

SEGMENT-BASED TRAFFIC SIGN DETECTION FROM MOBILE LASER SCANNING DATA

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Abstract—This paper presents a segment-based traffic sign detection method using vehicle-borne mobile laser scanning (MLS) data. This method has three steps: road scene segmentation, clustering and traffic sign detection. The non-ground points are firstly segmented from raw MLS data by estimating road ranges based on vehicle trajectory and geometric features of roads (e.g., surface normals and planarity). The ground points are then removed followed by obtaining non-ground points where traffic signs are contained. Secondly, clustering is conducted to detect the traffic sign segments (or candidates) from the non-ground points. Finally, these segments are classified to specified classes. Shape, elevation, intensity, 2D and 3D geometric and structural features of traffic sign patches are learned by the support vector machine (SVM) algorithm to detect traffic signs among segments. The proposed algorithm has been tested on a MLS point cloud dataset acquired by a Leader system in the urban environment. The results demonstrate the applicability of the proposed algorithm for detecting traffic signs in MLS point clouds.

Index Terms—mobile laser scanning; traffic sign detection; segmentation; clustering; SVM

I. INTRODUCTION

Traffic signs as essential elements in regulating and controlling traffic activities, provide drivers warning and advice for convenience and safe driving and also ensure the smooth flow of traffic. Accurate recognition and positioning of traffic signs are necessary for many intelligent traffic related applications (e.g., autonomous driving and driver-assisted systems), which help machines to respond in a timely and accurate manner facing different situations [1]. In addition, an increasing number of signs are added to newly built road due to the frequent expansion of cities. This increases the amount of tasks about regular maintenance and condition checking for each sign [2]. If the detection process is achieved by human, not only subjective error will be added, but also drivers' attention will be scattered in this laborious task [3]. Thus, an automated approach to traffic sign detection (TSD) is required for the transport organization to update the traffic sign inventory in time, to ensure quality and safety of traffic, and to assist the unmanned system to accurately interpret road information.

Traditionally, most TSD methods are based on the texture and color details of the video imagery [4, 5]. However, the accurate geometric attributes of traffic signs are missing due to

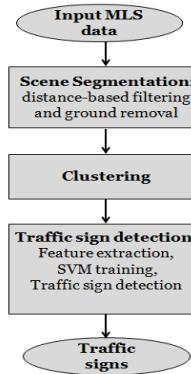


Fig. 1. Flowchart of the proposed traffic sign detection.



Fig. 2. Leader mobile laser scanning system

the lack of accurate three dimensional coordinate information. Recently, MLS technique has been widely applied in transportation applications e.g, line segment extraction[6], traffic sign inspection[7] and urban objects extraction [8]. A vehicle-borne MLS system uses laser scanners to acquire very dense point clouds (over 800 points/m²) along roads, covering the geometric features of the road environment and transportation facilities. Precise geometric and localization information of the 3D objects are included in the point clouds [9], which are suitable for TSD tasks.

In this paper, we propose a segment-based algorithm for

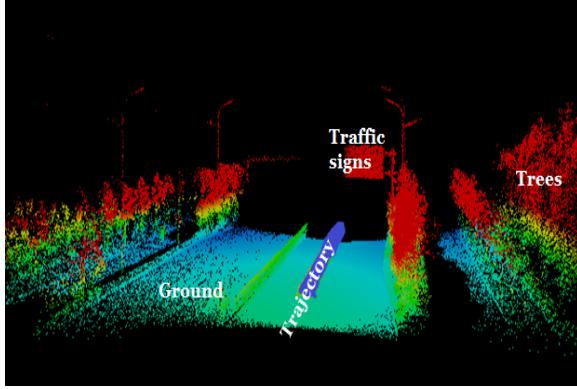


Fig. 3. Raw MLS point cloud data.

directly detecting traffic signs from MLS data, as shown in Fig.1. The whole scene is roughly segmented into ground and non-ground parts first by estimating road ranges with the consideration of vehicle trajectory and geometric features (e.g., surface normal and planarity). Then the ground parts are removed and the remaining non-ground parts that are probable regions of traffic signs are saved. Clustering is conducted to divide the non-ground point cloud into small parts. Finally, these segments are detected as traffic signs or non-signs. Shape, elevation, intensity, 2D and 3D geometric and structural features of traffic sign patches are learned by SVM to detect traffic signs among segments. The proposed algorithm has been tested on a dataset of point clouds in urban environment.

II. MOBILE LASER SCANNING SYSTEM

Fig. 2 shows the MLS system from Leador. The system consists of multiple sensors, including cameras, global navigation satellite system (GNSS), initial measurement unit (IMU), and laser scanners with 920 m measuring range. This system collects point cloud data when the vehicle is moving on the road, with the 0.002° attitude accuracy, 0.005° heading accuracy and 0.005° per hour zero drift.

III. METHODOLOGY

A. Scene Segmentation

In MLS, the points are scanned along the roads continually, which produces a huge amount of data to process. That data includes the roads, green belts, lights, trees, buildings, traffic signs and billboards. It is a large scene with complex surroundings. Note that the vehicle trajectory information is provided, the traffic signs distance to the scan line must be less than a certain distance. Thus, this distance can be used as a filter to remove remote irrelevant point. Here, we use 10 m as a metric to segment the scene. In view of the scanned MLS data in Fig.3, the ground points always occupy the largest part; however, our interest objects are set on the ground. Thus segmenting the whole data into different parts roughly, and then selecting the interest information locally, instead of processing the whole point cloud directly, are wise choices to extract traffic signs. Most researchers usually segment the

whole data into two groups: ground and non-ground points [9–11]. Here, the RANSAC algorithm [12] is used to extract the road plane. The normal (e.g., the road surface normal is horizontal) is considered as a metric to rule out non-road plane. After removing the ground points, the remaining off-ground points are reduced to a large extent compared with the raw data and used as the input data for further detection. The segmentation results are shown in Fig.4.

B. Clustering

Although we filter out large-scale terrain points, traffic signs, facades, light poles and vegetation are all contained in the non-ground point clouds. In addition, occlusions caused by medium and high vegetation and other objects result in great challenges to the detection of traffic signs along the road. A clustering method is needed to divide the non-ground point cloud into small parts so that the overall processing time for traffic sign detection is significantly reduced. Thus a distance-based clustering algorithm in a Euclidean sense is conducted to gather traffic sign points from non-signs points [13]. The results of clustering can be seen in Fig.5.

C. Segment-based traffic sign detection

1) Segment-based features extraction: Before introducing the traffic sign detection methods, it is necessary to briefly review the features of traffic signs in point clouds. Road Signs and Signals usually have the uniformed size and shape according to traffic regulation [14]. The 2D shape and area can be extracted in vertically projected surface. Apart from the above features, some geometric 3D features of segments [15] in MLS should also be considered. Generally, point clouds representing an observed 3D scene do not provide a completely random point distribution since the 3D points are the measured or derived counterpart of real object surfaces. Since traffic signs, the man-made objects, often tend to provide almost perfectly vertical structures, we may also involve geometric and structural features resulting from a 2D projection of the 3D point cloud onto a horizontally oriented plane, i.e. the XY-plane.

- Local 3D shape features: For a given traffic sign segment, it may have a set of 3D shape features in three directions (horizontal and vertical). This feature set includes linearity L , planarity P , scattering S , omnivariance O , anisotropy A , eigenentropy E , sum R of eigenvalues and change of curvature C [15].
- Elevation-Based Features: The elevation of traffic signs is an important feature, which is usually maintained at a fixed level. Relative elevation H_r , Elevation variance H_v , Elevation difference H_{diff} , Normalized elevation H_n [16] are utilized in this paper.
- Retro-intensity: Laser beams hitting a retro-reflective surface will return to the receiver without much signal loss. From Table 1, the traffic signs have the strongest retro-intensity. This is mainly because the metallic material of traffic signs.

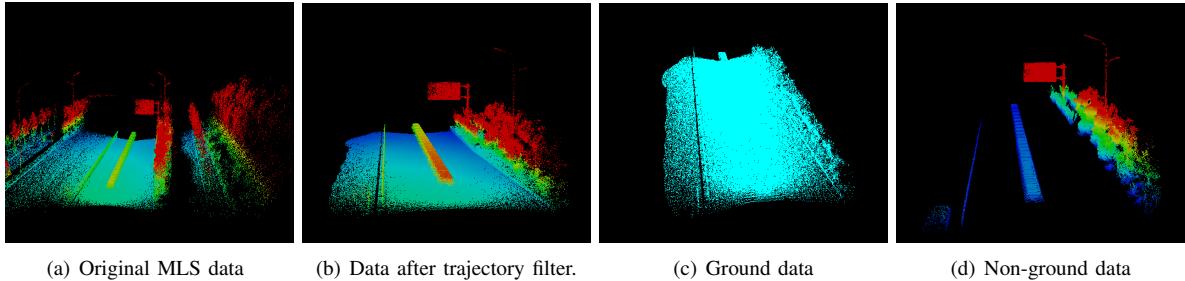


Fig. 4. Scene segmentation results (in elevation color)

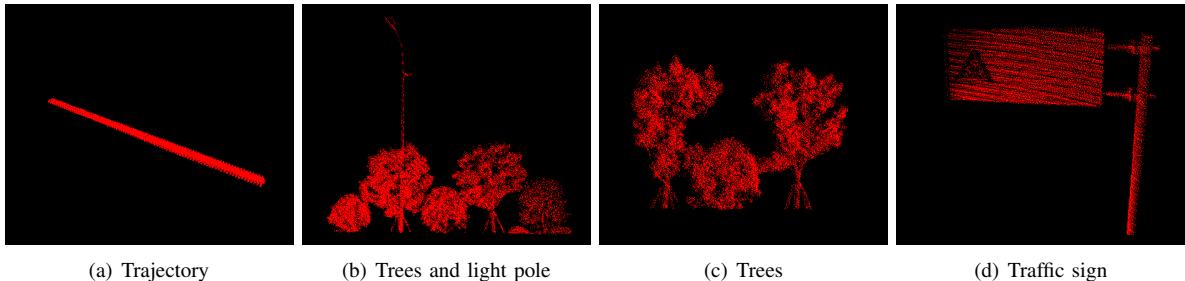


Fig. 5. Non-ground points clustering results

TABLE I
TYPICAL RETRO-INTENSITY OF COMMON ROAD OBJECTS [10].

| Roadside object | Typical retro-intensity value |
|----------------------|-------------------------------|
| vegetation | 0.33 |
| Vehicle | 0.34 |
| Building | 0.30 |
| Utility pole | 0.27 |
| Traffic sign | 0.75 |
| Commercial billboard | 0.20 |

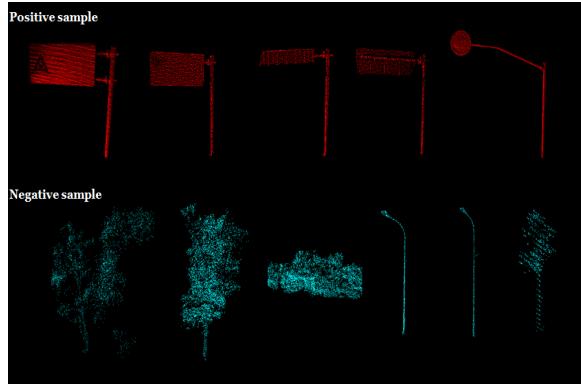


Fig. 6. Positive and negative samples. The upper includes different traffic signs. The bottom includes trees and light poles as negative sample.

2) *Traffic sign detection*: Each segment associated with the above geometric features is labeled as a traffic sign or non-sign by SVM, which is suitable for objects classification, regression, and distribution estimation and supports multi-class classification [17]. To obtain an optimal classification model, a training set and a validation set are generated manually within a real mobile laser scanning point cloud data, and the training

set is trained using SVM with a radial basis function(RBF) kernel. Finally, the point cloud segments are classified as a traffic sign or not using SVM with the optimal classification model, as shown by the red dots respectively (Fig. 3). The clustered point clouds are classified as a traffic sign in mobile laser scanning point clouds.

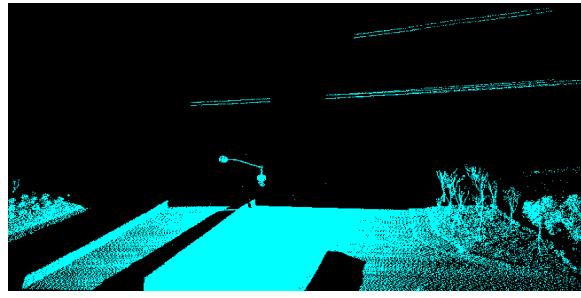
IV. RESULTS AND DISCUSSION

We tested the proposed traffic sign detection method on the MLS data in Wuhan, China. Fig. 4 shows a road section of the collected MLS data.

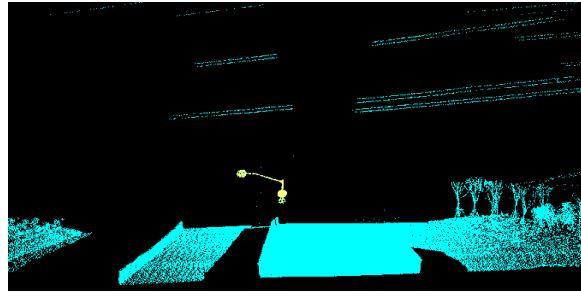
In the road scene segmentation step, according to the prior knowledge of the investigated road section, the parameter used in trajectory filter is selected according to the traffic regulation. The largest road width is 40 m of two-way lane in China, thus the distance of the traffic signs to the normal driving vehicle trajectory must be less than 10 m. We use 10 m to filter irrelevant point clouds. In the road scene segmentation, all the points within 1 m distance to the largest plane will be viewed as parts of the plane. The RANSAC algorithm runs iteratively with the limitation of 50 times to achieve the optimized model.

Experimental parameters are used in the clustering step. We set 30 cm radius to search for nearby points. Only the number of points between 1000 to 500000 in each cluster can be viewed as a candidate traffic sign segment, the other points are classified as scatter points. Each segment and the scatter parts are saved respectively. These segments are then input into SVM classifier to detect traffic signs.

Fig. 6 shows the positive samples and negative samples used to train SVM classifier. A total of 20 traffic signs are chosen as positive samples and 40 trees and light poles are selected as negative samples. We use 5 traffic signs and 5 other kinds of objects on road to validate our algorithm. The



(a) Original data



(b) Detected result (shown in yellow color).

Fig. 7. Traffic sign detection results (the detected traffic sign is shown in yellow color).

final testing results are shown in Figs.7 and 8. In complex area with disorganized tree and more than one traffic signs, the traffic signs in Figs.7 are extracted completely without noise; however, in Figs.8, the traffic sign in purple color is extracted with part of trees which is overlapped with the pole of traffic sign. Thus, a more detailed and effective clustering method which can split connected two objects is required in our future research.

V. CONCLUDING REMARKS

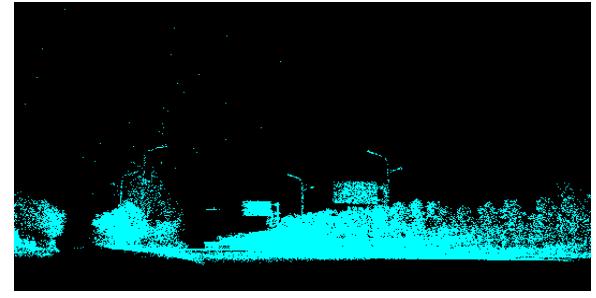
This paper proposed a segment-based traffic sign detection method, which integrates 2D and 3D geometric and structural features extracted from clustered segments. As can be seen from the detected traffic signs in different situations, we conclude that the proposed segment-based algorithm performs robustness and achieves reliable results.

ACKNOWLEDGMENT

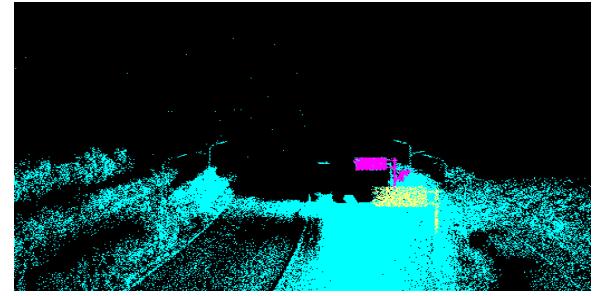
The authors would like to thank Leador Spatial Information Technology Corporation to provide MLS data.

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(a) Original data



(b) Detected result (shown in yellow and purple color).

Fig. 8. Traffic sign detection results (the detected traffic signs are shown in yellow and purple color).