A Marked Point Process for Automated Tree Detection from Mobile Laser Scanning Point Cloud Data

Yongtao Yu [1], Jonathan Li [1,2*], *Senior Member, IEEE*, Haiyan Guan [2], Cheng Wang [1], Ming Cheng [1]
[1] Department of Computer Science, Xiamen University, Xiamen, China 361005
[2] Department of Geography and Environmental Management, University of Waterloo, Canada N2L 3G1

***Abstract*—This paper presents a new algorithm for tree detection from airborne / mobile laser scanning or LiDAR point cloud data. The algorithm takes advantage of a marked point process to model the locations of trees and their geometries. The algorithm also uses the Bayesian paradigm to obtain a posterior distribution for the marked point process conditional on the LiDAR point cloud data. A Reversible Jump Markov Chain Monte Carlo (RJMCMC) algorithm is developed to simulate the posterior distribution. Finally, the maximum a posteriori (MAP) scheme is used to obtain optimal tree detection. This algorithm has been examined by a set of LiDAR point cloud data. The results demonstrate the efficiency of the proposed algorithm for automated detection of trees.**

Keywords - LiDAR; tree detection; marked point process; RJMCMC; maximum a posteriori; Bayesian inference

I. INTRODUCTION

Airborne / mobile laser scanner or light detection and ranging (LiDAR) sensor data have emerged in recent years as a leading source for automated extraction of various objects (e.g., buildings, trees, vehicles, terrain, etc.), particularly due to the direct measurements of surface topography both accurately and densely [1, 2]. To date, a variety of methods for tree detection and extraction have been proposed. For color infrared images, different tools have been developed. Some of them use pixel-based methods and give the delineation of the tree crowns, such as the valley following algorithms [3]. Other tools use an object-based method, by modeling a synthetic tree crown template to find the tree top positions [4, 5].

Point process in image processing has been introduced by Baddeley and Lieshout to detect an unknown number of objects [6]. A point process is made into a marked point process by attaching a characteristic (the mark) to each point of the process [7]. Currently, there are some researchers considering a marked point process framework for image analysis [8, 9, 11, 12, 13]. In this paper, we present a marked point process based approach to tree detection from airborne / mobile LiDAR point cloud data. The idea behind the approach is to model the number and locations of trees as point processes, to define their geometry as the mark, and to attach a set of random parameters to each tree.

The remainder of the paper is organized as follows. Section II describes the models and algorithm. Section III reports and discusses the experimental results on a set of Riegl VMX-450 MLS point cloud data. Finally, conclusion remarks are contained in Section IV.

*Corresponding author: junli@xmu.edu.cn or junli@uwaterloo.ca. This study was supported by a NSERC discovery grant awarded to Prof. Jonathan Li.

II. ALGORITHM DESCRIPTION

A. Data Model

A LiDAR point cloud is a collection of data points $\{(x_i,y_i,z_i); i=1,\dots,n\}$ where i is the index of data points, and n is the total number of data points. The ground point $(x_i,y_i) \in D \subset R^2$ is the geo-referenced coordination of the ith data point, D is a data domain on which all ground points are irregularly distributed, and z_i is the elevation (or return) acquired at the ground point (x_i,y_i) by a LiDAR sensor. The data points in a LiDAR point cloud can be also re-originated as $\mathbb{Z}=\{Z_i=\mathbf{Z}(x_i,y_i); i=1,\dots,n, (x_i,y_i) \in D\}$. From spatial statistics point of view, $\mathbb{Z}$ can be considered as a collection of discrete samples on the ground points $\{(x_i, y_i); i=1, \dots, n\}$ from random function $\mathbf{Z}(x, y)$ defined on D. On the other hand, $\mathbb{Z}$ can be characterized by a random field (RF), in which the collection of n geo-referenced observations that make up a LiDAR point cloud do not represent a sample of size n, but rather a sample of size one from an n-dimensional distribution [10].

Consider a RF $\mathbb{Z}=\{Z_i=\mathbf{Z}(x_i, y_i); i=1, \dots, n, (x_i, y_i) \in D\}$, from which a LiDAR point cloud is sampled, covering k trees, where k is an unknown random variable with prior probability distribution function (PDF) $p(k)$, which is assumed to be a Poisson distribution with mean λ [10], that is,

$$\mathrm{p}(k) = \frac{\lambda^k}{k!} e^{-\lambda}. \quad (1)$$

In order to distinguish trees from the ground in $\mathbb{Z}$, D is divided into two regions, that is, $D = D_g \cup D_t$, where D_g and D_t correspond to ground and tree regions, respectively, and $D_t = \cup_{j=1}^{k} W_j$, where k is the number of trees and W_j is the region (or window) of the jth tree. In this paper, we define a new distribution to model the ground and trees. We assume that the elevations in these regions are characterized by Bounded Undetermined Distribution (BUD) $\boldsymbol{R}(\mu, \sigma)$ where μ and σ are the base-height and deviation, respectively. As shown in Fig. 1, this model is controlled by μ and σ. Z_i distributes randomly and irregularly within the bound as follows

$$\begin{aligned} &Z_i \sim R(\mu_g, \sigma_g) \text{ if } (x_i, y_i) \in D_g \\ &Z_i \sim R(\mu_{t_j}, \sigma_{t_j}) \text{ if } (x_i, y_i) \in W_j \end{aligned} \quad (2)$$

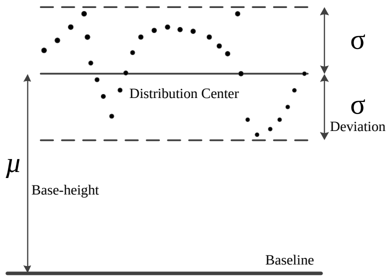


Figure 1. Bounded Undetermined Distribution (BUD).

where μ_g, μ_{t_j}, σ_g and σ_{t_j} are the base-heights and deviations of BUD for the elevations of ground and the *j*th tree, respectively. μ_g and σ_g are defined as constants, and μ_{t_j} and σ_{t_j} are random variables drawn from their prior distributions $p(\mu_{t_j})$ and $p(\sigma_{t_j})$ that are assumed to be Gaussian distribution and uniform distribution, respectively. That is,

$$\mathrm{p}\left(\mu_{t_j}\right) = \frac{1}{\sqrt{2\pi}\varepsilon_t} e^{-\frac{\left(\mu_{t_j}-\tau_t\right)^2}{2\varepsilon_t^2}} \quad (3)$$

$$\sigma_{t_j} \sim U(E_{min}, E_{max}) \quad (4)$$

In (3), τ_t and ε_t are the mean and standard deviation of a Gaussian distribution, and in (4), E_{min} and E_{max} are the lower bound and upper bound of a uniform distribution.

B. *Marked Point Process Model for Trees*

Point processes were introduced in image processing because they easily allow to model scenes of objects. A marked point adds some marks (parameters) to each point. In this paper, the model consists in a marked point process of discs which are the orthographic projections of the trees. Fig. 2 shows the parameters of a disc. (*u*,*v*) is the geometric central point and *r* the radius of the disc.

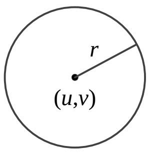


Figure 2. Parameterization model of a disc.

The associated state space $\boldsymbol{S} \subset R^5$ in which the objects (trees) stand is as follows

$$\boldsymbol{S} = \mathbf{X} \times \mathbf{Y} \times \mathbf{L} \times \mathbf{H} \times \boldsymbol{\Delta}$$

Let denote $\Theta = (u, v, r, \mu_t, \sigma_t) \in \boldsymbol{S}$ an instance from $\boldsymbol{S}$. So, **X**, **Y**, **L**, **H** and **Δ** are the domains of *u*, *v*, *r*, μ_t and σ_t, respectively. (*u*,*v*) is the central point of the disc, *r* is the radius, μ_t and σ_t are the base-height and deviation of BUD used for modeling a tree. Assume that (*u*,*v*) uniformly distributes on *D*, that is,

$$(u, v) \sim \mathrm{U}(D) \quad (5)$$

σ_t uniformly distributes on $[E_{min}, E_{max}]$ (see (4)), and *r* is assumed to be Gaussian distribution, that is,

$$\mathrm{p}(r) = \frac{1}{\sqrt{2\pi}\varepsilon_r} e^{-\frac{(r-\tau_r)^2}{2\varepsilon_r^2}} \quad (6)$$

where τ_r and ε_r are the mean and deviation of a Gaussian distribution. And μ_t is also assumed to be Gaussian distribution (see (3)).

Therefore, the *j*th tree can be modeled as

$$\Theta_j = (u_j, v_j, r_j, \mu_{t_j}, \sigma_{t_j})$$

Let denote

$$\mathbf{T} = \{\Theta_j; j = 1, \ldots, k\} \quad (7)$$

the set of all possible trees, where *k* is the number of trees. We aim at finding a **T** that can perfectly match the data containing an unknown number of trees.

C. *Bayesian Model*

Let denote $\mathbf{G} = \{(u_j, v_j); j = 1, \ldots, k\}$ the set of all central points and $\boldsymbol{\Psi} = \{(r_j, \mu_{t_j}, \sigma_{t_j}); j = 1, \ldots, k\}$ the set of all marks. Accordingly, **T** can be written as

$$\mathbf{T} = \{\mathbf{G}, \boldsymbol{\Psi}\} \quad (8)$$

Let denote $\boldsymbol{r} = \{r_j; j = 1, .., k\}$, $\boldsymbol{\mu_t} = \{\mu_{t_j}; j = 1, .., k\}$ and $\boldsymbol{\sigma_t} = \{\sigma_{t_j}; j = 1, .., k\}$ (noting that the notations in bold denote parameter vectors) the parameter vectors of radius, base-height and deviation, respectively. Therefore, **T** can be re-written as

$$\mathbf{T} = \{\mathbf{G}, \boldsymbol{r}, \boldsymbol{\mu_t}, \boldsymbol{\sigma_t}\} \quad (9)$$

By Bayesian paradigm, the posterior distribution of the parameters set **T** conditional on a given dataset $\mathbb{Z}$ can be expressed as

$$\mathrm{p}(\mathbf{T}, k|\mathbb{Z}) = \frac{\mathrm{p}(\mathbb{Z}|\mathbf{T}, k)\mathrm{p}(\mathbf{T}, k)}{\mathrm{p}(\mathbb{Z})} \propto \mathrm{p}(\mathbb{Z}|\mathbf{T}, k)\mathrm{p}(\mathbf{T}, k) \quad (10)$$

where $p(\mathbb{Z}|\mathbf{T}, k)$ is a likelihood with the following form

$$\mathrm{p}(\mathbb{Z}|\mathbf{T}, k) = \prod_{j=1}^{k} \prod_{(x_i, y_i) \in W_j} e^{-|Z_i - \mu_{t_j}|} \quad (11)$$

Assume that all parameter vectors in (9) are independent, then the joint distribution for $p(\mathbf{T}, k)$ can be expressed as

$$\mathrm{p}(\mathbf{T}, k) = \mathrm{p}(\mathbf{G}|k)\mathrm{p}(\boldsymbol{r}|k)\mathrm{p}(\boldsymbol{\mu_t}|k)\mathrm{p}(\boldsymbol{\sigma_t}|k)\mathrm{p}(k). \quad (12)$$

D. *Definitions*

1) Attractive Ratio: The attractive ratio of the *j*th marked point, denoting R_{att_j}, is a quantitative measure of a marked point model matching a tree. It is defined as follows

$$R_{att_j} = \frac{n_j}{N_j} \in [0,1] \quad (13)$$

where n_j is the number of data points from W_j that match the prior model within the *j*th marked point model, that is

$$\mathrm{n}_j = \mathrm{card}(\{Z_i; |Z_i - \mu_{t_j}| \leq \sigma_{t_j}, (x_i, y_i) \in W_j\}) \quad (14)$$

and N_j the total number of data points within the *j*th marked point model.

2) Set of Attractive Points (***Marked Points***): Let denote S_a the set of attractive points whose attractive ratio exceed a pre-defined threshold, that is

$$S_a = \{j; R_{att_j} \geq th_a, j = 1, \ldots, k\} \quad (15)$$

where $th_a \in [0,1]$ is a threshold and k is the number of marked points.

3) Green Ratio [12, 14]: Let denote $\mathrm{R}(\Theta_j, \Theta_i)$ the Green Ratio between Θ_j and Θ_i. Green Ratio gives a quantitative evaluation of the quality of matching the data points between two marked points. It is defined as follows

$$\mathrm{R}(\Theta_j, \Theta_i) = \frac{\mathrm{p}(\mathbb{Z}_{W_j}|\Theta_j)\mathrm{p}(\Theta_j)e^{R_{att_j}}}{\mathrm{p}(\mathbb{Z}_{W_i}|\Theta_i)\mathrm{p}(\Theta_i)e^{R_{att_i}}} \quad (16)$$

where

$$\mathbb{Z}_{W_j} = \{Z_i | (x_i, y_i) \in W_j\} \quad (17)$$

$$\mathrm{p}(\mathbb{Z}_{W_j}|\Theta_j) = \prod_{(x_i,y_i)\in W_j} e^{-|Z_i - \mu_{t_j}|} \quad (18)$$

$$\mathrm{p}(\Theta_j) = \mathrm{p}(r_j)\mathrm{p}(\mu_{t_j}) = \frac{1}{\sqrt{2\pi}\varepsilon_r} e^{-\frac{(r_j - \tau_r)^2}{2\varepsilon_r^2}} \frac{1}{\sqrt{2\pi}\varepsilon_t} e^{-\frac{(\mu_{t_j} - \tau_t)^2}{2\varepsilon_t^2}} \quad (19)$$

The same situations hold for the notations with subscript *i*.

E. Transformations of the Marked Point Process

We define six categories of transformations of a marked point process, they are (a) dilation / shrinkage, (b) base-height adjustment, (c) deviation adjustment, (d) translation, (e) birth / death of a tree and (f) death in a neighborhood. These transformations will be used in the **Simulation and Optimization** process (see subsection II-*G*).

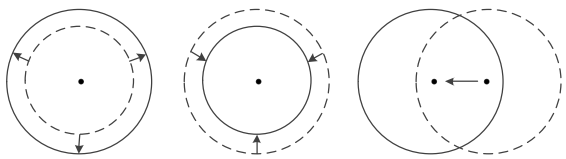


Figure 3. Illustration of transformations.

Fig. 3 shows some of these transformations. The dashed disc is the original one before transformation, the solid disc is the one after transformation and the black dot is the central point of a disc. A birth transformation may add a new marked point into **T**, while a death transformation may remove a marked point from **T** and / or S_a if necessary. All of these six categories of transformations constitute the movements of a marked point process.

F. Interaction between Discs

For a marked point process of discs, more than one disc may try to match a single tree simultaneously. Due to this reason, we design an alignment interaction [9] to deal with such situation. As shown in Fig. 4, d_c is the value defined for the alignment interaction, whose value is the distance between two central points minus two radiuses.

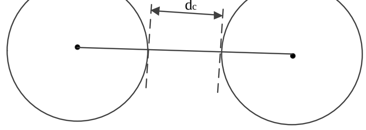


Figure 4. Alignment interaction.

Denoting $d_c(i,j)$ the interaction intensity between disc *i* and disc *j*, we only need one simple condition to define the alignment interaction, denoting $\sim^{al}$, that is,

$$\mathrm{i} \sim^{al} \mathrm{j} \Leftrightarrow d_c(i,j) \le d_{c_{max}} \quad (20)$$

where $d_{c_{max}}$ is the maximum distance. The smaller the value $d_c(i,j)$ is, the stronger the interaction between *i* and *j* is.

G. Simulation and Optimization

In order to simulate the posterior distribution in (10), the RJMCMC [14] algorithm is developed. The block diagram of the proposed method is shown in Fig. 5. The operations proposed in the scheme include (a) updating tree model parameters in $\boldsymbol{\Psi}$; (b) moving the locations of central points in **G**; (c) birth or death of a tree; and (d) death in a neighborhood.

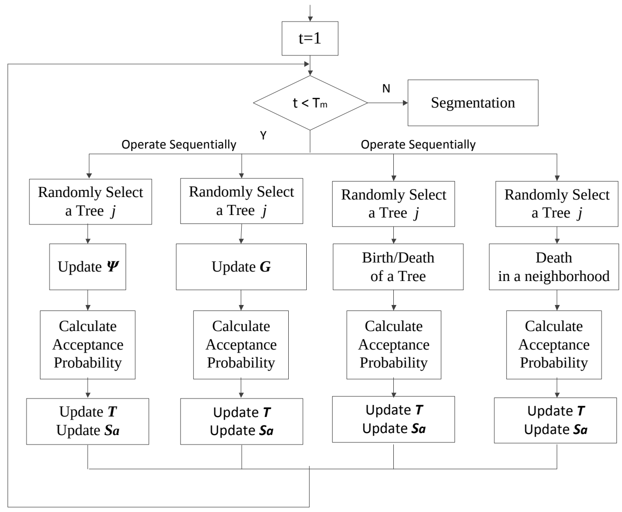


Figure 5. Block diagram of the proposed RJMCMC method.

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 trees, for simplicity, taking $k^0 = 1$, since k^0 doesn't impart the final result. Set the initial values of parameters vector $\boldsymbol{\Theta}^0 = (\boldsymbol{u}^0, \boldsymbol{v}^0, \boldsymbol{r}^0, \boldsymbol{\mu}_t^0, \boldsymbol{\sigma}_t^0)$, which are drawn from their appropriate distributions. And set the maximum iterations T_m.

2) Update tree model parameters. At the t'th iteration, sequentially update tree model parameters in $\boldsymbol{\Psi}$. For each parameter vector, uniformly select one label $j \in \{1, \dots, k\}$, where k is the number of trees. Then draw a proposal for the selected parameter, denoting Ψ_j^*,

$$\Psi_j^* \sim N(\Psi_j^{(t-1)}, \boldsymbol{\epsilon}) \quad (21)$$

where $N(\mu, \sigma)$ denotes standard normal distribution and $\boldsymbol{\epsilon} = (\epsilon_r, \epsilon_\mu, \epsilon_\sigma)$ in terms of the type of $\Psi_j^* = (r_j^*, \mu_{t_j}^*, \sigma_{t_j}^*)$. Calculate the acceptance probability for the proposal,

$$r_\Theta(\Theta_j^*, \Theta_j^{(t-1)}) = \min(1, \mathrm{R}(\Theta_j^*, \Theta_j^{(t-1)})) \quad (22)$$

where $\Theta_j^* = \{u_j^{(t-1)}, v_j^{(t-1)}, \Psi_j^*\}$ and

$$\mathrm{R}\left(\Theta_j^*, \Theta_j^{(t-1)}\right) = \frac{\mathrm{p}(\mathbb{Z}_{W_j^*}|\Theta_j^*)\mathrm{p}(\Theta_j^*)e^{R_{att_j}^*}}{\mathrm{p}(\mathbb{Z}_{W_j}|\Theta_j^{(t-1)})\mathrm{p}(\Theta_j^{(t-1)})e^{R_{att_j}^{(t-1)}}} \quad (23)$$

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

$$\Theta_j^{(t)} = \begin{cases} \Theta_j^* & if \;\; r_\Theta \geq \mathrm{p}_{fa} \\ \Theta_j^{(t-1)} & if \;\; r_\Theta < \mathrm{p}_{fa} \end{cases} \quad (24)$$

And if the proposal is accepted, calculate its attractive ratio $R_{att_j}^{(t)}$ and update the set S_a accordingly.

3) Update the locations of central points. At the t'th iteration, uniformly select one label $j \in \{1, \ldots, k\}$, with central point $G_j^{(t-1)} = (u_j^{(t-1)}, v_j^{(t-1)})$. Propose a new central point for the tree by uniformly drawing a point from W_j, denoting G_j^*, that is

$$G_j^* = (u_j^*, v_j^*) \sim \mathrm{U}(W_j) \quad (25)$$

Calculate the acceptance probability for the proposal,

$$r_\Theta\left(\Theta_j^*, \Theta_j^{(t-1)}\right) = \min(1, \mathrm{R}\left(\Theta_j^*, \Theta_j^{(t-1)}\right)) \quad (26)$$

where $\Theta_j^* = \{u_j^*, v_j^*, \Psi_j^{(t-1)}\}$ and

$$\mathrm{R}\left(\Theta_j^*, \Theta_j^{(t-1)}\right) = \frac{\mathrm{p}(\mathbb{Z}_{W_j^*}|\Theta_j^*)\mathrm{p}(\Theta_j^*)e^{R_{att_j}^*}}{\mathrm{p}(\mathbb{Z}_{W_j}|\Theta_j^{(t-1)})\mathrm{p}(\Theta_j^{(t-1)})e^{R_{att_j}^{(t-1)}}} \quad (27)$$

Accept the proposal if $r_\Theta \geq p_{fa}$, and then calculate its attractive ratio $R_{att_j}^{(t)}$ and update the set S_a accordingly.

4) Birth or death of a tree. Assume that the number of trees is k and let the probability of proposing a birth or death operation be b_k or d_k, respectively. Consider a birth operation that increases the number of trees from k to k+1 and assume that the new tree is labeled with k+1. Let denote Θ_{k+1}^* the parameter vector of tree k+1. Draw the central point $G_{k+1}^* = (u_{k+1}^*, v_{k+1}^*)$ from $D \backslash D_t$ uniformly. Draw the parameters $\Psi_{k+1}^* = (r_{k+1}^*, \mu_{t_{k+1}}^*, \sigma_{t_{k+1}}^*)$ for the new tree from their prior distributions. Therefore, $\Theta_{k+1}^* = \{G_{k+1}^*, \Psi_{k+1}^*\}$. Let the window induced by $\{u_{k+1}^*, v_{k+1}^*, r_{k+1}^*\}$ be W_{k+1}. As a result, the state space after the birth operation becomes $\mathbf{T}^* = \mathbf{T} \cup \{\Theta_{k+1}^*\}$. According to RJMCMC scheme [14], the acceptance probability for the birth operation can be written as

$$r_{\mathrm{b}}(\mathbf{T}^*, \mathbf{T}) = \min(1, \mathrm{R}_b(\mathbf{T}^*, \mathbf{T})) \quad (28)$$

where

$$\mathrm{R}_b(\mathbf{T}^*, \mathbf{T}) = \frac{\mathrm{p}(\mathbb{Z}|\mathbf{T}^*)\mathrm{p}(\mathbf{T}^*)j_{b_k}(\mathbf{T}^*)}{\mathrm{p}(\mathbb{Z}|\mathbf{T})p(\mathbf{T})j_{d_{k+1}}(\mathbf{T})\mathrm{p}(\Theta_{k+1}^*)}\left|\frac{\partial(\mathbf{T}^*)}{\partial(\mathbf{T}, \Theta_{k+1}^*)}\right| \quad (29)$$

where

$$j_{b_k}(\mathbf{T}^*) = b_k, j_{d_{k+1}}(\mathbf{T}) = \frac{d_{k+1}}{k+1}, \frac{\mathrm{p}(\mathbf{T}^*)}{\mathrm{p}(\mathbf{T})\mathrm{p}(\Theta_{k+1}^*)} = \frac{\mathrm{p}(k+1)}{\mathrm{p}(k)} = \frac{\lambda}{k+1}, \left|\frac{\partial(\mathbf{T}^*)}{\partial(\mathbf{T}, \Theta_{k+1}^*)}\right| = 1.$$

Thus, (29) can be written as

$$\mathrm{R}_b(\mathbf{T}^*, \mathbf{T}) = \frac{\lambda b_k \mathrm{p}(\mathbb{Z}|\mathbf{T}^*)}{d_{k+1}\mathrm{p}(\mathbb{Z}|\mathbf{T})} \quad (30)$$

For simplicity, let $d_{k+1} = \lambda b_k$, then (30) can be re-written as

$$\mathrm{R}_b(\mathbf{T}^*, \mathbf{T}) = \frac{\mathrm{p}(\mathbb{Z}|\mathbf{T}^*)}{\mathrm{p}(\mathbb{Z}|\mathbf{T})} = \frac{\prod_{(x_i, y_i) \in W_{k+1}} e^{-|z_i - \mu_{t_{k+1}}^*|}}{\prod_{(x_i, y_i) \in W_{k+1}} e^{-|z_i - \mu_g|}}. \quad (31)$$

Accept the new tree if $r_{\mathrm{b}} \geq \mathrm{p}_{fa}$, and then calculate its attractive ratio $R_{att_{(k+1)}}$ and update the set S_a accordingly.

The acceptance probability for the death of a tree is

$$r_{\mathrm{d}}(\mathbf{T}^*, \mathbf{T}) = \min(1, \mathrm{R}_d(\mathbf{T}^*, \mathbf{T})) \quad (32)$$

where $\mathrm{R}_d = R_b^{-1}$ and $\mathbf{T} = \cup\, \mathbf{T}^*\{\Theta_j\}$ in which j is uniformly selected from $\{1, \ldots, k\}$.

5) Death in a neighborhood. This operation is only operated on the trees from the set of attractive points S_a. At the t'th iteration, uniformly select one label $j \in \{1, \ldots, s\}$, where s is the size of S_a. First, calculate the interaction intensity of alignment interaction between tree j and other trees from {1,…, j-1, j+1, k}. Second, select the tree i with the minimum value of interaction intensity, denoting $d_c(i, j)$. Then decide the death between i and j as follows.

If $i \notin S_a$, eliminate tree i if $R_{att_i} < th_{au}$ where $th_{au} \in [0,1]$ is a threshold , otherwise, eliminate tree i with a probability p_{dn}, which is a pre-defined probability.

If $i \in S_a$, eliminate either tree i or j with a probability p_{dn}. Calculate the acceptance probability

$$r_{dn}\left(\Theta_j, \Theta_i\right) = \min(1, \mathrm{R}\left(\Theta_j, \Theta_i\right)) \quad (33)$$

where

$$\mathrm{R}\left(\Theta_j, \Theta_i\right) = \frac{\mathrm{p}(\mathbb{Z}_{W_j}|\Theta_j)\mathrm{p}(\Theta_j)e^{R_{att_j}}e^{r_j^2}}{\mathrm{p}(\mathbb{Z}_{W_i}|\Theta_i)\mathrm{p}(\Theta_i)e^{R_{att_i}}e^{r_i^2}} \quad (34)$$

If $r_{dn} \geq \mathrm{p}_{fa}$, eliminate tree i, otherwise eliminate tree j.

6) Let $t = t + 1$ and return to **(ii)** until $t = T_m$.

It is worth noting that for all operations inducing a new window, saying W_j^*, the following condition must hold, that is

$$W_j^* \cap \left(\cup_{l=1, l \neq j}^k W_l\right) = \mathbf{\Phi} \quad (35)$$

where $\mathbf{\Phi}$ denotes null set.

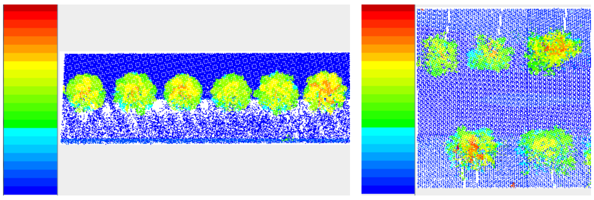
The maximum a posteriori (MAP) criterion is used to obtain the final segmentation, that is

$$\hat{\mathbf{T}} = \arg\{\max\left(p(\mathbf{T}|\mathbb{Z})\right)\}. \quad (36)$$

III. Results and Discussion

As we aim at developing an automated tree detection algorithm, we selected a set of topographic LiDAR point cloud dataset covering an area containing trees in this study to examine the proposed algorithm. For simplicity and without loss of generality, the elevations in those scenes are normalized to [0, E], where E = max($\mathbb{Z}$) – min($\mathbb{Z}$). Fig. 6 shows the dataset used in our experiment, where the colors represent elevation variations.

Table I lists the constants of the parameters and thresholds used in the experiment.



(a) (b)

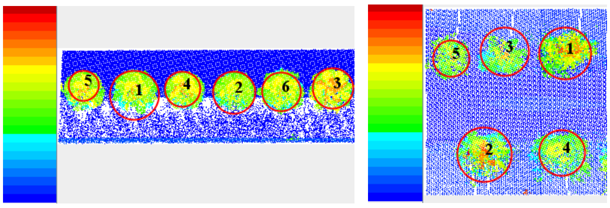
Figure 6. Illustration of testing LiDAR point cloud data.

TABLE I. CONSTANTS USED IN THE EXPERIMENT

μ_g	τ_t	ε_t	τ_r	ε_r	E_{min}	E_{max}	$d_{c_{max}}$
0.5	5E/8	E/8	1.5	0.4	E/8	E/3	0.3
ϵ_r	ϵ_μ	ϵ_σ	p_{fa}	th_a	th_{au}	p_{dn}	T_m
0.05	0.15	0.15	0.8	0.6	0.4	0.8	40,000

The constants ϵ_r, ϵ_μ and ϵ_σ are the proposal variances for r, μ and σ, respectively, which affect the sampling and convergence of the algorithm under the RJMCMC scheme [15]. Besag et al. [16] suggested choosing the proposal variances so that the acceptance probability lies in the interval (0.3, 0.7). However we have found that the proposal variances causing the acceptance probability less than 0.3 still make the algorithm work well. The constant T_m is the maximum iterations of the algorithm. Usually, it depends on the complexity of the scene revealed in LiDAR point cloud data.

Fig. 7 shows the distributions of detected windows in red corresponding to the outlines of the tree crowns. The numbers in windows indicate their labels. Table II gives the estimated geometric parameters of detected trees shown in Fig. 7 (b), including radius, base-height and deviation.



(a) (b)

Figure 7. Detected windows.

TABLE II. ESTIMATED GEOMETRIC PARAMETERS

Windows	$r(m)$	$\mu(m)$	$\sigma(m)$
1	3.04	5.56	2.13
2	3.15	5.37	2.96
3	2.85	5.36	3.12
4	2.68	4.99	1.86
5	2.11	5.40	2.34

Fig. 7 (a) and (b) illustrate that the proposed algorithm can detect the disc shape trees quite well. However, for some non-disc or irregular shape trees, the algorithm cannot completely match the outlines of the tree crowns. In practice, the intensity or spectrum information can be used to improve the detection results.

The proposed algorithm is developed using MATLAB running on an Intel i3-2120 computer. Take the dataset shown in Fig. 6 (b) as an example, which includes 196,664 data points and covers an area of 21.8*m* by 21.3*m*. The average computation time of an iteration is around 0.014 seconds. As a result, the total computation time for 40,000 iterations is about 10 minutes.

IV. CONCLUSIONS

In this paper, we have proposed a new method for performing tree detection from LiDAR point cloud data. The method was based on a marked point process and Bayesian inference. Results from a set of LiDAR point clouds collected by Riegl VMX-450 mobile laser scanning system showed that the proposed algorithm could detect the trees quite well. Instead of processing LiDAR point cloud data on a point-by-point basis towards tree detection, the proposed algorithm processed the data points in and out of windows simultaneously. On the other hand, we introduced a new distribution model for trees and ground. However, in this paper some assumptions on the statistical properties of data and / or the parameters were oversimplified. In reality, multi-model distribution might be appropriate for ground and vegetation.

Therefore, the future work will focus on (a) improving the proposed algorithm so as it would be suitable for the scenes with rough ground and different vegetation types; (b) considering a melting process to join the windows which correspond to one tree; (c) utilizing the intensity or spectrum information to improve the tree detection results.

ACKNOWLEDGMENT

The authors would like to thank Riegl Inc. for providing LiDAR point cloud data collected by its VMX-450.

REFERENCES

[1] J. Shan and C. Toth, *Topographic Laser Ranging and Scanning: Principles and Processing*, CRC Press, 2008.

[2] George L. Heritage and Andrew R.G. Large, *Laser Scanning for the Environmental Sciences*, Blackwell Publishing Ltd. 2009.

[3] F. A. Gougeon, "Automatic individual tree crwon delineation using a valley-following algorithm and rule-based system," *Proc. Of the International Forum on Automated Interpretation of High Spatial Resolution Digital Imagery for Foresty*, pp. 11-23, February 1998.

[4] M. Larsen, "Individual tree top position estimation by template voting," *Proc. of the Fourth International Airborne Remote Sensing Conference and Exhibition /21st Canadian Symposium on Remote Sensing*, vol. 2, pp. 83-90, June 1999.

[5] R. Pollock, "Individual tree recognition based on synthetic tree crowns image model," *Proc. of the International Forum on Automated Interpretation of High Spatial Resolution Digital Imagery for Forestry*, pp. 25-34, February 1998.

[6] A. Baddeley and M.N.M. Van Lieshout, "Stochastic geometry models in high-level vision," *Statistics and Images*, K.V. Mardia, Ed., vol. 1, pp. 231-256.

[7] D. Stoyan, W.S. Kendall, and J. Mecke, *Stochastic Geometry and its Applications* (2nd ed.), New York: Wiley, 1995.

[8] X. Descombes and J. Zerubia, "Marked point process in image analysis," *IEEE Sign. Process. Magazine*, vol. 19, pp. 77-84, 2002.

[9] M. Ortner, X. Descombes, and J. Zerubia, “A marked point process of rectangles and segments for automatic analysis of digital elevation models,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 30, No. 1, pp. 105-119, January 2008.

[10] O. Schabenberger and C.A. Gotway, *Statistical Methods for Spatial Data Analysis*, Chapman & Hall/CRC, Boca Raton, Florida, USA, 2005.

[11] C. Benedek, X. Descombes and J. Zerubia, “*Building Detecion in a Single Remotely Sensed Image with a Point Process of Rectangles*,” ICPR, pp. 1417-1420, August, 2010.

[12] M. Ortner, X. Descombes, and J. Zerubia, “Building outline extraction from digital elevation models using marked point processes,” *International Journal of Computer Vision*, vol. 72, no. 2, pp. 107-132, 2007.

[13] G. Perrin, X. Descombes, J. Zerubia, “A marked point process model for tree crown extraction in plantations,” *Proc. IEEE International Conference on Image Processing*, vol. 1, pp. I-661-4, 2005.

[14] J. Green, “Reversible jump Markov chain Monte Carlo computation and Bayesian model determination,” *Biometrika*, vol. 82, pp. 711-732, 1995.

[15] I. Dryden, M.R. Scarr, and C.C. Taylor, “Bayesian texture segmentation of weed and crop image using reversible jump Markov chain Monte Carlo methods,” *Appl. Statist.*, vol. 52, pp. 31-50, 2003.

[16] J. E. Besag, P. Green, D. Higdon, and K. Mengersen, “Bayesian computation and stochastic systems (with discussion),” *Statist. Sci.*, vol. 10, pp. 3-66, 1995.