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Automatic Road Inventory Using LiDAR

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Abstract

Road inventory is very important for effective transportation management. This process is usually done by a technician in the field, manually from obtained aerial/satellite images or semi-automatically by a software application. The first two options are very time consuming, hence expensive. Many companies therefore try to process at least part of this task automatically.
The road inventory process comprises an identification of objects that can be found either on the road or in the road proximity. Examples include road signs, road markings, guardrails and many more. We can register much information about these objects, such as their position, condition or type. Generally, there are two sources for the extraction of information needed for the inventory. The first source is a set of images captured by a camera. The second source is data captured by a LiDAR. Either of them can provide different information; therefore, the choice of the source must be made with regard to the required information.
In our article, we compare information that can be obtained from camera images and LiDAR measurements. This comparison is presented on three example objects: traffic signs, road markings and general pole-shaped objects (e.g. city lights or trees). Further, we describe a process based on our algorithm that detects traffic signs in LiDAR measurement and transforms the results to a common format used in geographic information systems. We test our method on an approximately two-kilometer long road in an urban area.

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1. Introduction

Inventory of vegetation, roads or e.g. buildings is a common process that provides the basis for any effective management. A digital record of the inventory is usually stored in a geographical information system in a form of different map layers. These map layers describe position/shape of the objects that are taken into inventory, as well as their properties (e.g. state or exact description). Generally, this process involves a substantial amount of manual work (field measurements), data post-processing etc. Hence it is time consuming and expensive. Therefore, we focused on methods that can improve inventory efficiency.

In this article, we focus particularly on road inventory. Objects that are taken into account are especially traffic signs, road markings and trees around roads. This set can be certainly extended by many other things (e.g. milestones or guardrails). We compare object detection methods based on RGB data obtained by common cameras and object detection methods based on LiDAR measurements with regard to those mentioned objects. The detection of two basic objects: traffics signs and road markings is described in detail.

This article is therefore focused on researchers and developers who consider the possibility of developing a system for automatic or semi-automatic inventory. The aim of this article is to provide an overview of technologies that are usually used, to explain their limitations and especially to clarify potentials of LiDAR-based methods that are not as thoroughly described as the detection methods based on common RGB images.

2. Methods and Resources

This section compares information that can be obtained from RGB images (from the visible part of the spectrum) and LiDAR measurements (so called point clouds) on three selected examples: road signs, road markings and general pole-like objects.

2.1. Road Signs

The automatic road signs inventory process comprises two steps: detection of the sign position and identification of the sign type (e.g. “Roundabout” or “Main road”). These two steps can be done separately. Moreover, even the sign position detection provides a substantial speedup of the inventory process. It provides exact sign location (possibly even its condition) and just the specific sign type must be chosen by the operator.

First group of road signs recognition methods uses RGB images from common cameras. These methods are generally very fast. According to Belaroussi et al. (2010), the detection of sign position is usually based on the sign shape or color. Both these approaches are used to identify the so called region of interest (ROI) in the source image. This ROI presents a part of an image that probably contains a sign. Then a sign identification algorithm is applied to this region to obtain an exact sign type. There are three common approaches: match template (calculation of pixel correspondence between a given image and a template), descriptor-based methods and neural networks.

The second group of methods, not as common as RGB based methods, uses only LiDAR point clouds. Each point in the point cloud represents a reflection from an object surface. Among this three-dimensional position given by the reflection point, other properties are measured (angle of the reflection, its intensity etc.).

Because of the point clouds properties, these approaches are widely used to detect sign positions in three-dimensional space. Virtually all methods that use point clouds to detect road signs use reflexivity of the sign as a key feature for the detection (Chen et al., 2009). However, as González-Jorge et al. (2011) points out, road signs can suffer degradation (from dirt, wind, vandalism etc.) or can be concealed (by trees, building, trucks…).

A point cloud contains color information only if it is provided by paired RGB images. The most important difference is therefore that the sign type can be obtained only from RGB data or a point cloud paired with such RGB data. However, the color deterioration that is in case of RGB data calculated from color pixels values can be calculated even from the point cloud by examination of a point’s reflection intensities.

Without discussed color information, it is further possible to gain accurate information about the sign location, shape (including its potential bumpiness), direction and the position of the sign base. The sign damage evaluation can be done by fitting of measured points to an arbitrary plane (González-Jorge et al., 2011). The sign direction can be calculated simply as a normal to a plane given by the sign points. The sign base position is provided by the position of points on the bottom of the sign pole. This process is covered in section (2.3). Some of these properties (e.g. position or direction) can be partially approximated also from RGB images; nonetheless, the precision is usually incomparable to the point clouds. These methods are based on perspective calculations that are not as precise as the exact position given by a laser beam reflection, not even mention the lens distortion or calibration problems.

Identification of the shape changes, direction, pole base and position is therefore substantially harder from RGB images; moreover, a significant advantage of point clouds over RGB images is their ability to work even in bad weather conditions. Road sign detection from RGB data needs a relatively good weather conditions and a reasonable amount of light to identify the sign with high probability. However, point clouds do not have this limitation. The data collection can be done even in bad weather (see Fig. 1).

Table 1. Road sign identification – c comparison of precise information that can be obtained from RGB images with information provided by point cloud.

RGB Images	Point Clouds
Type of the sign	Position of the sign
Paint deterioration	Paint deterioration
	Shape damage
	Precise position of the sign base
	Sign direction

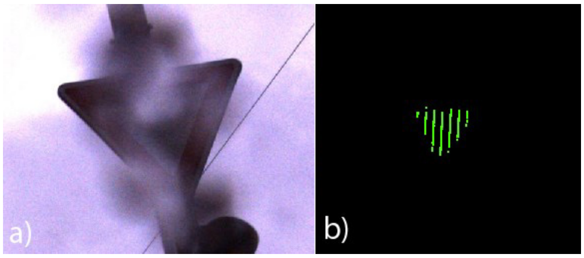

Fig. 1. (a) Sign from RGB data in bad weather conditions; (b) The same sign detected using LiDAR.

2.2. Road Markings

Road markings detection is widely used for autonomous car driving or as a driver assistance service. Hence, most of the approaches use data obtained from common RGB camera to detect road markings. The use of RGB cameras is substantially cheaper in comparison to LiDAR.

The common approaches for detection from RGB images are usually based on analysis of the pixels right in front of the car path. The camera image is thresholded in this case, potential road marking pixels are extracted and on the appropriate region with these pixels is applied perspective correction to bird's perspective (Wu, 2012). Pixels with corrected perspective that represents the markings are then detected. All approaches usually rely highly on the properties of the signs. For instance, the dashed line has always parameters given by the specified government decree (length, distance between individual lines). Similarly, it is defined for a full line. Among the lines, there are many different kinds of markings that can be detected – the zebra crossings (Ahmetovic and Bernareggi and Mascetti, 2011) and different arrows (Vacek and Schimmel and Dillmann, 2007) can be found most frequently.

The detection of road markings based on point clouds is also frequently done in real-time, when the car is on the road. The first step usually is the identification of ground points (defined by their position) and then filtering of those ground points that represent potential marking according to their reflexivity. The approaches for the identification of specific road marking kind (dashed line, arrow etc.) are very similar to the identification from RGB images and also rely highly on the properties of the markings (Yang, 2012; Thuy and León, 2010). Therefore, both groups of approaches work in this case with a set of points that represents a road marking. In the case of RGB images, these points are selected color pixels and in the case of point cloud, they are represented by filtered 3D points.

Both data sources can be used to detect the shape and type of the marking. Again the advantage of RGB images is the possibility to detect the lane color. On the contrary, the point clouds provide substantially more precise position of the marking.

Table 2. Road markings identification – comparison of precise information that can be obtained from RGB images with information provided by point cloud.

RGB Images	Point Clouds
Color of the marking	Shape of marking
Shape of the marking	Position of the marking
Type of marking	Type of marking

2.3. Pole-shaped object

There are many objects that can be classified as pole-shaped. This group comprises electricity poles, public lights that are placed along the road, in some cases even trees (particularly tree trunks). Detection of these objects is in most cases based on point clouds. The basic idea of pole-like object identification is the detection of points distributed in the horizontal direction as a cylinder. A method that classifies objects into three categories: utility poles, lamp posts and traffic signs is proposed in Yokoyama et al (2013). Liberge et al (2010) designed a method that allows distinguishing poles and trees. **A** similar approach can be found in Landa and Prochazka and Stastny (2013) where statistical methods are used to identify pol**es** like objects. Firstly, the cloud is split into horizontal cross sections. Secondly, each cross-section is evaluated by searching for groups of circular segments.

Table 3. Pole-shaped object identification – comparison of precise information that can be obtained from RGB images with information provided by point cloud.

RGB Images	Point Clouds
Color of the object	Position of the object
	Height of the object
	Trunk diameter
	Position of the object base

Generally, only information that can be obtained from RGB images is the color of the object. However, to detect the object color, the object itself must be identified first. Therefore, common RGB images are usually not suitable for detection or identification of pole-shaped objects and should be used mainly in a pair with the point clouds.

On the other hand, LiDAR data can be used to extract most of the information needed. The most widely used information is a position of the object. It can be either a position of the centroid or position of the base of the trunk. However even information such as height of the pole and trunk diameter can be easily extracted from the point cloud that represents the object.

3. Traffic sign detection implementation

This part of the article describes our method for road signs detection and localization from point clouds. The entire process of the road sign detection and localization is summarized in Fig. 2.The first part of the sign detection is Reflexivity filtering. The road signs are painted with special, highly reflexive material. Therefore, we can filter the input cloud to get only points with high reflexive value. The reflexive value depends on a used scanner and must be determined by experiment. The signs in tested clouds have the intensity range of 4000 and higher. The intensity filtering produces a new cloud that needs to be further segmented. This cloud still contains signs as well as many other objects, such as parts of the roads, vehicle registration plates and many more.

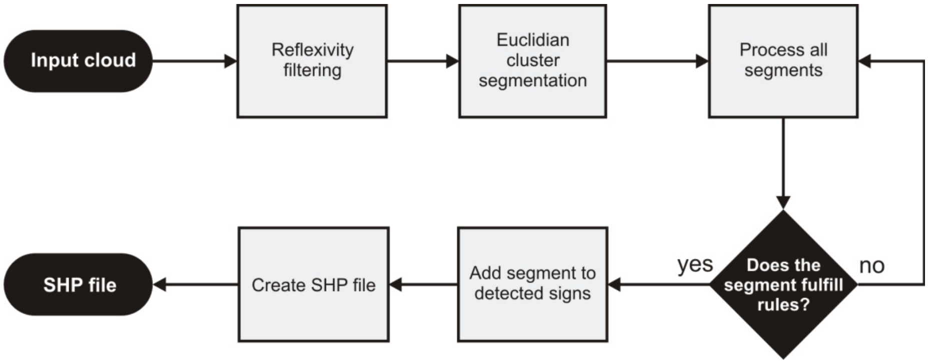

Fig. 2. Process of road sign detection and localization.

The second part of the process is segmentation. We use Euclidian cluster extraction[1] implemented in Point Cloud Library. This segmentation is based on Euclidian distance between two points. If the distance is lower than the threshold, the points are considered part of one segment. The threshold can be set to any value and depends on the resolution of the scanner. We use the half-meter distance threshold.

The next phase is segments processing. The problem with automatic road signs detection lies in defining the rules that must be fulfilled by each segment that contains a sign. For our method, three rules were defined:

- The segment must have at least 70 and at most 150 000 points. This rule is given by the resolution of the sensor and is used to filter out very small or large objects.
- The segment's centroid must be at least 1.5 m above the ground. This rule eliminates temporary signs.
- The difference between lowest and highest point of the segment is at least 0.4 m. This value was chosen according to the range of sign sizes given by national decree. This rule eliminates small segments, which are usually on building facades.

If a segment fulfills all these rules, it is marked as a road sign.

For each recognized sign, we store two features. The first one is the position of the sign centroid and the second one is a position of the sign pole base. Finally, these points are stored into an ESRI Shapefile as a common map layer. Hence, they can be processed virtually in any geographical information system.

4. Tests

The process is tested on points clouds captured with Riegl VMX 250. Riegl VMX 250 is a Mobile Laser Scanning system that has accuracy of 10mm and Precision of 5mm. The tested point clouds contain more than 150 million points. These clouds capture more than two kilometers of roads in an urban area – Mendel square in Brno, the Czech Republic (see Fig. 3).

[1] http://pointclouds.org/documentation/tutorials/cluster_extraction.php#cluster-extraction

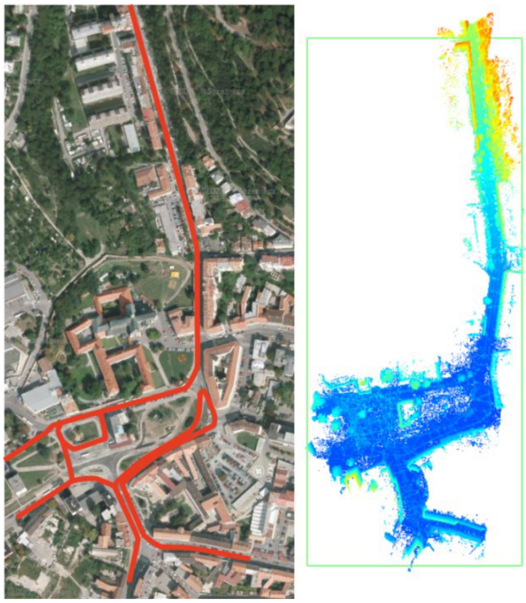

Fig. 3. (a) Map representing test area (red line is a path of the car); (b) Source Point Cloud.

To test our method, we implemented an application in C++ language using the Point Cloud Library. The following section summarizes our test results. The key factors are evaluated:

- Hits – How many segments were correctly detected as signs.
- Misses – How many signs were not detected.
- False hits – How many segments were falsely detected and marked as signs.

The initial reflexivity filter and segmentation captured 219 possible signs. The described filtering rules were applied to these segments. Out of a total number of 86 signs that were inside a tested area, 80 signs were detected correctly with only 6 misses. The number of falsely identified signs was 7. These values are summarized in Table 4. The entire test of sign detection and localization took 16 minutes on a low-performance portable computer (MacBook Air, Intel i5 1.7 GHz, 4 GB of RAM, SSD, no multi-threading optimization).

Table 4. Results of the detection method.

Factor	Point Clouds
Hits	80
False Hits	7
Misses	6

5. Discussion

Out of the 6 misses 3 were caused by low point density. This can be caused by a larger distance of the sign from the sensor or by the degradation of the paint. The other 3 misses were bus stop signs that were in close proximity to the sensor.

The main false hits sources were advertising signs. That was the case related to 5 of 7 false hits in our case. One false hit was some highly reflective material on a building and the last one was a traffic mirror. Even though the traffic mirror can be considered as a traffic sign, for the purpose of this article we mark it as a false hit.

Fig. 4. (a) Hit; (b) False Hit; (c) Misses (top miss is a bus sign and bottom miss is a sign from larger distance).

6. Conclusion

The proposed method works with single signs properly. Out of the 86 signs it detected 80 signs correctly. That presents a 93 % success rate. Also the false hit and false miss percentages are very low (both only approx. 8 %) and most of them cannot be eliminated using point clouds only. However, in case of multiple signs on one pole, our method cannot distinguish between the individual signs. This means that our method is suitable for semi-automatic detection where possible signs are marked and the operator corrects these specific issues.

It is necessary to mention that the number of misses could be much higher in some areas. Some traffic signs are so heavily occluded that they can be identified neither from RGB images nor from the point clouds. In these cases, they are usually barely visible even by a human observer.

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