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Decomposition of LiDAR waveforms by B-spline-based modeling

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ABSTRACT

Waveform decomposition is a widely used technique for extracting echoes from full-waveform LiDAR data. Most previous studies recommended the Gaussian decomposition approach, which employs the Gaussian function in laser pulse modeling. As the Gaussian-shape assumption is not always satisfied for real LiDAR waveforms, some other probability distributions (e.g., the lognormal distribution, the generalized normal distribution, and the Burr distribution) have also been introduced by researchers to fit sharply-peaked and/or heavy-tailed pulses. However, these models cannot be universally used, because they are only suitable for processing the LiDAR waveforms in particular shapes. In this paper, we present a new waveform decomposition algorithm based on the B-spline modeling technique. LiDAR waveforms are not assumed to have a priori shapes but rather are modeled by B-splines, and the shape of a received waveform is treated as the mixture of finite transmitted pulses after translation and scaling transformation. The performance of the new model was tested using two full-waveform data sets acquired by a Riegl LMS-Q680i laser scanner and an Optech Aquarius laser bathymeter, comparing with three classical waveform decomposition approaches: the Gaussian, generalized normal, and lognormal distribution-based models. The experimental results show that the B-spline model performed the best in terms of waveform fitting accuracy, while the generalized normal model yielded the worst performance in the two test data sets. Riegl waveforms have nearly Gaussian pulse shapes and were well fitted by the Gaussian mixture model, while the B-spline-based modeling algorithm produced a slightly better result by further reducing 6.4% of fitting residuals, largely benefiting from alleviating the adverse impact of the ringing effect. The pulse shapes of Optech waveforms, on the other hand, are noticeably right-skewed. The Gaussian modeling results deviated significantly from original signals, and the extracted echo parameters were clearly inaccurate and unreliable. The B-spline-based method performed significantly better than the Gaussian and lognormal models by reducing 45.5% and 11.5% of their fitting errors, respectively. Much more precise echo properties can accordingly be retrieved with a high probability. Benefiting from the flexibility of B-splines on fitting arbitrary curves, the new method has the potentiality for accurately modeling various full-waveform LiDAR data, whether they are nearly Gaussian or non-Gaussian in shape.

1. Introduction

LiDAR (Light Detection And Ranging) has been known as one of most promising remote sensing techniques because of its excellent altimetric accuracy and canopy penetration capability (Baltsavias, 1999; Glennie et al., 2013; Nelson, 2013). Different from the last-generation discrete-return LiDAR systems that can only record a very limited number of echoes in a laser shot, full-waveform laser scanners have the ability to record the complete waveform of the backscatter response, which offers the opportunity for researchers and end users to adopt advanced signal processing algorithms that can detect echoes with higher accuracy and reliability (Mallet and Bretar, 2009). More echo features (e.g., the pulse width and return energy) can also be extracted from waveform data (Hancock et al., 2015; Pirotti, 2011), and they have been shown to be greatly helpful in a variety of geoscience applications such as land cover classification (Fieber et al., 2013; Liu et al., 2015; Mallet et al., 2011; Tseng et al., 2015), building extraction (Michelin et al., 2012; Słota, 2015), canopy height retrieval (Gwenzi and Lefsky, 2014;

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Hayashi et al., 2013; Nie et al., 2015), and biomass estimation (Allouis et al., 2013; Boudreau et al., 2008; Zhuang et al., 2015).

Accurately extracting echoes from LiDAR waveforms is a challenging task. Currently, most of the sophisticated algorithms in the literature fall into two categories: waveform decomposition and deconvolution (Mallet and Bretar, 2009; Wang et al., 2015). In a waveform decomposition method, the backscattered signals are seen as a mixture of finite echo components in similar shapes. The number of the echoes and the initial shape parameters are first estimated (Hofton et al., 2000; Qin et al., 2012), and the echo parameters are then optimized by a non-linear least-square method such as the Levenberg-Marquardt algorithm (Tian et al., 2015; Wagner et al., 2006) or a statistical learning method, e.g., the Expectation-Maximization algorithm (Parrish et al., 2011; Parrish and Nowak, 2009) and the Reversible-Jump Monte-Carlo-Markov-Chain algorithm (Hernandez-Marin et al., 2007; Mallet et al., 2010). The waveform deconvolution method, on the other hand, follows a quite different philosophy. A reflected waveform is seen as the convolution product between the transmitted laser pulse and the backscatter cross section (Mallet and Bretar, 2009; Wagner et al., 2006). By reversing the effect of transmitted waveform, a waveform deconvolution algorithm retrieves the backscatter cross section and then detects echoes from it. Typical deconvolution methods that have been successfully introduced into the full-waveform LiDAR field include the Wiener deconvolution (Jutzi and Stilla, 2006), Richardson-Lucy deconvolution (Wu et al., 2011), B-spline deconvolution (Roncat et al., 2011), and Gold deconvolution (Gao et al., 2015). Being an ill-posed problem, the signal deconvolution is inherently unstable, and the regularization technique is highly recommended for acquiring reliable solutions (Wang et al., 2009).

As a special form of waveform decomposition, the Gaussian decomposition approach assumes that a LiDAR pulse can be modeled by the Gaussian function (Hofton et al., 2000). Owing to its conceptual simplicity and fairly good performance, the Gaussian decomposition has been very popular both in the academia and industry (Słota, 2014). A large number of studies have reported the successful use of the Gaussian decomposition algorithm for processing various LiDAR waveform data captured by satellite laser altimeters (Khalefa et al., 2013), airborne laser scanners (Yi et al., 2015), and terrestrial laser scanners (Hakala et al., 2012). However, some researchers have also pointed out that the Gaussian-shape assumption is not always satisfied for small-footprint LiDAR waveform data (Chauve et al., 2009; Hartzell et al., 2015; Mallet and Bretar, 2009), and they have suggested the use of the lognormal distribution (Chauve et al., 2007), generalized normal distribution (Chauve et al., 2009), Nakagami distribution (Mallet et al., 2010), Burr distribution (Mallet et al., 2010), or a piecewise exponential function (Hernandez-Marin et al., 2007) to model non-Gaussian waveforms in peaked and/or tailed shapes.

Previous non-Gaussian waveform modeling methods hold the assumption that all LiDAR pulses fit an a priori probability distribution, and they therefore can only be suitable for processing the waveforms in particular pulse shapes. In this paper, we propose a more universal waveform decomposition approach. Given the high shape similarity between the returned echoes and the corresponding transmitted laser pulse, a received LiDAR waveform is treated as the mixture of finite transmitted waveforms after linear transla-

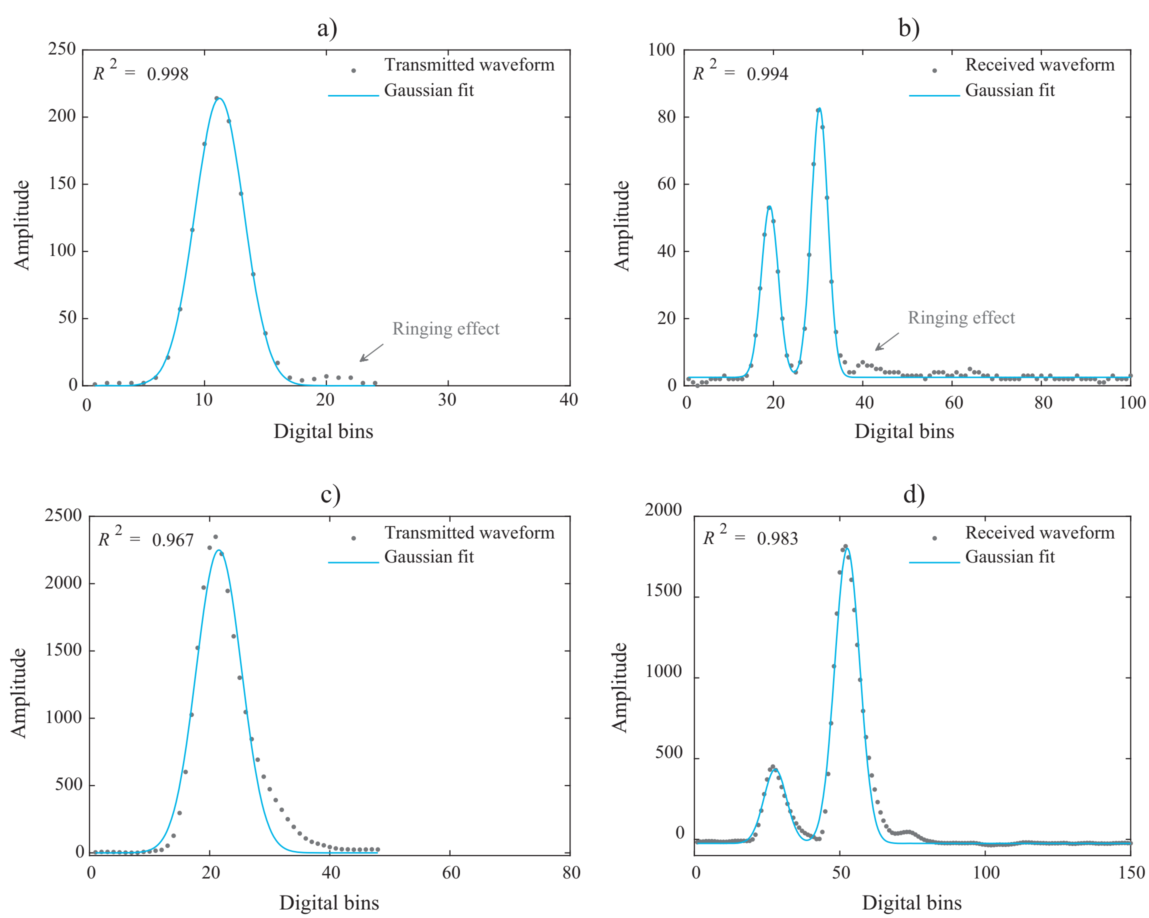

Fig. 1. Typical airborne LiDAR waveforms and their Gaussian fit results. (a) A transmitted waveform and (b) a received waveform recorded by a Riegl LMS-Q680i laser scanner; (c) a transmitted waveform and (d) a returned topographic waveform captured by an Optech Aquarius LiDAR bathymeter.