p_j^Z\right|^2}{\sigma_Z^2}\right), & \text{if } \left\|p_i^{XY} - p_j^{XY}\right\|_2 \le d_{XY} \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

where $p_i = (x_i, y_i, z_i)$ and $p_j = (x_i, y_i, z_i)$ are the centroids of voxel i and j, respectively. $P_i^{XY} = (x_i, y_i)$ and $P_j^{XY} = (x_j, y_j)$ are the coordinates of the centroids on the XY plane, $p_i^Z = z_i$ and $p_j^Z = z_j$ are the z coordinates of the centroids. σ_{XY} and σ_Z are the standard deviations, and d_{XY} is a threshold determining the maximal valid horizontal distance between two voxels.

Ncut segmentation aims to partition graph $\boldsymbol{G}$ into two disjoint voxel groups $\boldsymbol{A}$ and $\boldsymbol{B}$ by maximizing the similarity within each group and minimizing the similarity between voxel groups. The purpose is achieved by solving the corresponding generalized eigenvalue problem:

$$(D-W)y = \lambda Dy \quad (2)$$

where $W(i, j) = w_{ij}$ and D is a diagonal matrix with $D(i, i) = \sum_m w_{im}$.

Finally, by applying a threshold to the eigenvalue associated with the second smallest eigenvalue, a cluster is separated into two segments as shown in Fig. 3.

2.4. 3D Street lighting pole Extraction

We propose a robust algorithm based on a statistical analysis of the geometric properties of the data to extract 3D street lighting poles [9]. Given a clustered object, first, each point on the object is represented using a five-dimensional feature vector f_p for describing the local geometry and it is given by

$$f_p = \langle N_x, N_y, N_z, dis, n_{var} \rangle \quad (3)$$

where N_x, N_y, and N_z are the components of the normal vector at each point computed by averaging the eight-neighborhood normal vectors, dis is the distance between the point and the central of all points in the XoY coordinates, n_{var} is the local normal variance around the eight neighbors of the point. Next, this cluster's associated probability density function (pdf) ϕ_i is modeled by a five-dimensional Gaussian function $\phi_i = N_i(\mu_i, \Sigma_i)$, where μ_i and Σ_i are given by

$$\mu_i = \frac{1}{n}\sum_{j=1}^{n} f_{pj}\ , \ \Sigma_i = \frac{1}{n}\sum_{j=1}^{n}(f_{pj} - \mu_i)^T (f_{pj} - \mu_i) \quad (4)$$

The clusters corresponding to the same structure are likely to have similar geometric properties. Hence, their pdfs modeling the distribution of these properties are expected to be similar. We leverage this characteristic and compare the pdfs of a given clustered object and the known lighting pole model using as a metric the Bhattacharya distance. The Bhattacharya distance d_{bhat} is a computationally very simple quantity that measures the separability between two normal distributions $N_p = \langle \mu_p, \Sigma_p \rangle$ and $N_i = \langle \mu_i, \Sigma_i \rangle$ and it is given by

Table 2
Description of the ground truth and extraction results in the dataset

Ground Truth		Extraction Results			Accuracy Evaluations		
Lighting poles	Other poles	Lighting poles	Missed	Other poles	Completeness	Correctness	Quality
141	12	132	9	8	93.62%	94.29%	88.59%

$$d_{bhati} = \frac{1}{8}(\mu_i - \mu_p)^T \left[\frac{\Sigma_p + \Sigma_i}{2}\right]^{-1} (\mu_i - \mu_p) + \frac{1}{2}\ln\frac{\left|\frac{\Sigma_p + \Sigma_i}{2}\right|}{\sqrt{|\Sigma_p||\Sigma_i|}} \quad (5)$$

where N_p is the normal distribution of a known lighting pole model; N_i is the normal distribution of the cluster i.
Eq. (5) gives the separability between two normal distributions. The range of values for the Bhattacharyya distance $|d_{bhati}|$ is $[0, +\infty)$, where $d_{bhati} = 0$ indicates that the two normal distributions are identical. Table 1 gives the Bhattacharya distances between the light pole prototype and the different objects as shown in Fig. 3(c). Given a threshold d_{bhati}=0.01, we can extract lighting poles from all the objects. Fig. 4 shows the result of lighting pole extraction.

3. RESULTS AND DISCUSSION

The MLS point clouds used in this study were acquired by a RIEGL VMX-450 system in a tropical urban environment, Xiamen, a port city in southeast China. The average density of the point clouds is approximately 4000 point/m^2. The accuracy of the acquired point clouds is within 8mm (1σ standard deviation), and the precision is 5mm with a maximum effective rate of 1.1 million measurements per second.

To extract lighting poles, a road surface point cloud was selected from the surveyed data with a distance of approximately 3 km along the road. First we partitioned the road surface point cloud into a number of blocks. In each block, the ground points were removed by implemented the surface growing algorithm. The Euclidean distance clustering and Ncut segmentation algorithm were performed sequentially. Finally, we applied the proposed lighting pole extraction algorithm to extract lighting poles from the clusters. The ground truth and the extraction result are listed in Table 2. Compared with the ground truth, the majority of lighting poles were extracted with a small number of false alarms.

In order to quantitatively evaluate the accuracy of the detection results, we applied three indices presented in [10]: completeness, correctness, and quality. As shown in Table 2, our algorithm achieved a completeness of 93.62%, a correctness of 94.29%, and a quantity of 88.59%. These results demonstrate that the proposed approach performs very well and achieves reliable results as shown in Fig. 5.

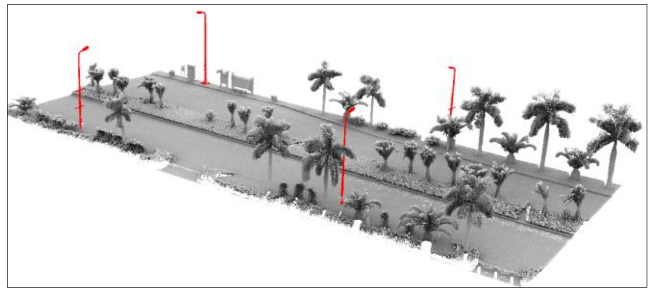


Fig. 5. Illustration of a part of street lighting pole extraction results using the proposed algorithm.

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