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Forest Characteristics and Effects on LiDAR Waveforms Modeling and Simulation

Xiaohuan Xi [+], Ran Li, Zhaoyan Liu and Xiaoguang Jiang

Academy of Opto-Electronic, Chinese Academy of Sciences
No.95 Zhongguancundonglu, Beijing, 100190, China

Abstract: LiDAR (Light Detection And Ranging) remote sensing has been used to extract surface information as it can acquire highly accurate object shape characteristics using geo-registered 3D-points, and therefore, proven to be satisfactory for many applications, such as high-resolution elevation model generation, 3-D city mapping, vegetation structure estimation, etc. Large footprint LiDAR especially, offers the great potential for effectively measuring tree parameters in forested areas. Based on the radiative transmission function for vegetation structure, a simplified model cited from previous paper was used to simulate how the vegetation parameters and slope degree affect LiDAR waveform characteristics. And an extinction coefficient is introduced to the model due to the influence of dense vegetation canopy and the simplified and ideal model. The experiment results show that vegetation canopy, trees distribution in one footprint and terrain slope influence LiDAR waveform shapes, while tree height just affects the starting position of the waveform. The model with the extinction coefficient explains that vegetation canopy can weaken laser which makes the return echo weaker in lower canopy. Although based on some assumptions, simple and ideal conditions, the above results obtained from GLAS data are suitable for other LiDAR systems and have great significance to LiDAR applications in forest parameters extraction, especially in sloped areas, it is necessary to correct terrain effects when deriving vegetation height from LiDAR returns. As a matter of fact, the model has to be perfected in later work so as to be more practical.

Keywords: LiDAR, GLAS, vegetation parameters, waveform, extinction coefficient

1. Introduction

Tree height is considered one of the most useful variables, along with stocking and diameter at breast height, in estimating forest stand wood volumes and productivity. It also determines the light penetration in the forest canopy and is of importance for certain habitat studies. However, it is one of the most difficult variables to measure when forest covers are dense.

LiDAR（Light Detection And Ranging）is a breakthrough remote sensing technology that promises to increase the accuracy of biophysical measurements successfully, especially for deriving forest canopy structural characteristics (vegetation height, cover and canopy structure), as well as sub-canopy topography, thus providing high resolution topographic maps. In addition, LiDAR has been shown to accurately estimate LAI and above ground biomass even in those high biomass ecosystems where passive optical and active radar sensors typically fail to do so.

There are kinds of LiDAR systems currently. The primary differences among them involve laser wavelength, pulse duration and repetition rate, beam size and divergence angle (which in combination with altitude dictates the ground footprint size), the model of scanning mechanism and the echoes recorded for each laser pulse. Compared to small footprint sensors, large footprint sensor has its greater potential use in forest application (Sun and Ranson, 2000), such as LVIS (Laser Vegetation Imaging System, the footprint diameters can be varied from 1 to 70m). First, they enable a wide image swath, which is the only feasible

[+] Corresponding author. Tel: 86-10-82625417; Fax: 86-10-62643022
E-mail address: xhxi@aoe.ac.n

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way to cover large areas on the ground given the expense of flight times. Secondly, large footprints avoid the biases that are inherent in small footprint height recovery, as the small footprints frequently miss the tops of trees (Nelson et al, 1997). So far no satellite LiDAR system designed for the primary purpose of global vegetation mapping is available (Wagner, et al, 2007). However, the Geoscience Laser Altimeter System (GLAS) on-board of the ICESat (Ice, Cloud, and land Elevation) satellite has acquired waveform data not only over the ice sheets, but also over land surfaces. This will allow testing the usefulness of large-footprint (about 70m) satellite-based waveform measurements for characterizing forest structure and biomass (Harding et al, 2005).

GLAS uses one laser altimeter at a time to transmit a laser pulse of 10 nanoseconds pulse duration and to consecutively record a return pulse as reflected from the 70m-diameter footprint on the ground. GLAS systematically samples the energy returned from the surface as a function of time of flight, the so-called full waveform (Harding et al, 2005). The waveform over forest area gives a multi-mode signal (Brenner et al., 2003), containing information about tree tops, crown thickness, canopy structure and ground surface.

Many researches carried out forest work with GLAS data for recovering forest structures (Sun et al, 2000, 2006; Lefsky, 2005; Wen et al, 2005; Pang et al, 2006). The two basic measurements from LiDAR are vegetation height, that is, the top of the canopy, however defined, relative to the ground below it, and the vertical distribution of intercepting surfaces within the canopy. Other attributes of forest structure are odelled or inferred from these direct measurements.

The main research question that will be addressed in this article is how the forest canopy characteristics influence the waveforms within one footprint of GLAS data. The focus topic will be on the simulating waveform and the factors (the shape of crown, tree heights, tree distribution within one footprint and terrain slopes) influencing its shape, and establishing a more suitable model by applying extinction coefficient to model the propagation of LiDAR pulse through forest canopies. The simulation results show that the model is more practical than before.

2. Background Theory and Models

A LiDAR sends out a short duration laser pulse and the beam illuminates a vertical vegetation stand of the diameter of the laser footprint. The digitizer samples the detector output voltage of return signal from targets at a certain rate, yielding a waveform for that laser shot (Harding, et al, 1998). This waveform is a record of return signal as a function of time. The vertical sampling resolution depends on the duration of the digitizer (Sun et al, 2000). According to radiative transfer concept (Xu, 2005), for the leaf canopy, the Gap probability is calculated by equation (1):

$$P_{gap} = \frac{1}{A} \iint_{(x,y)\in A} P(x,y)dxdy \tag{1}$$

For vegetation structure: $P_{gap} = e^{-kDs}$, $k = k(\lambda, LAD); D = FAVD$

Where LAD is the Leaf Angle Distribution. FAVD is the Foliage Area Volume Density. S is the straight distance for the beam traversed the canopy.

Let $\tau = kD$ (corresponds to extinction coefficient), the gap probability becomes $P_{gap} = e^{-\tau s}$.

$u_l(z)$ is the density of a one-sided leaf area at depth z, LAI is the Leaf Area Index, $\mathrm{LAI}(z) = \int_0^z u_l(z)dz$.

G-function: $G(z,\Omega_p)$ is the mean projection of a unit ($u_l(z) = 1$) foliage area at a depth z in the direction Ω_p. $\frac{1}{\pi}\int_0^{2\pi} d\varphi_p \int_0^1 G(z,\Omega_p)d\mu_p = 1$, $\mu_p = \cos\theta_p$.

Then, a Vegetation Radiative Transfer Equation is produced by equation (2):

$$-\mu\frac{\partial L(z,\Omega)}{\partial \tau} + G(\tau,\Omega)L(z,\Omega) = \frac{\omega}{4\pi}\int_{4\pi} P(\Omega' \to \Omega)G(\Omega')L(z,\Omega')d\Omega' \tag{2}$$

As to hotspot, one of the important features of the directional reflectance patterns of many land surface types, there is a reflectance peak around a viewing direction that is exactly opposite the solar illumination direction. The common practice in this model is to estimate the correlation between gap probabilities on both illumination and observing directions when calculating the so-called bidirectional gap probability (BDGP). Kuusk (1991) defined a cross-correlation function to account for correlation. It was approximated with an exponential function of the mean leaf chord length.

$$\text{BDGP: } P(z,\Omega_i,\Omega_v)=a(z,\Omega_i)a(z,\Omega_v)C_{HS}(z,\alpha) \tag{3}$$

$a(z,\Omega_i)$ and $a(z,\Omega_v)$ are the gap probabilities in illuminating and viewing directions. Z is the canopy depth, and $C_{HS}(z,\alpha)$ is the hotspot factor.

$$C_{HS}(z,\alpha)>1 \qquad \begin{cases} C_{HS}(z,\alpha)\approx 1, & \text{far from hotspot} \\ C_{HS}(z,\alpha)=1/a(z,\Omega_0)=1/a(z,\Omega), & \text{hotspot} \end{cases} \tag{4}$$

Because the light source and detector of a LiDRA are being the same point, LiDAR is working on a hotspot condition (Sun et al, 2000). According to Kuusk, for the leaf canopy, the bidirectional gap probability (BDGP) can be expressed as equation (5):

$$p(z,\Omega_i,\Omega_v)=a(z,\Omega_i)a(z,\Omega_v)C_{hs}(z,\alpha) \tag{5}$$

where $a(z,\Omega_i)=\exp[-\tau(z,\Omega_i)]$ and $a(z,\Omega_v)=\exp[-\tau(z,\Omega_v)]$ are the gap probabilities in illuminating (Ω_i) and viewing (Ω_v) directions respectively.

In the case of $\Omega_v\to\Omega_i$, the hotspot factor becomes as equation (6):

$$C_{hs}(z,0)=\lim_{\Omega_v\to\Omega_i}C_{hs}(z,\alpha)=\frac{1}{a(z,\Omega_v)} \tag{6}$$

The bidirectional gap probability in this backscattering case (hotspot) will be as equation (7):

$$p(z,\Omega_i)=a(z,\Omega_i)=e^{-\tau(z,\Omega_i)}=e^{-\int_0^z u_L(z')G(z',\Omega_i)dz'} \tag{7}$$

According to Sun (Sun and Ranson, 2000), the return from a horizontal slab with surface area ds and thickness dz at depth z, and reaching the top of the canopy (z=0) can be expressed as equation (8):

$$\Delta L=L_0e^{-\int_0^z u_L(z')G(z')dz'}u_L(z,s)\Gamma(z,s)dzds, \quad L(z)=\iint_S \Delta L \tag{8}$$

where Γ is the area scattering phase function for the canopy (For the geometry used in this study, i.e., a LiDAR operates in the nadir direction if the surface of foliage components is Lambertian surface with reflectance R_L); u_L is the density of a one-sided leaf area; G is Ross-Nilson G-function, and it may be functions of canopy depth z and the horizontal position s (G is a constant within the canopy volume, $\Gamma=GR$ will be a constant. μ_i and μ_v, the cosines of illuminating and observing angles, are both 1.0). L_0 is the incidence laser intensity and a function of the distance from the center of the footprint.

The canopy was divided into m layers ($C_j, j=1:m$) from top to bottom, with thickness of Δz, and the LiDAR pulse was divided into n narrow pulses ($L_i, i=1:n$) from front to tail, with duration of $\Delta t=2\Delta z/c$; (c is the speed of light). The return signal will be computed by equation (9). If the canopy cell is small, i.e., both Δz and Δs are small, we can assume that the density of scattering medium is constant within this cell.

$$L(i,j)=L_i(\Gamma u_L)_j\Delta s\Delta z\exp\left(-\sum_{k=1}^{j-1}(u_LG)_k\Delta z\right) \tag{9}$$

3. LiDAR Waveform Simulation and Analysis

In the following simulations conducted in this paper, the author mainly concern 5 factors influencing waveforms, such as tree height, crown size, tree distribution in one footprint, terrain slope and extinction coefficient. The reflectance value of single tree was magnified in order to see the result vividly and clearly when using equation (9). The same procedure is for other simulations..

3.1 Tree height

For this case, the assumptions are as following: (1) Crown type is ellipsoid; (2) Tree heights are 10m, 9m and 8m, and crown width is 1/5 of tree height, crown length is 0.45 times of tree height; (3) The u_L, foliage area volume density is 1.27; G is 0.5 and leaf reflectance is 0.46. Fig. 1 shows the simulating result, a typical shape of LiDAR waveform. It can be clearly seen that tree height doesn't affect the shape of waveform, while the start point of waveforms are different.

3.2 Crown Size

The most assumptions are the same as above-mentioned in 3.1 section, the differences are the 3 trees with the same height of 10m, and with different canopy width and length (Fig.2). It shows that crown can change the shape of waveforms greatly which means that people can retrieve tree canopy structure by LiDAR returned waveforms.

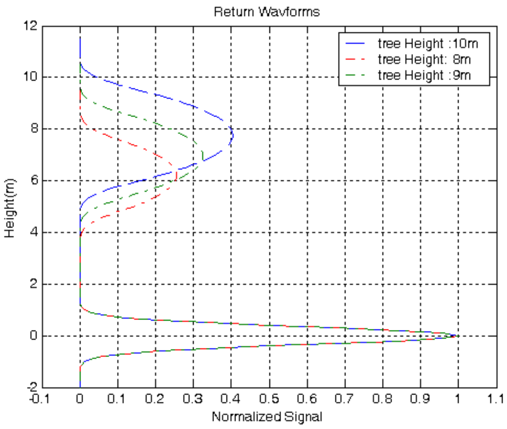

Fig.1 Waveforms of trees with height of 10m, 9m and 8m

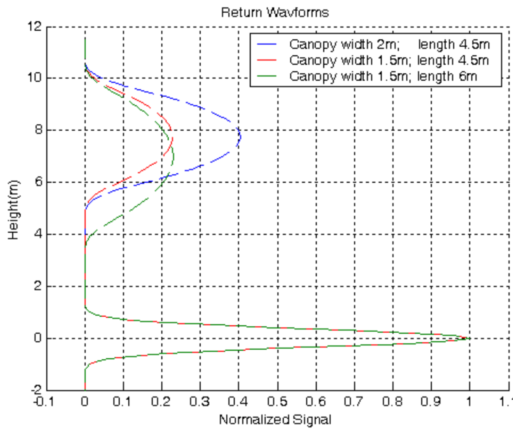

Fig.2 Waveforms of trees with different size of crowns

3.3 Trees Distribution pattern in one footprint with the diameter of 70m

First, the authors used two trees with different heights and positions in one footprint in order to simulate effects of trees distribution pattern on LiDAR waveform. One tree lies in the center of the footprint, the other is 10m far away from the center point. Secondly, the authors simulated a forest scene with trees distributing averagely in one footprint (Fig.3). The height of all trees is 10m. Other assumptions, such as the type of canopy, crown size etc, are the same as section 3.1. Fig.4 is LiDAR waveforms of the two trees. The dashed lines denote single tree's waveform, and the real line is the actual result of this footprint by overlapping two trees. The simulating result will be similar if adding more trees to the model. For second situation, there are two cases, one is for trees the same height of 10m (Fig.5), the waveform is very similar to one tree with 10m. The other is for different height of trees and trees with various distances from the center of footprint (Fig.6). From fig.6, we can see that the waveforms shape show greatly discrepancy from that of single tree. The starting position of waveform peak explains the height of the highest tree, however, the waveforms shape returned from ground do not change.

3.4 Terrain Slope

In this situation, we assumed that there are many trees distributing averagely in one footprint, all the trees are 10 meters high, and terrain slope is an important factor. Fig.7 shows the waveforms for the same height trees (with different distance far away from the center of footprint) and the slope of 2 degree. The thick line denotes overlapping result of all trees. As we know, terrain slope can cause uneven energy distribution in one footprint, which leads to different waveform peak values and position. Fig.8 shows the simulating waveforms under different terrain sloped conditions. From it we can see the length of waveform increases as terrain slope increases, however, the waveforms of ground and vegetation decrease and the echoes from ground decrease greatly.

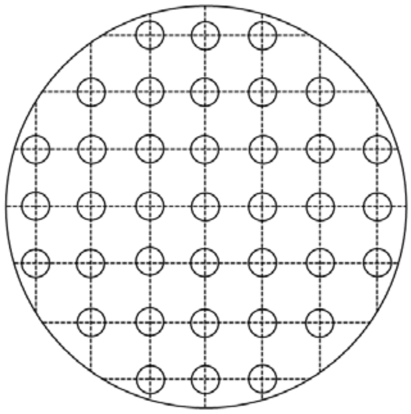

Fig.3 Schematic trees distribution in one footprint the distance of every two trees is 10m.

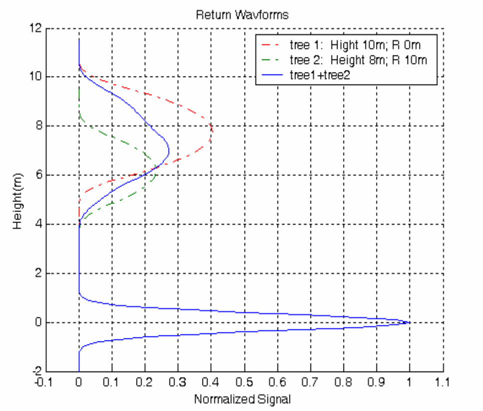

Fig.4 Waveform of two trees in one footprint with different distances from the footprint center

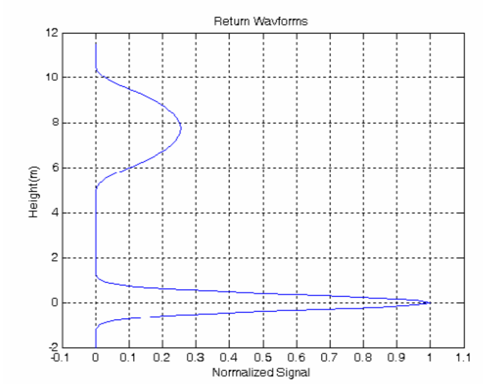

Fig.5 Waveform of trees with the same height of 10m

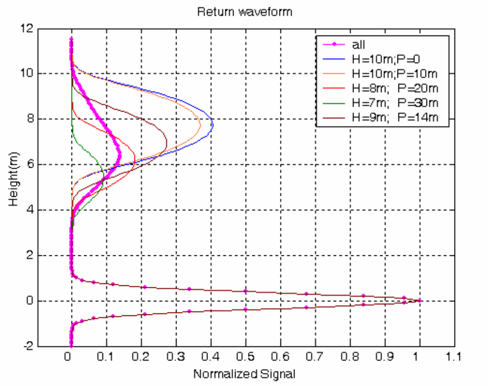

Fig. 6 Waveforms of trees with different heights

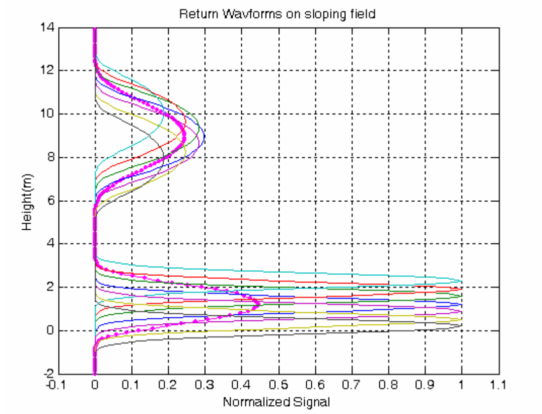

Fig.7 Waveform of trees with the same height of 10m and different distances from the center point of footprint

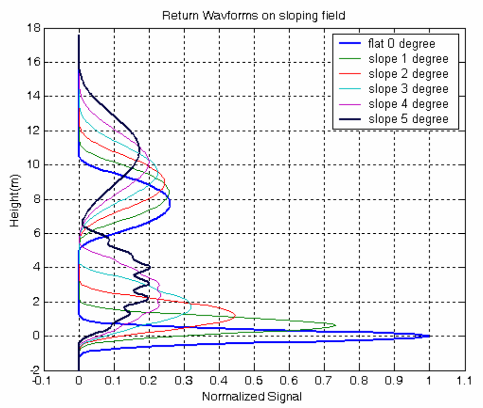

Fig.8 waveforms by different terrain slope

3.5 Extinction Coefficient

From section 3.4, we find that terrain slope can make LiDAR waveform widen and overlap, which will depress the accuracy of LiDAR echoes. Additionally, for very dense canopy, it is too ideal to simulate by gap probability model, for instance, waveforms are quite alike to assumed canopy. Therefore, an extinction coefficient is introduced to improve the model. The extinction coefficient refers to the ability of a substance to absorb light or electromagnetic radiation. Substances with a low extinction coefficient allow light to pass through easily, opaque substances absorb light (extinct light) and have a high extinction coefficient. Under forest conditions, canopy will decrease light and returned waveform in lower tree is weaker. It can be defined by equation (10):

$$-\mu \frac{dL(z,\Omega)}{dz} + \sigma_e(z,\Omega)L(z,\Omega) = \int_{4\pi} \sigma_s(z,\Omega' \to \Omega)L(z,\Omega')d\Omega' \tag{10}$$

Here, $L(z,\Omega')$ is light brightness; σ_e is extinction coefficient; σ_s is reductive coefficient by scatter, which explains brightness increment in light path by multiple scatters. Extinction coefficient is dependent on the relative position of light path direction (Ω) and foliage profile Ω_l. The probability of light decrease is $\sigma_e(z,\Omega)ds$ through a distance of ds.

$$\sigma_e(z,\Omega) = G(z,\Omega)u_l(z) \tag{11}$$

Here $ds = dz/\mu$, and for LiDAR system the ds is equal to dz.

Based on above theory, we can obtain the waveform results when adding an extinction coefficient to model.

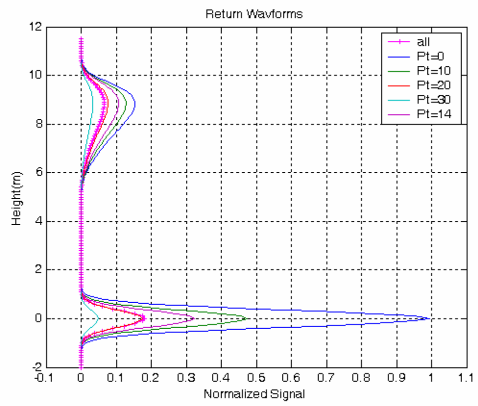

Fig. 9 Improved waveforms in Fig.7 when introducing extinction coefficient

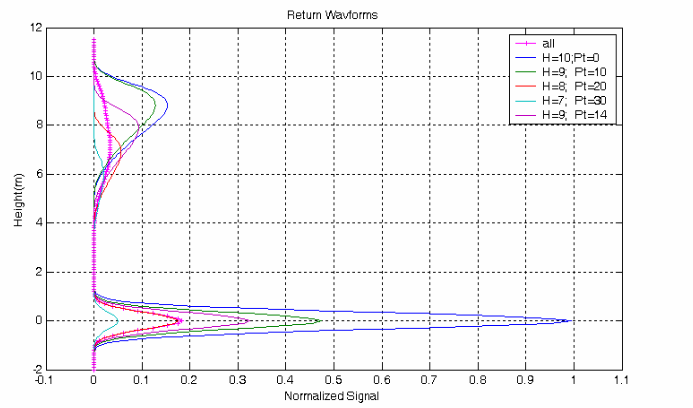

Fig.10 Waveforms of Trees with different heights and position in one footprint when adding extinction coefficient to model

4. Conclusion

Forest structural characteristics, such as tree height, crown size, terrain slope and so on, will have effects on LiDAR waveform features. Tree height influences only the starting point of waveform and has no effects on the shape of waveform, while crown size does. That implies people can retrieve tree height and canopy structure from LiDAR waveforms. The starting point of waveform means echoes returned from the highest tree though there are many trees with different heights distributing in one footprint. Terrain slope can make waveform widen greatly and change the waveforms position and intensity reflected from ground, which means it is necessary to take the slope effects into account when retrieving forest parameters. The model may be improved when adding an extinction coefficient to it.

The model and simulating result is very simple and ideal, such as trees distribution pattern in one footprint and ellipsoid crown, and small crown size, therefore, the model has to be perfected in later work so as to be more practical.

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