A COMPARISON OF LIDAR WAEVEFORM DECOMPOSITION MODELS

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ABSTRACT: The storage capability of full waveform is the state-of-the-art technology of LIDAR. In addition to the 3D point information recorded by conventional LIDAR systems, waveform LIDAR systems encode the intensity of returned signal along the time domain. This provides a user the possibility to decompose the waveform for the detection of illuminated target points. Therefore, the locations of the illuminated targets can be refined by analyzing the waveform data. So far, a standard approach to waveform decomposition is still not available. A waveform may be a composition of some prominent, overlapped and weak return pulses. A waveform decomposition method may easily detect a prominent return pulse, but it usually has some difficulties to deal with overlapped and weak pulses. In this paper, a waveform fitting method which takes the overlapped pulses into consideration will be applied. To fit a waveform, the number of returns is needed. The initial number of returns commonly is determined by a simple way such as the number of local maximum of a waveform which is influenced by noises and overlapped echoes. For this reason, the wavelet transform is used to estimate the initial number of returns in this research. Moreover, compared with taking Gaussian as the fitting basic model, another basic model, log-normal is included. Our preliminary results show the effectiveness of wavelet transform to determine the initial number and the ability to detect overlapped pulses. The Log-normal model has better fitting results than Gaussian model in forest areas. As the results, the points extracted by our developed methods increase compared with the points extracted by commercial system. The increased points can be useful to future applications especially in a forest area.

1. Introduction

Recently the development of LIDAR system makes the ability to store the full waveform data, the 3D spatial coordinates and physical features can now be derived more flexibly for end users compared with the conventional systems. The further information derived from waveform such as width, amplitude, backscatter cross-section and number of return have been used for improving classification. So far, there are three main applications catching the attention to research: DTM generation; forestry; and urban applications. Applications also extend to airport obstruction observations(Parrish and Nowak 2009). Since more weak and overlapped points can be extracted from waveform data and resulting in more dense points, the broadcast tower/antenna or some small airport obstruction objects can be described very well which may be hardly recognized or missed in the conventional discrete pulse record LIDAR system.

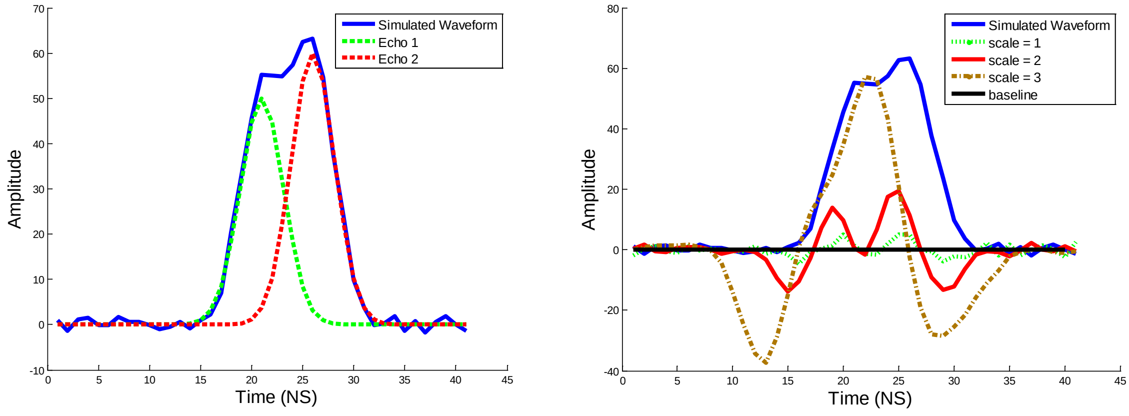
To extract information from the waveform, waveform fitting and decomposition is a way to apply. Many decomposing methods have been presented to generate the 3D point clouds and features; however, some challenges are being met. The most two are the overlapped echoes and weak pulses. For the overlapped echoes, it is difficult to estimate the number of echoes inside one overlapped return waveform. Wagner, Roncat et al.(2007) have pointed out that determining the number of returns in a waveform is not simple as it sounds because of the complexity of waveform shapes. If the number of returns is wrongly determined, the extracted points would be missed or invented even the fitting accuracy is acceptable. General pulse detection methods such as local maximum, center of gravity, zero-crossing of the first derivative fail to estimate the correct number of returns within complex overlapped waveforms. Therefore a way to estimate the number of returns is needed. The wavelet transform has been shown the ability to detect the number of components in an overlapped signal (Shao, Cai et al. 1998; Jiao, Gao et al. 2008). Since the wavelet transform can decompose the signal into multi-scale details and approximations, the independent echo can be found most clearly at a certain scale. Then the independent echo can be counted to be used for the estimated number of returns in waveform fitting process.

In this paper, we focus on the overlapped waveform, different kinds of test fields and different LIDAR system. The Riegl system and Leica system which capture the city area and forest field respectively are compared.

2. Material and methods

2.1 Estimation of number of return

To fit a waveform, the number of components of a waveform needs to be determined firstly. However due to the overlapped affection, it is not straight forward to know the number of components of a return echo without preprocessing the raw waveform. The wavelet analysis provides a way to estimate the number of components. The wavelet transform has the ability to decompose an overlapped signal into contributions of different scale. Since the scale of each independent component is higher than the noise and lower than the overlapped echo, each component will come out at a certain scale. For this reason, the number of components can be estimated. Figure 1 shows the conception of solving overlapped echoes using wavelet transform. The baseline is to discriminate the independent echoes in wavelet detail domain at different scales. One can see that the two echoes can be seen at scale 1 and 2(scale 2 is more clear because the coefficients at scale 1 are more influenced by noises), and cannot be seen if the scale is larger than 2.



(a) (b)

Figure 1. (a) simulated waveform: the interval between two echoes is 5 ns, the FWHM of both echoes is 5 ns. (b) simulated waveform and the corresponding wavelet coefficients at scale 1, 2, and 3. The base line is used to discriminate the echoes.

2.2 Basic fitting models

For fitting purpose, a basic mathematical model has to be chosen to represent each return echo. Generally speaking, the Gaussian function is the most common used among several researches. *(Wagner, Ullrich et al. 2006)* has shown that the system waveform of Reigl LMS-Q560 can be represented by a Gaussian-like model. And if the scattering property of the target scatterer is also a Gaussian function, the received LIDAR waveform can be fitted by the Gaussian model.

In this paper, however, we chose another basic model to compare with the Gaussian model. As we observed that the right tails of the return echoes normally behave much longer than the left tails of the return echoes. This situation may be caused by the slope of the scatterers*(Jutzi and Stilla 2006)*. Therefore the log-normal function is chosen because the shape of log-normal model behaves like the waveform we observed, and the number of parameters is only 3 just like Gaussian model. The Gaussian model and log-normal model are expressed by:

$$\text{Gaussian:} \quad f(x) = ae^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{1}$$

$$\text{Log-normal:} \quad f(x) = ae^{-\frac{(\ln(x)-\mu)^2}{2\sigma^2}} \tag{2}$$

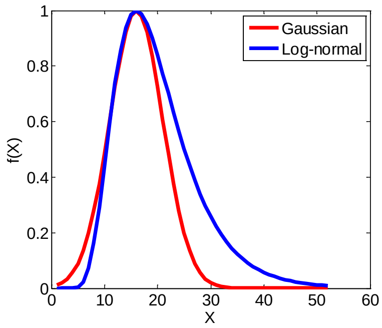


Figure 2. Comparison of Gaussian and Log-normal models

2.3 Fitting Procedure

Figure 3 shows the procedure of waveform fitting in this paper. Firstly the noises need to be estimated so that we can avoid noises during the fitting process. The number of returns can be therefore estimated by wavelet coefficients. Once the initial number of components of a waveform is determined, the waveform can be fitted and refined by iteration fitting process.

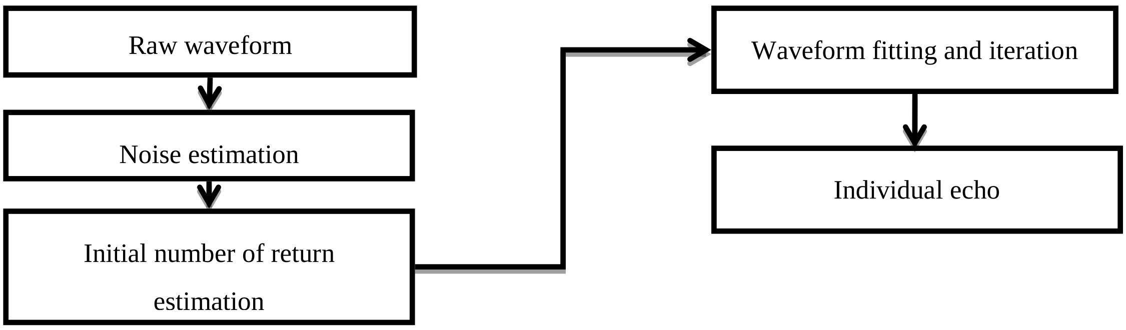
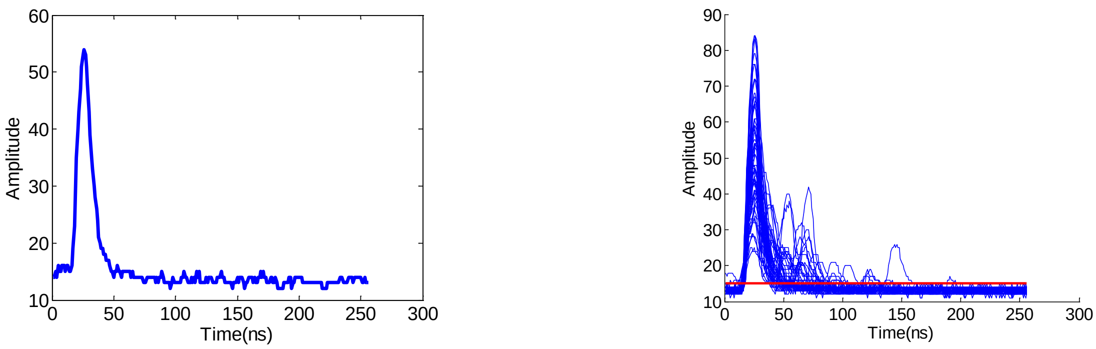


Figure 3. Procedure of waveform fitting

2.3.1 Noise estimation: As a practical waveform shown in Figure 4(a), the return echo and noises are both recorded. Fortunately that even the noises are contained everywhere in the waveform, the return echoes are located in a certain interval of the waveform. Figure 4(b) shows 60 waveforms and we can see that the noises are the only information of the interval between 200(ns) to 256(ns). Therefore, the mean μ_n and standard deviation σ_n of noises can be estimated by the segments of 60 waveforms. A threshold $\mu_n + 3\sigma_n$ is chosen to separate the noises and the effective return echoes (see the red line in Figure 4(b))



(a) (b)

Figure 4. Noise estimation

2.3.2 Fitting process: Once the effective return echoes are separated from the noises, the number of returns can be estimated by wavelet coefficients as mentioned in section 2.1. Then the waveform can be decomposed into several independent echoes (components), i.e. a fitting process:

$$y \cong f(x) = \sum_{j=1}^{n} f_j(x) \tag{3}$$

where y denotes the original waveform, $f_j(x)$ denotes a component (echo), *j* denotes the *j*th component, n denotes the initial number of returns, $f(x)$ denotes the fitted waveform which is the sum of each component. In this paper, the base model of $f_j(x)$ can be Gaussian function or log-normal function.

The fitting equation is solved by nonlinear least square. Once the first fitting is finished, a rule is applied to check if some echoes inside the waveform are miss-detected or not. The difference Δ between the y and $f(x)$ is used for this purpose. If $\max(\Delta) > t_{diff}$, one return echo is added at the maximum, and the fitting process continues. The fitting process will stop if $\max(\Delta) \le t_{diff}$ or the number of returns exceeds 6 components

2.3.3 Parameter constrain: For reasonable solution of fitting, the unknown parameters of components have to be constrained according to the property of return echo. For Gaussian model, the three unknown parameters are mean, standard deviation and multiplying factor which represent the location of the time axis, the width of independent echo, and the energy ratio. Therefore the mean is limited inside the interval of each return echo; the multiplying factor must be larger than zero. The standard deviation which is the most important of the three parameters needs to be further constrained. Many researches have shown that the width of return echoes would vary according to the material of illuminated targets. Normally the width of return echo from trees is larger than the width of return echo from ground. So 50 waveforms of each class are selected to be fitted and the numerical domain of the width is restricted by:

$$\left\{ \mu^{n}_{ground\_width} - 3\sigma^{n}_{ground\_width} < width < \mu^{n}_{tree\_width} + 3\sigma^{n}_{tree\_width} \right\} \tag{4}$$

2.3.4 Goodness of fit: To evaluate the fitting results of waveforms, the summation E_i of 2-norm differences between a fitted waveform $f(x)$ and the corresponding original waveform y is utilized:

$$E_i = \sum_{x=1}^{n_i} \left(\frac{f_i(x) - y_i(x)}{norm(f_i(x))} \right)^2 \tag{5}$$

i denotes the ith waveform, n_i denotes the number of samples of a waveform.

3. RESULTS AND DISCUSSIONS

3.1 Data

The full waveform data used in this paper are obtained by simulation, Leica, Riegl system. The simulated waveforms are simulated by referencing the Leica system waveform. The FWHM of simulated waveform is 5 ns and the noises estimated from Leica system are also added. The simulated waveform is used for demonstrating the ability for estimating the number of returns. The data from Leica system is in a forest field while the data from Riegl system is in a city area. The two data are used to compare with each other.

3.2 Number of returns estimation

Figure 5 shows the estimated results of return number in different cases. Figure 5(a)-(b) shows the simulated waveform combined by two echoes which are separated in 4 and 5 ns respectively. The results show the two echoes can be seen if the interval of the two echoes is equal or larger than 5 ns. Figure 5(c)-(e) shows the simulated waveform combined by three echoes. The intervals of echo1-echo2 and echo2-echo3 are 4 ns, 4 ns respectively in (c); and 4 ns, 5 ns respectively in (d); and 5 ns, 5 ns respectively in (e). One can notice that the same conclusion can be made that once the interval between two echoes is equal or larger than 5 ns, the echoes can be separated. This result also comes to demonstrate the theory by (Wagner, Ullrich et al. 2006) that when the separation of the scatters is smaller than the resolution of Leica system (FWHM: 5 ns for Leica system), the effect is to smear out the original pulse. In other words, the scatters can be considered as a scatter cluster.

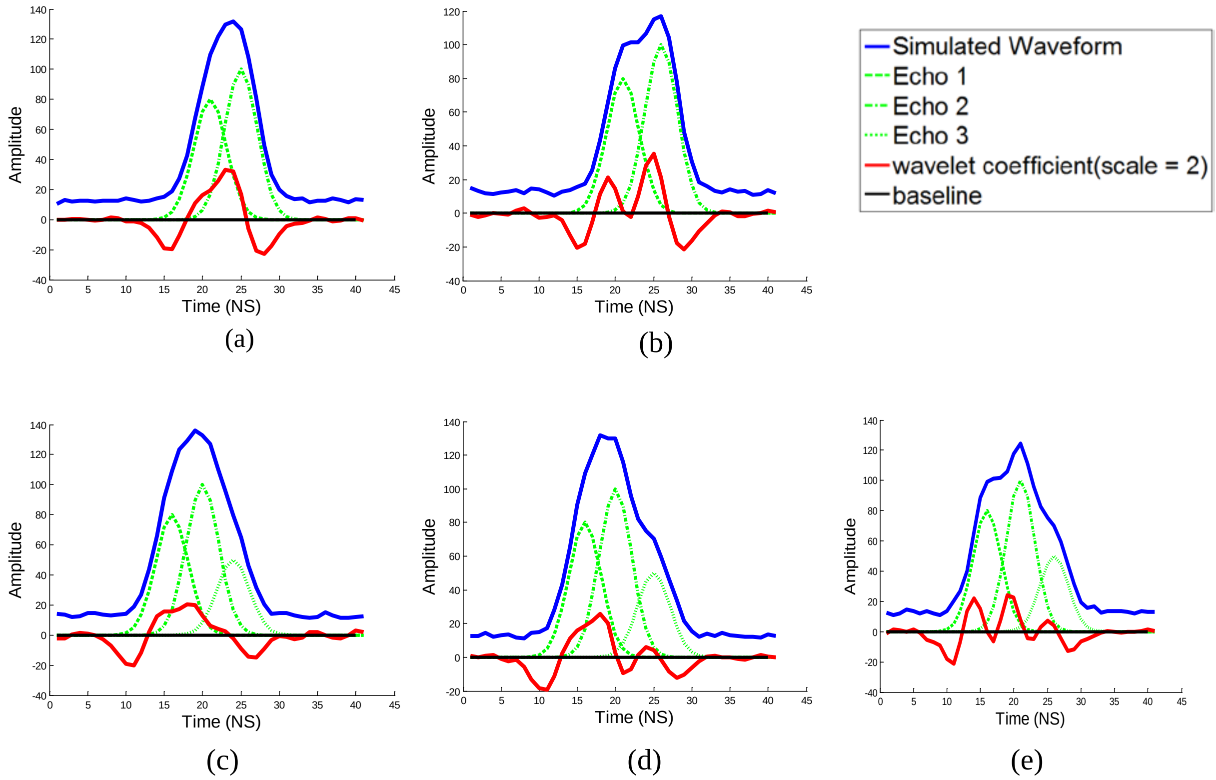


Figure 5. Simulated waveform: let A_i denotes the amplitude of *i*th echo, $D_{i,j}$ denotes the interval between echo i and echo j. (a) A_1=80, A_2=100, $D_{1,2}$=4; (b) A_1=80, A_2=100, $D_{1,2}$=5; (c) A_1=80, A_2=100, A_3=50; $D_{1,2}$=4, $D_{2,3}$=4; (d) A_1=80, A_2=100, A_3=50; $D_{1,2}$=4, $D_{2,3}$=5; (e) A_1=80, A_2=100, A_3=50; $D_{1,2}$=5, $D_{2,3}$=5

3.3 Fitting results

To comprehend the fitting results of ground and trees individually, 50 waveforms each class are chosen for testing. Each waveform is manually selected only if it contains one return echo. Table 1 and table 2 shows the fitting results of the two LIDAR systems. For Leica system, the fitting accuracy of Log-normal in both of grounds and trees is better than Gaussian's. The reason that the log-normal fits to the waveforms from trees better than Gaussian is the slope of trees is large. However, in the case of Leica, the waveforms from grounds still behave like Log-normal function. It could be caused by the slope of terrain, since the waveform data from Leica system is acquired in a mountain forest. In the case of Riegl system, the fitting accuracy using two basic models is less difference both in grounds and trees.

Table 1. Average of residual norm over 50 samples each class (Leica system)

Residual Norm(Average)	Gaussian	Log-normal
Ground	0.0094	0.0073
Tree	0.0103	0.0040

Table 2. Average of residual norm over 50 samples each class (Riegl system)

Residual Norm(Average)	Gaussian	Log-normal
Ground	0.0015	0.0016
Tree	0.0060	0.0055

Table 3 shows the fitting accuracy over 10000 waveforms each LIDAR system. From the results, one can see that the Log-normal is the best fitting model in the forest area. It is worth to notice that the fitting accuracy (0.0083) of Leica system is worse than the manual selecting samples (in Table 2, ground: 0.0094; tree: 0.0073). The major reason is the manual selecting waveform only contain one return echo each waveform while the 10000 waveforms can contain two or above returns especially in forest areas. Since the Riegl data is in a City area, and test area contains grounds, buildings more than trees. As we know that the hard material has less penetrations and the corresponding waveform could behave only one return. Therefore the fitting accuracy is between Ground and trees in Table 2.

Table 3. Average of residual norm over 10000 waveforms from Leica system and Riegl system

Residual Norm (Average)	Gaussian	Log-Normal
Leica system	0.0139	0.0083
Riegl system	0.0024	0.0024

4. CONCLUSIONS

In this paper, a way to estimate the number of returns in LIDAR full waveform system is presented. Experiments show the feasibility of waveform transform to pre-estimate the number of returns and ease the overlapped problems for fitting purpose. For fitting model test, basic on our results, the Log-normal is suggested to fit the waveform in the forest fields. After fitting process, the coordinates of points can be extracted. For the 10000 waveform data, the number of points increases 16% in forest field and 11% in city area by our method. The increased point density can be further used for improving some applications, for example, the DEM and CHM generation in forest fields.

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