Towards DTM Generation from LIDAR Data in Hilly Terrain using Wavelets

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Abstract

LIght Detection And Ranging (LIDAR) 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 especially for highly sloped landscapes. 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 aiming at the generation of Digital Terrain Models (DTMs). In this paper, object and ground separation in hilly terrain from LIDAR point clouds is addressed by employing wavelets. The results show its potential for terrain feature extraction from LIDAR data as input for further classifiers.

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]. 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, respectively [2]. The irregularly distributed LIDAR point cloud is often gridded and interpolated prior to post-processing with standard image processing techniques.

LIDAR data filtering algorithms have been developed mostly for local and less sloped areas. Only a few authors have addressed the problem of hilly terrain. Weidner and Förstner [3] separated ground and object points in estimating a normalised Digital Surface Model (nDSM) by subtracting a morphologically filtered DTM from the original DSM. Maas *et al.* [4] modelled buildings from LIDAR data in a less sloped area. For hilly terrain, Maas [5] suggested to apply a filter bank to the interpolated data. Vosselman's slope based algorithm [6] employed morphological filtering and has been further improved by Sithole's adaptive terrain slope algorithm [7]. Cobby *et al.* [8, 9] segmented rural area from a LIDAR point cloud and classified vegetation. The authors first separated the slightly hilly terrain from the objects using detrending [10] to obtain a bilinear interpolated DTM for a hydraulic flood model [11].

Wavelets have been used successfully in the development of the lossless image compression standard JPEG 2000 [12], the fingerprint database of the United States FBI [13], denoising signals [14] and the detection of singularities [15]. A wavelet approach to separate ground and object points in gridded LIDAR data was proposed by Vu *et al.* [16]. K-means were employed on height to assign pixels to buildings, motorway, boundaries and two types of trees. A further multi resolution algorithm was demonstrated by Vu *et al.* [17, 18, 19, 20] which compared succeeding median filtered resolutions of gridded LIDAR data to detect boundaries. The approximation of wavelet decomposition and the actual height were used as features for segmentation. Bartels *et al.* [21] proposed a noise robust texture-based segmentation approach for hilly LIDAR data using wavelet packets, co-occurrence matrices and normalised modified histogram thresholding.

In this paper, the separation of ground and object points on gridded LIDAR data in hilly terrain using wavelets is addressed. The LIDAR community defines the top layer soil, thin man-made layering such as asphalt as *bare earth*, appearing as ground points [22]. At this stage, grass is considered as *bare earth*, too. Object points comprise *detached objects* (buildings, trees and bushes) and *attached objects* (bridges and ramps) [22]. The paper is organised as follows: in Section 2, the background and approach of feature extraction using wavelets is derived. Section 3 presents results on LIDAR data and discusses the observations. The paper concludes and proposes future avenues in Section 4.

2. Segmentation

2.1. Background

In order to partition LIDAR data into objects and ground, setting a global height threshold is not always feasible. Houses could reside in valleys or on hills, while inland waters could be located on higher levels (plateaux), too, as discussed in our previous work [21]. The problem is that there are not only local differences in elevation (*e.g.* fields to scrub land or streets to houses) but also global altitude differences (*e.g.* valleys to hills). In order to remove the undesired global slope, wavelets are applied to separate global *and* local gradients of height. This effect is achieved by examining the image at multiple resolutions as worked out by Mallat [23]. Applied to LIDAR data, wavelets separate low and high frequencies, *i.e.* hilly terrain and objects.

2.2. Feature Extraction

Feature extraction of LIDAR data by using wavelets in this paper is based on the decomposition of the image in order to detect salient changes in height. In the context of airborne scanned laser data, a filter response represents a discontinuity caused by an object whereas the underlying ground or flat areas such as plateaux do not response. By employing feature extraction using wavelets as listed in Algorithm 1, low frequencies such as hills or so-called first order slopes [10] are separated from the high frequency components which represent objects.

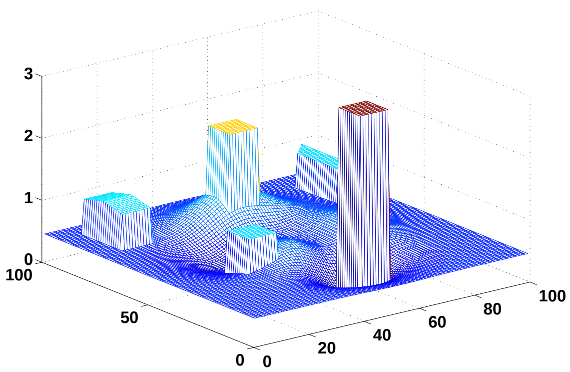
Algorithm 1 Feature Extraction

Load LIDAR data point cloud C
Grid C into matrix M
Decompose M: $[cA, cH, cV, cD] \leftarrow dwt(M)$
$cA \leftarrow 0$
Obtain feature matrix: $M_f \leftarrow |idwt(cA, cH, cV, cD)|$

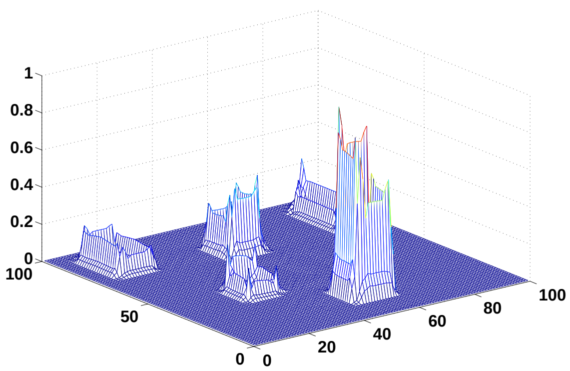
The LIDAR point cloud is first regularly gridded as provided by the data supplier, the Environment Agency, UK. The resulting matrix is then decomposed using the Discrete Wavelet Transform (DWT) [24] into low frequencies (approximations, denoted as cA) and high frequencies (horizontal cH, vertical cV and diagonal cD details). The energy is evenly distributed among sub-images and therefore, the amplitudes of sub-images becomes lower [21]. Furthermore, by analysing the LIDAR data sub-image's energy and entropy of wavelet packets it can be shown that a decomposition of LIDAR data using wavelet packets is meaningful up to level 2. In this study, only level 1 decomposition is applied to the LIDAR data.

Discontinuities give responses in the details depending on their relative position to the wavelet kernel. Therefore, the details cH, cV and cD are evenly treated to achieve a rotation invariant representation of discontinuities. As low frequencies represent hills and flat area, cA is replaced with a zero matrix of the same size for the synthesis using the inverse DWT [24], deliberately accepting a loss of energy.

Figure 1 depicts experimental tests on artificial data using a second order Daubechies wavelet filter [25]. The scene in Figure 1(a) represents building blocks of different height and roof types on hilly terrain. Applying Algorithm 1, the normed magnitude filter responses to discontinuities in the scene is extracted as shown in Figure 1(b). As expected, two observations can be made. First, hilly terrain could be successfully separated from the objects. Second, discontinuities typical for man-made structures (*e.g.* houses) could be detected. It can clearly be seen that the filter response depends on the degree of the salient height, *i.e.* the larger difference between adjacent height values the higher is the magnitude of the responses. However, as expected, it can also clearly be seen that flat roofs are not detected as there is no distinctive change in height.



(a) Artificial scene



(b) Normed magnitude of wavelet responses to the scene

Figure 1. Artificial test site

3. Results and Discussion

The developed feature extraction algorithm has been applied to two DSMs recorded by the Environment Agency, UK, with a spatial resolution of $2m$ per pixel as depicted in Figure 2. Figure 2(a) shows the area around Newcastle, UK, flown in March 1998 representing $12km^2$ of a mixed urban and rural area characterised by a valley with the river Tyne and surrounded by hills. In these LIDAR data tiles, there are both various *attached* and *detached* man-made objects such as industrial and residential buildings, sheds, streets, bridges and railways, and vegetation such as trees, grass, fields and bushes. The challenging task is the segmentation of objects located both on the hills and in the valley of the river Tyne. The second tile in Figure 2(b) shows $8km^2$ of the less sloped urban area around Shrewsbury, UK, in March 1999 characterised mainly by man-made structures such as buildings, streets, bridges across the river Severn, with only few fields.

These object points have been segmented from the ground points as indicated by dark red in Figure 2, despite underlying the hilly terrain. Few under-segmentations can be found on objects with flat roofs and bridges because they do not have salient edges to respond to the filter as anticipated in Section 2. Further features have to be introduced to tackle this phenomenon. The results are validated with digital topographic maps from the Ordnance Survey, UK.

4. Conclusions and Future Work

In this paper, an object feature extractor in challenging hilly DSMs derived from LIDAR data has been presented to support further terrain feature classification. It has been shown that when wavelets are applied to LIDAR data, *detached objects* can be detected by their appearance as discontinuities. However, as expected, large flat roofs and *attached objects* such as bridges are excluded, since there is no salient change in height and therefore no response to the wavelet filter. Using additional features such as height information, these few under-segmentations will be corrected in future investigations.

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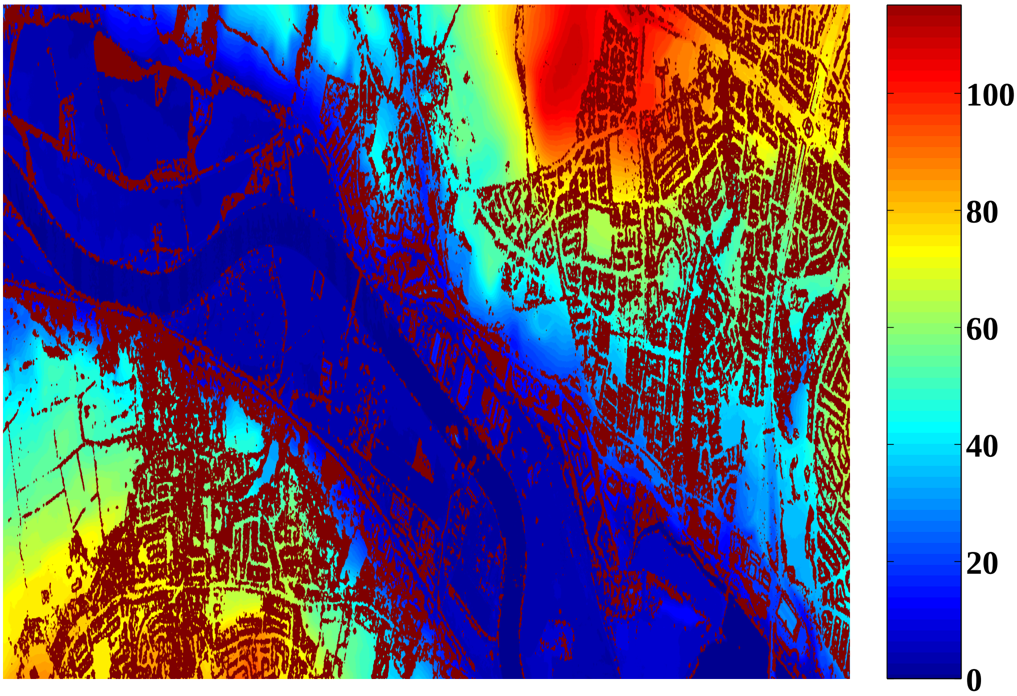
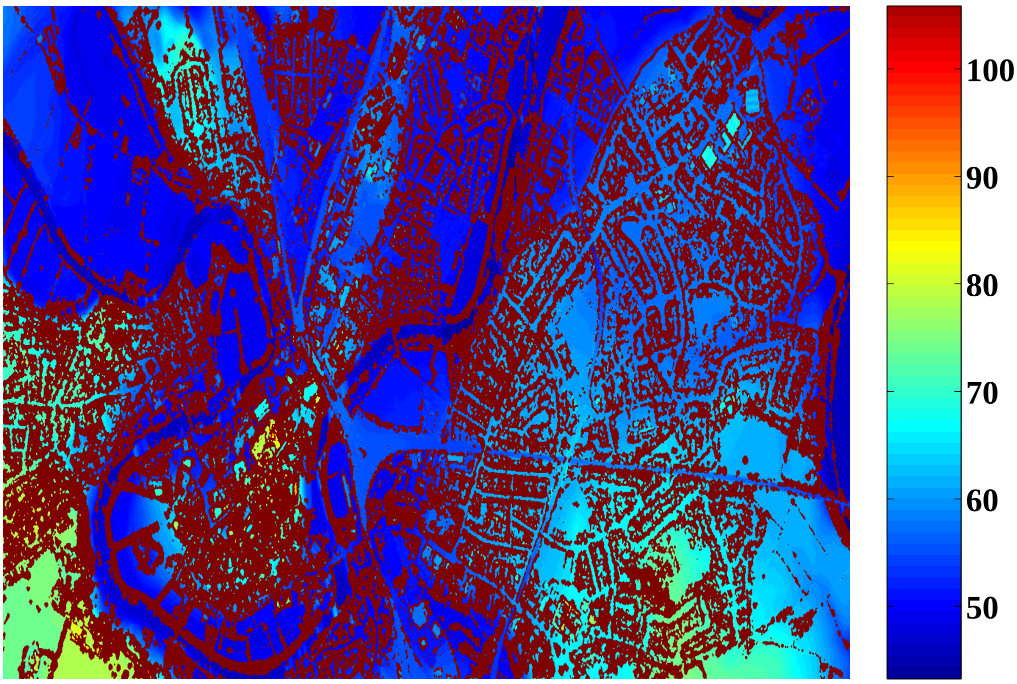


(a) Newcastle upon Tyne, UK, $0m - 115.10m$, March 1998



(b) Shrewsbury, river Severn, UK, $43.26m - 105.85m$, March 1999

Figure 2. Segmented DSMs (original data: copyright © Environment Agency, UK)