International Journal of Applied Earth Observation and Geoinformation 52 (2016) 252–262

Contents lists available at ScienceDirect

International Journal of Applied Earth Observation and Geoinformation

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

Estimation of regeneration coverage in a temperate forest by 3D segmentation using airborne laser scanning data

Nina Amiri[a,b,*], Wei Yao[a], Marco Heurich[c], Peter Krzystek[a], Andrew K. Skidmore[b]

[a] Department of Geoinformatics, Munich University of Applied Sciences, 80333 Munich, Germany
[b] Faculty of Geo-Information Science and Earth Observation, University of Twente, P.O. Box 217, 7500 AE Enschede, The Netherlands
[c] Department of Conservation and Research, Bavarian Forest National Park, 94481 Grafenau, Germany

ARTICLE INFO

Article history:
Received 8 March 2016
Received in revised form 17 June 2016
Accepted 29 June 2016

Keywords:
Understory
Regeneration
Full waveform ALS
3D segmentation
Mean shift

ABSTRACT

Forest understory and regeneration are important factors in sustainable forest management. However, understanding their spatial distribution in multilayered forests requires accurate and continuously updated field data, which are difficult and time-consuming to obtain. Therefore, cost-efficient inventory methods are required, and airborne laser scanning (ALS) is a promising tool for obtaining such information. In this study, we examine a clustering-based 3D segmentation in combination with ALS data for regeneration coverage estimation in a multilayered temperate forest. The core of our method is a two-tiered segmentation of the 3D point clouds into segments associated with regeneration trees. First, small parts of trees (super-voxels) are constructed through mean shift clustering, a nonparametric procedure for finding the local maxima of a density function. In the second step, we form a graph based on the mean shift clusters and merge them into larger segments using the normalized cut algorithm. These segments are used to obtain regeneration coverage of the target plot. Results show that, based on validation data from field inventory and terrestrial laser scanning (TLS), our approach correctly estimates up to 70% of regeneration coverage across the plots with different properties, such as tree height and tree species. The proposed method is negatively impacted by the density of the overstory because of decreasing ground point density. In addition, the estimated coverage has a strong relationship with the overstory tree species composition.

1. Introduction

The process of forest regeneration, understanding as young trees below 5 m height, is a central component in forest succession, which ensures a continuous forest cover and adds structural complexity (Swanson et al., 2010). Therefore, it plays an important role in maintaining biological diversity in forest ecosystems. Regeneration appears either as advanced regeneration under canopy gaps or on open areas after large scale natural disturbance and forest management actions. Information on understory vegetation can benefit the assessment of tree species richness and vertical structure of forests (Wing et al., 2012).

Conventional forest inventory of the understory is based on limited sample plots, which are used to calculate means and confidence intervals for the larger forest areas. However, one of the main disadvantages of this approach was the limited number of plots which often covered less than a few percent of the total forest area (Köhl et al., 2006). Therefore, it was not possible to extract area-wide information. In addition, ground-based methods for understory inventory are generally time-consuming and labor-intensive (Tuanmu et al., 2010; Wing et al., 2012). Remote sensing can provide objective, cost-effective, and practical solutions for developing and maintaining automated area-wide forest mapping (Janssen and Huurneman, 2000). Passive remote sensing methods are useful alternative tools for gathering information across large areas (Wing et al., 2012). However, because of the complexity of the overstory, they cannot penetrate the forest ground layer.

ALS systems with direct measurement of 3D structural information have been shown to be a promising tool for characterizing vegetation (Lefsky et al., 2002). The decomposition of waveforms can overcome the limitations of conventional first/last pulse data in the analysis of the forest understory by providing the intensity and pulse width (Reitberger et al., 2009). In addition, based on former approaches, the waveform decomposition process gives higher spatial point density and information about the vertical structure

* Corresponding author at: Department of Geoinformatics, Munich University of Applied Sciences, 80333 Munich, Germany.
E-mail address: n.amiri@hm.edu (N. Amiri).

http://dx.doi.org/10.1016/j.jag.2016.06.022
0303-2434/

of the understory (Yao et al., 2013). Therefore, after waveform decomposition, full waveform ALS data are more representative in multilayered forests (Eskelson et al., 2011; Latifi et al., 2015).

Efforts towards the application of ALS data for understory and regeneration studies have been promoted in earlier research. However, so far, only limited experiments have been done to estimate regeneration coverage in multilayered forests using ALS data (Yao et al., 2013). Su and Bork (2007) examined the CHM (Canopy Height Model) frequency histograms of a first/last pulse ALS system and tested two thresholds of 0.3 m and 1.3 m to separate the overstory and understory in aspen forests. Hill and Broughton (2009) detected the presence of regeneration in temperate broadleaf forests, using leaf-off and leaf-on ALS data. Later, Morsdorf et al. (2010) tested both height and intensity information to detect canopy layers (understory and a shrub layer) in a dry Mediterranean forest. They applied a supervised cluster analysis, assuming that intensity measurements of some tree species can improve the classification; however, they achieved an accuracy rate of 48% in detecting understory. Korpela et al. (2012) used ALS data to study the understory by designing a conceptual model for the transmission losses of laser pulse intensity through the overstory. Their results showed that it is impossible to obtain normalized second-return intensity data from the forest floor or ground vegetation. Ferraz et al. (2012) used mean shift clustering on ALS data in a multilayered forest to detect suppressed trees, and achieved a detection rate of 12.8%. Yao et al. (2013) noted the potential of height distributions and geometric properties for regeneration detection using full waveform ALS data. Latifi et al. (2015) highlighted the value of Lidar metrics for characterizing the structural properties of the lower forest layer in temperate mixed stands. These studies indicate that the problem of correctly detecting regeneration using ALS height distributions is related to the presence of ground vegetation and overlapping crowns in the overstory. Although the availability of ALS data and appropriate post-processing methods has increased, there is still limited experience in applying them to estimate regeneration coverage in multilayered forests. In the mean shift clustering-based approach on ALS data, multiple clusters may correspond to a single tree. This fragmentation in the understory level makes it difficult to distinguish whether the cluster belongs to the regeneration or it is a part of neighboring single tree. Therefore, an approach that can provide regeneration coverage based on automated segmentation of forest understory structures in 3D space is needed.

The objectives of this study are (i) to estimate the regeneration coverage with an adapted 3D segmentation algorithm using full waveform ALS data, (ii) to investigate the effect of overstory density and tree species composition on the accuracy of estimated regeneration coverage. Moreover, we provide a sensitivity analysis for specific control parameters of the method.

The remainder of this work is structured as follows: Section 2 describes the details of our approach; Section 3 illustrates the study area, materials, and field measurements. The results are presented in Section 4 and discussed in Section 5. Finally, the conclusions are stated in Section 6.

2. Method

We use an adapted 3D segmentation algorithm (see Yao et al., 2013), to estimate the regeneration coverage (the ratio between the area covered by regeneration trees and the total area of the sample plot). The 3D segmentation algorithm is a two-tiered segmentation procedure. The normalized cut segmentation as the core part of our method is computationally expensive. To reduce the computational costs for the bipartition of the weighting matrix in normalized cuts, we combine the normalized cut segmentation with the mean shift clustering. The advantage of a mean shift is to generate a small number of clusters to represent the graph nodes instead of voxels. The former approach by Yao et al. (2013) also confirmed that the mean shift clusters can better indicate smaller trees in the understory, which is not possible to do using the normalized cut segmentation based solely on voxels. The ground truth data is available as proportional values of regeneration coverage. The steps of the entire procedure are as follows: (i) above-ground height threshold determination, (ii) local tree maxima filtering, (iii) mean shift clustering, (iv) feature derivation for mean shift clusters, (v) normalized cut segmentation, and (vi) height filtering of the segmentation results. In the following, we explain the steps of the adapted 3D segmentation.

2.1. Above-ground height threshold

The input data after waveform decomposition with superimposed Gaussian functions is a set of 3D point clouds with 3D coordinates $X_i(x_i, y_i, z_i)$ and two physical properties (intensity and pulse width) for each point (Reitberger et al., 2009). The derived 3D point clouds from decomposition contain the entire overstory, understory, and ground vegetation (herbal layer). To focus on regeneration, we need to remove the points belonging to the ground vegetation up to a height of 1 m from the ground surface level, which is estimated from a given Digital Terrain Model (DTM). This height threshold value in the 3D segmentation affects the results of the regeneration coverage estimation by commission and omission errors.

2.2. Local tree maxima filtering

In our approach, within each grid cell, the highest 3D point is estimated from a given DTM. The local maxima positions are provided by the watershed segmentation on the Canopy Height Model (CHM), and act as prior knowledge to detect where the overstory trees are located (see Reitberger et al., 2009). This prior knowledge is directly included in the similarity function of normalized cut segmentation (see Section 2.4).

2.3. Mean shift clustering

In forestry applications, ALS point clouds are noted as a multimodal distribution where each mode as a local maximum both in height and density, corresponding to a crown top (Ferraz et al., 2012). Our experiment investigates the ability of mean shift clustering combined with the normalized cut segmentation to extract the modes of point clouds in each cluster. Although the mean shift procedure is able to define the modes of a density function, this procedure requires a testing framework because of the complexity of the understory. Here, our approach is to segment vertical and horizontal structures of the forest understory in 3D space.

The mean shift is a nonparametric, feature-space clustering technique, which neither requires prior knowledge of the cluster number nor constrains the shape of the clusters (Comaniciu and Meer, 2002; Wu and Yang, 2007). For each point in 3D space, the mean shift in a defined kernel window performs a gradient ascent procedure on the local estimated density until convergence to the local maxima. In this technique, for given n points of X_i, $i = 1, 2, \ldots, n$ in 3D space, the probability density function with the obtained kernel $K(X)$ is:

$$f_{h_r,K}(X) = \frac{1}{nh_r^3}\sum_{i=1}^{n} K\left(\frac{X - X_i}{h_r}\right) \quad (1)$$

where h_r as the kernel bandwidth is the smoothing parameter that specifies the contribution of each point in Eq. (1). The kernel bandwidth h_r refers to the kernel radius. K is a nonlinear function of