SEGMENTATION OF LIDAR DATA USING MEASURES OF DISTRIBUTION

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ABSTRACT:

In the past decade, LIght Detection And Ranging (LIDAR) has been recognised by both the commercial and public sector as a reliable and accurate technique for land surveying. 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 an unsupervised *skewness balancing* segmentation algorithm to separate object and ground points efficiently from high resolution LIDAR point clouds by exploiting measures of distribution. The results presented in this paper have shown that the proposed algorithm is robust and has potential for commercial applications.

1 INTRODUCTION

LIght Detecting And Ranging (LIDAR) for terrain and land surveying has made significant contributions to many environmental, engineering and civil applications. It is therefore not surprising that LIDAR data is being used more and more by the public sector and commercial world since the early 1990s (Maas, 2005). Applications such as forestry, building reconstruction, flood modelling and corridor mapping are based on post processing of LIDAR data point clouds as they are accurate for less hilly terrain (Huising and Pereira, 1998). Often, the very first task is to separate ground and objects from a Digital Surface Model (DSM). This process often yields the generation of a Digital Terrain Model (DTM) and a normalised DSM (nDSM) which are complementary to the DSM (Elberink and Maas, 2000). As pointed out recently, DTM generation prior to further segmentation is still a challenge (Vu et al., 2004).

In one of the early investigations (Weidner and Förstner, 1995), ground and object points were separated in estimating an nDSM by subtracting a morphologically filtered DSM from the original data. Buildings were then extracted using parametric and prismatic models based on the minimum description length (MDL) principle (Weidner, 1996; Weidner, 1997). An approach to model buildings from LIDAR data in a less sloped area was developed by (Maas and Vosselman, 1999) and was sub-divided into two parts: texture based segmentation as proposed in (Maas, 1999b; Maas, 1999c) and the actual building modelling from the point cloud (Maas, 1999a). Realistic 3D city models from LIDAR data were presented (Haala and Brenner, 1997; Haala and Brenner, 1998) by reconstructing buildings, facades and vegetation using multiple data sources, such as colour infra-red (CIR) and terrestrially captured digital images (Haala et al., 1998b). The building ground planes were estimated with a 2D Geographical Information System (GIS) map complemented with a cadastral map. Geometric primitives were estimated based on histogram analysis of surface normals (Haala and Brenner, 1997; Haala et al., 1998a). Vosselman assumed that buildings consist of planar faces which can be recognised by applying the Hough transform (Vosselman, 1999). The slope based algorithm (Vosselman, 2000) employed morphological filtering and has been further improved in (Sithole, 2001) with an adaptive terrain slope algorithm. Working with ungridded LIDAR data, ground points were estimated with the maximum height difference between two points in (Roggero, 2001). The author then classified objects into buildings and vegetation using a Laplacian of Gaussian (LoG). A DTM using convex-concave hulls was generated in (Vögtle and Steinle, 2003). In order to classify objects with fuzzy logic, an nDSM from the difference of the DSM and the generated DTM was calculated. A DTM was also first identified using active shape models before object points are further classified using slope and second derivative with a Maximum Likelihood classifier (Elmqvist et al., 2001). A grid based DTM generation approach has been developed in (Wack and Wimmer, 2002) who found ground points by estimating gradients and the objects via LoG. A DTM was generated in a first step by finding ground points using active contours (Ahlberg et al., 2004). In the second step, the authors estimated high buildings and high vegetation $2m$ above the ground by exploiting multiple returns of LIDAR data. A hierarchical rule-based filtering has been presented in (Nardinocchi et al., 2003). Gridded data was processed using region growing to find connected discontinuities for estimating ground, buildings and vegetation. Building reconstruction fusing LIDAR data and aerial images was presented in (Rottensteiner and Briese, 2003). First, the authors detected building regions in ungridded data. Then, roofs were detected using a curvature-based segmentation technique and additional planar faces were estimated with aerial images. For flood modelling, rural area was segmented from LIDAR point clouds and vegetation was classified into three height classes (Cobby et al., 2001; Cobby, 2002). The authors first separated the slightly hilly terrain from the objects using detrending (Davenport et al., 2000). The obtained bilinear interpolated surface formed a DTM for a hydraulic flood model (Cobby et al., 2002). For measuring the height of forest canopies, LIDAR data are superior than aerial photos (St-Onge and Achaichia, 2001). Vegetation height can be estimated by taking the difference between first echo (canopy) and last echo (ground) into account (Maas, 2005; St-Onge and Achaichia, 2001; Kraus and Pfeifer, 1998). A wavelet approach to separate ground and object points on gridded LIDAR data has been proposed by (Vu and Tokunaga, 2001). The authors used Kmeans on height to assign pixels to buildings, motorway, boundary and two tree types. A noise robust texture-based segmentation approach using wavelet packets, co-occurrence matrices and normalised modified histogram thresholding has been proposed in (Bartels et al., 2005) who partitioned ground and objects into rivers, fields and residential areas.

To summarise, most authors first separate ground and object points in LIDAR data before further post-processing. This paper addresses this task according to the following definitions. Ground points include the top layer soil, thin man-made layering such as asphalt or tarmac as defined as *bare earth* in (Sithole and Vosselman, 2003). At this stage, grass and low vegetation are also considered as ground points. Object points including *detached objects* (buildings, trees and bushes) and *attached objects* (bridges and ramps) as described in (Sithole and Vosselman, 2003) are segmented, too. The paper is organised as follows: In Section 2, the theoretical background and approach of the unsupervised segmentation algorithm is derived. Section 3 presents results on real data and discusses them. The paper concludes and gives possible future avenues in Section 4.

2 SEGMENTATION ALGORITHM

2.1 Theoretical Background

Naturally measured samples will lead to a normal distribution due to the *central limit theorem* (Duda et al., 2001). Assumption is also made that object points may disturb the normal distribution, and by removing those from the raw point cloud, normal distributed ground points are obtained. Thus, the principle of this segmentation algorithm using measures of distribution is the successive removal of those object points from the point cloud until a normal distribution is achieved. For this, meaningful measures are required to describe the point cloud distribution sufficiently.

An important measure of asymmetry of a distribution in a sample is the skewness sk (Davies and Goldsmith, 1984), often referred as the third moment about the mean (David, 1953).

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

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 Equations (2) and (3), respectively:

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

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

Another measure of distribution is the kurtosis ku (Davies and Goldsmith, 1984), also called the fourth moment (David, 1953). It is a measure of the size of a distribution's tail and is a degree of the dominance of peaks in a distribution.

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

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

Table 1: Measures of distribution of different characteristics

Table 1 lists skewness and kurtosis of different distribution's characteristics. 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 (Davies and Goldsmith, 1984).

2.2 Proposed Algorithm

The proposed algorithm works on balancing the distribution of points in LIDAR data. Statistical measures of distribution are independent from the relative position of the points. That is why 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. Thus, this algorithm is called *skewness balancing* as shown in Figure 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 shown in Table 1. Thus, 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. The remaining points in the point cloud finally belong to the ground.

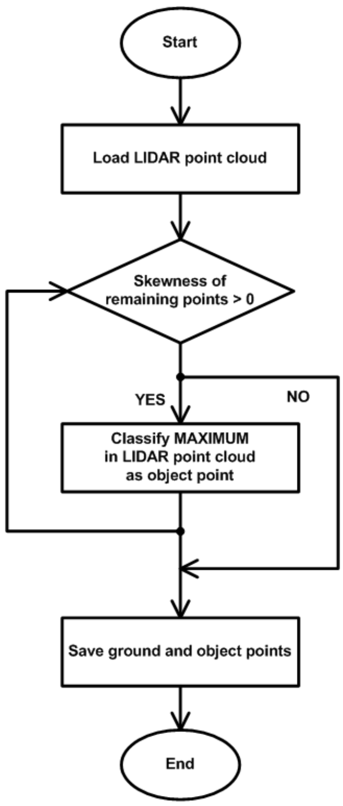
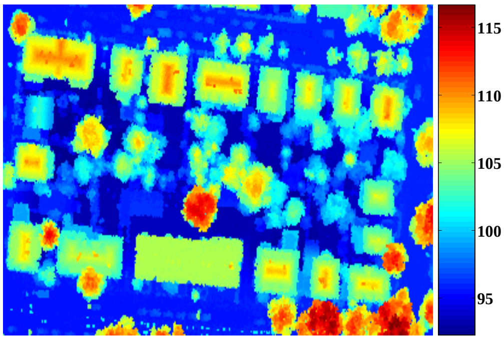


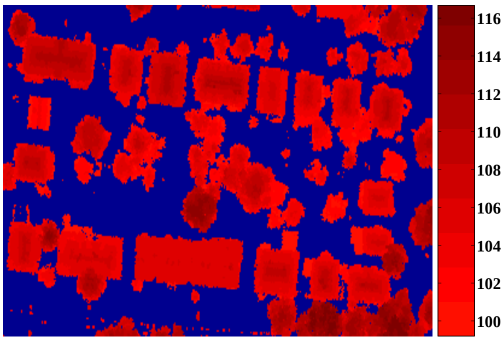
Figure 1: Proposed *skewness balancing* algorithm for object and ground point separation from LIDAR point clouds

3 RESULTS AND DISCUSSION

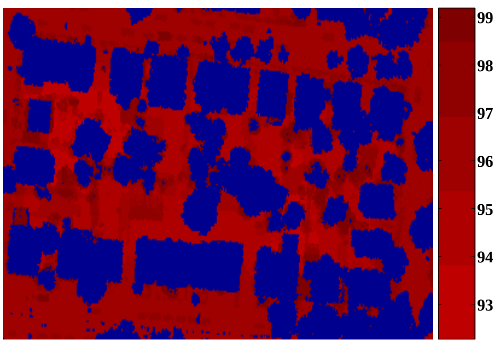
The test results, gridded for visualisation purposes only, are depicted in Figure 2 with height bars measured in metres. Figure 2(a) shows a part of a first echo DSM of Neuostheim in Mannheim, Germany, representing an urban area with both buildings and vegetation of different height. This LIDAR data tile consists of $75,051$ measured points and is part of the DSMs recorded with the TopoSys Falcon II LIDAR system in 2004. The data were kindly provided by TopoSys GmbH, Germany, by courtesy of the Stadt Mannheim, Germany, the copyright holder ©. As depicted in Figures 2(b) and 2(c), respectively, object and ground points have been successfully separated using the *skewness balancing* algorithm as illustrated in Figure 1.



(a) DSM ($92.27m$ - $116.67m$)



(b) Object points ($99.20m$ - $116.67m$)



(c) Ground points ($92.27m$ - $99.19m$)

Figure 2: Ground and object separation using *skewness balancing*

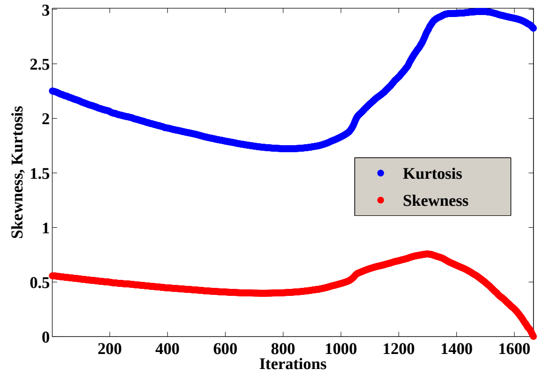


Figure 3: Skewness and kurtosis vs. iterations

As shown in Figure 3, the skewness converges to zero after 1665 iterations and by then, as expected, the kurtosis to about three. Noteworthy also is the histogram of the LIDAR data tile in Figure 4 showing both classified ground (blue) and object (red) points. One can easily imagine that finding a height threshold directly from the non-parametric histogram would not have been straightforward for the purpose of ground and object separation. However, applying the *skewness balancing* algorithm, the boundary between object and ground points is found.

The *skewness balancing* algorithm is applied to two further point clouds gridded for visualisation. The LIDAR data tile in Figure 5(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. As depicted in Figures 5(b) and 5(c), respectively, detached objects were clearly detected, however, a few of the attached objects were not due to the complex scene. The first echo DSM of parts of Neuostheim, Mannheim in Germany, in Figure 6(a) is constructed from $2,748,790$ LIDAR points. It shows a highly dense urban area with mostly detached objects, both with building and vegetation of various height. Nearly all detached object points are correctly classified and removed from the ground as shown in Figures 6(b) and 6(c), respectively.

The segmentation results of the *skewness balancing* algorithm were validated with simultaneously recorded aerial and colour infra-red photos which were kindly provided by TopoSys GmbH, Germany, by courtesy of the Stadt Mannheim, Germany.

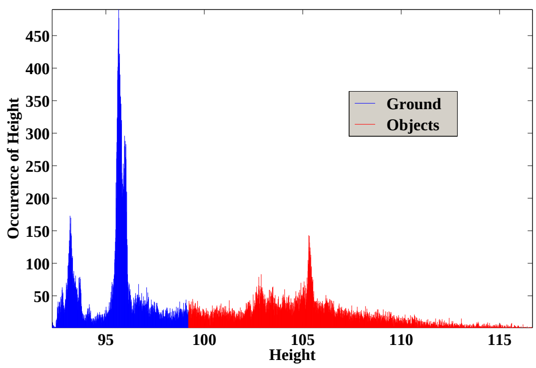
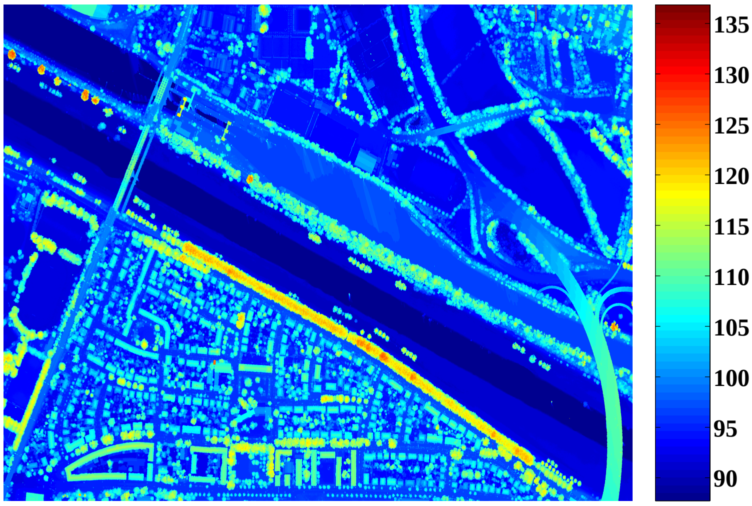
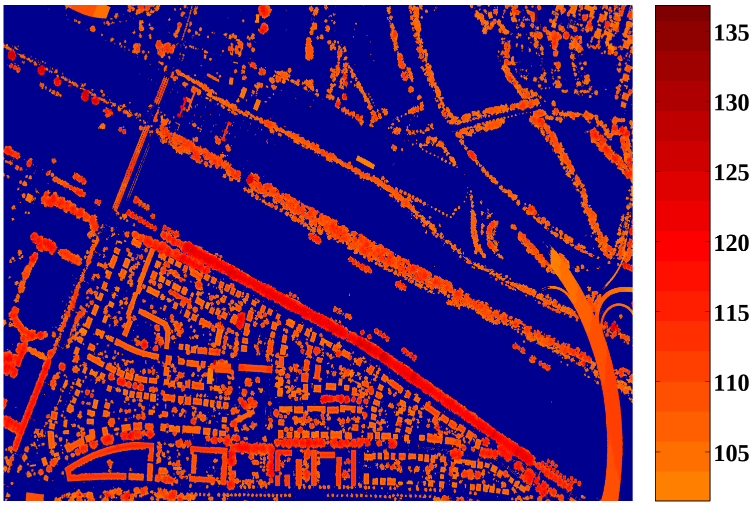


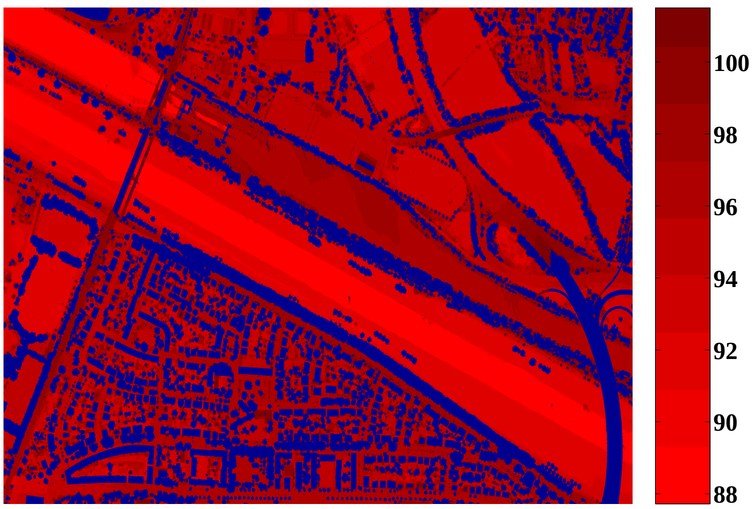
Figure 4: Histogram of classified points



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

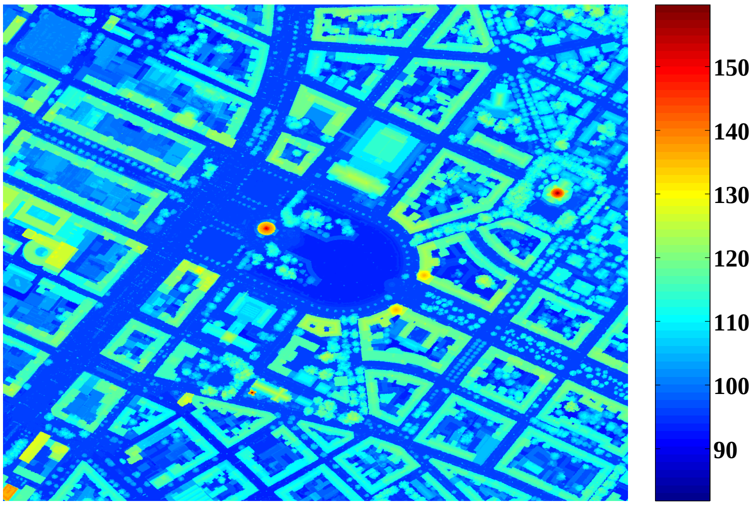


(b) Object points ($101.51m$ - $136.85m$)

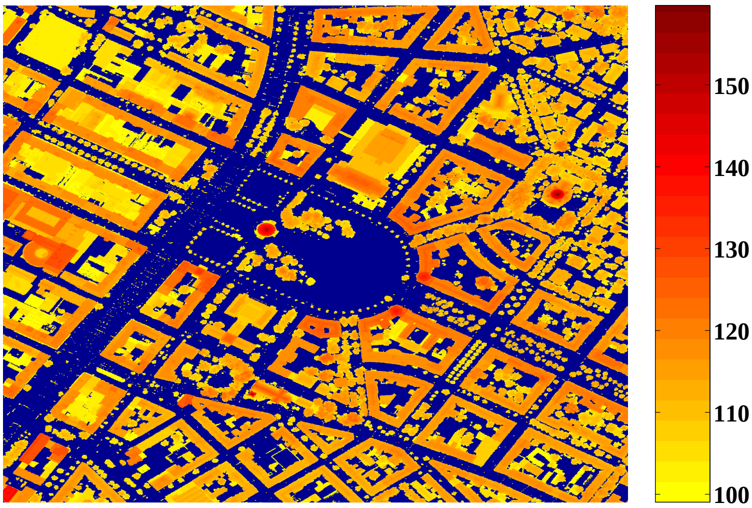


(c) Ground points ($87.72m$ - $101.50m$)

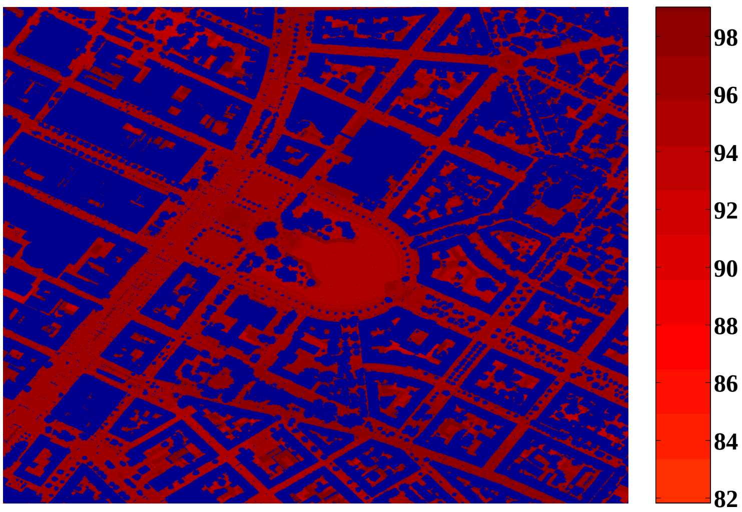
Figure 5: Separation of ground and object points from DSM of Neuostheim in Mannheim, Germany



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



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



(c) Ground points ($81.83m$ - $99.02m$)

Figure 6: Separation of ground and object points from DSM of Oststadt in Mannheim, Germany

4 CONCLUSIONS AND FUTURE WORK

In this paper, a robust *skewness balancing* algorithm for object and ground point separation from first echo LIDAR data in less hilly terrain is presented. Working on the original, ungridded point cloud, measures of distribution have been used to characterise the point cloud distribution and subsequently to filter it. 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 to implement.

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 further features derived from different bands such as first and last echo LIDAR, intensity data, aerial and colour infra-red photos will be taken into account.

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