

CLASSIFICATION OF LIDAR POINT CLOUD AND GENERATION OF DTM FROM LIDAR HEIGHT AND INTENSITY DATA IN FORESTED AREA

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KEYWORDS: LIDAR, Intensity, Skewness, Point Cloud, DTM, Forested Areas.

ABSTRACT:

LIDAR (Light Detection And Ranging) is a mature remote sensing technology which can provide accurate elevation data for both topographic surfaces and above-ground objects. Derivation of accurate digital terrain models is one of its important applications, especially for complex scenes. In recent years, many different approaches have been developed to separate ground points from object points, including mathematical morphology, adaptive and robust filtering, and unsupervised segmentation. Most of these algorithms are based on geometric characteristics of LIDAR points. This paper presents an approach to separate vegetation points from ground points in a mountainous area. The approach is mostly based on skewness change of LIDAR intensity information from both all laser returns. LIDAR data for the study area provided by ISPRS Commission III Working Group 3 are used to test the algorithm. Results show that the method can efficiently separate ground points from above-ground points in a forested area.

1. INTRODUCTION

A LIDAR (Light Detection And Ranging) system includes a Global Positioning System (GPS) and an Inertial Measurement Unit (IMU), which complement the LIDAR data with position and orientation information respectively. This new remote sensing technology is capable of providing both horizontal and vertical information. LIDAR is one of the most promising remote sensing techniques now available and has been applied to 3D building reconstruction, flood modeling, and quantitative retrieval of forest structure parameters. For accurate retrieval of forest structure information from discrete LIDAR data, it is necessary to classify the LIDAR points into ground and object points, a procedure commonly called filtering (Kraus and Pfeifer, 1998). This filtering is an essential step for digital terrain model (DTM) generation because it makes possible the estimation of canopy height.

Many algorithms have been developed for generation of DTMs using LIDAR data. These algorithms can be classed into two categories based on used data type: point clouds and raster range image. The first kind of algorithms is used on point clouds of LIDAR directly. Many studies about it are developed. Kraus and Pfeifer (1998) filter out trees in forested areas by fitting an interpolated surface to the data and using an iterative least-squares algorithm to reduce the contribution of points above the surface. Rottensteiner and Briese (2002) extended this method to filter out buildings as well. Based on connectivity and a principal components analysis, Roggero (2002) clustered points using geometric descriptors such as curvature, data anisotropy, and static moments. With the same goal, Filin (2002) developed a method for clustering data points

into surface categories such as low and high vegetation or smooth and planar surface. Axelsson (2000) separated terrain points from non-terrain points by iterative threshold-dependent densification of a triangulated irregular network (TIN). After Kilian et al. (1996) first used morphological filtering to remove the contribution of non-ground points, different kinds of morphological filtering have been developed for distinguishing terrain from non-terrain points (Vosselman, 2000; Vosselman and Mass, 2001; Zhang et al., 2003; Chen et al., 2007). Vosselman (2000) used the height differences between ground points to determine the optimal filtering function, and Zhang et al. (2003) developed a progressive morphological filter to remove non-ground points by gradually increasing the window size of the filter and using elevation difference thresholds. In the work of Chen et al. (2007) a new morphological filtering approach was presented that did not require the assumption (Zhang et al., 2003) that the slope is constant and methods for filling in missing data and removing outliers were also described. In addition to these methods, other algorithms have been developed in recent years (Elmqvist, 2001; Elmqvist et al., 2001; Akel et al., 2003; Brovelli et al., 2002; Krzystek, 2003). These algorithms work with a raster image, so the irregularly distributed LIDAR point cloud must be gridded and interpolated before post-processing with standard image processing techniques. To decrease interpolation errors, a few researchers have presented other algorithms for processing the LIDAR raw data point cloud to generate a DTM. Roggero (2001) used raw laser range data only to detect terrain, vegetation, and buildings and successfully classified these points, but extraction of the DTM has some errors on steep slopes. In the work of Zakšek and Pfeifer (2006), a morphological filter is used directly for DTM generation from

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the LIDAR point cloud. Bartels et al. (2006) presented a novel unsupervised segmentation algorithm—skewness balancing—to separate object and ground points efficiently from high-resolution LIDAR point cloud.

In addition to LIDAR height information, most discrete LIDAR systems also record the intensity (sometimes referred to as the amplitude) of each received echo. Depending on the wavelength of the used laser some systems operate in the visible domain (e.g. SHOALS). The intensity represents the reflectance characteristics of the surface in the near infrared spectra between wavelengths of 800 nm and 1550 nm. LIDAR intensity is also an important information source which can be exploited in forest characterization, urban delineation, and other applications. Many studies have used LIDAR intensity information to classify forest species (Donoghue et al. 2007; Holmgren and Persson, 2003; Moffiet et al., 2005; Ørka et al., 2007; Schreier, 1985). Height- and age-related differences in intensity correspond to both structural and compositional features of each stand, which has been demonstrated using global and local estimates of spatial autocorrelation derived from LIDAR intensity information (Langford et al., 2006).

The generation of a DTM is often affected by steep terrain, and classification of forest species from intensity information is also affected by the ground intensity. Additionally, the simplicity of the morphologic filter is the reason for its effectiveness in the areas with small elevation differences, but the algorithm is not so successful in areas with steep slopes, especially if very dense vegetation in present (Zakšek and Pfeifer, 2006). For these reasons, a method needs to be developed for separation of ground points and vegetation points from LIDAR raw data points in dense forest areas with steep slopes.

The aim of this study is to present a new method for separation of ground points and above-ground points from LIDAR intensity information in a forested area. This method is based on intensity differences between ground points and vegetation points, and it is especially applicable in steep, wooded areas. First, the theory of the algorithm is introduced, and then its use for discriminating vegetation points from ground points. A DTM can then be generated from the filtered ground points. Based on the generation of the digital elevation model (DEM), a canopy height model (CHM) can be calculated from the digital surface model (DSM) and the DTM.

2. STUDY AREA AND DATA

The LIDAR data used in this paper are free sample data provided by the International Society for Photogrammetry and Remote Sensing (ISPRS) Commission III Working Group 3. The LIDAR data were collected in the second phase of an OEEPE (European Organization for Experimental Photogrammetric Research) project on laser scanning, and their range includes the Vaihingen/Enz test field in southern Germany and the Stuttgart city center. The LIDAR data were extracted from laser scanning data generated using an Optech ALTM1201 laser scanner, FOTONOR AS, and both first and last return pulse data were recorded. The application of the procedure proposed in this paper is illustrated using the Site 5 data set from the ISPRS laser scanning test, which covers a location with high vegetation on a steep hillside. Figure 1 shows an image of the study area and a 3D view of its LIDAR points. The red frame in Fig. 1(a) denotes the selected study area.

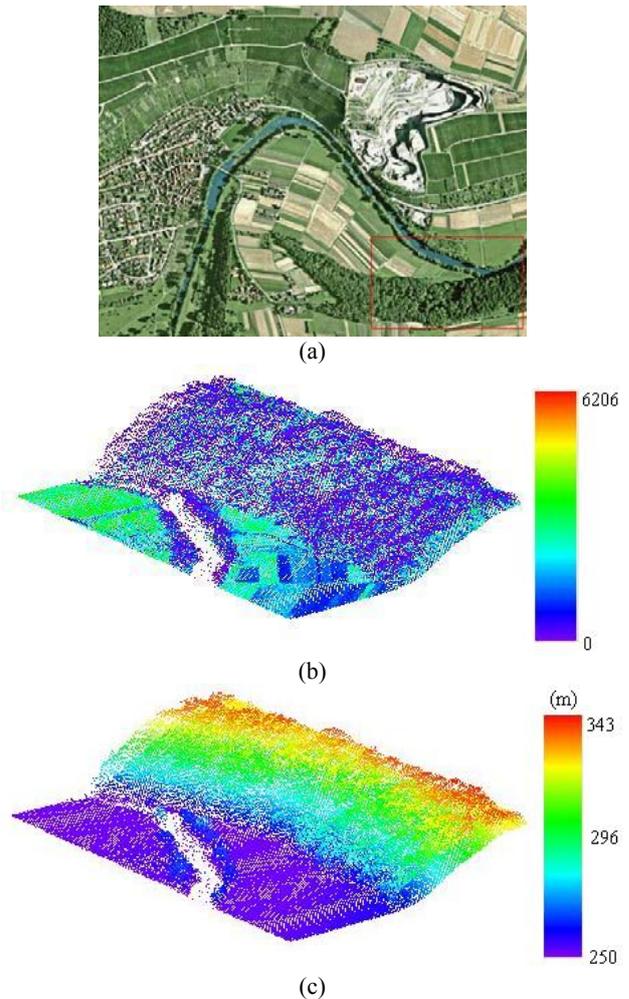


Figure 1. Image and LIDAR data of the selected study area in Forest Site 5 of the ISPRS LIDAR data set: (a) image of study area (from Google Earth); (b) 3D view of LIDAR intensity; (c) 3D view of LIDAR elevation.

3. METHODOLOGY

As mentioned in the introduction, LIDAR data is commonly gridded into a raster image for easier processing. However, due to this mapping of the 3D data onto a 2D raster, details are lost, which is especially disadvantageous for forest applications. To preserve the raw information in LIDAR data, this paper proposes a new method for separating ground points and above-ground points in a mountainous area and generating a DTM and a canopy height model (CHM). The process includes three parts:

1. Introduction to the theory of the algorithm.
2. Use of the method to separate ground points and above-ground points in a mountainous area.
3. Generation of DTM, DSM, and CHM.

3.1 Theory and background

LIDAR intensity is influenced not only by reflectivity, moisture content, roughness, and other target surface properties, but also by the dynamic geometric relationship between sensor and target (Donoghue et al. 2007; Langford et al., 2006). The dynamic sensor-target geometry includes the laser path length,

which varies with the distance between the sensor and target; the orientation of the target relative to the sensor, which varies with the laser scan angle or topography; the footprint size, which varies with laser beam divergence; and the attenuation in the atmosphere (Donoghue et al. 2007). How each of these factors influences LIDAR intensity requires further investigation. The strength of these influences is unknown, but in an experimental situation, the impact of some of these factors may be decreased by making assumptions appropriate to the situation under study; the laser intensity returns is not affected when the scan angle is smaller than 10° (Donoghue et al. 2007). So it may be assumed that the laser beam divergence and attenuation in the atmosphere in a given study area is constant during the same flight and the scan angle has no effects on the laser intensity. In this way, the interpretation of LIDAR intensity can be simplified.

Under the following assumptions (Höfle and Pfeifer, 2007): (1) the entire footprint is reflected onto one surface (the extended target) and the target area A_s is circular, hence defined by the laser beam width β_t and the range R , and (2) the target has a solid angle of π steradians ($\Omega=2*\pi$ for scattering into a half sphere), the received laser power can be expressed in the form (Wagner et al., 2006):

$$P_r = \frac{P_t D_r^2 \rho}{R^4 \beta_t^2 \Omega} \eta_{sys} \eta_{atm} A_s \quad (1)$$

where P_r and P_t are the received and transmitted laser energy respectively, R is the distance between sensor and target, β_t is the laser-beam divergence, D_r is the diameter of the receiver aperture, Ω is the scattering solid angle of the target, ρ is the reflectivity of the target surface, A_s is the target area, and η_{sys} and η_{atm} are the system and atmospheric transmission factor respectively.

Equation (1) represents the area of an extended diffuse target. The areas of non-extended diffuse targets show different range dependencies; for example, point targets (e.g., a leaf) with an area smaller than the footprint are range-independent (Höfle and Pfeifer, 2007). Consequently, the received power reflected from point targets is represented by an inverse higher-order range-dependent function ($1/R^4$):

$$P_r = \frac{P_t D_r^2 \rho dA}{4R^4 \beta_t^2} \eta_{sys} \eta_{atm} \quad (2)$$

where dA is the area of the point target.

Let A_f be the area of the LIDAR footprint at the target elevation. Then the received signal power at the extended target and the point target can respectively be expressed as:

$$P_{extended} = K \frac{\rho}{(4R)^2} \quad (3)$$

$$P_{point} = K \frac{\rho}{(4R)^2} \frac{dA}{A_f} \quad (4)$$

where

$$K = P_t D_r^2 \eta_{sys} \eta_{atm} ,$$

$$A_f = \pi R^2 \beta_t^2 / 4 .$$

LIDAR intensity is the ratio of received to transmitted laser energy (Langford et al., 2006). From Equations (3) and (4), it is apparent that the LIDAR intensity increases with the reflectivity of the target and decreases with the distance between sensor and target. In a forested area, there are differences between vegetation and ground soil in both reflectivity and height. Because the reflectivity of vegetation is higher than that of ground soil at the 1064-nm wavelength and the elevation of vegetation is higher than that of the ground in a small local area, the LIDAR intensity from vegetation should be more than the intensity from ground, other things being equal. However, it can be seen from Fig. 1(b) that the intensity of the vegetation is much less than that of the ground. The reason is that the area of each point target (e.g., a leaf) is much smaller than the footprint area, that is the ratio of dA and A_f is much smaller than 1. Based on equation (3) and (4), the difference between $P_{extended}$ and P_{point} can be thought as large enough to discriminate. With such a theory, it is possible to separate most, if not all, vegetation points from ground points-- especially in conifer forest areas.

3.2 Separation of ground points and above-ground points

In this work, statistical approaches have been used to filter ground points based on intensity relationships in the LIDAR point cloud. Based on the central limit theorem, naturally measured samples will follow a normal distribution. The object points may disturb the normal distribution (Bartels et al., 2006). The skewness and kurtosis of this distribution are two characteristics, used in many statistical analyses, which can be used to describe the distribution of LIDAR points. The algorithm works as follows: first, the skewness and kurtosis of the LIDAR intensity data are calculated. After the peak points are removed, the skewness and kurtosis of the remaining points are calculated again till the last point. Then two change curves are drafted on these skewness and kurtosis values. As shown in Figure 2, the skewness and kurtosis have different changes against vegetation and ground. And seen from these curves, the changes of skewness and kurtosis are based on change of points in the scene. When points in a flat ground scene only have ground points, the change of skewness or kurtosis should be smooth. The last inflexion is often viewed as the true point separating object points from ground points. So the location of A in the skewness curve and location of B in the kurtosis curve should become inflexions between ground points and object points. The ground points and vegetation points in steep mountainous areas are separated based on the principle.

Bartels et al. (2006) used a skewness balancing algorithm to remove object points from ground points and thus obtain a normal distribution. Bao et al. (2007) improved this algorithm to address more complex scenes. In this study, the improved algorithm was used to process the LIDAR intensity and elevation data and to separate vegetation points from ground points. From Figure 1(a), it can be seen that the selected study area includes flat areas with vegetation and steep terrain with vegetation. For the flat area, the skewness algorithm (Bartels et al., 2006; Bao et al., 2007) was used to classify points as ground and non-ground points on the basis of height information. For the steep terrain, the skewness change algorithm was used to

separate ground points from above-ground points based on intensity information.

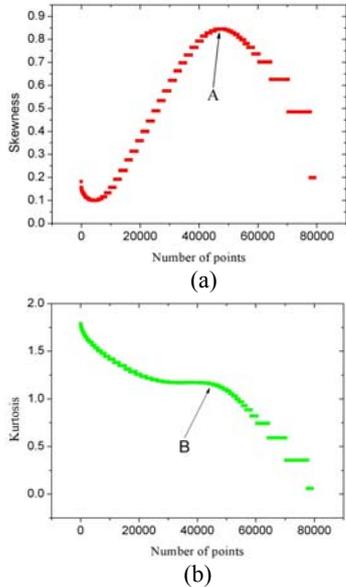


Figure 2. Change curves of Skewness and Kurtosis of LIDAR intensity data (A point on the change curve of Skewness in (a) is the location differencing ground and vegetation points; B point on the change curve of Kurtosis in (b) is the location differencing ground and vegetation points).

3.3 Generation of DTM, DSM, and CHM

A digital terrain model (DTM) can be constructed from the ground points, and a digital surface model (DSM) can be derived from the highest points within a defined grid box (Hollaus et al., 2006). The canopy height model (CHM) can be calculated by subtracting the DTM from the DSM. First a triangulated irregular network (TIN) is constructed for the point cloud, based on a Delaunay triangulation of its elevation data. Then a rectangular grid of pixels is extracted from each TIN using linear interpolation with a constant sampling interval of one meter. Finally, the raster DTM and DSM of one-square-meter spatial resolution are generated. The raster DTM and DSM can be used to generate a grid-based canopy height model with one-square-meter spatial resolution.

4. RESULTS AND DISCUSSION

4.1 Separation of ground points and above-ground points

The Forest Site 5 data set from the ISPRS laser scanning test was used to test the method. Figure 3 illustrates the results obtained. In Figure 3, part (a) shows the LIDAR raw data points, part (b) the filtered ground points, and parts (c) and (d) show the profiles corresponding to the blue lines in (a) and (b) respectively. Comparing the profiles in Figure 3(c) and 3(d), it is clear that vegetation points in the flat area are well distinguished from ground points. In steep terrain, most of the higher vegetation points are separated from ground points, but a few higher vegetation points are still classified as ground, and the classification of low vegetation is not satisfactory. These results show that the proposed method can separate higher vegetation from ground and that few higher vegetation points are falsely classified. For the separated vegetation points, a new

algorithm needs to be developed to retrieve vegetation structural parameters.

4.2 Generation of DTM, DSM, and CHM

Using the method described above, the raster DTM and DSM of one-square-meter spatial resolution are generated. The canopy height model can then be calculated by subtracting the DTM from the DSM. In other words, a grid-based canopy height model with one-square-meter spatial resolution can be generated from the raster DTM and DSM. Figure 4 shows the shaded relief images of DTM, DSM, and CHM. From Figure 4(b), it is apparent that because of low vegetation on steep terrain, the generation of the DTM has been affected. The other algorithm could be integrated to separate low vegetation points.

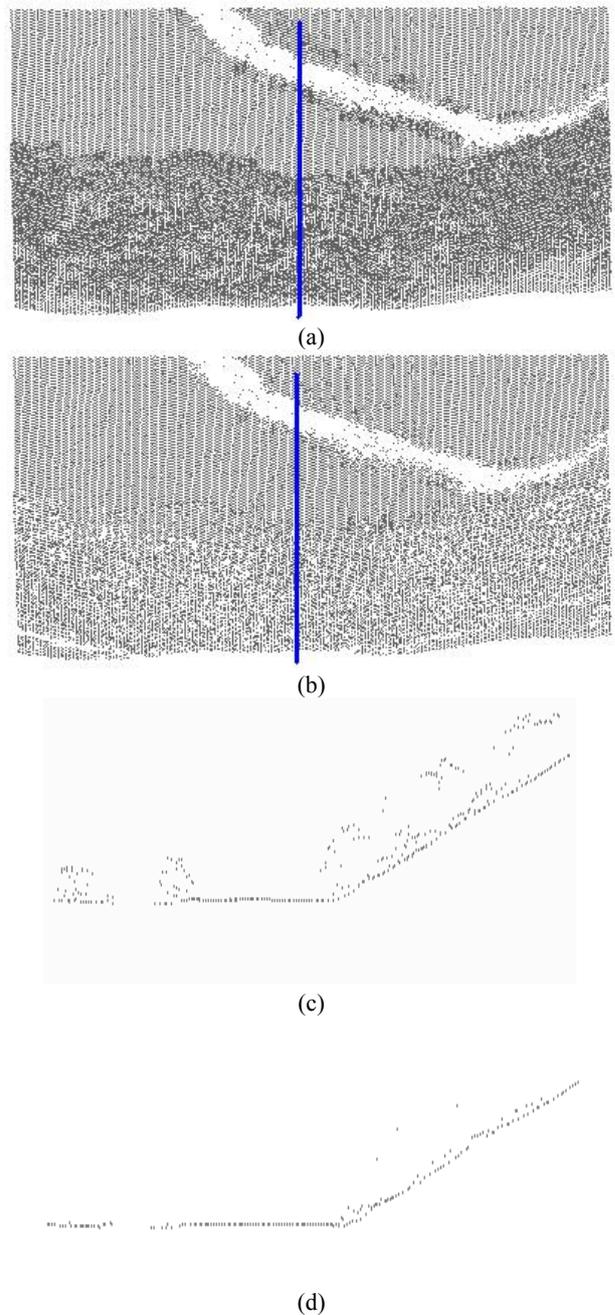


Figure 3. LIDAR point cloud and corresponding profile for each data set: (a) raw data points, (b) separated ground points,

(c) profile corresponding to (a), (d) profile corresponding to (b). The blue lines in (a) and (b) show the direction of the profile.

5. CONCLUSIONS AND FUTURE WORK

Many algorithms have been developed for distinguishing between ground reflections and above-ground points, but a number of these algorithms fail in forested areas with steep terrain or require excessive computation time. This paper presents a statistical algorithm for quick separation of ground and above-ground points in a forested area. This method is based on LIDAR intensity information and on theoretical considerations about the interaction of the laser beam with different targets. Laser interaction with an extended target is different in many ways from interaction with point targets. Because LIDAR intensity also changes with elevation, few vegetation points with higher intensity are classified as ground points, and few ground points are classified as above-ground points. Future work will focus on enhancing precision using both LIDAR intensity and height information. The validation of the canopy height profile will also be done in other study areas using field measurements. In addition, the vegetation points separated from the full set of LIDAR points could be used for further research, such as retrieval of forest structure parameters and classification of forest species.

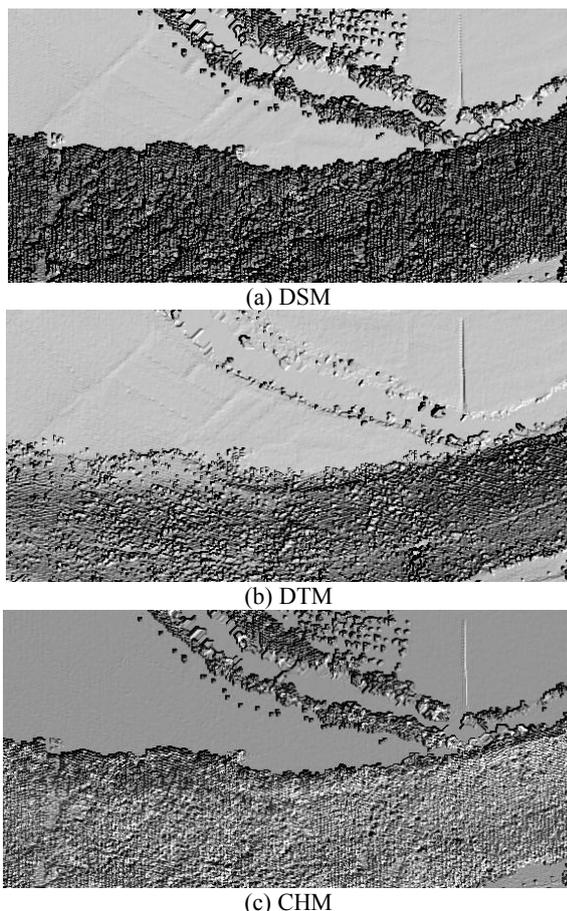


Figure 3. Shaded relief images of DSM, DTM, and CHM.

ACKNOWLEDGEMENTS

This research has been supported by a grant from the Major State Basic Research Development Program of China (973

Program) (NO. 2007CB714400) and State Key Laboratory of Remote Sensing Science, China (NO. 03Q0030449). Thanks also to ISPRS Commission III Working Group 3 for providing the LIDAR data sets. We appreciate the constructive comments of the anonymous reviewers.

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