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A sequential iterative dual-filter for Lidar terrain modeling optimized for complex forested environments

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ABSTRACT

This paper introduces a sequential iterative dual-filter method for filtering Lidar point clouds acquired over rough and forested terrain and computing a digital terrain model (DTM). The method belongs to the family of virtual deforestation algorithms that iteratively detect and filter objects above-the ground surface. The method uses both points and raster models to do so. The algorithm performance was first tested over a complex badlands environment and compared to a reference model obtained using a traditional TIN-Iterative approach. It was further tested on a benchmark site of the ISPRS (site 5) representing mainly forests and slopes. Over badlands, the resulting DTM elevation RMSE was 0.14 m over flat areas, and increased to 0.28 m under forested and rough terrain. The later value was 12.5% lower than the one obtained with a TIN-Iterative approach. Over the ISPRS site, the TIN-Iterative model provided better results for 3 out of the 4 sample sites. But the proposed algorithm, still worked fairly well provided a total classification error of 5.52%, and is well ranked compared with other algorithms. While the TIN-iterative approach might work better with low density, the proposed one is a good alternative to process high density point cloud and compute DTMs suitable for modeling either hydrodynamic or morphological processes under forest cover at a local scale.

1. Introduction

Digital Terrain Models (DTMs) provide information about the Earth's surface and its related parameters such as slope, aspect or curvature (Wilson, 2012). Considering the importance of land surface characteristics in environmental processes, DTMs are extensively used in a variety of fields including among others, landform classification (Prima et al., 2006), monitoring of erosion (Karátson et al., 2012), soil mapping (Dobos et al., 2001), flood modeling (Tarekegn et al., 2010), habitat classification (Sesnie et al., 2008), forest management (Véga and St-Onge, 2009) and urban planning (Stabel and Fischer, 2001).

Data and methods for DTMs production have evolved rapidly during the last two decades as a result of advancement in remote sensing and field surveying technologies, as well as in computational methods (Wechsler, 2007; Wilson, 2012). The main data sources for generating DTMs include traditional ground surveys, extractions from existing topographic maps and remote sensing in either a passive or an active mode (Nelson et al., 2009). While passive remote sensing methods, mostly based on photogrammetry, are limited to the computation of a Digital Surface Model (DSM), which includes elevation of landscape features (i.e., trees or buildings), active remote sensing such as Light Detection and Ranging (Lidar) and radar allows penetration through forest covers to sample the ground. Among methods based on remote sensing data, those based on Lidar data are found to be the most efficient to produce accurate DTMs from local to regional scales (Hodgson et al., 2003) and national-level Lidar programs have already been carried out to provide national high resolution DTMs (2–5 m), for example in Netherlands, Belgium, Switzerland or parts of the United States of America.

Basically, Lidar consists in measuring the round-trip time of flight of short light pulses emitted towards an object (e.g., the ground). The precise position of the target that interacted with the light pulse is then deduced by combining this round-trip time with both the position and the attitude of the sensor recorded during the flight using, respectively a differential Global Positioning System (dGPS) and an inertial measurement unit (IMU) (Baltsavias, 1999a). Under best conditions, accuracies of ~0.15 m in altimetry and ~1 m in planimetry can be reached (Baltsavias, 1999b). However, several studies demonstrated that the accuracies of a DTM depends on (1) the sensor and flight

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parameters, e.g., scanner device, flight altitude and speed (Ahokas et al., 2003; Hopkinson, 2007), (2) the Earth's surface characteristics (i.e., topography, land cover) (Hodgson et al., 2005; Webster et al., 2006) and (3) the methods used to produce the DTM, e.g., resolution, filtering and interpolation methods (Bater and Coops, 2009; Su and Bork, 2006; Wilson, 2012). The separation of Lidar returns into "ground" and "non-ground" (i.e., infrastructure, vegetation) is a critical step towards the generation of precise DTM, especially in forested areas.

Several authors have proposed algorithms to tackle such classification problems based on the analysis of raw data only (i.e., points), the analysis of interpolated surfaces (i.e., TIN or raster) derived from Lidar point clouds or on mixed approaches using both raw and interpolated data (e.g., Liu, 2008; Meng et al., 2010; Sithole and Vosselman, 2004; Zhang and Whitman, 2005; also for description and comparison of algorithms). In a review paper, Meng et al. (2010) classified ground filtering approaches into six broad classes, namely segmentation/cluster, morphology, interpolation, TIN, contour and directional scanning and pointed out that current ground filters are mostly based on four ground characteristics including: "lowest feature in a specific area, ground slope threshold, ground surface elevation difference threshold, and smoothness". In another comparison between several filtering methods, Sithole and Vosselman (2004) indicated that the surface-based filters tend to perform better than other ones. In general, the overall performance of most generic algorithms was found to decrease in forested as well as in rough terrains (Bretar et al., 2009; Meng et al., 2010; Zhang and Whitman, 2005). Decrease in DEM accuracy with terrain slope and vegetation cover was mainly attributed to Lidar system measurement, including both elevation errors resulting from the Lidar measurement system and the filtering process (Adams and Chandler, 2002; Hodgson and Bresnahan, 2004; Hodgson et al., 2003; Su and Bork, 2006). Also it has been found that vegetation cover and vegetation type have a great impact on DTM accuracy (Hodgson et al., 2003; Su and Bork, 2006; Zhang and Whitman, 2005). As an example, Hodgson et al. (2005) found highest root mean squared errors (RMSE) in the presence of either tall canopy vegetation (24.3–27.6 cm) or scrub/shrub (36.1 cm). Such phenomenon can be first explained by a failure of filtering algorithm in removing low vegetation, especially within slopes (Zhang and Whitman, 2005). In this regard, James et al. (2007) pointed out the limitations of Lidar DTMs for describing gully morphology under forest canopies due to erroneously removed bare earth points along rims. Along with classification errors, the lower ground point densities obtained under vegetation cover can also partly explain increased error in DTM with vegetation density (Hodgson and Bresnahan, 2004). And it has been suggested to use high Lidar point densities to improve DTM quality and correctly model surface morphology in complex environment (Hodgson and Bresnahan, 2004; James et al., 2007).

Concerning the filtering step, the overall decrease in performance of the algorithms within topographically complex and forested environment is also likely to originate from the fact that most of the generic algorithms are based on the assumption that the bare Earth's surface is less sloping and has a more even surface, i.e., is characterized in a local neighborhood by lower frequency patterns, than the DSM surface including aboveground objects (Liu, 2008; Meng et al., 2010; Sithole and Vosselman, 2004). This assumption is no more valid in complex and forested environments where the DTM morphology might present similarities with the DSM's one and can sharply vary from one part to another part of the studied area. Consequently, optimizing the algorithm parameters to process large and topographically complex areas still remains difficult while maintaining good accuracies in the various surface conditions (Kobler et al., 2007; Zhang and Whitman, 2005).

In this paper, we propose a sequential iterative dual-filtering method to address the problem of Lidar filtering over rough and forested surfaces. The originality of the approach is to rely on assumptions regarding the effect of remaining non-ground structures (i.e., over-ground returns classified as ground or. commission errors) on the local characteristics of the modeled surface instead of assumptions on expected ground morphology only. While most of the current approaches aim at identifying and densifying unambiguous ground points on the basis of rules related to geometrical and/or morphological properties of terrain (Zhang et al., 2003), the proposed algorithm aims to iteratively detect and remove non-ground points in the philosophy of virtual deforestation methods (Haugerud and Harding, 2001). We first tested this algorithm over a vegetated catchment located in badlands with very complex morphology (Rey, 2003). The performance of the algorithm was assessed in reference to the widespread TIN iterative algorithm. A benchmark evaluation was further realized using ISPRS test data (Sithole and Vosselman, 2003) in order to compare this algorithm with nine other ones (Meng et al., 2010).

2. Principle of the proposed Lidar filtering method

The proposed algorithm is based on two driving assumptions. First, that part of the non-ground Lidar returns can be separated from those from the ground ones based on the existence of a sharp difference in height at the boundary between ground and above-ground objects. Second, after removal of the aforementioned returns, the filtering of non-ground returns remaining in a close neighborhood of the ground surface can be addressed by using the local characteristics of the surface as suggested in Sithole and Vosselman (2004). Based on these assumptions the following four-step algorithm is defined: (1) extraction of the lowest points by surface unit, (2) iterative removal of Lidar returns that are easily identifiable as belonging to the above-ground surface using a difference in height threshold, (3) iterative removal of the remnant above the ground Lidar returns located in a close neighborhood of the ground surface using neighborhood statistics, and (4) densification of the resulting ground point cloud and computation of the final DTM (see workflow in Fig. 1). Details of the procedure:

Step 1 Extraction of lowest points (Fig. 1, Step 1).
First, the original Lidar Point Cloud (LPC) is restricted to points with the minimum elevation in a given pixel or unit area. These minima are tagged as "low points" (LP).

Step 2 Iterative removal of points that are distinctly above the ground surface (Fig. 1, Step 2).
A Digital Elevation Model (DEM) is generated by rasterizing the LPs selected in a given pixel and supplemented missing values with natural neighbor interpolated surface of neighboring LPs.
Following the generation of DEM, "Salient pixels", those pixels having an elevation higher by α (m) than at least one of their immediate surrounding pixels (i.e., 8-connectivity), are first identified. α (m) is a threshold fixed by the user according to the landscape structure. The resulting salient pixels or group of pixels form a "mask" that describes structures characterizing either above-the-ground objects (i.e., trees, buildings) or sloping areas like parts of natural terrain slopes. This procedure may extract only outlines of objects creating holes in the mask (doughnuts), rather than filling the whole of it. Such omissions may especially occur inside objects with small slopes like flat roof tops or rounded tree crowns. On the