AUTOMATED DETECTION OF ROAD MANHOLE COVERS FROM MOBILE LIDAR POINT-CLOUDS BASED ON A MARKED POINT PROCESS

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Abstract

This paper presents a novel algorithm for detecting road manhole covers from mobile LiDAR point-clouds. This algorithm takes advantage of a marked point process of discs and rectangles to model the locations and geometric structures of the manhole and sewer well covers. The algorithm also uses the Bayesian paradigm to obtain a posterior distribution for the marked point process conditional on the geo-referenced intensity image. A Reversible Jump Markov Chain Monte Carlo (RJMCMC) algorithm is implemented to simulate the posterior distribution. Finally, the maximum a posteriori (MAP) scheme is used to obtain an optimal detection. This algorithm has been examined by a set of mobile LiDAR point-clouds acquired by a RIEGL VMX-450 mobile laser scanning system. The results demonstrate the efficiency and feasibility of the proposed algorithm for automatically detecting road manhole and sewer well covers.

Keywords: Mobile LiDAR, point-cloud, manhole cover, sewer well cover, road surface, marked point process, RJMCMC, Bayesian inference

Introduction

Manholes and sewer wells function to conduct rainwater, drainage, and other things. They are usually covered with a metal-made cover to keep things from dropping into the wells (Figure 1). However, if the cover is removed by someone or broken caused by some uncertain factors, it is dangerous to the moving cars and the pedestrians. Manhole cover theft has become a serious problem in South Africa, India, and China. The missing manhole covers can cause not only trash pollutions but also casualties (Figure 2). Therefore, efficient and cost-effective techniques that can monitor and prevent the potential disasters on the road are urgently in demand.

Figure 1: Illustration of (a) manhole and (b) sewer well covers.
In the past decades, light detection and ranging (LiDAR) technology has been rapidly developed and used by a variety of applications [1], [2]. Due to the long-range, high-speed, and low-cost data acquisition, high-accuracy and high-precision ranging, and high point density, mobile LiDAR systems have been widely used for urban surveying and mapping. Basically, mobile LiDAR systems use near-infrared radiations to measure geospatial information, and acquire the reflectance returned by the measured objects. Due to high effective rate and high line scan speed, the density of the acquired point-clouds is very high. Therefore, the mobile LiDAR point-clouds provide a suitable solution to detecting manhole and sewer well covers on road surfaces.

Point processes were introduced in [3] to detect an unknown number of objects in images. A point process is made into a marked point process by attaching marks to each point of the process [4]. In this paper, we present a novel algorithm to automatically detect road manhole and sewer well covers from mobile LiDAR point-clouds based on a marked point process of discs and rectangles. The idea behind the approach is to model the number and locations of manhole and sewer well covers as point processes, to define their geometries as marks, and to attach a set of random parameters to each manhole and sewer well covers.

Algorithm Description

**Generation of 2D geo-referenced intensity image**

We utilize the intensity information of the road surface point-clouds to detect manhole and sewer well covers. Instead of processing the point-clouds in 3D space, we rasterize the road surface point-clouds into a 2D geo-referenced intensity image based on the intensity information of the data points. First, we project the road surface point-clouds onto the XoY plane, and then vertically partition the projected point-clouds into grid structures with a grid spacing of $r_g$, as shown in Figure 3. Next, we adopt an Inverse Distance Weighted (IDW) interpolation method [5] to generate a 2D geo-referenced intensity image based on the intensities of the data points within each grid. The weights of the data points are determined as follows: (1) a point with a distance farther away from the central point will get a smaller weight, and (2) a point with a higher intensity will get a greater weight. Figure 4 shows a visual example of the generated geo-referenced intensity image using the IDW interpolation.
Data model

A geo-referenced intensity image is a collection of data points \( \{(x_i, y_i, I_i); i=1,2,...,n\} \) where \( i \) is the index of data points, and \( n \) is the total number of data points. The point \((x_i, y_i) \in D \subset \mathbb{R}^2\) is the coordinate of the \( i \)th data point, \( D \) is a data domain on which all points are irregularly distributed, and \( I_i \) is the intensity at point \((x_i, y_i)\). The data points in a geo-referenced intensity image can be also re-originated as \( I_i = f(x_i, y_i); i=1,2,...,n, (x_i, y_i) \in D \). From spatial statistics point of view, \( I \) can be considered as a collection of discrete samples on points \( \{(x_i, y_i); i=1, 2,...,n\} \) from a random function \( f(x, y) \) defined on \( D \). On the other hand, \( I \) can be characterized by a random field (RF), in which the collection of \( n \) intensities that make up a geo-referenced intensity image do not represent a sample of size \( n \), but rather a sample of size one from an \( n \)-dimensional distribution [6].

Consider an RF \( I = \{I_i = f(x_i, y_i); i=1,2,...,n, (x_i, y_i) \in D\} \), covering \( k \) manhole covers and \( l \) sewer well covers, where \( k \) and \( l \) are unknown random variables with prior probability distribution functions (PDF) \( p(k) \) and \( p(l) \), which are assumed to be Poisson distributions with means \( \lambda_m \) and \( \lambda_s \) [6].

In order to distinguish manhole and sewer well covers from the background in \( I, D \) is divided into three regions, that is, \( D = \{D_b, D_m, D_s\} \), where \( D_b, D_m, \) and \( D_s \) correspond to the background, manhole cover, and sewer well cover regions, respectively. \( D_m = \{M_i; j=1,2,...,k\} \), where \( M_i \) is the region of the \( j \)th manhole cover and \( k \) denotes the number of manhole covers. \( D_s = \{S_j; j=1,2,...,l\} \), where \( S_j \) is the region of the \( j \)th sewer well cover and \( l \) denotes the number of sewer well covers. Assume that the intensities in these three regions are characterized by Gaussian distributions as follows:

\[
p(I) = \frac{1}{\sqrt{2\pi \sigma_b}} \exp\left\{-\frac{(I-\mu_b)^2}{2\sigma_b^2}\right\}, \quad (x_i, y_i) \in D_b
\]
\[
\frac{1}{\sqrt{2\pi \tau_j}} \exp\left\{-\frac{(I-\nu_j)^2}{2\tau_j^2}\right\}, \quad (x_i, y_i) \in M_j
\]
\[
\frac{1}{\sqrt{2\pi \epsilon_j}} \exp\left\{-\frac{(I-o_j)^2}{2\epsilon_j^2}\right\}, \quad (x_i, y_i) \in S_j
\]

where \( \mu_b, \nu_j, \) and \( o_j \) are the means and \( \sigma_b, \tau_j, \) and \( \epsilon_j \) are the standard deviations of Gaussian distributions for the intensities in the background, the \( j \)th manhole cover, and the \( j \)th sewer well cover regions, respectively.

Marked point process model

As shown in Figure 5(a), a manhole cover is characterized by a marked point of disc with marks \((u, v, r)\), where \((u, v)\) is the centre of the disc, and \( r \) is the radius. A sewer well cover is characterized by a marked point of rectangle with marks \((u, v, w, h, \alpha)\), where \((u, v)\) is the centre of the rectangle, \( w \) and \( h \) are the width and height, respectively, and \( \alpha \) is the orientation of the rectangle, as shown in Figure 5(b).

![Figure 5](image.png)

**Figure 5:** Marked point models for (a) the manhole and (b) the sewer well covers.

Denote \( B = \{M, S\} \) as the set of manhole and sewer well covers, where \( M = \{C_m, R, k\} \) and \( S = \{C_s, W, H, \alpha, l\} \) are the parameter sets of the manhole and sewer well covers, respectively. \( C_m = \{u_j, v_j\}; j=1,2,...,k\) and \( C_s = \{u_j, v_j\}; j=1,2,...,l\) are the centres of the manhole and sewer well covers, respectively. \( R = \{r_j; j=1,2,...,k\} \) contains the radii of the manhole covers, \( W = \{w_j; j=1,2,...,l\} \), \( H = \{h_j; j=1,2,...,l\} \), and \( \alpha = \{\alpha_j; j=1,2,...,l\} \) contain the widths, heights, and orientations of the sewer well covers, respectively. Assume that the centres and orientations uniformly distribute on \( D \) and \((-\pi/2, \pi/2]\), respectively; the prior distributions of \( k \) and \( l \) are assumed to follow Poisson distributions with means \( \lambda_m \) and \( \lambda_s \) and other parameters are assumed to be Gaussian distributions.
Bayesian model

By Bayesian paradigm, the posterior distribution of the parameter set $B$ conditional on a given geo-referenced intensity image $I$ can be expressed as:

$$P(B \mid I) = \frac{P(I \mid B) P(B)}{P(I)} = P(I \mid B) P(B).$$  \hspace{1cm} (2)

where $P(I \mid B)$ is a likelihood with the following form:

$$P(I \mid B) = P(I \mid M, S) = P(I_n \mid C_n, R, k) P(I \mid C_w, W, H, a, l).$$  \hspace{1cm} (3)

and

$$P(B) = P(C_n \mid k) P(R \mid k) P(C_w \mid l) P(W \mid l) P(H \mid l) P(a \mid l) P(l).$$  \hspace{1cm} (4)

Transformations of the marked points

We define three categories of transformations for the marked points of discs (Figure 6), and four categories of transformations for the marked points of rectangles (Figure 7). The dashed line denotes the original marked point before transformation, the solid line denotes the marked point after transformation, and the black dot is the centre of the marked point.

![Figure 6: Transformations for the marked points of discs.](image)

![Figure 7: Transformations for the marked points of rectangles.](image)

Simulation and optimization

In order to simulate the posterior distribution in equation (2), the RJMCMC [7] algorithm is implemented. The block diagram of the proposed RJMCMC algorithm is shown in Figure 8. The operations proposed in the scheme include: (1) updating model parameters; (2) moving the locations of centres; and (3) birth or death of a marked point.

![Figure 8: Block diagram of the proposed RJMCMC algorithm.](image)

Once the operations are determined, the scheme can be designed as follows.
(1) **Initialization.** Initialize the iteration counter \( t = 1 \). Set the initial number of manhole and sewer well covers, for simplicity, taking \( k^0 = 1 \) and \( \ell^0 = 1 \), since \( k^0 \) and \( \ell^0 \) don’t impart the final result. Set the initial values of the parameter vector \( \mathbf{B}^{0} = \{ \mathbf{M}^{0}, \mathbf{S}^{0} \} \), which are drawn from their appropriate prior distributions. And set the maximum iterations \( T_m \).

(2) **Updating model parameters.** At the \( t \)’th iteration, sequentially update the model parameters of each marked point. For example, for a marked point of disc, uniformly select one label \( j \in \{1, 2, \ldots, k\} \), where \( k \) is the number of manhole covers. Then, draw a proposal for the selected marked point, denoting \( \mathbf{M}_j^{t} \),

\[
\mathbf{M}_j^{t} \sim N(\mathbf{M}_j^{t-1}, \delta).
\]

where \( N(\mu, \sigma) \) denotes the standard normal distribution with mean \( \mu \) and standard deviation \( \sigma \). Calculate the acceptance probability for the proposal as follows:

\[
r_b(\mathbf{M}_j^{t}, \mathbf{M}_j^{t-1}) = \min(1, R(\mathbf{M}_j^{t}, \mathbf{M}_j^{t-1})),
\]

where the Green Ratio [7] is defined as follows:

\[
R(\mathbf{M}_j^{t}, \mathbf{M}_j^{t-1}) = \frac{P(\mathbf{I} | \mathbf{M}_j^{t})P(\mathbf{M}_j^{t})}{P(\mathbf{I} | \mathbf{M}_j^{t-1})P(\mathbf{M}_j^{t-1})}.
\]

Then, accept the proposal if the acceptance probability exceeds a pre-defined constant false alarm ratio \( p_t \), that is:

\[
\mathbf{M}_j^{(t)} = \begin{cases} 
\mathbf{M}_j^{*}, & r_b \geq p_t, \\
\mathbf{M}_j^{t-1}, & r_b < p_t.
\end{cases}
\]

(3) **Updating locations of centres.** At the \( t \)'th iteration, uniformly select a marked point. Propose a new centre for the selected marked point by uniformly drawing a location from the domain of this marked point. Then, calculate the acceptance probability for the proposal, and accept it if and only if \( r_b \geq p_t \).

(4) **Birth or death of a marked point.** Assume that the number of manhole covers is \( k \) and let the probability of proposing a birth or death operation be \( b \) or \( d \), respectively. Consider a birth operation that increases the number of manhole covers from \( k \) to \( k+1 \), and assume that the new manhole cover is labelled with \( k+1 \) and denoted by \( \mathbf{M}_{k+1} \).

Draw the centre \( (u_{k+1}, r_{k+1}) \) from \( \mathbb{D} - \mathbb{D}_k \cup \mathbb{D}_j \) uniformly, and draw its radius \( r_{k+1} \) from a Gaussian distribution. According to the RJMCMC scheme [7], the acceptance probability for the birth operation can be written as:

\[
r_b(\mathbf{B}', \mathbf{B}) = \min\left\{1, \frac{P(\mathbf{I} | \mathbf{B}')P(\mathbf{B}') J_b(\mathbf{B}')}{P(\mathbf{I} | \mathbf{B})P(\mathbf{B}) J_b(\mathbf{B})} \frac{\sigma^2(\mathbf{B}')}{\sigma^2(\mathbf{B})}, \right\},
\]

where \( J_b(\mathbf{B}') = b \), \( J_d(\mathbf{B}) = \frac{\sigma^2(\mathbf{B})}{\sigma^2(\mathbf{B})} \), and \( \frac{\sigma^2(\mathbf{B}')}{\sigma^2(\mathbf{B})} = 1 \). For simplicity, let \( d = \lambda w b \), then (9) can be rewritten as:

\[
r_b(\mathbf{B}', \mathbf{B}) = \min\left\{1, \frac{P(\mathbf{I} | \mathbf{B}')}{P(\mathbf{I} | \mathbf{B})} \right\}.
\]

The acceptance probability for the death operation is calculated as follows:

\[
r_d(\mathbf{B}', \mathbf{B}) = \min\left\{1, \frac{P(\mathbf{I} | \mathbf{B}')}{P(\mathbf{I} | \mathbf{B})} \right\}.
\]

After the maximum iteration \( T_m \), the maximum a posteriori (MAP) criterion is used to obtain the final segmentation, that is:

\[
\hat{\mathbf{B}} = \arg\max (P(\mathbf{B} | \mathbf{I})).
\]
**Study area and mobile LiDAR point-clouds**

The road surface mobile LiDAR point-clouds used in our experiments were acquired by the RIEGL VMX-450 mobile laser scanning system on Ring Road South on Xiamen Island, China. Figure 9 shows the study area and the RIEGL VMX-450 mobile laser scanning system. The RIEGL VMX-450 system is integrated with (1) two RIEGL VQ-450 laser scanners, (2) a Global Navigation Satellite System (GNSS), (3) an Inertial Measurement Unit (IMU), (4) a Distance Measurement Indicator (DMI), and (5) four high-resolution digital cameras. The two VQ-450 laser scanners are symmetrically configured with an “X” pattern on both sides of the main frame. The accuracy of the acquired point-clouds is within 8 mm, and the precision is 5 mm with a maximum effective rate of 1.1 million measurements per second and a line scan speed of up to 400 scans per second.

![Figure 9: (a) Study area, and (b) RIEGL VMX-450 mobile laser scanning system.](image)

**Detection of road manhole and sewer well covers**

First, we segmented the road surface point-clouds from the raw mobile LiDAR point-clouds. Then, we rasterized the road surface point-clouds into geo-referenced intensity images with a resolution of $r_g = 2.5$ cm. Next, we applied the proposed marked point process based detection algorithm to these geo-referenced intensity images to detect manhole and sewer well covers.

![Figure 10: (a) Geo-referenced intensity image, and (b) detected road manhole and sewer well covers.](image)

![Figure 11: Geo-referenced intensity image, and (b) detected road manhole and sewer well covers.](image)
Figures 10 and 11 show some geo-referenced intensity images and the corresponding detection results. As seen from the detection results, the manhole and sewer well covers can be correctly and accurately detected. Therefore, the proposed algorithm is feasible in detecting road manhole and sewer well covers from road surface mobile LiDAR point-clouds, and provides a suitable and promising solution to monitoring road manhole and sewer well covers for preventing disasters on road surfaces.

**Conclusions**

In this paper, we have proposed a novel algorithm for automatically detecting road manhole and sewer well covers from road surface mobile LiDAR point-clouds. The algorithm was based on a marked point process of discs and rectangles and Bayesian inference. By using marked point processes, the proposed algorithm can process large-volume road surface point-clouds containing unknown number of manhole and sewer well covers. Instead of processing the mobile LiDAR point-clouds on a point-by-point basis in 3D space, the proposed algorithm rasterized the point-clouds into 2D geo-referenced intensity images and processed the images on an object-oriented basis. Results from a set of mobile LiDAR point-clouds acquired by the RIEGL VMX-450 mobile laser scanning system showed that the proposed algorithm could detect manhole and sewer well covers quite well.

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**References**