

RAPID TRAFFIC SIGN DAMAGE INSPECTION IN NATURAL SCENES USING MOBILE LASER SCANNING DATA

Changbin You¹, Chenglu Wen¹, Huan Luo¹, Cheng Wang¹ and, Jonathan Li^{1,2}

1 Fujian Key Laboratory of Sensing and Computing for Smart Cities, Xiamen University, Xiamen, Fujian 361005, China

2 Department of Geography and Environmental Management, University of Waterloo, Waterloo, Ontario N2L 3G1, Canada
clwen@xmu.edu.cn

ABSTRACT

This paper proposes a novel approach for traffic sign detection and rapid damage inspection in natural scenes based on mobile laser scanning (MLS) data, including images and point clouds. The inspection results assist traffic management departments to take immediate measures to update and maintain traffic signs after natural disasters leading to many damaged traffic signs. Our approach involves four steps: Firstly, we use a deep learning network, Fast regions with convolutional neural network (Fast R-CNN), to train a traffic sign detector in an open benchmark, where the images are more variable and have a higher resolution. Then, traffic signs in images are detected by using the trained detector. Next, the area of the traffic sign, based on the sign area in the image, is roughly detected in MLS point clouds. Then, an accurate traffic sign is detected. Finally, some placement parameters of the traffic sign are measured for damage inspection and further inventory. Our proposed approach is validated on a set of point-clouds acquired by a RIEGL VMX-450 MLS system. Experimental results demonstrate that the rapidity and reliability of our proposed approach in traffic sign detection and damage inspection are robust.

Index Terms— traffic sign detection, damage inspection, natural disaster, mobile laser scanning, point cloud

1. INTRODUCTION

Traffic signs are one of the most significant parts of road transportation systems. They provide important information about the road and the environment to guide, warn, or regulate the behaviors of drivers for safer and easier driving. After a natural disaster, like a typhoon or an earthquake, a large number of traffic

signs will be deformed, tilted, fallen or even disappear, thus severely threatening traffic safety. Because of this situation, it is urgent for traffic management departments to detect traffic signs and inspect damages after a natural disaster so as to take measures to update and maintain the traffic signs.

Although the detection of traffic signs has been studied for years, many challenges still exist because detecting damaged traffic signs is complicated. For example, signs adhered to other objects may introduce strong disturbances, which lead to ambiguity. In addition, an incomplete traffic sign board that has lost structural information is hard to distinguish. Moreover, partial occlusion caused by fallen trees dramatically affects detection performance. Fig. 1 shows some examples of damaged traffic signs.

Traditional traffic sign inventory and inspection procedures are mainly implemented manually. Because of the huge workload, ensuring real-time and accuracy is difficult. Therefore, in recent years, more and more (semi-)automated methods have been proposed for implementing these procedures. Most existing methods are based on images. Abukhait J et. al [1], to detect if a traffic sign position has been altered, proposed an automated geometric method based on images to inspect a traffic sign tilt angle. A semi-automated approach was introduced in [2] to detect mutations in existing traffic sign inventories. However, image data is sensitive to illumination conditions, angle of view, etc. Furthermore, 3D geometric information is lost.

Light Detection and Ranging (LiDAR) data has been used for applications and research in natural disasters, such as floods [3], hurricanes [4], and landslides [5]. Among the LiDAR products, Mobile Laser Scanning (MLS), used for 3D city modeling [6], has become a cost-effective solution to capture various dense point clouds with high precision. Because of the advantage of high-density, long-

range, and high-efficiency properties of data acquired by MLS, the system has been used to detect traffic signs [7], [8] and inspect signs for Inventory [9], etc. Thus, there is a potential, with great challenge, to apply MLS to detect and inspect damaged traffic signs.



Fig. 1. Examples of damage traffic signs.

In this paper, we propose a novel approach, based on MLS data including images and point clouds, to detect traffic signs and rapidly inspect damages in natural scenes. We first use a Fast R-CNN framework to train a traffic sign detector on an open benchmark, Tsinghua-Tencent 100K [10]. Then, using a detector, traffic signs are detected in images. Next, based on the sign area in image, the area of the traffic sign is roughly detected in MLS point clouds. Then an accurate traffic sign is detected. Finally, some placement parameters of the traffic sign in a point cloud are measured for damage inspection and further inventory.

2. METHODOLOGY

Our proposed approach contains the following three main parts: (1) Fast R-CNN training for traffic sign detection; (2) Traffic sign detection in images and MLS point clouds; and (3) Traffic sign damage inspection. The flowchart of the proposed approach is given in Fig. 2.

2.1. Fast R-CNN training for traffic sign detection

Because of the loss of structural or other useful information in damaged traffic signs, most of the existing traffic sign detection methods perform poorly. Many excellent public traffic sign benchmarks with class label already exist. We use

them with deep learning methods, which have shown superior performance for many tasks, including image classification and detection for damaged traffic signs.

In this paper, we use the benchmark, Tsinghua-Tencent 100K, which contains 100,000 high resolution images where all traffic signs are annotated with class label, bounding box, and pixel mask, to train a Fast R-CNN for traffic sign detection. This robust network is used as a traffic sign detector.

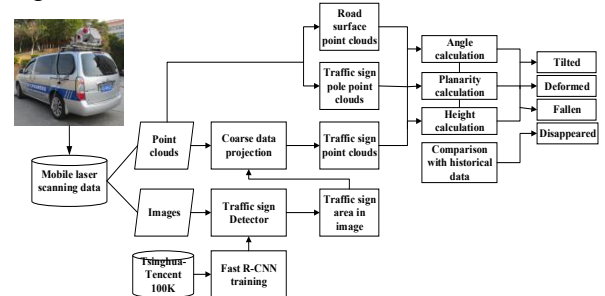


Fig. 2. Flowchart of the proposed method for traffic sign detection and damage inspection.

2.2. Traffic sign detection in images and MLS point clouds

Using the traffic sign detector, we detect traffic signs in images captured by a RIEGL VMX-450 MLS system with four high-resolution cameras and two laser scanners. The system provides a coarse corresponding relationship between the image and the point clouds. Based on the detected traffic sign area in an image, the area of the traffic sign in the corresponding MLS point clouds is roughly detected.

For damaged traffic signs, which cannot be detected directly based on MLS point clouds, we first judge whether traffic signs are detected in images, indicating that the corresponding MLS point cloud also has traffic signs.

If a traffic sign is found in the image, the corresponding MLS point cloud data contains a traffic sign. Then, according to the sign area in the image, we find the coarse area of the traffic sign in the point cloud. As long as the coarse area of a sign is determined, detecting accurate traffic signs in point clouds data is easy.

2.3. Traffic sign damage inspection

After observing real samples, we found that the main damage in traffic signs can be generalized as the following four types: (1) Tilted pole (Fig. 1 a, b); (2)

Deformed board (Fig. 1 b, c); (3) Fallen board or pole (Fig. 1 d, e); and (4) Disappeared.

In this paper, the following placement parameters describing some types of damages are measured for traffic sign damage inspection: (1) height of the traffic sign above the ground (h_t); (2) angle between traffic sign board and the plane of the road surface (α_r); (3) inclination of the traffic sign with respect to the traffic sign board orientation (α_i); (4) inclination of the traffic sign with respect to the traffic sign board profile (α_p); and (5) planarity of the traffic sign. As shown in Fig. 3, according to the measured parameters, the types of damage to traffic signs can be inspected.

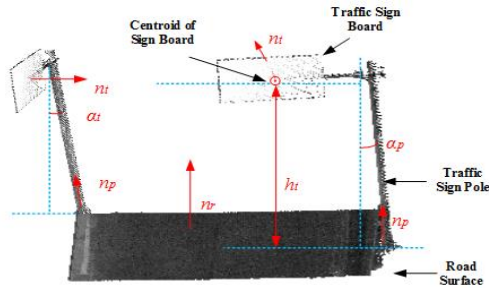


Fig. 3. Illustration of traffic sign placement measurement.

To determine whether a traffic sign falls to the ground, h_t is firstly measured. h_t is defined as the height of the centroid of the traffic sign board above the ground.

To determine whether a traffic sign pole is tilted, some inclination angles are measured. The included angle, α_r , between the plane fitted to the traffic sign board and the plane of the road surface, is evaluated using the following equation:

$$\alpha_r = \arccos\left(\frac{n_i \cdot n_r}{\|n_i\| \|n_r\|}\right) \quad (1)$$

where n_i is the normal vector to the traffic sign, n_r is the normal vector to the road surface plane. The included angle, α_i , between the traffic sign pole's distribution direction (n_p) and the vertical direction with respect to the traffic sign board's orientation, is defined as:

$$\alpha_i = \arcsin(n_i^z) \quad (2)$$

where n_i^z is the z component of n_i . The included angle, α_p , between the traffic sign pole's distribution direction (n_p) and the vertical direction with respect to the traffic sign board's profile is defined as:

$$\alpha_p = \arcsin(n_p^z) \quad (3)$$

where n_p^z is the z component of n_p ;

To determine whether a traffic sign board is deformed, the planarity is measured by the standard

deviation of the laser points on the traffic sign board.

If outdated inventory data already exists, e.g. performed in a previous year, some traffic signs, which have disappeared, can be identified by comparing the resulting inventory with an existing inventory. This approach enables semi-automatic or automatic updating of the existing inventory.

3. RESULTS AND DISCUSSIONS

Experiments on traffic sign detection and damage inspection were conducted from the MLS point clouds acquired by the RIEGL VMX-450 MLS system on Huandao Road in Xiamen, China after the attack of typhoon Meranti. The proposed approach was applied to the MLS point clouds to detect traffic signs and inspect the damage.

Some results of the damaged traffic signs, generated by our detection approach, are given in Fig. 4. From the results, we conclude that our proposed approach performs well and achieves good results on damaged traffic sign detection and damage inspection.

Table 1 lists the ground truth, detection and inspection results, and processing time. Compared with the ground truth, the majority of the traffic signs were detected. Fig. 5 shows an example of part of the traffic sign detection results in MLS point clouds.



Fig. 4. Some examples of damaged traffic sign detected.

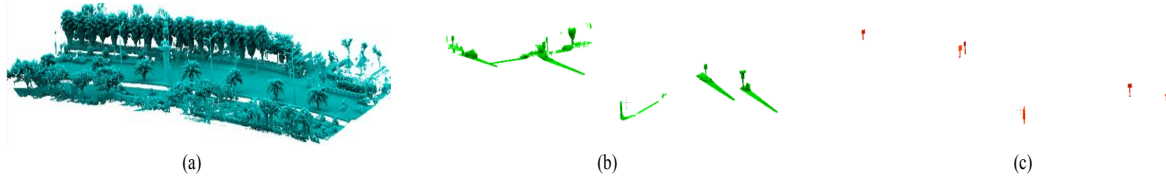


Fig. 5. Illustration of a part of traffic sign detection results in MLS point clouds. (a) A raw point cloud, (b) Coarse area of traffic signs in the MLS point cloud and (c) detected traffic signs.

Table 1
Description of the ground truth and detection and inspection results in the dataset

Ground Truth		Detection Results			Inspection Results		Processing time(s)
Point number	Traffic sign	Traffic sign	Missed	Rate(%)	Tilted	Fallen	Detection and Inspection
571,924,457	132	122	10	92.42	11	1	2510.191

Because the planarity of a traffic sign board varies from type to type, only when compared with the original traffic sign's planarity can we determine whether or not the sign is deformed. Thus, in the inspection results, we list only the number of tilted and fallen traffic signs. Traffic signs are regarded as tilted if one of the inclination angles (including a_r , a_t and a_p) is greater than five degrees. Traffic signs are regarded as fallen if the height of the centroid of the traffic sign board above the ground (h_t) is less than 1.0 meter.

Our proposed approach is implemented using C++. As shown in Table 1, a large data set with more than 500 million point numbers, can be processed within about 42 min. Therefore, our proposed approach achieves high accuracy and an acceptable time complexity and provides a promising solution to traffic sign detection and damage inspection from large-volume MLS point clouds.

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