An Adaptive Density-Based Model for Extracting Surface Returns From Photon-Counting Laser Altimeter Data

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Abstract—The Ice, Cloud and land Elevation Satellite-2 (ICESat-2) mission of the National Aeronautics and Space Administration is scheduled to launch in 2017. This upcoming mission aims to provide data to determine the temporal and spatial changes of ice sheet elevation, sea ice freeboard, and vegetation canopy height. A photon-counting lidar onboard ICESat-2 yields point clouds resulting from surface returns and noise. In support of the ICESat-2 mission, this letter derives an adaptive density-based model that is capable of detecting the ground surface and vegetation canopy in photon-counting laser altimeter data. Based on results from point clouds generated by a first principle simulation and those observed by the Multiple Altimeter Beam Experimental Lidar, the ground and canopy returns can be reliably extracted using the proposed approach. Further study on performance assessment shows that smoother surfaces will result in improved accuracy of ground height estimation. In addition, the proposed detection approach has better performance in environments with lower noise, although the performance evaluation metric $F$-measure does not vary significantly over a range of noise rates (0.5–5 MHz). This proposed approach is generally applicable for surface and canopy finding from photon-counting laser altimeter data.

Index Terms—Density-Based Spatial Clustering of Applications with Noise (DBSCAN), Ice, Cloud and land Elevation Satellite-2 (ICESat-2), lidar, surface finding.

I. INTRODUCTION

Observations from satellites and aircraft have revealed the remarkable recent changes in polar ice sheets [1]. A long-term mission observing ice sheet elevation is required to monitor the ice sheet balance and sea level change [2]. To serve that purpose, the National Aeronautics and Space Administration launched the Ice, Cloud and land Elevation Satellite (ICESat) to obtain measurements of ice sheet and sea ice on a global scale. ICESat (2003–2009) used the Geoscience Laser Altimeter System sensor, which is a laser altimeter based on the ATLAS uses a high-repetition-rate (10 kHz) low-pulse-energy laser in conjunction with single-photon-sensitive detectors. It has been theoretically demonstrated that spaceborne lidar performance can be enhanced when operated in a photon-counting mode [9]. To validate ICESat-2’s measurement approach, high-altitude data from airborne photon-counting lidar imaging are required [10]. One example is the experimental Multiple Altimeter Beam Experimental Lidar (MABEL) [11]. MABEL is a dual-wavelength (532 and 1064 nm) photon-counting lidar and offers insights into the signal qualities that are anticipated for ICESat-2. However, photon-counting detectors introduce significant noise, such as that from solar photons and system dark current. Therefore, an effective approach would be necessary for denoising and classifying returns from surface as well as the canopy.

Previous research has demonstrated noise filtering techniques for simulated ICESat-2 [12] and MABEL data [13]. In this letter, a clustering method is modified and used for the detection of the ground surface and vegetation canopy in photon-counting laser altimeter data. This approach is based on the concept of Density-Based Spatial Clustering of Applications with Noise (DBSCAN) [14]. Due to the high density in the horizontal direction in photon-counting lidar point clouds, the shape of the search area is modified from a circle to an ellipse. This will have higher accuracy in surface finding and significantly reduces computational time.

The rest of this letter is organized as follows. First, two sets of photon-counting lidar data sets are reviewed. One is created using first principle simulations, and the other is from MABEL. Then, the density-based clustering method will be discussed and further modified particularly for the photon-counting lidar altimeter point cloud characteristics. Implementation and evaluation of this method will be addressed in the final part.

II. OVERVIEW OF PHOTON-COUNTING LASER ALTIMETRY

Photon-counting laser altimetry records the time position of each individual received photon. Then, the surface elevation of illuminated area can be derived by calculating photon travel time and knowing the altitude of the sensor. Two sources of simulated ICESat-2 data are used in this letter.

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The second source of simulated ICESat-2 data is from MABEL [18]. The test data (L2A) were collected in WI, USA, on September 26, 2012, where lots of canopy-covered ground are present.

B. Modified DBSCAN

The key idea of DBSCAN is that, for each point of a cluster, the neighborhood of a given radius has to contain at least a minimum number of points, i.e., the density in the neighborhood has to exceed some threshold. The shape of a neighborhood is determined by the choice of a distance function for two points \( p \) and \( q \), denoted by \( \text{dist}(p,q) \). Two parameters mentioned here are an Eps-neighborhood of a point, defined by \( \text{dist}(p,q) \leq \text{Eps} \), and the minimum number of points (MinPts) in that Eps-neighborhood [14].

For a data set in two dimensions, the distance between two points \( p(t_p, h_p) \) and \( q(t_q, h_q) \) is defined as

\[
\text{dist}(p,q) = \sqrt{\left(\frac{t_p - t_q}{t_{scale}}\right)^2 + \left(\frac{h_p - h_q}{h_{scale}}\right)^2} \tag{1}
\]

where \( t \) represents delta_time in Fig. 1, which can be considered as an along-track distance, and \( h \) represents elevation. \( t_{scale} \) and \( h_{scale} \) are used for normalization so that the points in the test data set have comparable order over \( t \)- and \( h \)-axes. Hence, \( \text{dist}(p,q) \) is now unitless.

In our algorithm, since most of the clusters (surface returns) have higher density in the horizontal than the vertical direction, it is reasonable to modify the shape of search area accordingly. Therefore, the distance between points \( p(t_p, h_p) \) and \( q(t_q, h_q) \) is now modified as

\[
\text{dist}(p,q) = \sqrt{\left(\frac{t_p - t_q}{t_{scale}}\right)^2 + \left(\frac{h_p - h_q}{h_{scale}}\right)^2} \frac{1}{a^2 + b^2} \tag{2}
\]

As can be seen in Fig. 3, the search area is modified as an ellipse with centroid \( p \), major axis with length \( 2a \), and minor axis with length \( 2b \), while \( a > b \). Due to the change in search area, points in the horizontal direction have more weight with
respect to the search area center than points in the vertical direction. Therefore, continuous points in a roughly horizontal direction are more likely to be classified as belonging to the cluster. That is also the same as in the detection of ground for MABEL lidar point clouds.

C. Estimation of Clustering Parameters

As the ellipse shape is determined by \( a \) and \( b \) in (2), two parameters are needed for modified DBSCAN implementation: \( \text{MinPts} \) and \( \text{Eps} \). Here, we develop a simple but effective heuristic way to determine the two parameters. For simplicity, \( \text{Eps} = 2 \) is used all the time so that only \( \text{MinPts} \) will be modified. It can be done by estimating the average point density within the search ellipse.

1) A partition of points from the test data set is first extracted. This example covers a flight time of \( \delta t \) and an elevation range of \( \delta h \). The area \( S \) of this sample data set is

\[
S = \delta t \cdot \delta h. \tag{3}
\]

2) For an ellipse with \( \text{dist}(p, q) = \text{Eps} \), its area \( s1 \) is

\[
s1 = \pi \cdot \text{Eps}^2 \cdot \frac{s_{\text{scale}}}{2} \cdot ab \tag{4}
\]

where \( a = 0.5 \) and \( b = 0.2 \). Hence, the number of ellipses within the example data set is roughly estimated as \( S/s1 \).

3) The number of points in the example data set is found to be \( N \). Therefore, the average point density (\( \rho \)) within the search ellipse can be calculated

\[
\rho = \frac{N}{S} \cdot s1. \tag{5}
\]

4) To better estimate \( \rho \), more than one of the example data sets are extracted from the test data set, processed through steps 1) to 3), and then averaged. In the proposed clustering method, the point density for clusters should be higher than the average density of the whole data set. \( \text{MinPts} \) can be empirically estimated as

\[
\text{MinPts} \geq 4 \cdot \rho. \tag{6}
\]

Practically, we can always start with the minimum integer larger than \( 4\rho \) and increase by one gradually. For the simulated photon-counting lidar data sets as in Fig. 1, \( \rho \approx 0.3 \), and \( \text{MinPts} = 4 \) is finally applied. For the MABEL data sets as in Fig. 2, \( \rho \approx 3.7 \), and \( \text{MinPts} = 16 \) is used. This proposed clustering algorithm can be quickly implemented and adaptive to photon-counting lidar data sets with different point densities.

IV. PERFORMANCE AND EVALUATION

Our algorithm is tested using the aforementioned two sets of photon-counting laser altimeter data. In the first principle simulation, parameter \( p \) in the \( 1/f_p \) filter for generating the 3D synthetic surface is 2.0 [15]. The noise rate is set as 2 MHz. As can be seen in Fig. 4, surface returns can be reliably classified as ground returns using the proposed algorithm. A quantitative evaluation on the performance of the proposed method is presented later.

This density-based clustering approach is also tested for the MABEL data set. For the experimental data set, the classification result is shown in Fig. 5, which demonstrates that the proposed algorithm is capable of detecting both canopy and ground surface. The adaptive nature of our proposed algorithm allows it to work on a variety of surfaces and with data from a variety of photon-counting lidars. More classification results using the proposed algorithm for surface detection are presented in another letter [20], where point clouds of photon-counting lidar collected from different scenes and atmospheric conditions are studied.

To quantitatively evaluate the performance of the proposed algorithm, ground truth information is required. From the synthetic terrain, a 2-D profile of illuminated terrain can be directly extracted, which contains ground elevation versus flight distance or time. Note that the laser footprint has a radius of 5 m. Hence, due to the variance of ground within the circular laser footprint, it is hard to designate the returning photon to
a specific location within the illuminated area. A statistical method is then necessary to define a region for accuracy evaluation. Here, an upper/lower boundary along the 2-D ground truth is created with a specific height above/below the terrain profile. The two boundaries enable a window which can be regarded as the criterion of true surface returns. Therefore, each photon is assigned to an elevation with respect to flight distance and can be categorized as surface returns if it is within the contour “window.” A height of 10 cm, which is close to the expected elevation bias standard deviation for ICESat-2, is chosen for performance assessment [15], [16].

In addition, the statistical indicators known as recall and precision are computed. Recall $R$ is the fraction of true signal points that are successfully enclosed within the contour window. Precision $P$ is the fraction of true signal points from all points enclosed within the detected contours. They are defined as follows [21]:

$$R = \frac{TP}{TP + FN} \quad P = \frac{TP}{TP + FP} \quad \text{(7)}$$

where TP, FP, and FN represent the numbers of true positives (hit), false positives (false alarm) and false negatives (miss), respectively. To be more specific, true positives represent points that are enclosed in the contour window being detected as surface returns, and false positives represent points that are not enclosed in the contour window being detected as surface returns. For better estimation, the proposed algorithm is evaluated for five sets of point clouds, each of which was collected by different test tracks (as shown in Fig. 6).

For each track, a statistical indicator is calculated to find TP, FP, and FN, respectively. As can be seen in Fig. 7, the contour window is labeled as a black dashed line. Returns classified as ground and enclosed inside the window are TP (Hit), and those not enclosed inside the window are FP (False Alarm). Meanwhile, classified noise enclosed inside the window is FN (Miss).

In order to use a single performance measure that will allow for comparison of results, the harmonic mean of recall and precision will be used

$$F = \frac{2PR}{P+R} \quad \text{(8)}$$

For all five tracks, the $F$-measure value is calculated, respectively, and then averaged. Thus, uncertainty caused by ground surface variation will be mitigated. The result of $F$-measure versus surface roughness parameter $p$ is shown in Fig. 8. Note that, as $p$ increases, the synthetic terrain becomes less rough [15] and the $F$-measure increases significantly from 0.58 to 0.86. Therefore, the proposed algorithm has better performance on a smoother surface.

In addition, the impact of noise rate is studied. Noise rate varies based on atmospheric and solar conditions: 0.5 MHz simulates nighttime acquisitions, while 2 and 5 MHz represent daytime acquisitions with clear sky and hazy atmosphere, respectively [19]. As we increase the noise rate from 0.5 to 5 MHz, the $F$-measure maintains an average of 0.8 (blue curve in Fig. 9), and the elliptical DBSCAN algorithm is seen to be robust. However, it is shown that lower noise rate will lead to slightly better detection performance.
Meanwhile, the improvement of ground detection accuracy is studied using the proposed elliptical DBSCAN over the conventional circle DBSCAN method. For comparison, all parameters used in the proposed algorithm remain the same for the circle DBSCAN method, except that in (2), in which $a = b = 0.5$ is used to change the search area to a circle. The result of ground detection accuracy using circle DBSCAN is plotted in red color in Fig. 9. With a low noise rate (around 1 MHz), both reach the $F$-measure of around 0.8. As the noise rate increases, the ground detection accuracy is significantly improved while using elliptical DBSCAN method. This quantitative plot also shows that the proposed method using elliptical DBSCAN has better performance despite the solar noise rate. Note that this conclusion works for photon-counting laser altimeter data whose point density of surface returns is higher than the background noise. If the surface return rate is too low to visually distinguish surface returns from noise, it is difficult to achieve good performance of the proposed algorithm.

V. CONCLUSION

In this letter, a density-based algorithm has been proposed for classifying photon-counting lidar point clouds as surface or noise returns. In consideration of finding surface returns more accurately from the lidar point cloud, the area shape of a data point search for its nearest neighbors was modified to be an ellipse to match general characteristics of terrain or vegetation. This adaptive clustering method was then implemented and tested on photon-counting lidar altimetry data. Validation showed that surface and canopy can be expected to be observable using the proposed algorithm during the ICESat-2 mission. Performance measurement demonstrated that this method has better performance for smoother surfaces and lower noise rate conditions.

Future work will consider the following issues. First, in our current work, only objects which have high density in horizontal direction were studied. We will develop a definition to extend the approach for more complicated objects such as steep crevasses in photon-counting point cloud. Second, more realistic lidar data sets will be studied to evaluate the proposed algorithm performance for more complicated terrains and atmospheric conditions. Third, additional tests will be performed to quantify the algorithm performance in detecting both vegetation canopy and ground in dense forests.

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