Extraction of Tree Crowns From Mobile Laser Scanning Data Using A Marked Point Process Model

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ABSTRACT

For the purpose of realistic visualisation in 3D city models, we present a marked point process based method for extracting tree-crowns from mobile laser scanning (MLS) data. First, we apply a modified IDW interpolation to generatea a geo-referenced feature image, by which a histogram analysis is applied to separate high objects(e.g. trees and lightpoles) from low objects(e.g. road, ground, low vegetation). Next, we calculate grey differences of each pixel with its neighbors to find the local maxima as potential tree-crown seeds, and then use a grouping-and-centralizing procedure to remove the redundants from the seeds. Finally, we emply a marked point process to the generated geo-referenced image via the seeds. Two experiments have been conducted to test the efficiency and feasibility of our tree-extraction algorithm using RIEGL VMX-450 MLS data.

Keywords: marked point,mobile laser scanning data, tree extraction, geo-referenced image

1. INTRODUCTION

Over the past years, increasing interest has been shown in mobile laser scanning (MLS), a rapid and flexible method for acquiring high-accuracy and high-resolution three-dimension (3D) topographic data. An MLS system generally implies that laser scanners are deployed on the top of a land-based vehicle, integrated with Global Navigation Satellite System (GNSS), Inertial Measurement Unit (IMU), Distance Measurement Indicator(DMI), and other synchronizing units. Due to the spatial coverage achieved by movement of the vehicle, MLS systems can survey large areas with a high point density in a relatively short amount of time, compared with airborne laser scanning (ALS) systems[1]. Meanwhile, they have advantages of terrestrial laser scanning (TLS) systems characterized by high accuracy and point density. Thus, MLS technologies are ideally suited for street-scene object recognition due to “drive-by” data acquisition pattern.

A number of applications of MLS to environmental remote sensing have presented on urban road-surface extraction, while many studies concentrate on the recognition of a wide range of street-scene objects directly from MLS data, such as treet-scene object extraction, lanes, road markings, traffic signs, tunnels, pole-like objects, road curb, and trees. Extracting urban trees from MLS data have been increasingly investigated for the purpose of visualisation in 3D city models. Rutzinger et al.[2] segmented the point cloud into planar regions using a 3D Hough transform and surface growing algorithm, and then classified the regions by a connected component analysis. Brenner[3] detected depth jumps representing trunk objects and posts, such as traffic signs, lamp posts, traffic lights and poles by comparing vertical scan lines with their neighbouring scan lines. Monnier et al.[4] detected trees from MLS data based on local geometric descriptors computed on each laser point using a determined neighbourhood, followed by a 2D horizontal accumulation space followed by a combination of morphological filters provides individual tree clusters. However, the main challenges in this field of research are the large data requirements. For example, an LYNX Mobile Mapper can capture a total of 144 million points of 5 blocks in 20 minutes at a speed of 25 km/h [5]. Therefore, many limitations on the memory and computation in computers have been recognized for the voluminous 3D point measurements and the detailed data description.

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To solve this problem, some works have been researched from a point of view of 2D image. Hernandez and Marcotegui [6] presented a method for detecting and extracting artifacts and pavement segmentation from a range image of MLS data with a set of morphological operators. Yang et al.[7] extracted road surface and street-scene objects by converting raw MLS data to 2D geo-referenced feature images regarding height and distance weights.

A point process is made into a marked point process by attaching a characteristic (the mark) to each point of the process [8]. Currently, there are some researchers considering a marked point processes framework for image analysis [9]. It has been showed that marked point process is more adapted than Markov Random Field (MRF), if some geometrical constraints are included in a solution and there are strongly correlated noise needed to be dealt with [10]. In this paper, we present a marked point process based approach to tree detection based on the 2D range-like image converted from 3D MLS point clouds.

The remainder of the paper is organized as follows. Section II describes the algorithm. Section III reports and discusses the experimental results on a set of MLS data, collected by RIEGL VMX-450 system, for tree detection. Finally, concluding remarks are contained in Section IV.

2. METHODOLOGY

In this study, an elevation geo-referenced image is first generated from the original MLS point clouds using an inverse distance weighted (IDW) method. Then a threshold for separating high objects (e.g., trees) from low objects (e.g., ground, low vegetation) is calculated using a histogram analysis on elevation geo-referenced image. Next, coarse locations of top points of tree crowns are computed by selecting the pixels that show local maxima. Afterwards, a single candidate top belonging to a single tree crown is generated by a grouping and centralizing procedure. Finally, tree crowns are extracted using a marked point process of discs.

2.1 Generation of Elevation Geo-referenced Image

Instead of processing the 3D MLS point clouds, we first convert the MLS point cloud into a 2D range image, in which the gray value of a pixel is interpolated from its nearest neighbors using an inverse distance weighted (IDW) method. To this end, we grid and project the point clouds onto the XoY plane. The width (*W*) and height (*H*) of the elevation geo-referenced image are calculated as follows:

$$\begin{cases} W = (X_{max} - X_{min}) / r_g + 1 \\ H = (Y_{max} - Y_{min}) / r_g + 1 \end{cases} \tag{1}$$

where X_{max}, Y_{max}, $X_{min}$and Y_{min} are the maximal and minimal coordinates of the point cloud and r_g is the grid size or the resolution of the 2D range image. Similar to the rasterization method mentioned in Yang at al.[7], the proposed rasterization method is based on the following rules: (a) a point with a higher elevation gets a greater weight and (b) a point with a farther distance away from the central point gets a smaller weight. We denote the generated 2D range image as elevation geo-referenced image.

2.2 Generation of Candidate Tops of Tree Crowns

Now, we focus on the elevation geo-referenced image. In order to filter out the low objects (e.g., ground and low vegetation), a histogram analysis procedure is carried out on the elevation geo-referenced image to obtain a threshold. Next, coarse locations of top points of tree crowns are computed by selecting the pixels with local maxima within the pre-defined circular neighborhood whose radius is r_n in the elevation geo-referenced image. We denote these points as candidates of top points. As more than one point may coincide in a single tree crown, a grouping and centralizing procedure then acts on the candidates. A candidate is grouped into group *i* if its shortest Euclidean distance with the candidates from this group is less than or equal to d_m. After grouping of all candidates, centralizing is carried out on each group to compute the geometrical center of all the candidates within this group. Therefore, each group will generate a single candidate point which we regard as the candidate top of a tree crown. These candidate points will be used for the initialization of a marked point process of discs later on.

2.3 Tree Crown Extraction Using Marked Point Process

Point processes were introduced in image processing because they easily model scenes of objects. A marked point adds some marks (parameters) to each point. In this study, we employ a marked point process of discs to model the shape of tree crowns. The marked point depicting the tree crown is denoted by (x, y, r), where (x, y) is the location of the disc and *r* is the radius. Three categories of transformations of the marked point process are defined as follows: (a) dilation, in which the radius of the marked point will be elongated; (b) shrinkage, in which the radius of the marked point will be shortened; (c) translation, in which the location of the marked point will be changed.

The associated state space ***S*** in which the tree crowns stand is as follows:

$$S = X \times Y \times R \tag{2}$$

Let denote $\varphi = (x, y, r) \in S$ an instance from ***S***. And ***X***, ***Y*** and ***R*** are the domains of *x*, *y* and *r*, respectively. (*x*,*y*) is the center of the disc and *r* is the radius, and assume them to follow the uniform distribution and Gaussian distribution, respectively.

We define an attractive ratio for each marked point as a quantitative measure of a marked point model matching a tree crown and give the attractive ratio of the jth marked point, denoting R_j, the following form:

$$R_j = \frac{n_j}{N_j} \tag{3}$$

where n_j is the number of points matching the prior model within the region of disc *j*, and N_j is the total number of points within the region the disc *j*.

The Green Ratio[10] between two marked points (φ_i and φ_j) gives a quantitative evaluation of the quality of matching the points between two marked points, and is defined as follows:

$$R(\varphi_i, \varphi_j) = \frac{p(\varphi_i) e^{R_i}}{p(\varphi_j) e^{R_j}} \tag{4}$$

2.4 Simulation and Optimization of Marked Point Process

In order to simulate the marked point process of discs, the RJMCMC[11] algorithm is developed. The operations proposed in the scheme include (a) updating tree crown radii and (b) moving the locations of centers. Once the operations are decided, the scheme is designed as follows.

1) **Initialization**. Initialize the iteration counter *t*=1. Set the initial number of tree crowns as the number of candidate tops. And set the initial values of parameters vector $\Phi_0 = (X_0, Y_0, R_0)$, whose centers are assigned with the locations of the candidate tops and radii are drawn from its appropriate distributions. Then set the maximum iterations T_m.

2) **Update tree crown radii**. At the *t*'th iteration, sequentially update the radii of tree crowns. To this end, uniformly select one label $j \in [1, ..., k]$, where *k* is the number of tree crowns. Then draw a proposal for the selected marked point, denoting $\varphi_j^* = \{x_j^{(t-1)}, y_j^{(t-1)}, r_j^*\}$,

$$\varphi_j^* \sim N(\varphi_j^{(t-1)}, \varepsilon) \tag{5}$$

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

$$r_\Phi(\varphi_j^*, \varphi_j^{(t-1)}) = \min(1, R(\varphi_j^*, \varphi_j^{(t-1)})) \tag{6}$$

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

$$\varphi_j^{(t)} = \begin{cases} \varphi_j^* & if \quad r_\Phi \geq P_f \\ \varphi_j^{(t-1)} & if \quad r_\Phi < P_f \end{cases} \tag{7}$$

And if the proposal is accepted, calculate its attractive ratio $R_j^{(t)}$ accordingly.

3) **Update the locations of centers**. At the *t*'th iteration, uniformly select one label $j \in [1,...,k]$. Propose a new center for the tree crown by uniformly drawing a point from the region dominated by $\varphi_j^{(t-1)} = (x_j^{(t-1)}, y_j^{(t-1)}, r_j^{(t-1)})$, that is,

$$\varphi_j^* \sim U(\varphi_j^{(t-1)}) \tag{8}$$

Calculate the acceptance probability for the proposal using equation (6), and accept it if $r_\Phi \geq P_f$. Then compute its attractive ratio $R_j^{(t)}$ accordingly.

3. EXPERIMENTS AND DISCUSSIONS

3.1 Test Data

Figure 1 shows the point clouds used in this study were acquired by a RIEGL VMX-450 MLS system in Xiamen, China. RIEGL VMX-450 MLS system is mounted on the roof of a vehicle running at a normal speed and integrated with 2 full-view RIEGL VQ-450 laser scanners, GNSS/IMU unit, a wheel-mounted Distance Measurement Indicator (DMI), and at most 6 high-resolution cameras. Two VQ-450 laser scanners are symmetrically configured on the left and right sides with a “Butterfly” (or “X”) pattern. The accuracy of the scanners is 8mm, precession 5mm, laser pulse repetition rate (PRR) up to 550kHz, maximal effective measurement rate up to 550,000 measurements per second and scan speed up to 200 scans per second. We selected a set of point clouds (in the yellow rectangle in Figure 1) from the surveyed data in our experiments to test the performance of the proposed tree crown extraction algorithm.

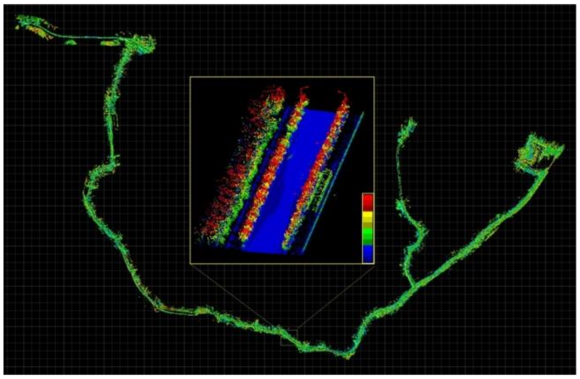

Figure 1. MLS data collected by the RIEGL VMX-450 MLS system.

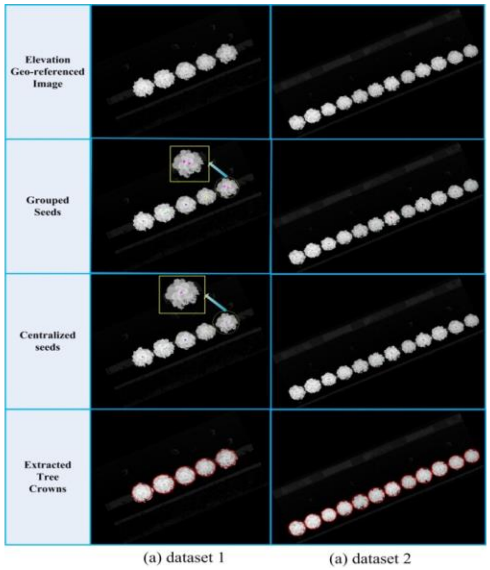

Figure 2. Illustration of two datasets and extracted tree crowns.

3.2 Experiment Results and Discussions

We apply the proposed algorithm to two datasets to test its accuracy and efficiency in extracting tree crowns from the elevation geo-referenced image generated from the MLS point clouds. The whole process and extraction results are shown in Figure 2. The first row shows the results of the elevation geo-referenced images converted from 3D MLS data by a modified IDW interpolation. We can find that trees are shown by much higher grey values than those of road surface. Thus, based on the histogram analysis of the tree images, we can segment trees from the elevation geo-referenced images. The second row shown in Figure 2 are the results of all seeds of tree crowns. A close view suggests that the seeds selected by the local maxima are satisfactory; however, more than one seed may coincide in a single tree crown.

After grouping and centralizing procedure, only one seed belonging to a single tree crown remains, as shown in the third row in Figure 2. The last row is the extraction results of tree crowns. Observing from the extracted results, each single tree crown is completely separated from background; thus, we can conclude that the marked point process of discs is effective in extracting tree crowns.

4. CONCLUSION

In this study, we proposed a marked point based tree-crown extraction method that consists of (1) generating elevation geo-referenced feature image from a huge volume of MLS data, (2) obtaining a seed for each tree-crown based on local maxima of grey differences and a grouping-and-centralizing procedure, and (3) extacting each tree-crown by a disc-shaped marked point process. The experiment results suggested that the proposed method is feasible and practicable to deal with a huge volume of MLS data and achieves a good performance of tree-crown extraction.

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