ISPRS Journal of Photogrammetry and Remote Sensing 130 (2017) 385–392

Contents lists available at ScienceDirect

ISPRS Journal of Photogrammetry and Remote Sensing

journal homepage: www.elsevier.com/locate/isprsjprs

Vertical stratification of forest canopy for segmentation of understory trees within small-footprint airborne LiDAR point clouds

Hamid Hamraz [a,*], Marco A. Contreras [b], Jun Zhang [a]

[a] Department of Computer Science, University of Kentucky, Lexington, KY 40506, USA
[b] Department of Forestry, University of Kentucky, Lexington, KY 40506, USA

ARTICLE INFO

Article history:
Received 16 April 2017
Received in revised form 7 June 2017
Accepted 6 July 2017

Keywords:
Remote sensing
Discrete return LiDAR
Multi-story stand
Canopy layering
Individual tree segmentation

ABSTRACT

Airborne LiDAR point cloud representing a forest contains 3D data, from which vertical stand structure even of understory layers can be derived. This paper presents a tree segmentation approach for multi-story stands that stratifies the point cloud to canopy layers and segments individual tree crowns within each layer using a digital surface model based tree segmentation method. The novelty of the approach is the stratification procedure that separates the point cloud to an overstory and multiple understory tree canopy layers by analyzing vertical distributions of LiDAR points within overlapping locales. The procedure does not make a priori assumptions about the shape and size of the tree crowns and can, independent of the tree segmentation method, be utilized to vertically stratify tree crowns of forest canopies. We applied the proposed approach to the University of Kentucky Robinson Forest – a natural deciduous forest with complex and highly variable terrain and vegetation structure. The segmentation results showed that using the stratification procedure strongly improved detecting understory trees (from 46% to 68%) at the cost of introducing a fair number of over-segmented understory trees (increased from 1% to 16%), while barely affecting the overall segmentation quality of overstory trees. Results of vertical stratification of the canopy showed that the point density of understory canopy layers were suboptimal for performing a reasonable tree segmentation, suggesting that acquiring denser LiDAR point clouds would allow more improvements in segmenting understory trees. As shown by inspecting correlations of the results with forest structure, the segmentation approach is applicable to a variety of forest types.

1. Introduction

In the past two decades, airborne light detection and ranging (LiDAR) technology has extensively been used for forestry purposes because of its ability to acquire data at unprecedented spatial and temporal resolutions (Ackermann, 1999; Hyyppä et al., 2012; Maltamo et al., 2014; Swatantran et al., 2016). This data is typically captured in the shape of 3D point clouds and can be used to retrieve more detailed tree level information, hence improving the accuracy of forest assessment, monitoring, and management activities (Duncanson et al., 2012; Vastaranta et al., 2011; Weinacker et al., 2004; Wulder et al., 2012). Due to the ability to penetrate vegetation canopy, LiDAR 3D point clouds also contain vertical information from which vegetation structural information can be retrieved (Hall et al., 2011; Lefsky et al., 2002; Maguya et al., 2014; Reutebuch et al., 2005). This structural information may also include understory layers, which is of great value for various forestry applications and ecological studies (Espírito-Santo et al., 2014; Ishii et al., 2004; Singh et al., 2015; Wing et al., 2012). Although understory trees provide limited financial value and form a minor proportion of total above ground biomass, they influence canopy succession and stand development, create a heterogeneous and dynamic habitat for numerous wildlife species, and are an essential component of forest ecosystems (Antos, 2009; Jules et al., 2008; Moore et al., 2007). However, to obtain individual tree attributes (e.g., location, crown width, height, DBH, volume, biomass) from different canopy layers, accurate and automated tree segmentation approaches that are able to separate tree crowns both vertically and horizontally are required (Duncanson et al., 2014; Ferraz et al., 2012; Shao and Reynolds, 2006; Wang et al., 2008).

Numerous methods for individual tree segmentation within LiDAR data have been developed. Earlier methods use pre-processed data in the form of digital surface models (DSMs) or

* Corresponding author.
E-mail addresses: hhamraz@cs.uky.edu (H. Hamraz), marco.contreras@uky.edu (M.A. Contreras), jzhang@cs.uky.edu (J. Zhang).

http://dx.doi.org/10.1016/j.isprsjprs.2017.07.001

canopy height models to segment individual trees (Jing et al., 2012; Koch et al., 2006; Kwak et al., 2007; Popescu and Wynne, 2004; Véga and Durrieu, 2011). These methods have an inherent drawback of missing understory trees by considering only the surface data (Hamraz et al., 2016; Wang et al., 2008). More recent methods process the raw point clouds in order to utilize all horizontal and vertical information and, from the computational viewpoint, can be classified to volumetric or profiler methods. Volumetric methods directly search the 3D volume for the individual trees (Amiri et al., 2016; Ferraz et al., 2012; Lahivaara et al., 2014; Li et al., 2012; Lindberg et al., 2014; Lu et al., 2014; Rahman and Gorte, 2009; Sačkov et al., 2017; Véga et al., 2014). For example, Ferraz et al. (2012) used the mean shift clustering to segment the point cloud and assigned each segment to overstory, understory, or ground vegetation layer. Véga et al. (2014) performed segmentations at different scales and used criteria based on the shape of an ideal tree crown to dynamically select the best set of apices. Sačkov et al. (2017) developed a moving window analysis method to identify potential apices and used several tree allometry rules to increase the likelihood of detecting the actual tree profiles. However, volumetric methods are generally computationally intensive and may be prone to suboptimal solutions due to the large magnitude of the search space.

On the other hand, profiler methods reduce the computational load through a modular process. They typically have a module for vertical segmentation (i.e., to strip the 3D volume to multiple 2D horizontal profiles), a module for horizontal segmentation (i.e., to search the trees within the profiles), and a module to ultimately aggregate the results across the profiles (Ayrey et al., 2017). However, these methods generally lose information about the vertical crown geometry when processing a 2D profile. To minimize information loss due to profiling, other profiler methods have analyzed vertical distribution of LiDAR points to identify 2.5D profiles embodying more information about vertical crown geometry. Wang et al. (2008) searched trees within each profile and used a top-down routine to unify any detected crowns that may be present in different profiles. They analyzed vertical distribution of all LiDAR points globally within a given area to determine the height levels for stripping profiles. However, depending on the vegetation height variability, a globally derived height level may lead to under/over-segmenting tree crowns across the profiles. Other approaches addressed this issue by identifying constrained regions including one or more trees using a preliminary segmentation routine and independently 2.5D profiling each region (Duncanson et al., 2014; Paris et al., 2016; Popescu and Zhao, 2008), yet the final result is dependent on the preliminary segmentation.

Although a number of methods for segmenting individual trees in multi-story stands have been proposed, they are still unable to satisfactorily detect most of the understory trees. Typically, detection rate of dominant and co-dominant (overstory) trees is around or above 90% and detection rate of intermediate and overtopped (understory) trees is below 50%. This inefficacy can be attributed to the reduced amount of LiDAR points penetrating below the main cohort formed by overstory trees (Kükenbrink et al., 2016; Takahashi et al., 2006), although incompetency of the current approaches to effectively use all vertical and horizontal information also plays a role. In this paper, we present a profiler approach for segmenting crowns of all size trees in multi-story stands. The approach derives height levels locally hence stratifies the point cloud to 2.5D profiles (hereafter referred to as canopy layers). Each canopy layer is sensitive to stand height variability and includes a layer of non-overtopping tree crowns within an unconstrained area. The approach utilizes a DSM-based method as a building block to segment individual tree crowns within each canopy layer.

2. Materials and methods

2.1. Study site and LiDAR campaign

The study site is the University of Kentucky's Robinson Forest (RF, Lat. 37.4611, Long. -83.1555) located in the rugged eastern section of the Cumberland Plateau region of southeastern Kentucky in Breathitt, Perry, and Knott counties (see the supplementary interactive map). RF features a variable dissected topography (Carpenter and Rumsey, 1976), with moderately steep slopes ranging from 10 to over 100% facing predominately northwest to southeast, with elevations ranging from 252 to 503 m above sea level. Vegetation is composed of a diverse contiguous mixed mesophytic forest made up of approximately 80 tree species with northern red oak (*Quercus rubra*), white oak (*Quercus alba*), yellow-poplar (*Liriodendron tulipifera*), American beech (*Fagus grandifolia*), eastern hemlock (*Tsuga canadensis*) and sugar maple (*Acer saccharum*) as overstory species. Understory species include eastern redbud (*Cercis canadensis*), flowering dogwood (*Cornus florida*), spicebush (*Lindera benzoin*), pawpaw (*Asimina triloba*), umbrella magnolia (*Magnolia tripetala*), and bigleaf magnolia (*Magnolia macrophylla*) (Carpenter and Rumsey, 1976; Overstreet, 1984). Average canopy cover across RF is about 93% with small opening scattered throughout. Most areas exceed 97% canopy cover and recently harvested areas have an average cover as low as 63%. After being extensively logged in the 1920's, RF is considered second growth forest ranging from 80 to 100 years old, and is now protected from commercial logging and mining activities (Department of Forestry, 2007). RF currently covers an aggregate area of ~7440 ha, and includes about 2.5 million (±13.5%) trees, over 60% of which are understory trees (Hamraz et al., 2016, 2017b).

The LiDAR acquisition campaign over RF was performed in the summer of 2013 during leaf-on season (May 28–30) using a Leica ALS60 sensor, which was set at 40° field of view and 200 kHz pulse repetition rate. The sensor was flown at the average altitude of 214 m above ground at the speed of 105 knots with 50% swath overlap. Up to 4 returns were captured per pulse. Using the 95% middle portion of each swath, the resulting LiDAR dataset given the swath overlap has an average density of 50 pt/m^2. The provider processed the raw LiDAR dataset using the TerraScan software (Terrasolid Ltd, 2012) to classify LiDAR points into ground and non-ground points. Ground points were then used to create a 1-meter resolution digital elevation model (DEM) using the natural neighbor as the fill void method and the average as the interpolation method.

2.2. Tree segmentation approach for multi-layered stands

Using the DEM, normalized heights of the LiDAR points are initially calculated and ground points are removed from further processing. The approach consists of a vertical stratification procedure and a tree segmentation method. The procedure stratifies the top canopy layer of the point cloud by analyzing the vertical distributions of the LiDAR points within overlapping locales and removes the layer from the point cloud. Iterative application of the stratification procedure yields multiple canopy layers. Each canopy layer is independently segmented using a surface-based method. Fig. 1 visualizes the tree segmentation approach.

2.2.1. Vertical stratification

To stratify the top canopy layer, the point cloud is binned into a horizontal grid with a cell width equal to the average footprint (AFP). AFP equals the reciprocal of square root of point density, which itself is defined as the number of points divided by the horizontal area covered by the point cloud (as layers are removed from