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Two-step adaptive extraction method for ground points and breaklines from lidar point clouds

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ABSTRACT

The extraction of ground points and breaklines is a crucial step during generation of high quality digital elevation models (DEMs) from airborne LiDAR point clouds. In this study, we propose a novel automated method for this task. To overcome the disadvantages of applying a single filtering method in areas with various types of terrain, the proposed method first classifies the points into a set of segments and one set of individual points, which are filtered by segment-based filtering and multi-scale morphological filtering, respectively. In the process of multi-scale morphological filtering, the proposed method removes amorphous objects from the set of individual points to decrease the effect of the maximum scale on the filtering result. The proposed method then extracts the breaklines from the ground points, which provide a good foundation for generation of a high quality DEM. Finally, the experimental results demonstrate that the proposed method extracts ground points in a robust manner while preserving the breaklines.

1. Introduction

Airborne LiDAR is integrated by the global positioning system, the inertial navigation system and the laser scanning sensor, and it could capture the large-scale, dense, three-dimensional point clouds of the earth's surface for many applications, such as generation of digital elevation models (DEMs) and forest investigations. In general, a filtering operation for separating ground points and non-ground points is the first step in the processing pipelines of airborne LiDAR point clouds, particularly the generation of DEMs. In addition, the breaklines should be well extracted for generating high quality DEMs.

Many studies have investigated the filtering of airborne LiDAR point clouds in the last decade (Sithole and Vosselman, 2004; Liu, 2008; Meng et al., 2010; Shan and Toth, 2008; Vosselman and Maas, 2010), but most of filtering methods still require parameters tuning to adapt for various types of terrain (e.g., urban, mountains), and incurring heavy manual editing costs. Therefore, automated filtering still faces great challenges, and a further study on the filtering is necessary. According to the definitions of entities in Xu et al. (2014), the previously reported filtering methods can be mainly classified into two types, i.e., filtering methods based on point entities and filtering methods based on segment entities.

Filtering methods based on point entities calculate the geometric properties of each point and its neighboring points to determine whether one point belongs to be ground or non-ground, e.g., slope-based filtering (Vosselman, 2000; Sithole, 2001), surface-based filtering (Kraus and Pfeifer, 1998; Axelsson, 2000; Mongus and Žalik, 2012; Mongus et al., 2014), and morphological filtering (Kilian et al., 1996; Zhang et al., 2003; Chen et al., 2007; Cui et al., 2013; Li et al., 2013; Pingel et al., 2013; Mongus et al., 2014). The main differences between these methods are the selection of the geometric properties and the filtering rules employed. For example, slope-based filtering assumes that the gradient between ground points is smaller than that between ground and non-ground points, which yields good quality filtering results in relatively flat areas (Sithole and Vosselman, 2004; Liu, 2008). Surface-based filtering iteratively removes non-ground points or detects ground points based on distances, angles or other measures between points and a reference surface (Kraus and Pfeifer, 1998; Axelsson, 2000; Sohn and Dowman, 2002). Generally, these methods may fail to remove non-ground points with low elevations or to detect ground

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points around breaklines (Meng et al., 2010). To improve the adaptability of the filtering, multi-scale surface-based filtering was proposed (Evans and Hudak, 2007; Mongus and Žalik, 2012; Chen et al., 2013; Hu et al., 2014). However, these methods incur heavy calculation costs. Morphological filtering is robust in detecting some cliffs and exhibits a high time efficiency, but the filtering quality is sensitive to the window size. A large window size may degrade rugged terrain features (e.g., mountain peaks), which is known as the cut-off problem, whereas a small window size may fail to remove large objects. Many studies have tried to reduce the effect of the window size on the final filtering quality (Zhang et al., 2003; Chen et al., 2007; Li et al., 2013; Pingel et al., 2013; Mongus et al., 2014), but morphological filtering is still affected by feature preservation issues in rugged terrain and failures in removing large objects.

Filtering methods based on segment entities firstly partition airborne LiDAR point clouds into segments based on the smoothness constraint (Tóvári and Pfeifer, 2005), the slope (Filin and Pfeifer, 2006), RANSAC (Yang et al., 2013) and so on. Then, the properties of each segment (e.g., shape, size and completeness) and the topological relationships between segments are calculated to remove non-ground segments (Sithole and Vosselman, 2005; Shen et al., 2012; Yan et al., 2012). This type of approach works well in urban areas, especially in terms of the preservation of terrain features. In addition, Zhang and Lin (2013) embedded point cloud segmentation in surface-based filtering to improve the filtering performance of forest areas. However, it is still a challenge of removing non-ground points from the segments mixed ground and non-ground points.

In general, a single filtering method has difficulties to filter airborne LiDAR point clouds with various complex scenes and various terrain types (Sithole and Vosselman, 2004; Podobnikar and Vrečko, 2012). Podobnikar and Vrečko (2012) regionalized the entire test area into four different subareas, where all of the parts were filtered using different filters. Deng and Shi (2013) integrated progressive triangulated irregular network (TIN) densification and a hierarchical robust interpolation method. The fusion of different filtering methods could improve the filtering performance, but this fusion is only based on point entities, and thus this method may still perform poorly when differentiating a cliff from a building in a local area (Sithole and Vosselman, 2005). Fortunately, the fusion of filtering methods based on different entities (e.g. points and segments) can perform better in distinguishing various differences between ground points and non-ground points, thereby improving the filtering performance and preserving the terrain features better. However, the existing filtering methods do not consider the fusion of filtering methods based on different entities.

To generate high quality DEMs, breaklines should be considered as constraints in the interpolating the grid DEMs or fixed edges in the TINs. Breaklines could be classified into jump breaklines, crease breaklines, and curvature breaklines (Brügelmann, 2000). Brügelmann (2000) extracted breaklines based on a range imagery interpolated from ground points. However, the accuracy of breakline extraction is affected by the interpolation of the range imagery. Then, Several researchers extract breaklines from LiDAR point clouds by iteratively intersecting patch pairs within a buffer zone around the approximate breaklines (Kraus and Pfeifer, 2001; Briese, 2004). Briese and Pfeifer (2008) improved the method for extracting different types of breaklines by using different solutions.

In this study, we propose a method to extract ground points from airborne LiDAR point clouds in a robust manner by fusing two filters based on different entities, and to detect multiple types of breaklines from the extracted ground points, thereby laying a good foundation for generating high quality DEMs.

The main contributions of the proposed method are as follows.

- Improve the adaptabilities of the filtering in areas with various types of terrain by classifying points into a set of segments and one set of individual points before removing the non-ground points using segment-based filtering and multi-scale morphological filtering;
- Eliminate the effect of the maximum scale in multi-scale morphological filtering, resulting in improved performance in filtering the areas with rugged terrain; and
- Generate high quality DEMs with the preservation of breaklines (i.e., jump breaklines, crease breaklines, and curvature breaklines).

The remainder of this paper is organized as follows. The proposed method is elaborated in Section 2. In Section 3, the experimental studies were undertaken to evaluate the proposed method. Finally, conclusions are drawn at end of this paper.

2. Two-step extraction method

Fig. 1 illustrates the workflow of the proposed method. The proposed method firstly removes low outliers by the method of Shao and Chen (2008). And, the pseudo-grids with a certain size W_{grid} are generated from airborne LiDAR point clouds based on the literature of Cho et al. (2004). The point of the lowest elevation in each pseudo-grid is labeled as a grid point and the other points are defined as unlabeled points, as shown in Fig. 2. When the number of points in a pseudo-grid is zero, a grid point will be interpolated by the points in its neighboring pseudo-grids. Secondly, the proposed method classifies the grid points into a set of segments and one set of individual points, which are processed by a segment-based filtering and an improved multi-scale morphological filtering method respectively, to generate a provisional DEM. Thirdly, the unlabeled points are processed by a back selection procedure based on the provisional DEM, and the final ground points are obtained. Finally, in order to generate high quality DEMs, the breaklines are extracted from the final ground points through the point cloud segmentation.

2.1. Extracting ground points from grid points

2.1.1. Classification of grid points

To better describe the relationship between each grid point and its neighboring grid points, the proposed method employs point cloud segmentation with smoothness (e.g., normal vector and residual) constraints (Tóvári and Pfeifer, 2005) to classify the grid points into a set of segments and one set of individual points. Each segment is labeled as ground or non-ground, each point in the set of individual points will be further processed to be labeled as ground or non-ground one by one. Based on the method of Tóvári and Pfeifer (2005), the grid points are firstly segmented into disjoint segments $S = \{S_1, S_2, \ldots, S_{n-1}, S_n\}$, where n is the number of segments. Fig. 3a and b illustrate the grid points and the corresponding results of point cloud segmentation. It shows that some areas (e.g. vegetation areas) are covered by small segments. However, grid points of a small segment are more likely to be heterogeneous, and the segment should be removed from S to decrease the omission and commission errors in the filtering. Hence, the number of points in each segment is calculated. Then, the proposed method applies a threshold N_t to classify all grid points into two classes. If the number of grid points in one segment is more than N_t, the segment is retained; otherwise, this segment is removed from S, and grid points of the segment are expressed by point entities. In general, N_t equals to the minimum area of the remaining segments divided by the square of the grid size (W_{grid}). After this classification, two classes are generated, a set of segments consist