RAPID UPDATE OF ROAD SURFACE DATABASES USING MOBILE LIDAR: ROAD-MARKINGS

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Abstract

Road surface markings are used on paved roadways to provide guidance and information to drivers and pedestrians, which are a critical feature in the traffic management systems. This paper presents an automated approach to detection and extraction of road markings from mobile laser scanning (MLS) point clouds by taking advantages of multiple data features. To improve computational efficiency, the raw MLS point cloud data are first converted to geo-referenced images, based on elevation, intensity and point density, using inverse distance weighted interpolation, respectively. Afterwards, three filters are designed to extract road markings step-by-step: (1) the elevation filter is used to generate an elevation mask to remove high objects from the geo-referenced intensity image; (2) the point density filter is implemented to extract road surfaces in the geo-referenced intensity image; (3) the filtered geo-referenced intensity image is processed by thresholding and point density to obtain road markings, followed by a Canny detector and Hough transform used to extract straight-lines of road markings. Two RIEGL VMX-450 datasets demonstrate that the proposed multi-feature road marking extraction method has a good performance of road marking extraction from a large volume of mobile laser scanning data.

Keywords: MLS, Road Marking, Geo-Referenced, Point Density, Intensity, Elevation

Introduction

Road surface markings are used on paved roadways to provide guidance and information to drivers and pedestrians, which are a critical feature in the traffic management systems. For example, driver assistance systems require a reliable environment perception for the improvement of the traffic safety by informing the motorists and preventing accidents. In line with the condition of the pavement, the topography of the road, the visibility of road markings are the key elements in accidents where the road itself is the cause. Especially, in the urban environments, with the increase of population and urbanization, high accident rates are caused by the absence of clearly-presented road signalisation [1]. Thus, road infrastructure divisions need a practical tool that can monitor the situation of road markings to maintain to high technique standards for perfect visibility of road markings, accordingly.

McCall and Trivedi summarized lane marking detection techniques that include the use of edges, regions and tracking for continuity [2]. Li et al. presented a method, which uses a fuzzy-reasoning-based general technique for edge detection to classify a pixel into a uniform region based on luminance differences between the pixel and its neighbors [3]. Li et al. detected arrow markings on road surfaces based on shape information [4]. Most algorithms of road markings recognition are commonly comprised by the extraction of candidates and a classification step [5-9].

Although works on the detection of road markings from either digital photographs or videos have been pursued for a number of years, the image based recognition systems are limited to extract precise geometry information under poor illumination conditions. Compared to photogrammetry, laser scanning, as an active remote sensing technology, captures very highly accurate 3D point clouds with a high point density in a relatively short amount of time [10-12]. Typically, a mobile lidar technology is ideally suited for corridor mapping due to its “drive-by” data acquisition pattern, and therefore market focus is on road and rail networks. This technology collects survey-grade data of...
unprecedented detail at highway speeds and at less than traditional survey costs. In the transportation discipline it is a safer means of data collection while reducing risk for the entire project. Thus, mobile lidar systems, a complement of existing survey techniques, can guarantee the end product as good as the originally gathered field data. This also has the added benefit of eliminating road closures and traffic disruption, as well as minimising exposure of staff to high risk environments such as roads, highways and rail tracks.

Moreover, digital images or videos, on the one hand, contain increasingly abundant spectral information with increase of spatial resolution; on the other hand, it brings difficulties for object recognition. Thus, to perform road marking recognition task, a variety of algorithms have been developed to find road markings from such complex environments. However, the use of MLS data, combining elevation and intensity information with a unique scanning pattern, decreases topographic and scene complexity without the loss of data accuracy.

However, although MLS is a feasible way for road infrastructure and street-scene objects, it is challenging to transform such a massive 3D MLS data into readable and comprehensive visualization information for governments at all levels, commercial users to deliver their decision. Smadja et al. stated that there were a few solutions to laser scanning data, which offer a full comprehension of road environment, gather road geometry, road marking and traffic sign analysis [13]. To crack this issue, our proposed research aims to develop algorithms to effectively organize such a substantially large volume of MLS data and to automatically detect horizontal road markings and follow white lines painted on the road, and to detect their types, condition and suitability to local driving conditions from them. This information is collected and used to determine whether the road markings need to be repainted or changed.

Methodology

In this study, we present an algorithm that combines the advantages of geo-referenced feature image and multiple features of MLS data. The paper first details the study areas and data, and then generates geo-referenced images from three features of elevation, intensity and point density, respectively. Afterwards three filters are applied to detect and extract road markings from a large volume of MLS data.

Geo-Referenced Images

We rasterize MLS data into 2D range images, in which the grey value of a pixel is interpolated from its nearest neighbors using inverse distance weighted (IDW). Although there are interpolation errors, it is computational efficiency using established image processing algorithms. Analogue to airborne laser scanning (ALS) data, MLS data can be converted into range-like images. To generate the geo-referenced images, the value of each grid cell in gridded images has to be assigned in line with three kinds of information used in this paper: elevation, intensity and point density, respectively.

Road-marking Extraction

Afterwards, three geo-referenced images are used to build up filters for the extraction of road markings: elevation, point-density, and intensity-density filters. In light of high reflectance of road markings shown in the geo-referenced intensity image, we applied the intensity information as a base image to be processed for the extraction of road markings. First, the geo-referenced elevation image, based on a histogram analysis, is automatically segmented to generate a binary image as a mask to remove objects higher than road surfaces in the geo-referenced intensity image. Then, a second mask is created from the geo-referenced point-density image, to eliminate objects not belonging to road surfaces in the intensity image. The philosophy behind this process is to use the distinctive characteristic of the mobile laser scanning pattern that is similar to a Gaussian distribution model. Next, for the filtered geo-referenced intensity image, we employ the histogram analysis based method to extract road markings, apply the Gaussian distribution model to remove low vegetation close to road surface from the geo-referenced point-density image, and use edge detection and straight-line extraction techniques to obtain road markings.

Elevation Filter

In the geo-referenced elevation image, the larger a grey value of a pixel is, the more points with higher elevations are included within the grid corresponding to the pixel. Thus, based on the elevation information provided from the geo-referenced elevation image, ground points can be separated from non-ground points by a simple thresholding method. To automatically and adaptively determine the elevation threshold (denotes as \( e_{\text{g}} \)), a histogram of the geo-referenced elevation image, transferring the elevation information into a discrete probability distribution based graph, is analyzed.
for classifying the ground and non-ground points by finding an optimal threshold, as shown in Figure 1. Afterwards, the transformed binary image is used as an elevation mask to eliminate the non-ground points in the geo-referenced intensity image.

Figure 1. The determination of thresholds to segment the geo-referenced elevation image.

Point-density Filter

As for the MLS data, the points closer to laser scanners on the trajectory are denser than those away from the laser scanners. More specifically, the point density distribution of MLS points centered by the laser scanners follows the Gaussian distribution with mean $\mu$ and standard deviation $\sigma$. Therefore, such situation can be reflected by the grey values of the pixels orthographic to the trajectory in the geo-referenced point-density image, as shown in Figure 2(a). In Figure 2(a), the green lines represent a 20-cm-cross-section of MLS data perpendicular to the trajectory. There are two peaks of the 20-cm-cross-section because the RIEGL VMX-450MLS system collects data back and forth to acquire full coverage of roads. Observed from the 20-cm-cross-section, the intersection ($X_d$) of the back-and-forth data can be obtained. The red curve displayed in Figure 3(b) thus is a fitted curve using two Gaussian distribution models, according to the following equation:

$$
G_d = \begin{cases} 
G_1 e^{-\frac{(x-\mu)^2}{2\sigma^2}}, & x \leq X_d \\
G_2 e^{-\frac{(x-\mu)^2}{2\sigma^2}}, & x > X_d 
\end{cases}
$$

Figure 2(b) displays the fitted curve. In theory, for the normal distribution, about 68% information can be drawn within one standard deviation $\sigma$ away from the mean; about 95% of the values lie within two standard deviations; about 99.7% of the values are within three standard deviations. This can also be called as “68-95-99.7” rule or 3-sigma rule. Based on this theory, the binary image (BD) is generated as the second mask: the grey value of a pixel is 255 if the pixel is located in the scope of $[\mu - 3\sigma, \mu + 3\sigma]$; on the contrary, the grey value is 0 if the pixel is located out of this scope. The filtered geo-referenced intensity image by elevation filter is further processed using the binary image (BD) to remove non-road data.

Figure 2. X-profile of the laser scanning data: (a) the profile data, (b) the fitted normal distribution line

Intensity-Density Filter

After performing the elevation filter and the point density filter, we almost eliminate the non-ground objects (e.g., pedestrians, cars and other moving objects) from the geo-referenced intensity image. The road surface thus is
extracted. In light of road marking materials, the energy of the laser pulse reflected from road markings is stronger than that reflected from asphalt or cement-made roads, in the near infrared spectrum scope. Thus, this characteristic is applied to extract road markings using a grey-value threshold in the geo-referenced intensity image, according to the histogram analysis.

As we aim to extract the road markings of linear shapes, a Hough transformation operator followed by the Canny edge detector is applied to extract linear road markings from the filtered intensity geo-referenced image. Usually, the Hough transformation was introduced by Hough [15] and first used to find lines in images a decade later [16], requires a lot of memory and computation. To accelerate the process of finding peak points in the accumulator, we estimate straight-line orientations by calculating the gradient value of every road marking pixel.

**Experiments And Discussion**

The data were acquired on April 23, 2012 by a RIEGL VMX-450 MLS system, which was smoothly integrated with 2 RIEGL VQ-450 scanners, IMU/GNSS unit, a wheel-mounted Distance Measurement Indictor (DMI), and four high-resolution cameras. The set of the VMX-450 MLS system was mounted on the roof of a vehicle at an average speed of 50 km/h. The accuracy of MLS data is about 8 mm (1 σ standard deviation) with maximum effective measurement rate of 1 million points/second and line scan speed of 400 lines/seconds. To assess the performance of the proposed method of road markings, we, selected one section road from the two surveys. Figure 3 (a) shows a close view of the selected dataset. The displayed part is a typical urban area that contains high trees, low vegetation, poles, buildings, some moving objects; as a result, we use it to assess the presented method.

![Figure 3](image)

**Figure 3.** A close view of the data set: (a) a sample of raw mobile laser scanning data, (b) the geo-referenced elevation image, (c) the geo-referenced intensity image, and (d) the geo-referenced point-density image.

First, three geo-referenced images are generated based on the height, intensity and point density, as shown in Figures 3(b), (c) and (d), respectively. Notice that road surfaces and high objects such as trees and light poles can be easily separated in the geo-referenced elevation image. However, clusters of low vegetation such as bushes and shrubs have close grey values to the road surface. As seen in the geo-referenced intensity image, it is difficult to separate road markings from vegetation including bushes, shrubs and high trees. Even some shape-based methods mentioned in Yang et al. may fail in this situation [14]. The geo-referenced point-density image is featured by high grey values centered at the locations of the scanning trajectory, which provides clues to remove objects not belonging to the road surface. Therefore, the combination of three features can fully utilize their advantages and compensate for each other. Meanwhile, this multi-feature method is effective by converting a large volume of MLS data into a geo-referenced image using established image processing algorithms.

Figure 4 shows the hierarchical filtered results using three filters. As shown in Figure 4(a), high objects such as trees, light poles are removed using the height mask that is a binary image generated from the geo-referenced elevation image using the histogram analysis based thresholding method. However, the low brushes still stay in the middle and outside of the road surface. Thus, we utilize the geo-referenced point-density image to extract the road surface by the reason that the MLS pattern follows the normal distribution to a certain extent. Figure 4(b) shows the filtered geo-referenced intensity image using the point density mask. After performing the point density mask, the geo-referenced image...
intensity image contains the isolation strip in the middle of the road surface and road markings. The reflective energies from vegetation and road markings are too much close, resulting in some difficulties to separate them based on grey values and shape information. Due to the isolation strip is located outside of the road surface, we reuse the point density information to remove it based on one standard deviation. Figure 4(c) is the resultant geo-referenced intensity image that contains only road markings. The Canny detector and the Hough transform operator are used to extract edges and straight-lines from the road markings, as shown in Figures 4(d) and (e), respectively. Local details in the red rectangle in Figure 4(e) demonstrate that the proposed method can extract a good result of road markings. Figure 4(f) shows the extracted road markings overlaid on the MLS data, which further confirm that the proposed multi-feature-based method in this study can efficiently and correctly extract road markings. This is because (1) converting 3D mobile laser scanning points onto a geo-referenced image makes the data processing easily thanks to without considering any data indexing structure for a large voluminous data, (2) Such a higher point density (e.g. 3000 - 4000 points per sq. m) can capture more detailed road surfaces, which provide explicit and implicit features for the correctness of the extracted road markings.

Figure 4. The process of road marking extraction using three filters: (a) the filtered results by the height filter, (b) the filtered results by the point density filter, (c) the filtered results by the intensity-density filter, (d) the filtered results by the Canny, (e) the filtered results by the Hough transform, and (f) the filtered results overlaid on the mobile laser scanning data.

Conclusions

This paper proposed a road marking extraction method from MLS data. Based on three data features including geometry, intensity and point density, the multi-feature road marking extraction method first generated three geo-referenced images, through IDW interpolation. And then, three filters were established to extract road markings step-by-step: (1) the elevation filter, which automatically segmented the geo-referenced elevation image to generate an elevation mask for removal of high objects on the geo-referenced intensity image; (2) the point density filter, which, through Gaussian distribution models, generated a road-surface mask for extracting road surfaces on the geo-referenced intensity image; (3) the filtered geo-referenced intensity image was segmented by Gaussian distribution models, aiming to remove the isolation strip in the middle of roads, and was further processed by the Canny edge detector and Hough transform operator to finally obtain road markings.

The test dataset collected by a RIEGL VMX-450 MLS system was used in this paper for the validation of the proposed method. The experimental results demonstrated that the proposed method has a good performance on the extraction of road markings from a large volume of MLS data. Moreover, it is an efficiently computational method because such dense MLS points have been converted into a geo-referenced image, on which the established image processing algorithms were applied to road marking extraction. This paper focuses on the extraction of lane markings and road crossing for road network modelling; thus, the road marking extraction system will be improved by adding other complex shapes of road markings in the future.

References


