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# A hybrid framework for single tree detection from airborne laser scanning data: A case study in temperate mature coniferous forests in Ontario, Canada

Junjie Zhang [a,1], Gunho Sohn [a,*], Mathieu Brédif [b,2]

[a] GeoICT Lab, Department of Earth and Space Science & Engineering, York University, 4700 Keele Street, Toronto, ON M3J 1P3, Canada
[b] Université Paris Est, IGN, MATIS 73, avenue de Paris, 94165 Saint-Mandé, France

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ABSTRACT

This study presents a hybrid framework for single tree detection from airborne laser scanning (ALS) data by integrating low-level image processing techniques into a high-level probabilistic framework. The proposed approach modeled tree crowns in a forest plot as a configuration of circular objects. We took advantage of low-level image processing techniques to generate candidate configurations from the canopy height model (CHM): the treetop positions were sampled within the over-extracted local maxima via local maxima filtering, and the crown sizes were derived from marker-controlled watershed segmentation using corresponding treetops as markers. The configuration containing the best possible set of detected tree objects was estimated by a global optimization solver. To achieve this, we introduced a Gibbs energy, which contains a data term that judges the fitness of the objects with respect to the data, and a prior term that prevents severe overlapping between tree crowns on the configuration space. The energy was then embedded into a Markov Chain Monte Carlo (MCMC) dynamics coupled with a simulated annealing to find its global minimum. In this research, we also proposed a Monte Carlo-based sampling method for parameter estimation. We tested the method on a temperate mature coniferous forest in Ontario, Canada and also on simulated coniferous forest plots with different degrees of crown overlap. The experimental results showed the effectiveness of our proposed method, which was capable of reducing the commission errors produced by local maxima filtering, thus increasing the overall detection accuracy by approximately 10% on all of the datasets.


## 1. Introduction

### 1.1. Airborne laser scanning in forest inventory

Remote sensing techniques have become an integral part of forest inventory to provide accurate, precise and timely forest and tree characteristics at different scales to support practices of forest management and planning (Dubayah and Drake, 2000; Naesset et al., 2004; Tomppo et al., 2002; Wulder, 1998; Xie et al., 2008). Among these techniques, small-footprint airborne laser scanning (ALS), also known as airborne LiDAR, has rapidly gained popularity in forest inventory in recent decades. The unique capability of ALS to directly measure the 3D structural information of trees and the elevation of the terrestrial surface under the canopy in forests makes ALS an alternative to traditional passive optical remote sensing technology, or even the preferred method, to derive certain forest parameters, such as canopy height, crown dimensions, stand volume, basal area, and above-ground biomass (Bortolot and Wynne, 2005; Hyyppä and Inkinen, 1999; Means et al., 2000; Næsset, 1997; Naesset, 2002).

Characterization of forest resources using ALS can be broadly categorized into area-based approaches (ABAs) and individual-tree-based approaches (ITDs) (Hyyppä et al., 2008). ABAs rely on the statistical principle and predicts forest attributes based on parametric regression or nonparametric imputation models built between field measured variables and features derived from ALS data (Maltamo et al., 2006; Naesset, 2002). ABAs can perform under a low ALS point density, and is the method currently applied in operational forest inventory to provide a wall-to-wall estimation of forest attributes (Naesset, 2004; White et al., 2013). ITDs measure or predict tree-level variables on the basic unit of the

* Corresponding author. Tel.: +1 416 650 8011.
*E-mail addresses:* junjiez@yorku.ca (J. Zhang), gsohn@yorku.ca (G. Sohn), mathieu.bredif@ign.fr (M. Brédif).
[1] Tel.: +1 416 736 2100x22611.
[2] Tel.: +33 1 43 98 83 19.

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individual trees from ALS data and then aggregate them to obtain stand-level forest inventory results (Hyyppä et al., 2012).

Despite the added costs and amount of information to store and process high-density ALS data, ITDs are of significant interest in forest inventory and is a motivating research topic. The primary advantage of ITDs over ABAs is the supply of tree lists and the ability to directly derive the true stem distribution series, which would result in better prediction for timber assortments (Vastaranta et al., 2011a). Generally, this information is invaluable in forest planning-related simulation and optimization, logging operation planning and wood supply logistics (Vastaranta et al., 2011b), e.g., detection of harvest trees and forest growth determination (Yu et al., 2004). Another advantage of ITDs is that they can reduce the amount of or potentially replace the expensive fieldwork required for ABAs (Hyyppä et al., 2008; Vastaranta et al., 2012). Additionally, tree species classification based on ITD has been reported in recent studies (Brandtberg, 2007; Heinzel and Koch, 2011; Orka et al., 2009; Suratno et al., 2009), which could potentially improve the prediction of species-specific forest attributes (Heurich, 2008; Yao et al., 2012; Yu et al., 2010). Furthermore, the combination of ITD and ABA, called the semi-ITD method, to improve the estimation accuracy has also been viewed as a future method for forest inventory (Breidenbach et al., 2010; Hyyppä et al., 2012; Vastaranta et al., 2012). Therefore, individual tree detection techniques are still of significant importance from the practical forestry viewpoint.

### 1.2. Related works on single tree detection

Accordingly, numerous methods have been proposed to detect single trees from ALS data. Most of the methods focus on the generation of the canopy height model (CHM), which provides an accurate representation of the outer surface of the tree canopy. The peaks and valleys on the CHM generated from high-density ALS data are better estimations of treetop positions and crown edges than can be obtained from aerial photographs or satellite imageries. Therefore, many studies have extended methods developed for passive optical imageries to detect single trees from ALS data. Those methods include, but are not limited to, local maxima filtering (Popescu et al., 2002; Wulder et al., 2000), region growing (Erikson, 2003; Solberg et al., 2006), valley following (Gougeon, 1995; Leckie et al., 2003), template matching (Korpela et al., 2007; Pollock, 1996), watershed segmentation and its variance marker-controlled watershed segmentation (Chen et al., 2006; Pyysalo and Hyyppa, 2002; Wang et al., 2004), and multi-scale segmentation (Brandtberg and Walter, 1998; Brandtberg et al., 2003).

Among the proposed methods, local maxima filtering (LM) and marker-controlled watershed segmentation (MCWS) are the most commonly used and are ready for operational application because of their rapid implementation while maintaining the capability to produce relatively accurate results (Kaartinen et al., 2012). Popescu et al. (2002) have been the first to test a variable window local maxima filtering on the CHMs, attempting to overcome errors of omission and commission associated with fixed window local maxima filtering (Hyyppä et al., 2001).

Once the treetops are detected, MCWS is well suited to delineate the tree crown segments from the CHM. MCWS, which possesses the advantages of other segmentation methods of region growing and edge detection, was introduced by Meyer and Beucher (1990) to overcome the over-segmentation problem of ordinary watershed segmentation. In MCWS, user-specified markers are used as the marker function to perform the segmentation; for additional details, see Gonzalez and Woods (2008). In the resultant segmentation, there will be one segment corresponding to each marker; in the case of single tree detection, one tree crown will be captured by one treetop. This result indicates the detection accuracy of MCWS, subject to the accuracy of the pre-determined local maxima as true treetops in the previous stage.

The issue with LM is the selection of the filter window size and the determination of the relationship between the crown size and the tree height. In the comparison of tree detection algorithms (Kaartinen et al., 2012), the local maxima-based approach tends to produce high commission errors. Especially in coniferous forests, spurious treetops are detected within the tree crowns from large branches. In other cases, local maxima filtering produces a low commission error, and the omission error often increases because small tree crowns are more likely to be undetected (Gebreslasie et al., 2011).

### 1.3. Probabilistic methods for image analysis

Probabilistic methods represent another branch of powerful tools in image analysis. These methods have proven to hold great promise in solving inverse problems, including image segmentation, image restoration, and feature extraction (Descombes and Zerubia, 2002). In particular, stochastic models have evolved from random fields to object processes, and the work has shifted from an early focus on 'low-level' tasks that aim to de-noise, sharpen, and segment images to solving 'high-level' tasks of feature recognition, i.e., describing an image by its content (Van Lieshout, 2009). Additional details on low-level and high-level image analysis tasks can be found in Sonka et al. (2008).

Marked point processes, detailed in Van Lieshout (2000), are among the most efficient stochastic models used to exploit the random variables whose realizations are configurations of geometric objects or shapes. Generally, in these processes, after a probability distribution measuring the quality of each object configuration is defined in the configuration space, the maxima density estimator is searched for by the Markov Chain Monte Carlo (MCMC) sampler (Hastings, 1970) coupled with conventional simulated annealing (Metropolis et al., 1953). This process has led to convincing experimental results in various image analysis and feature extraction applications, such as road networks extraction (Lacoste et al., 2005), road mark detection (Tournaire and Paparoditis, 2009), and 3D building reconstruction (Lafarge et al., 2008; Ortner et al., 2008; Tournaire et al., 2010).

Likewise, several stochastic models have been proposed to detect tree crowns from remote sensing data. Descombes and Pechersky (2006) have presented a three-state Markov Random Field (MRF) model to detect the tree crowns from aerial imageries. This approach addressed the problem as an image segmentation problem and works on the pixel level. Each pixel is assigned to one of the following three states: (i) *vegetation*, (ii) *background*, and (iii) *center of trees*. Although the MRF was defined on the pixel level, the label update was performed on the object level using elliptical templates of crowns. Furthermore, Perrin et al. (2005, 2006) has employed marked point processes to detect tree crowns in plantations from color infrared (CIR) aerial imageries. Tree crowns in the remote sensing image are modeled as a configuration of disks or ellipses. In both of the studies, tree crowns were detected by maximizing a Bayesian criterion, such as *Maximum A Posteriori* (MAP), which became an energy minimization problem and was solved in a simulated annealing framework.

These stochastic models provide a powerful framework to allow the inclusion of spatial interactions between objects in the prior while enabling a measure of consistency between objects and the image in the data term. However, the inherited property of stochastic models requires exploration of a large configuration space searching for the optimal configuration, especially for non-data-driven models, which do not employ any low-level information that can be extracted from the images. The optimization process is typically lengthy and computationally expensive.