DTM Generation from LIDAR Data using *Skewness Balancing*

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Abstract

LIght Detection And Ranging (LIDAR) data for terrain and land surveying has contributed to many environmental, engineering and civil applications. However, the analysis of Digital Surface Models (DSMs) from complex LIDAR data is still challenging. Commonly, the first task to investigate LIDAR data point clouds is to separate ground and object points as a preparatory step for further object classification. In this paper, the authors present a novel unsupervised segmentation algorithm - skewness balancing - to separate object and ground points efficiently from high resolution LIDAR point clouds by exploiting statistical moments. The results presented in this paper have shown its robustness and its potential for commercial applications.

1. Introduction

In the past decade, LIght Detection And Ranging (LIDAR) has been recognised both by the commercial and public sector as a reliable and accurate technique for land surveying [1]. It contributes to applications such as forestry, 3D building reconstruction, flood modelling and corridor mapping. Mounted on an airborne platform, a LIDAR data acquisition system estimates the distance between the instrument and a point on the surface by measuring the time the laser pulse needs to hit its receiver [2]. A Global Positioning System (GPS) receiver and an Inertial Navigation System (INS) complement the data with position and orientation components, respectively [2].

Often, the very first task is to separate ground and objects from a Digital Surface Model (DSM) generated from LIDAR data. This process yields the generation of a Digital Terrain Model (DTM) and a normalised DSM (nDSM) which are complementary to the DSM as described by Elberink *et al.* [3]. To generate the DTM prior to further segmentation is still a challenge as pointed out recently by Vu *et al.* [4]. Weidner and Förstner [5] separated ground and object points in estimating an nDSM by subtracting a morphologically filtered DSM from the original data. Maas *et al.* [6] developed an approach to model buildings from LIDAR data in a relatively flat area. Brenner and Haala *et al.* [7, 8] presented realistic 3D city models from LIDAR data by reconstructing buildings, facades and vegetation using multiple data sources. Vosselman [9] assumed that buildings consist of planar faces which can be recognised by applying the Hough transform. Vosselman's slope based algorithm [10] employed morphological filtering and has been further improved by Sithole's adaptive terrain slope algorithm [11]. Cobby *et al.* [12, 13] segmented rural area from the LIDAR point cloud and classified different types of vegetation. The authors first separated the slightly hilly terrain from the objects using detrending [14]. The obtained bilinear interpolated surface formed a DTM which was then used for a hydraulic flood model [15]. A noise robust texture-based segmentation approach using wavelet packets, co-occurrence matrices and normalised modified histogram thresholding has been proposed by Bartels *et al.* [16] who partitioned ground and objects into rivers, fields and residential areas.

This paper is concerned with the separation of ground and object points from LIDAR data. Ground points include the top layer soil, thin man-made layering such as asphalt, defined as *bare earth* by Sithole *et al.* [17]. At this stage, grass and low vegetation are considered as ground points, too. Object points comprise *detached objects* (buildings, trees and bushes) and *attached objects* (bridges and ramps) [17]. The paper is organised as follows: In Section 2, the theoretical background and approach of the unsupervised segmentation algorithm is derived. Section 3 presents and discusses results on high resolution LIDAR data. The paper concludes and proposes future avenues in Section 4.

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2. Segmentation Methodology

2.1. Background

The *central limit theorem* as described by Duda *et al.* [18] states that naturally measured samples will lead to a normal distribution. Thus, the initial assumption is that object points may disturb the normal distribution, and by removing those from the raw point cloud, ground points are obtained. To underpin these assumptions, meaningful measures are required to describe the point cloud distribution properly.

An important measure of asymmetry of a distribution in a sample is the third moment about the mean [19], often referred as the skewness as defined by Davies *et al.* [20] as

$$sk = \frac{1}{N \cdot \sigma^3} \cdot \sum_{i=1}^{N} (s_i - \mu_a)^3 \tag{1}$$

where N is the total number of the LIDAR points s_i with $i \in \{1, 2, \ldots, N\}$, σ the standard deviation and μ_a the arithmetic mean as defined in Equation (2) and Equation (3), respectively:

$$\sigma = \sqrt{\frac{1}{N-1} \cdot \sum_{i=1}^{N} \left(s_i - \mu_a\right)^2} \tag{2}$$

$$\mu_a = \frac{1}{N} \cdot \sum_{i=1}^{N} s_i \tag{3}$$

The fourth moment [19] is a measure of the size of a distribution's tail and is also called the kurtosis ku. It represents the degree of dominance of peaks in a distribution and is defined as [20]

$$ku = \frac{1}{N \cdot \sigma^4} \cdot \sum_{i=1}^{N} (s_i - \mu_a)^4 \tag{4}$$

As listed in Table 1, for a normal distribution, ku is three and sk is zero; if peaks dominate a sample, ku is greater than three and sk is greater than zero; if a sample is characterised by valleys, ku is less than three and sk is less than zero [20].

Table 1. Measures of distribution

Characteristic of distribution	Dominance of peaks	Dominance of valleys	Normal distribution
Skewness	$sk > 0$	$sk < 0$	$sk = 0$
Kurtosis	$ku > 3$	$ku < 3$	$ku = 3$

2.2. Skewness Balancing

The proposed algorithm works on balancing the distribution of points in LIDAR data. The statistical measures of distribution are independent from the relative position of the points, thus they do not have to be regularly arranged in a DSM. Therefore, the proposed technique works on both gridded data and point clouds. As kurtosis and skewness both express the characteristics of the point cloud distribution, they can equally be treated as termination criteria in a segmentation algorithm. In this unsupervised segmentation algorithm, skewness is chosen as a measure to describe the point cloud distribution.

The segmentation algorithm is therefore called *skewness balancing* as listed in Algorithm 1 and works as follows: First, the skewness of the point cloud is calculated. If it is greater than zero, peaks dominate the point cloud distribution as demonstrated in Table 1. In this case, the highest value of the point cloud is removed by classifying it as an object point. To separate all ground and object points, these steps are iteratively executed while the skewness of the point cloud is greater than zero. Finally, the remaining points in the point cloud belong to the ground.

Algorithm 1 Skewness Balancing

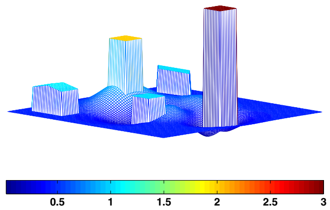
```
Load LIDAR point cloud
while Skewness of LIDAR point cloud > 0 do
  Classify maximum value as object point
end while
Save ground and object points
```

After having separated ground and object points from the LIDAR data point cloud, an nDSM from the DSM, *i.e.* the original data, and the DTM as described by Elberink *et al.* [3] is estimated using Equation (5)

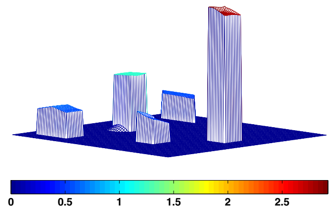
$$nDSM = DSM - DTM \tag{5}$$

3. Results and Discussion

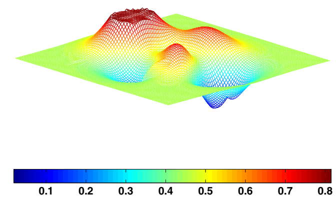
Before investigation on real LIDAR data, the *skewness balancing* algorithm is applied to a set of artificial data in Figure 1. The model represents hilly terrain and building blocks of different height, orientation and roof slope as depicted in Figure 1(a). Having applied the *skewness balancing* algorithm, ground points are separated from object points and form a DTM as shown in Figure 1(c). Using Equation (5), an nDSM is calculated. Empty spaces such as successfully filtered objects are neighbourhood interpolated to approach the terrain as close as possible.



(a) DSM



(b) nDSM

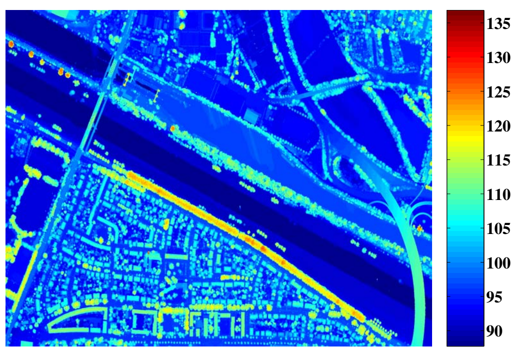


(c) DTM

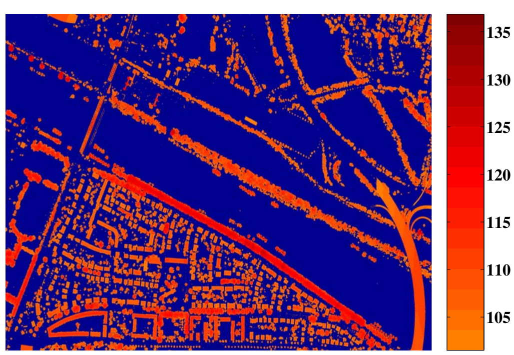
Figure 1. Ground and object separation using *skewness balancing*

The *skewness balancing* algorithm is applied to two LIDAR point clouds, gridded for visualisation in Figures 2 and 3, respectively. The DSMs were recorded with the TopoSys Falcon II LIDAR system in 2004 and were kindly provided by TopoSys GmbH, Germany, by courtesy of the Stadt Mannheim, Germany, the copyright holder ©.

The LIDAR data tile in Figure 2(a) shows a first echo DSM of Oststadt in Mannheim, Germany, generated from $5,730,946$ measured valid points. This DSM represents a challenging urban area with mixed detached objects (buildings and vegetation of different height), various attached objects (bridges and motorway junctions) and a river.

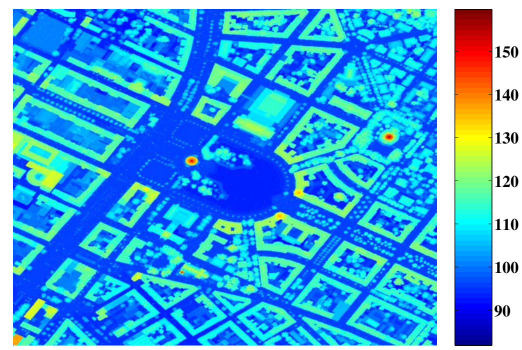


(a) DSM ($87.72m$ - $136.85m$)

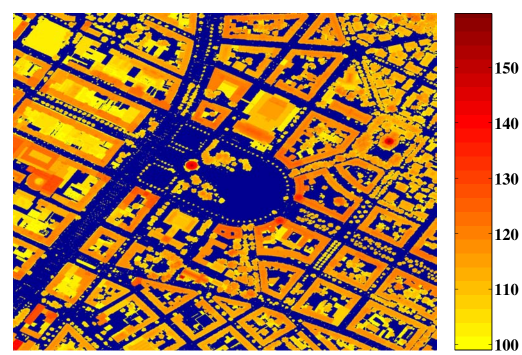


(b) Object points ($101.51m$ - $136.85m$)

Figure 2. Object segmentation from LIDAR data of Neuostheim in Mannheim, Germany



(a) DSM ($81.83m$ - $159.71m$)



(b) Object points ($99.03m$ - $159.71m$)

Figure 3. Object segmentation from LIDAR data of Oststadt in Mannheim, Germany

As depicted in Figure 2(b), detached objects were clearly detected, however, a few attached objects not, due to the complex scene. The first echo DSM of parts of Neuostheim, Mannheim in Germany, in Figure 3(a) is constructed from $2,748,790$ LIDAR points. It shows a highly dense urban area with mostly detached objects, both with buildings and vegetation of various height. Nearly all detached object points are correctly classified and removed from the ground as shown in Figure 3(b).

The *skewness balancing* algorithm for all tiles is validated using ground truth produced from simultaneously recorded aerial and near infra-red (NIR) photos which were kindly provided by TopoSys GmbH, Germany, by courtesy of the Stadt Mannheim, Germany. As both tiles in Figures 2 and 3 cover an area of $1.510km^2$ and $0.688km^2$, respectively, an area of $0.019km^2$ is chosen for accuracy assessment. For this area, the overall accuracy is about 95.65% and a kappa of approximately 91.27% is achieved.

4. Conclusions and Future Work

In this paper, a robust unsupervised segmentation algorithm called *skewness balancing* for object and ground point separation from first echo LIDAR data is presented. Working on the original, ungridded point clouds, statistical moments have been used to characterise the point cloud distribution. The results presented in this paper have shown a clear separation of detached and most of the attached objects from the ground. The *skewness balancing* algorithm therefore has potential for commercial applications as it is efficient and straightforward for implementation.

For future work, the *skewness balancing* algorithm will be extended to even more complex scenes in order to make it robust against very sloped areas. The issue of detecting all attached objects will be addressed, too. It is also planned for further research to classify the detected object points into finer categories. A data fusion approach with features derived from different bands such as near infra-red (NIR), aerial (RGB), first and last echo and intensity data will be taken into account.

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References

[1] H.-G. Maas. Akquisition von 3D-GIS Daten durch Flugzeuglaserscanning. *Kartographische Nachrichten*, 55(1):3–11, 2005.

[2] E. J. Huising and L. M. Gomes Pereira. Errors and accuracy estimates of laser data acquired by various laser scanning systems for topographic applications. *ISPRS Journal of Photogrammetry & Remote Sensing*, 53:245–261, 1998.

[3] S. Oude Elberink and H.-G. Maas. The use of anisotropic height texture measures for the segmentation of laserscanner data. *International Archives of Photogrammetry and Remote Sensing*, B3:678–684, 2000.

[4] T. T. Vu, M. Tokunaga, and F. Yamazaki. LiDAR signatures to update japanese building inventory database. *25th Asian Conference on Remote Sensing*, 2004.

[5] U. Weidner and W. Förstner. Towards automatic building extraction from high resolution digital elevation models. *ISPRS Journal of Photogrammetry & Remote Sensing*, 50(4):38 – 49, 1995.

[6] H.-G. Maas and G. Vosselman. Two algorithms for extracting building models from raw laser altimetry data. *ISPRS Journal of Photogrammetry & Remote Sensing*, 54:153–163, 1999.

[7] N. Haala and C. Brenner. Fast production of virtual reality city models. *International Archives of Photogrammetry and Remote Sensing*, 32(4):77–84, 1998.

[8] N. Haala and C. Brenner. Generation of 3D city models from airborne laser scanning data. *EARSEL Workshop on LIDAR remote sensing of land and sea*, pages 105–112, 1997.

[9] G. Vosselman. Building reconstruction using planar faces in very high density height data. *International Archives of Photogrammetry and Remote Sensing*, 32(3/2W5):87 – 92, 1999.

[10] G. Vosselman. Slope based filtering of laser altimetry data. *International Archives of Photogrammetry and Remote Sensing*, 33(B3/2):935 – 942, 2000.

[11] G. Sithole. Filtering of laser altimetry data using a slope adaptive filter. *International Archives of Photogrammetry and Remote Sensing*, 34(3/W4):203 – 210, 2001.

[12] D. M. Cobby, D. C. Mason, and I. J. Davenport. Image processing of airborne scanning laser altimetry data for improved river flood modelling. *ISPRS Journal of Photogrammetry & Remote Sensing*, 56:121–138, 2001.

[13] D. M. Cobby. *The use of airborne scanning laser altimetry for improved river flood prediction*. PhD thesis, University of Reading, 2002.

[14] I. J. Davenport, R. B. Bradbury, G. Q. A. Anderson, G. R. F. Hayman, J. R. Krebs, D. C. Mason, J. D. Wilson, and N. J. Veck. Improving bird population models using airborne remote sensing. *International Journal of Remote Sensing*, 21(13 & 14):2705–2717, 2000.

[15] D. M. Cobby, D. C. Mason, M. S. Horritt, and P. D. Bates. Two-dimensional hydraulic flood modelling using a finite-element mesh decomposed according to vegetation and topographic features derived from airborne scanning laser altimetry. *Hydrological Processes*, 17(10):1979 – 2000, 2002.

[16] M. Bartels, H. Wei, and D. C. Mason. Wavelet packets and co-occurrence matrices for texture-based image segmentation. *IEEE International Conference on Advanced Video and Signal-Based Surveillance*, 1:428–433, 2005.

[17] G. Sithole and G. Vosselman. Automatic structure detection in a point cloud of an urban landscape. *Proceedings of 2nd Joint Workshop on Remote Sensing and Data Fusion over Urban Areas (Urban 2003)*, pages 67–71, 2003.

[18] R. O. Duda, P. E. Hart, and D. G. Stork. *Pattern classification*. New York: Wiley, 2001.

[19] F. N. David. *A statistical primer*. London: Griffin, 1953.

[20] O. L. Davies and P. L. Goldsmith. *Statistical methods in research and production, with special reference to the chemical industry, 4th rev. ed.* London: Longman, 1984.