ANALYSIS OF LIDAR WAVEFORM DATA FOR GROUND FILTERING IN A FOREST AREA

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Abstract: The airborne laser scanning (ALS) data is becoming a standard approach for generating digital elevation model (DEM) in recent years. To generate the DEM, the ground points in the point clouds need to be classified firstly. Traditionally, the points provided by the multi-return LiDAR system only provide the three-dimension coordinates of points and the classification approaches normally can mainly utilize the geometric conditions to separate the ground points from the non-ground points. If the terrain relief is varied quickly, the geometry-based classifier could not be satisfied for ground filtering purpose. In recent years, the commercial waveform LiDAR system has advanced developed. The waveforms can preserve more information of targets than the traditional multireturnLiDAR data.Since waveform is the interactions between targets and laser signals, this interaction can be considered as the convolution between the transmitted laser pulse and the backscatter cross-section function of the targets.For this reason,more radiation and geometric characteristics of targets can be extracted. As the observations of real waveform data, we found out that the width of trees is larger than the ground. For this reason, we utilized the backscattered cross-section of targets and the echo width extracted from waveform data as new properties of points for improving the classification accuracy. Firstly some training data is chosen for designing the classifier to separate the non-ground points from the point clouds. We aimed at the analysis of the performance in classifying ground points by using the extracted waveform features. Our preliminary results show the potential of the waveform features for ground classification purpose in a forest area and also reveal thatthe characteristics of waveform is useful in classification.

1. INTRODUCTION

The airborne laser scanning (ALS) data is becoming a standard approach for generating digital elevation model (DEM) in recent years. Due to the light penetration property,LiDAR can go through the vegetation and obtain amount of high accuracy three-dimensional point clouds efficiently by receiving the transmitted laser signal from the illuminated surfaces. This property can substantiallyraise the opportunity for exploring the surfaces which are covered by the forest canopy

Before generating DEM, the ground points in the point clouds need to be classified firstly. Traditionally, the points provided by the multi-return LiDAR system only provide the three-dimension coordinates of points and the classification approaches normally can only utilize the geometric conditions to separate the ground points from the non-ground points. If the terrain relief is varied quickly, the geometry-based classifier could not be satisfied for ground filtering purpose. In recent years, the commercial waveform LiDAR system has advanced developed. The waveforms can preserve more information of targets than the traditional multi-returnLiDAR data. The return waveform data can record reflective signals more completely. The interactions between targets and laser signals are recorded in waveforms. This interaction can be considered as the convolution between the transmitted laser pulse and the backscatter cross-section function of the targets (Alexander et al.,2010). The backscatter cross-section of targets than the traditional multi-return data can preserve more information and the target. This is the reason that waveform data can preserve more information and the targets than the traditional multi-return between the transmitted laser pulse and the backscatter cross-section function of the target. This is the reason that waveform data can preserve more information to improve the ground filtering process.

Many researcheshave reported that the waveform is useful for classification. For example, tree species classification (Heinzel et al., 2011), road detection based on the width of LiDAR echoes, digital terrain model generation by

finding the ground point in waves and classification by waveform features (Mallet et al., 2011). For DEM generation, Lin (2011) has used some features derived fromfull-waveform data and integrated those features into a filtering algorithm to improve the generated DTMs.

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In this study, our goal is to explore somewaveform features for discriminating the ground returns from the nonground returns. In the section 2, the overall methods including data description, pre-processing, waveform features and the classification algorithm will be explained. The results are shown in section 3. Section 4 and 5 will go to our discussion and conclusion respectively.

2. METHODOLOGY

Figure 1 shows the flow chart of classification for point clouds in this research. Firstly the raw waveforms were fitted as a combination of Gaussian functions. The waveform features can be then represented in the form of Gaussian parameters. Some points with known waveform features were chosen as training data and then input to the SVM classifier. After the training was done, all unclassified points were input into the classifier and classification accuracy can be obtained.



Figure 1: Flow chart of classification for point clouds

2.1 Raw data:

The LiDAR data utilized in this study was acquired from Leica ALS60 system in Nanrenshanmountain where is an ecological conservation area during November 2011. This system emits laser pulses at a wavelength of 1064 nm and the pulse rate is 57 kHz. The flight altitude was about 1000 AGL and the bean divergence is 0.22 mrad. This study area is abroadleaf forest in southern Taiwanand the terrain relief sometimes varies very quickly.

2.2 Pre-processing:

There are two main pre-processing steps for the raw waveform data: echo detection and waveform decomposition. The echo detection is to detect the number of returns in each waveform. The detection method used in this research in based on a wavelet-based detector proposed by (Wang, 2012). This method can further deal with theweak and overlapped returns from waveforms so that more extra points can be found especially for the ground points in forests. Therefore unlike the conventional LiDAR systems only provide less number of ground points in a dense forest area, the point clouds extracted by this detector can better represent the forest terrains. After the number of echoes in each waveform is determined, the waveform decomposition can be applied. In our study, we used Gaussian function as the mathematical model to represent a return echo. The reason we used Gaussian function is that the Gaussian function was reported that it fit a return echoe (Wanger et al., 2006). To fit a raw waveform is then to solve a minimum difference between the waveform and the combination of Gaussian functions.

2.3 Feature extraction:

Many papers haveutilizedsome waveform features such as echo width, amplitude, intensity, rise time (Figure 2(a)) and so on(Neuenschwander et al., 2009, Alexander et al., 2010) for their studies. In this study, wemainly test thosewaveform features of variant objectssuch as trees, rocks, roads and buildings. Those features on different objects were staticallyanalyzed. Figure 2(b) shows the scatter plot of waveform features for the four kinds of objects. One can see that the four kinds of objects have a great separation between each other. This shows the potential of waveform features for doing classifications. In this paper, we focus on the separation of ground points from non-ground points by using those waveform features. Three waveform features which are amplitude, width and area were chosen for testin this experiment.

Figure 2(a) shows the diagram of the three waveform features. The amplitude is drawn in the red arrow which represents the strength of a return echo. The area (shown as thedash line area in figure 2(a))means the rise area of the raw waveform subtract from the noise signal.Consequently, we can find that the amplitude andarea of waveform are bothconnected to the laser energy of return waveform signal. The width of the waveform means the full width at half maximum (Alexander et al., 2010), i.e. the two times of standard deviation of Gaussian function (shown as the green arrow in figure 2(a)).



Figure 2: (a) The properties of the waveform. (b) Three dimensional analyses of groups.

2.4 Support Vector MachinesClassifier:

The classifier utilized in this study is thesupport vector machines (SVM) which is a supervised classifier. It can perform non-linear classification using kernel trick and map the data into high-dimensional feature spaces. The objective of SVM is to find ahyper-plan maximizing the separation distance between the closet inputting samples in multi-dimension space (Mallet et al., 2011). For our case, two classes were defined as ground and non-ground. We use the LIBSVM software (Chang and Lin, 2001) in MATLAB to perform the SVM classification.

3. RESULTS AND DISCUSSION

Table1: The accuracy of using different number features. A: Amplitude, B: Width, C: Area

ĺ	Feature	А	В	С	AB	AC	BC	ABC
	Accuracy	71.9333%	70.3667%	80.5333%	77.0333%	86.4333%	82.7%	87.4333%

The classification accuracy utilizing different combinations of waveform features is shown in Table 1. At first, we only use one feature to classify the ground points. The results show that the waveform feature, area, exhibits better classification accuracy than the other two features. It can be explained that the waveform area represents the whole

reaction of a scatter. The discrimination by using area can be then increased. For this reason it can separate the grounds from point clouds more effectively. For the classification by using two alternative features, the accuracy will improve compared with using only one waveform feature. As table 1 shows, combing amplitude and width can raise the calssification accuracy from 70% to 80%. Moreover, using all the three features resulted in the greatest accuracy (87.4333%). This result implies that the waveform features is useful for ground filtering purpose and the accuracy increased as the number of utilized features increased.

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4. CONCLUSIONS & RECOMMENDATIONS

Our experiment in this paper shows the potential of waveform features for the improvement of ground filtering. According to the result, the accuracy can reach to 87.5% by only using 3 waveform features. In this paper, some other important features have not yet included which are expected to have a great advantage for filtering. For example the elevation of points is a key feature to discriminate the ground points from non-ground points. In the future we will utilized the elevation information and explore more waveform features for further promote the classification accuracy.

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