A Sequential LiDAR Waveform Decomposition Algorithm

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Abstract: LiDAR waveform decomposition plays an important role in LiDAR data processing since the resulting decomposed components are assumed to represent reflection surfaces within waveform footprints and the decomposition results ultimately affect the interpretation of LiDAR waveform data. Decomposing the waveform into a mixture of Gaussians involves two related problems: 1) determining the number of Gaussian components in the waveform, and 2) estimating the parameters of each Gaussian component of the mixture. Previous studies estimated the number of components in the mixture before the parameter optimization step, and it tended to suggest a larger number of components than is required due to the inherent noise embedded in the waveform data. In order to tackle these issues, a new LiDAR waveform decomposition algorithm based on the sequential approach has been proposed in this study and applied to the ICESat waveform data. Experimental results indicated that the proposed algorithm utilized a smaller number of components to decompose waveforms, while resulting IMP value is higher than the GLA14 products.

Key Words: LiDAR, Wave decomposition, Gaussian, EM algorithm, ICESat.

1. Introduction

LiDAR (Light Detection And Ranging) provides information on 3D coordinates of the Earth’s surface by actively sending out laser pulses and performing range measurements from the sensor. The range measurements are calculated by measuring the flight time of the laser pulse, and the time measurements are combined with the location (obtained from GPS (Global Positioning System)) and the attitude (obtained from IMU (Inertial Measurement Unit)) information of the system at the time of laser shot. Early LiDAR systems were limited to record small number of returns from the back scattered energy due to the hardware limitation. The volume of data acquired by the LiDAR system is enormous due to its high pulse repetition rate (PRF) of the system, and it was not feasible to record a whole spectrum of the return signal in the early systems. For this reason, early LiDAR systems extracted the location of peaks from the return signals, and the recorded peak locations were transformed into points with 3D coordinates information. However, recent advances in LiDAR hardware now enabled to record back
scatter energy which is also called a LiDAR waveform. The full waveform LiDAR system has recently attracted considerable attention of researchers since detailed information on the vertical structure of the targets can be better represented by the LiDAR waveform data than by the traditional discrete return LiDAR data. Various full waveform LiDAR systems have been developed since 1980s. The first LiDAR full waveform digitizer system was developed in the 1980s for bathymetric applications, and topographic full waveform profiling digitizer systems began to be marketed in the 1990s (Mallet and Bretar, 2009). More recently, the Laser Vegetation Imaging Sensor (LVIS) was developed as a prototype for the Vegetation Canopy LiDAR (VCL) mission (Blair et al., 1999). In addition to the airborne full waveform LiDAR system, the Ice, Cloud and Land Elevation Satellite (ICESat), a spaceborne large footprint full waveform LiDAR system, was launched in 2003 and operated until recently (Zwally, 2002). Even though full waveform LiDAR data provide high resolution vertical structure information, the high dimensional LiDAR waveform data inherently present challenges in processing the data. One of the most critical steps in processing the waveform data is LiDAR waveform decomposition, and it refers to the process of decomposing a return waveform into a mixture of components which are then used to characterize the original waveform data (Fig. 1). The LiDAR waveform decomposition plays an important role in LiDAR waveform processing since the resulting decomposed components are assumed to represent reflection surfaces within waveform footprints and the decomposition results ultimately affect the interpretation of LiDAR waveform data.

\[
\omega(t) = \sum_{k=1}^{K} \alpha_k \frac{1}{\sqrt{2\pi\sigma_k^2}} \exp\left\{ -\frac{(t-\mu_k)^2}{2\sigma_k^2} \right\} + \epsilon
\]  

(Eq. 1)

Among various kinds of mixture models, a Gaussian mixture model (Eq. 1) is the most common statistical model for the waveform decomposition process, and its parameters include the recorded time by the digitizer (t), mixing coefficients (\(\alpha_k\)) and the mean (\(\mu_k\)), standard deviation (\(\sigma_k\)) of each component, and background noise (\(\epsilon\)). Decomposing a waveform into distinct components by fitting a mixture of Gaussian distributions is an unsupervised machine learning problem which involves two separate, but related problems; i) determining the

![Image](a)

![Image](b)

Fig. 1. Example LiDAR waveform and its decomposition results; A solid blue line in (a) represents a received waveform, and solid red lines in (b) represents the decomposed components.