

Road traffic sign detection and classification from mobile LiDAR point clouds

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ABSTRACT

Traffic signs are important roadway assets that provide valuable information of the road for drivers to make safer and easier driving behaviors. Due to the development of mobile mapping systems that can efficiently acquire dense point clouds along the road, automated detection and recognition of road assets has been an important research issue. This paper deals with the detection and classification of traffic signs in outdoor environments using mobile light detection and ranging (LiDAR) and inertial navigation technologies. The proposed method contains two main steps. It starts with an initial detection of traffic signs based on the intensity attributes of point clouds, as the traffic signs are always painted with highly reflective materials. Then, the classification of traffic signs is achieved based on the geometric shape and the pairwise 3D shape context. Some results and performance analyses are provided to show the effectiveness and limits of the proposed method. The experimental results demonstrate the feasibility and effectiveness of the proposed method in detecting and classifying traffic signs from mobile LiDAR point clouds.

Keywords:LiDAR, traffic sign detection, classification, shape context

1. INTRODUCTION

Traffic sign detection and recognition are crucial for vehicle guidance, as they can provide warnings and suggestions to drivers for driving safety and convenience. It is important that transportation departments should regularly conduct inventory mapping of traffic signs to realize their locations and corresponding functions. In general, this process involves a large amount of manual work, which needs the engineers to physically measure traffic signs and manually process the data. However, it is dangerous, costly, and time consuming. Therefore, we propose a method that can accurately complete the recognition task with a minimal of manual assistance.

In this paper, we focus particularly on morphological classification methods for traffic sign recognition, because of their usefulness for road inventory and the Intelligent Transportation System (ITS). Detecting traffic signs and obtaining their morphological information are key steps in traffic sign recognition. Such morphological information of traffic signs could simplify the recognition process.

Video log images have been used to automatically detect traffic signs for more than a decade^{1,2,3}. However, image based acquisition requires relatively good weather and lighting conditions. In poor conditions, it is hard to identify object positions correctly. However, the data collection work in point clouds do not have such limitation and can be done even in bad weather conditions. Compared to artificial vision systems, laser scanning captures highly dense and accurate point clouds in a relatively short time, which is popular in transportation engineering^{4,5,6}. Typically, mobile LiDAR systems can fully capture the road environment, including real geospatial information and backscattered energy, which can reflect the material properties of object surface, etc. Therefore, mobile LiDAR technology is ideally suited for urban road feature inventory.

In recent years, road asset extraction from mobile LiDAR point clouds has been increasingly studied. In⁷, a method based on Laplacian smoothing using the k-nearest neighbors graph and Principal Component Analysis was proposed to

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recognize pole-like objects. Based on a proposed 3D object matching framework, a model-driven method was developed in⁸ for updating urban road feature inventory, including street light poles, traffic signposts, and bus stations. By generating multi-scale supervoxels from 3D point clouds and defining a set of rules for merging segments into meaningful units, a hierarchical strategy was proposed in⁹ to extract urban objects. These methods all use geometry features to extract traffic signs. Although they have potentials to be applied in the detection, but they are time-consuming and can be easily confused with the other objects of similar geometry properties. As the intensity information can effectively distinguish traffic signs with other road assets, such property have been used in^{10,11} to perform the detection, which estimates only the position. In¹², a template-driven method was developed for extracting traffic signposts.

This paper is organized as follows. The first section introduces the necessity and objective of our research. The second section presents the proposed traffic sign detection method. The third section elaborates the classification method using geometric shape property and the 3D shape context. Finally, we test and validate the method with two mobile LiDAR data, after that the conclusions are drawn and recommendations for the future research are discussed.

2. METHODOLOGY

2.1 Detection

In this section, we present the traffic sign detection method using mobile LiDAR technologies.

The entire process of traffic sign detection is divided into two steps, including retro-intensity filtering and segmentation. The workflow of the proposed traffic sign detection approach is presented in Fig.1.

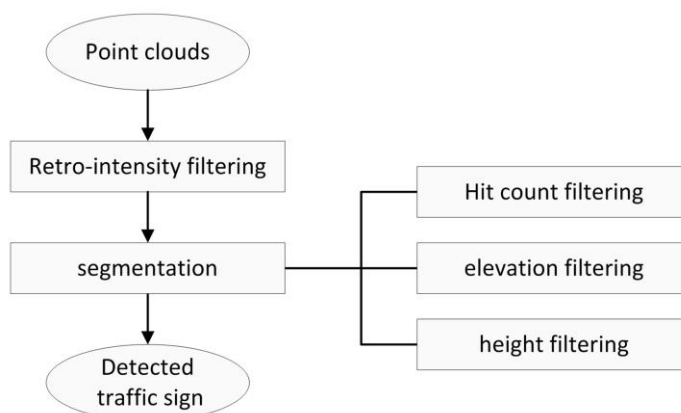


Figure 1. Flowchart of traffic sign detection algorithm

2.1.1. Retro-intensity filtering

Retro-intensity describes how energy is reflected from the target and returned to scanners which emit energy originally. It reflects the retro-reflectivity defined by Ministry of Transport of the People's Republic of China (MOT), which shows the property of a traffic sign to reflect light back to the driver. The retro-intensity ranges between 0 and 1. Since the road signs are painted with particular materials with high reflectivity, their intensity values in point clouds are higher than the other objects. Therefore, The majority of uninterested objects in the road scene can be filtered by setting the intensity value above a proper threshold^{10,11}. The threshold must be continuously readjusted by experiment to obtain the best filtering capability. The new point cloud produced in this step may still contain signs along with some other objects, such as temporary signs, vehicle license plates, and many more. It needs to be further processed in the next step.

2.1.2. Segmentation

In this part, we introduce a Euclidean distance clustering approach, which clusters points based on their Euclidean distances to their neighbors. Theoretically, an un-clustered point is considered as a part of a specific segment if and only if its shortest Euclidean distance to the points within this segment lies below a predefined threshold. Depending on the different resolutions of scanners, the threshold can be set to be any value. We set the distance threshold to be 0.1 meters. However, to detect traffic signs automatically, some rules need to be defined to estimate whether a segment contains a sign. In our work, three rules are defined:

a) Hit count filtering. The segment should include a bare minimum of 70 points. A clustered object which contains fewer points than the least value would be not enough to be a traffic sign. Consequently, such traffic sign candidates will be discarded from the detection results.

b) Elevation filtering. The difference of z-coordinates between the segment centroid and the ground points should be at least 2 meters. This rule eliminates non-traffic-sign objects of high retro-intensity values such as vehicle license plates, road cones, and temporary signs.

c) Height filtering. The highest point of the segment should be at least 0.4 m higher than the lowest one. As the height of traffic signs is given by national decree for different attributes, this rule will effectively filter out the non-traffic-sign candidate segments with small elevation values.

After this step, the remaining parts will be considered to be road traffic signs.

2.2 Shape classification

As presented in the previous sub-section, traffic sign blobs are extracted from the scene. In this section, the blobs will be classified into specific shapes. The presented method is on the basis of the attributes and relations analysis of their convex hulls in order to retrieve circular and rectangular candidates. For the triangular and octangular candidates, a pairwise 3-D shape context algorithm is introduced to detect them. It is to be noticed that, the quality of input is not highly demanded, e.g. the candidate sign needs not to be intact.

2.2.1. Circular and rectangular road signs

The proposed shape recognition procedure is summarized in the following:

a) The convex hull of each segment is generated. The convex hull can quickly capture a rough idea of the shape or extent of a point data set with relatively low computing cost.

b) Each segment is fitted to its Minimum Enclosing Rectangle, and Minimum Enclosing Circle, respectively. The minimum enclosing rectangle is defined as a rectangle which contains each point in the point set. Evidently, the rectangle would cover all points if and only if it covers their convex hull and the rectangle at least has one edge overlapped with the convex hull's edge [9]. The calculation algorithm of minimum enclosing circle is based on a simple property: If a new half plane is added to some specific given points, as long as the half plane contains the previously key vertices which determine the minimum bounding circle, the optimal solution will remain the same; Otherwise, the new optimal vertex must be located on the boundary of the new half space [10]. Both the Minimum Enclosing Rectangle and Minimum Enclosing Circle can all be calculated in linear time.

c) The areas of the convex hull, Minimum Enclosing Rectangle and Minimum Enclosing Circle are calculated. Then we further get the area ratio between the convex hull and the Minimum Enclosing Rectangle and Minimum Enclosing Circle. The ratio is compared to a predefined matching threshold, which is set to decide whether the segment is rectangular or circular. In the paper, the threshold is set to be 80% based on empirical value. The result consists of three types: Only one ratio reaches over 80%: the segment's shape is considered to be this specific one. Both ratios reach over 80%: the higher one will represent the shape of segment. Both ratios are below 80%: the segment will not be labeled and will be further classified in the next step.

Fig. 2 illustrates the shape recognition of laser segments. The matching rates of the convex hull with Minimum Enclosing Rectangle and Minimum Enclosing circle are listed in Table 1. As shown by the result in Fig. 2(a), this segment is completely detected, and scanned with sufficient point density, therefore the matching rate is up to 98%. The circular segments in Fig. 2(b) is relatively sparse on point density, thus the matching rates is a little above the threshold. For Fig. 2(c), the matching rates are both rather low. It is concluded that even if the points are not so dense or not completely scanned or detected, we can still draw the correct conclusions.

Table 1. Matching rate of segments

Matching shape	Original shape		
	rectangle	circle	triangle
rectangle	98%	82%	59%
circle	60%	85%	49%

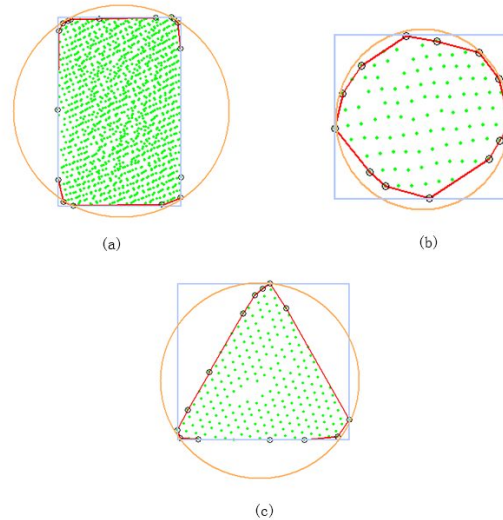


Figure 2. Shape recognition (green: segments; red: connection line of convex hull; orange: Minimum Bounding Circle; blue: Minimum Bounding Rectangle)

2.2.2. Triangular road signs

Detecting triangular road signs is more difficult than the circular and rectangular ones. A pairwise 3-D shape context algorithm described in this Section would be used for object matching on mobile LiDAR point clouds [11,12,13]. As the algorithm is invariant to scale, invariant to orientation, and partial insensitivity to topological changes, leading to a very robust algorithm for detecting traffic sign shapes.

The 3D shape is represented by a set of histograms, which correspond to the points sampled from the shape. Each point is associated with a descriptor, which denotes the appearance of the whole shape with respect to the accordingly points. The object matching procedure based on 3D shape context can be described as follows:

a) 3D shape histograms. Shape histogram is defined by the number of 3D points that reside in a partitioned subspace. The space that contains whole 3D object is divided into cells corresponding to the bins of the histograms. There are several separation models to decompose the space. Among those models, the shell model is chosen in our work. Specifically, the histogram h_i for a point p_i can be given as follows:

$$h_i(k) = \#\{q \neq p_i : (q - p_i) \in \text{bin}(k)\} \quad (1)$$

b) Matching. Assume a point p_i existing in point set P and a point q_j in the other point set Q. Then $C(i,j)$, the cost of matching points i and j , could be expressed as follows:

$$C(i, j) = \frac{1}{2} \sum_{k=1}^k \frac{[h_i(k) - h_j(k)]^2}{h_i(k) + h_j(k)} \quad (2)$$

$h_i(k)$ and $h_j(k)$ denote the K-bin normalized histogram at p_i and p_j , respectively. Accordingly, the total matching cost between the points on the first shape P and the points on the second shape Q can be given as follows:

$$M(\pi) = \min_{\pi} \frac{1}{N} \sum_{i=1}^N C(i, \pi(i)) \quad (3)$$

, where π is a permutation of $\{1, 2, \dots, N\}$.

After the pairwise 3-D shape context is constructed, the curvature for each sample point p is computed by

$$\sigma_p = \frac{\lambda_0}{\lambda_0 + \lambda_1 + \lambda_2} \quad (4)$$

The objective function for measuring the similarity and matching between objects P and Q is defined as

$$O(P, Q) = \min_{\pi} \frac{1}{N} \sum_{i=1}^N C(i, \pi(i)) + \frac{1}{N} \sum_{i=1}^N |\sigma_{p_i} - \sigma_{q_i}| \quad (5)$$

$$+ \frac{1}{N(N-1)} \sum_{i=1}^N \sum_{j=1}^{N-1} \min_{m,n} \|H_{p_i}(j) - H_{q_m}(n)\|_1$$

The unlabeled segment is further classified in this step using the above described pairwise 3-D shape context algorithm. For each un-clustered candidate, their similarity to the template triangular sign is calculated respectively. If the value of similarity lies below a predefined threshold, this block is considered as triangular signs, otherwise it will be discarded. We set the threshold to be 0.2 in our experiment. The threshold can be set lower to be more accurate or higher to be more flexible.

3. RESULTS

The 3D mobile LiDAR point cloud data were acquired by a RIEGL VMX-450 system, which consists of two RIEGL VQ-450 scanners with a laser pulse repetition rate of up to 550 kHz, an Inertial Measurement Unit/Global Navigation Satellite System unit, a wheel-mounted Distance Measurement Indicator, and four high-resolution cameras, as shown in Fig. 3.

The data is collected on Huandao road in Xiamen under real traffic status. Fig. 4(a-d) demonstrated images of an urban transportation scene in point clouds visualized using intensity, traffic signs extracted from point clouds, and the classified signs in step 1, classified signs in step 2, respectively. Some other examples of classification results are shown in Fig. 5.



Figure 3. RIEGL VMX-450 system

Our proposed algorithm was implemented using C++ and executed on a personal Intel Core(TM) i5-3470 3.2 GHz CPU and 4.0 GB RAM. The time of the detection phase is 52.6 s for fig.4 contained about 6.7million points. The classification takes 68 s. Therefore, the result demonstrates that this algorithm is suitable for automated extraction and classification of road traffic signs.

It can be seen that this proposed method can successfully classify various traffic signs. However, in some cases the algorithm will fail to classify the signs. As shown in Figure. 4(b), a bill board (showed in yellow) is detected as traffic signs incorrectly and classified successfully in the next step. As we only concerned the shape classification, the false segments in the detection procedure should be discarded in our system. Moreover, some traffic signs have been discarded because the similarity between candidates and the template sign is lower than the fixed threshold value. Anyway, it can be concluded that when the traffic sign is correctly segmented, our system generally classifies successfully.

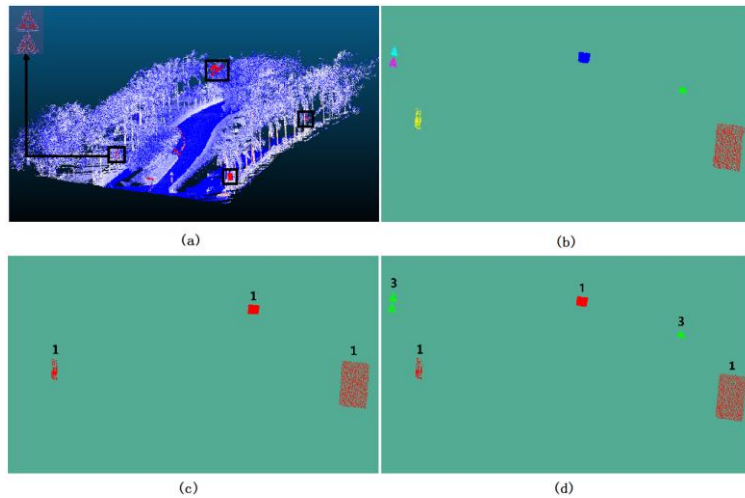


Figure 4. Flowchart of traffic sign detection algorithm

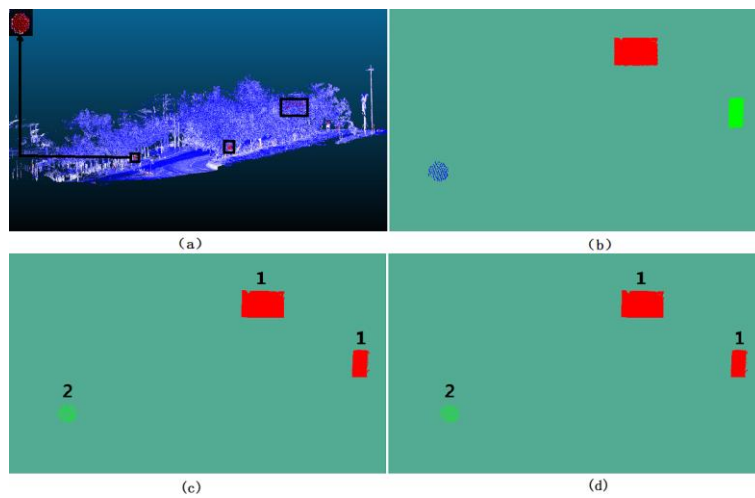


Figure 5. Flowchart of traffic sign detection algorithm

4. CONCLUSIONS

This paper proposes a hybrid method for the shape classification of traffic signs of interest. The shapes considered are the circle, the rectangle, and the triangle. The algorithm contains two main parts: the detection and the classification. For the first part, the reflectivity of the signs were selected as features to extract signs from the scene based on the fact that traffic signs are designed to be prominent so that they can be distinguished from its surroundings. For the classification, the circular and rectangular signs are recognized by their geometric properties. A pairwise 3-D shape context algorithm is chosen to detect the triangular signs. Experimental results have indicated that the algorithm is feasible for classifying various types of traffic signs present in point clouds. Finally, in our future work, the recognition task should be further studied.

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