Shape Extraction for Guardrails on Roads Using Point-Clouds and Images

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Abstract

Mobile mapping systems are useful for creating 3D street maps. They capture point-clouds and digital images of roads and roadside objects. We discuss methods for extracting guardrails, which are important objects that separate roadways and walkways. Since there are various shape patterns for guardrails in Japan, flexible methods are required for extracting guardrails. In this paper, we propose a new extraction method based on point-clouds and digital images. Recently, the convolutional neural network (CNN) has be intensively improved for recognizing images. Therefore, we subdivide point-clouds to small segments and detect their 2D images. Then the images are investigated using CNN whether they are guardrails or not. When the images are classified as guardrails, corresponding points are collected and guardrails are reconstructed. In our experiments, we could extract guardrails at high success rate.

Key words: point processing, reverse engineering, mobile mapping, machine learning, CNN

1. Introduction

Mobile Mapping System (MMS) is a measuring device equipped with cameras, laser scanners, GPS on a vehicle. MMS can capture roadside information as point clouds and camera images. There are various objects on roadsides, such as traffic signals, traffic signs, utility poles, trees, and so on. For supporting maintenance tasks, survey of current situations, and 3D map creation, it is necessary to extract each object from a large-scale point-clouds, and reconstruct 3D shapes.

So far, many researchers have studied shape reconstruction of man-made objects in urban environment. Since it is difficult to capture complete point-clouds of objects while a MMS is moving, domain-specific knowledge is often used for reconstructing 3D shapes. Pauly, et al. [1] reconstructed object shapes by extracting regular patterns of objects. Nan, et al. [2] reconstructed buildings from incomplete point-clouds using knowledge of buildings in cities. Lin, et al. [3] reconstructed shapes of American houses using knowledge on typical structure of houses. However, their target objects were limited to specific objects.

Other researchers extracted and classified pole-like objects on roads. They extracted pole-like objects on roads from point-clouds and classified them into signals, signs, trees, and so on. There are two typical methods. One is based on geometric properties of point-clouds ([4], [5], [6], [7], [8], [9]) and the other is based on supervised machine learning ([10], [11], [12], [13], [14], [15]). However, they processed only pole-like objects. He, et al. reconstructed road surfaces using adjacency relationships among points captured using a MMS ([15], [16]]. They also estimated boundaries between roadways and sidewalks by detecting road curbs. However, they separated roadways and sidewalks only when they are separated by road curbs.

In this research, we discuss methods for robustly extracting guardrails from point clouds, because guardrails are typically used in Japan for separating roadways and walkways. The detection of walkways is important for developing various applications, such as walker navigation and evacuation guide simulation.

However, it is not easy to develop knowledge-based point processing methods for guardrails, because, in Japan, there are a large variety of designs for guardrails including typical shapes consisting of plates or pipes. For handling various types of shape patterns, we consider a more general approach. Recently, the convolutional neural network (CNN) has be intensively improved for recognizing images, and the capability is close or equivalent to human visual recognition. Since CNN can learn images of various types of guardrail shapes, various patterns of guardrails can be flexibly detected by combining point processing and CNN.

In this paper, we propose a new method based on point-clouds and digital images for extracting guardrails. In the preprocessing phase, images of guardrails are collected in a certain residential area, and they are input for training a machine learning system. In the recognition phase, point-clouds are captured in the residential area, and candidate points of guardrails are extracted from point clouds. Then images of the candidate points is detected and cropped from a set of digital images. The images are investigated using CNN whether they are guardrails or not. Finally, detected points are converted to a 3D model of a guardrail if needed.

Fig. 1. Mobile Mapping Systems. (a)Vehicle with an MMS, and (b) Close-up of MMS.

2. Overview

The MMS used in this research is the Mitsubishi MMS-X, as shown in Fig. 1(a). This MMS has laser scanner RIEGL VQ250 and digital cameras on a vehicle. Point clouds and camera images are captured during the MMS is driving. Each point and each image has the GPS time, which is the time sent from satellites and represents when the point was captured.

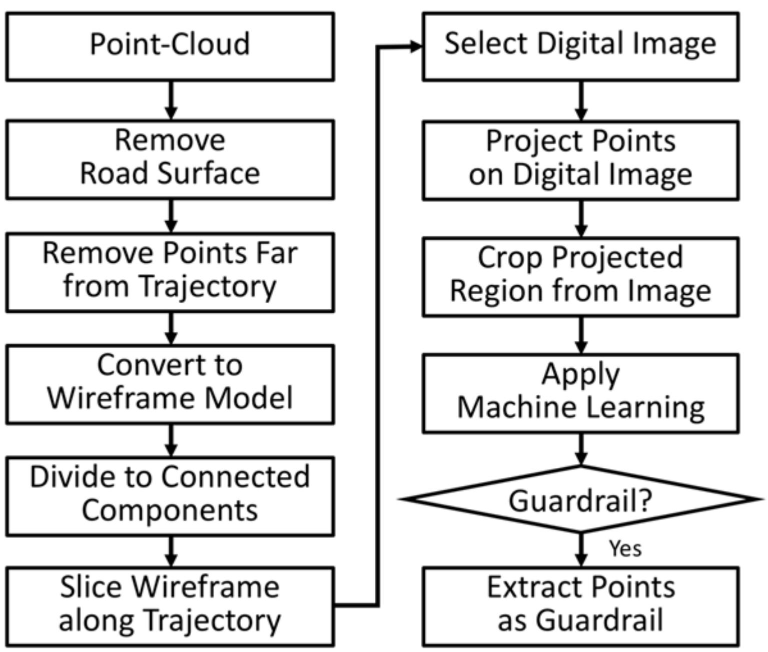


Fig. 2. Process for extracting guardrails.

Fig 2 shows the process for extracting guardrails from point-clouds. First, points on road surfaces are detected and removed from point-clouds. By removing points on road surfaces, only roadside objects remain in point-clouds. In addition, points far from the vehicle trajectory are also removed, because guardrails exist near roadways.

Then points are projected onto 2D lattice for obtaining adjacency relationships among points. This projection is possible because the direction of the laser beam rotates at constant speed and points are sampled at constant time intervals.

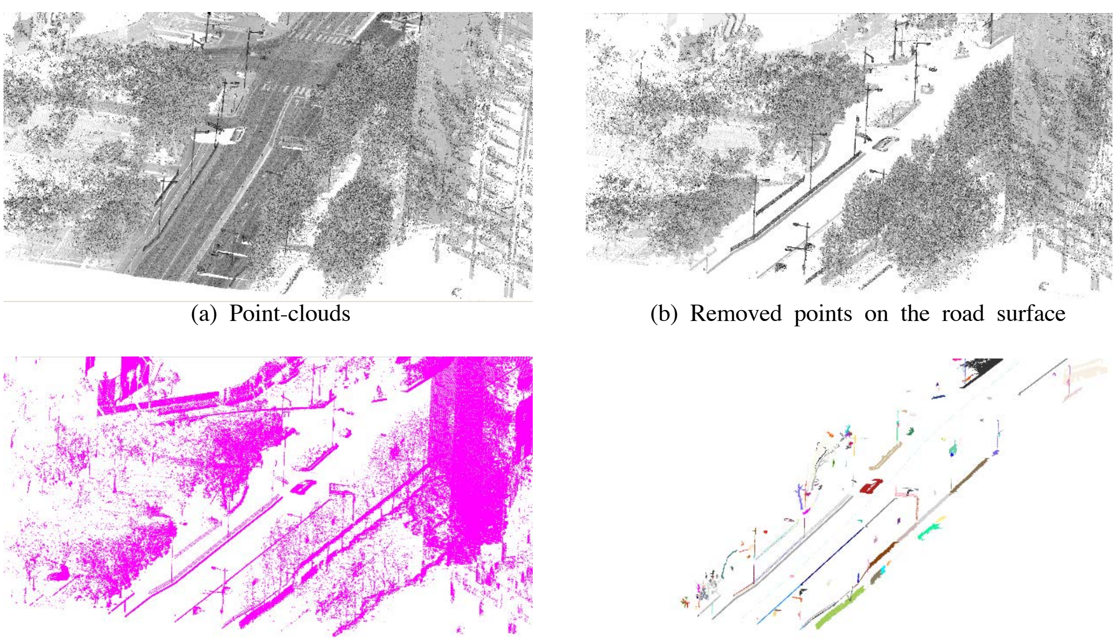
When point-clouds are mapped onto the 2D lattice, wireframe models can be created by connecting neighbor points on the 2D lattice. Then the wireframe is subdivided into a set of connected components. Since each connected component is not segmented to an object, we slice connected components using planes perpendicular to the trajectory of the vehicle at equal intervals. Then many fragmented wireframe models are generated.

Each sliced segment is verified whether it is a part of a guardrail or not. Since the MMS captures points and images synchronously, we use digital images for verifying the points are a part of a guardrail. The relative position between the laser scanner and the digital camera is fixed, and the camera parameters, such as the focal length, can be calculated using a typical camera calibration algorithm. Therefore, it is possible to project each point on a digital image.

When points are projected on a digital image, the projected region is cropped from the digital image. Then the cropped image is investigated whether it can be classified as a guardrail using image-based machine learning. If the image is classified as a guardrail, the projected points are regarded as a part of a guardrail. Partial shapes of a guardrail are connected, and finally each guardrail is extracted and reconstructed from point-clouds.

3. Extraction of Roadside Objects

First points of road surfaces are detected and removed from point-clouds. In our case, the trajectory of the vehicle is given as MMS data. Since the heights of roads can be calculated using the trajectory data, a point is regarded as a road point if the z value is nearly equal or smaller than the estimated road height and the normal vector at the point is close to the Z axis. Fig. 3(b) shows a point-cloud in which road points were removed.



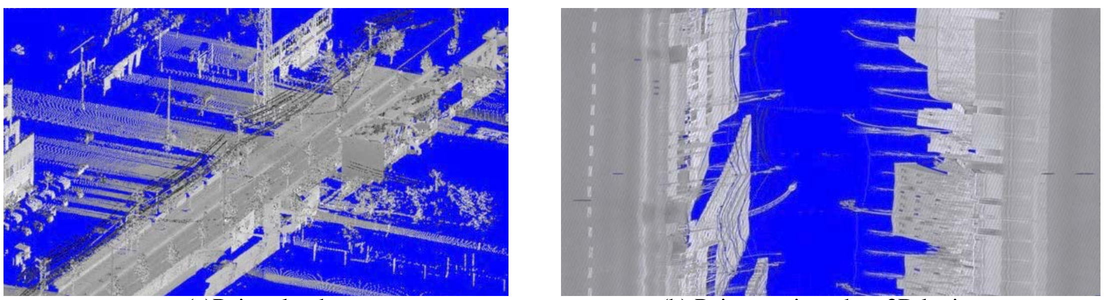
(a) Point-clouds
(b) Removed points on the road surface
(c) Generated wireframe
(d) Removed edges far from the vehicle trajectory

Fig. 3. Extraction of target objects.

In addition, points far from the vehicle trajectory are also removed, because guardrails exist between roadways and walkways. In our MMS data, the trajectory of the vehicle is maintained as a sequence of coordinates. We remove points when the distances from the trajectory are larger than 15 m.

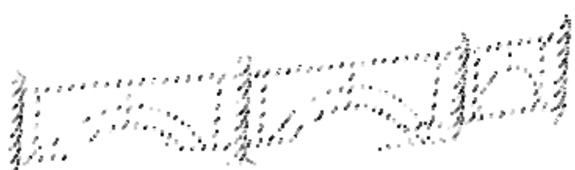
Then point-clouds are projected onto the 2D lattice using the method proposed by Kohira, et al. In this method, a pair of integers (I, J) is assigned to each 3D points using GPS time, the rotation frequency f, and the pulse reputation frequency ω. The rotation frequency and the pulse reputation are given as basic specifications of the laser scanner. The rotation frequency is the number of rotations of the laser beam per second, and the pulse reputation frequency is the number of measurements per each rotation. Points in each rotation can be obtained by subdividing a sequence of measured points every $1/f$ second. In order to map a point-cloud on a 2D image, the phase number I and the rotation number J are assigned to each point. The phase number is the sequential number of measurement in each rotation, and the rotation number indicates how many times the laser beam has rotated since the start of measurement. Fig. 4 shows an example of projected points.

Then point-clouds are converted into a wireframe model using the adjacency relationships on the 2D lattice. We generate edges between adjacent points when the distance is smaller than a threshold. Fig. 3(c) shows a wireframe model. Then the wireframe model is subdivided into connected components. In Fig. 3(d), connected components are shown in different colors.

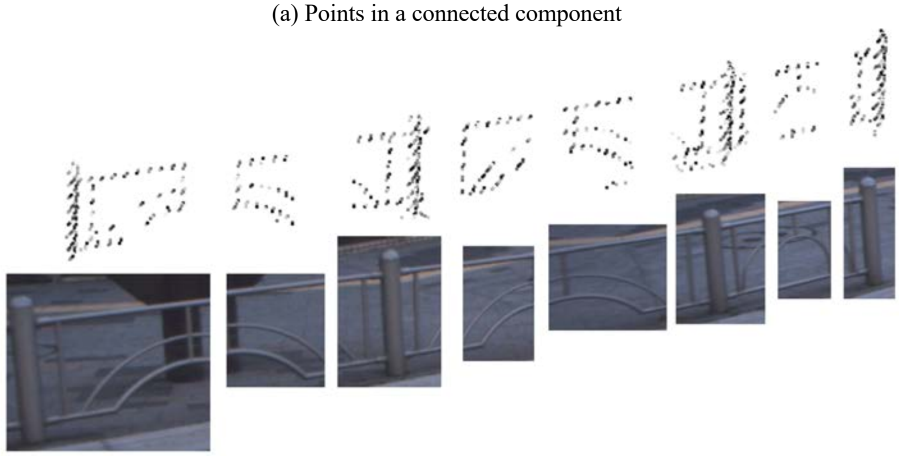


(a)Point-cloud (b) Points projected on 2D lattice.

Fig. 4. Points projected on 2D lattice.



(a) Points in a connected component



(b) Points in sliced wireframe models

Fig. 5. Segments divided by section planes

However, each connected component does not always represent each object. Multiple objects may be connected due to tree leaves or shrubs, or a single object may be divided into multiple connected components due to occlusion. Therefore, we slice connected components using section planes perpendicular to the trajectory of the vehicle. In our method, each connected component is subdivided at the interval of 0.5 m. Fig. 5 shows sliced segments of a guardrail. Each segment is separately investigated whether it is a part of a guardrail.

4. Extraction of Cropped Images

Each sliced segment is investigated using CNN whether it is a part of a guardrail or not. For this purpose, an digital image corresponding to each sliced segment is extracted from a sequence of images captured by a MMS. MMS captures points and images synchronously. Each point and each image has a timestamp called GPS time, which is determined based on the signal from satellites. Therefore, we can obtain images captured at close time to the GPS time of the points in a sliced segment.

Then points are projected onto an image. The relative position between the laser scanner and the digital

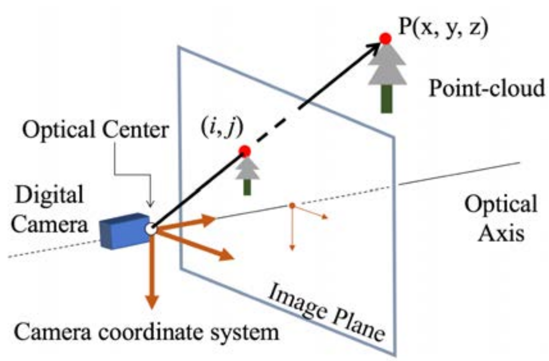
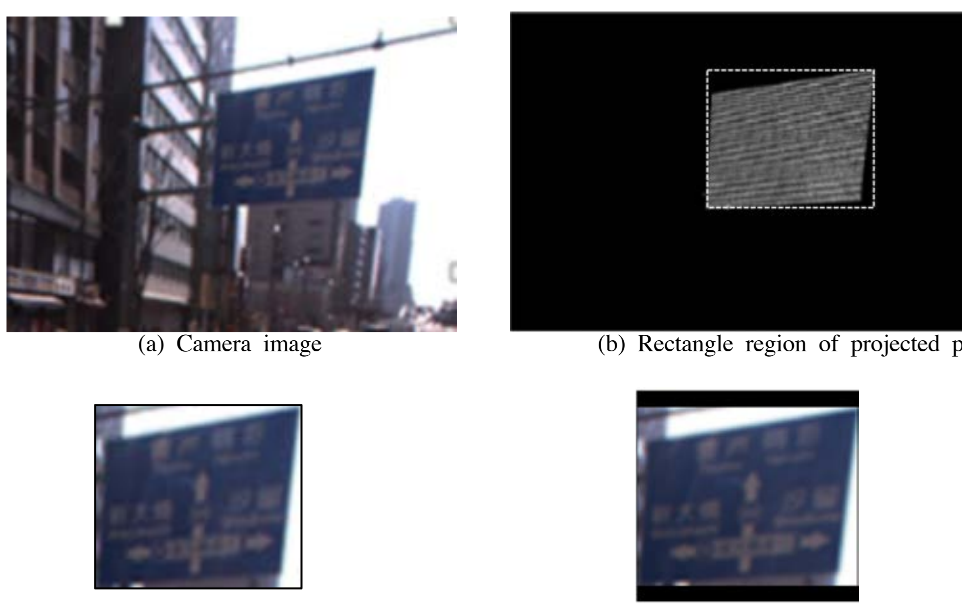


Fig. 6. Projection of points onto an image plane.



(a) Camera image

(b) Rectangle region of projected points

(c) Cropped image

(d) Normalized image

Fig. 7. Cropped image corresponding to points

camera is fixed, and the trajectory of the laser scanner is maintained as a sequence of positions and attitudes. Camera parameters can be calculated using a typical camera calibration algorithm. Therefore, the coordinate of each point can be transformed to the camera-centered coordinate system, and it can be projected on the image plane, as shown in Fig. 6.

Fig. 7 shows a process for extracting the cropped image. When points are projected on an image as shown in Fig. 7(b), a rectangle region is defined so that all points are included. There are multiple images with GPS times close to the GPS time of points. We select the image that includes all projected points and has the largest rectangle area. Then the rectangle region is cropped from the image. Finally, the size of pixels are adjusted according to the requirement of CNN. In our case, the image size is normalized to 227 x 227 by inserting black pixels.

5. Extraction of Guardrails

Cropped images are investigated whether they are guardrails or not. We use CNN for image classification. We introduce two classes, “guardrail” and “other object”, and input training images to CNN.

In general, CNN requires a huge number of training images for precise classification. However, we can prepare only a small number of guardrail images. Therefore, we use a transfer-learning technique, which allows to accurately classify even with a small amount of training images. Transfer-learning is a method of adjusting parameters of neural network using a large amount of images before the input of a specific class. The well-trained CNNs are available in the public domain.

When cropped images are classified as “guardrail”, corresponding points are also labelled as “guardrail”. However, some images may be misclassified because each image includes only a small part of a guardrail. In our method, a guardrail is subdivided into multiple sliced segments. Therefore, we correct labels of segments so that segments labelled as “guardrail” are continuously aligned along roads. As a result, we can obtain points of each guardrail.

6. Experimental Result

Point-clouds and digital images for evaluating our method were captured in a residential area in Japan. We processed point-clouds and images using our method, and obtained cropped images. We manually added labels “guardrail” or “other object” to each cropped image, and compared the labels to the input from CNN. We use **VGG16 [17]** as a CNN classifier. The network was pre-trained using large-scale image database. The number of images we input for this evaluation is shown in Table 1. Training data were input with correct labels.

Table 2 shows classification results. In out method, each guardrail is subdivided to multiple segments. In this experiment, most segments could be correctly identified as guardrails or other objects. Misclassified segments occupied very small portions of guardrails. In Fig. 8(a), the green circle indicates a guardrail classified as “other object”, and the blue circle indicates an object incorrectly classified as “guardrail”. In our method, these misclassified segments are corrected using the labels of adjacent segments. As shown in Fig. 8(b), misclassified segments could be adequately corrected.

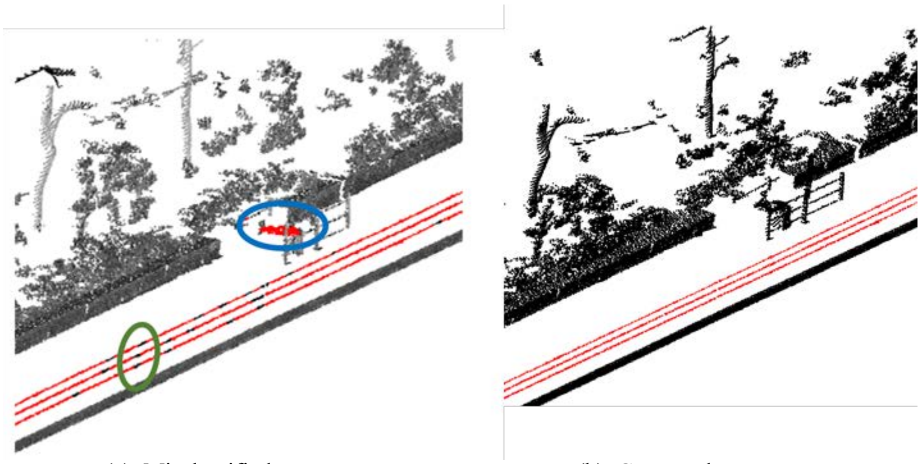
Table 1. The number of sample data.

	Training data	Test data
Guardrails	686	713
Other objects	905	1563

Table 2. Result of classification

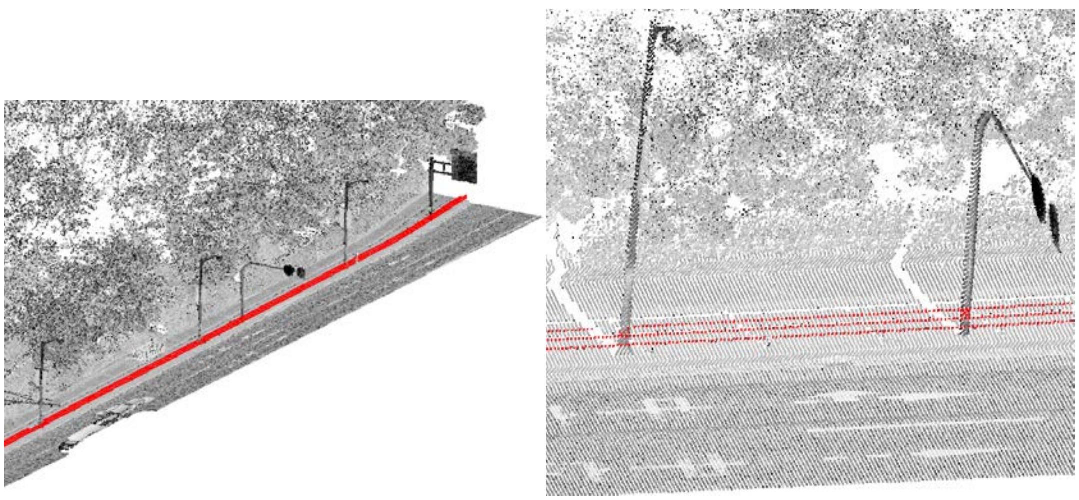
	Guardrails	Other objects	Recall	F-measure
Guardrails	660	53	92.6%	0.951
Other objects	15	1548	99.0%	0.967
Precision	97.8%	96.7%		

Fig. 9 shows guardrails that were finally extracted from point-clouds. Fig. 9(b) shows close-ups of extracted guardrails. In this evaluation, all guardrails could be extracted correctly and stably.



(a) Misclassified segments (b) Corrected segments

Fig. 8. Correction of misclassified segments



(a) Guardrails detected form a point-cloud (b) Close-ups of guardrails

Fig. 9. Detected guardrails

7. Conclusion

In this paper, we proposed a method for extracting guardrails from point-clouds and digital images captured by MMS. We extract roadside objects from point-clouds, and detected their 2D images by projecting points on images. Then we verified using CNN whether the images were guardrails or not. In our evaluation, we could extract points of guardrails reliably.

In future work, we would like to collect various shape patterns of guardrails in many areas. We would also like to reconstruct solid models of guardrails from extracted points, and import them to 3D city map database. We believe that our approach can be extended to shape reconstruction of various types of objects. We would like to investigate more flexible shape modeling methods for general objects.

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