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An adaptive surface filter for airborne laser scanning point clouds by means of regularization and bending energy

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ABSTRACT

The filtering of point clouds is a ubiquitous task in the processing of airborne laser scanning (ALS) data; however, such filtering processes are difficult because of the complex configuration of the terrain features. The classical filtering algorithms rely on the cautious tuning of parameters to handle various landforms. To address the challenge posed by the bundling of different terrain features into a single dataset and to surmount the sensitivity of the parameters, in this study, we propose an adaptive surface filter (ASF) for the classification of ALS point clouds. Based on the principle that the threshold should vary in accordance to the terrain smoothness, the ASF embeds bending energy, which quantitatively depicts the local terrain structure to self-adapt the filter threshold automatically. The ASF employs a step factor to control the data pyramid scheme in which the processing window sizes are reduced progressively, and the ASF gradually interpolates thin plate spline surfaces toward the ground with regularization to handle noise. Using the progressive densification strategy, regularization and self-adaption, both performance improvement and resilience to parameter tuning are achieved. When tested against the benchmark datasets provided by ISPRS, the ASF performs the best in comparison with all other filtering methods, yielding an average total error of 2.85% when optimized and 3.67% when using the same parameter set.

1. Introduction

Airborne Laser Scanning (ALS) systems present promising alternatives to traditional airborne photogrammetry (Wehr and Lohr, 1999; Zhang et al., 2003; Vosselman and Maas, 2010) in the generation of Digital Elevation Models (DEMs), surface reconstructions, environmental surveys and many other applications (Haala and Kada, 2010; Mongus and Žalik, 2012; Hauglin et al., 2013). Because the raw data consist of a combination of the significant number of points returned from diverse terrain features (e.g., ground, buildings, vegetation and other objects), before being adapted to many other applications, ground and non-ground points must be separated first. This process is referred to as ALS points filtering (Meng et al., 2010). The filtering of ALS data is a particularly demanding task because the data normally cover large areas and various types of surface objects. Previous related publications indicate that ALS data filtering is an extraordinarily difficult task (Sithole and Vosselman, 2004) and is still currently actively under investigation (Mongus and Žalik, 2012; Véga et al., 2012; Chen et al., 2013; Li, 2013; Maguya et al., 2013; Pingel et al., 2013; Zhang and Lin, 2013). Because more ALS datasets are becoming readily available, an innovative ALS filtering algorithm with improved and stable performance is urgently needed to reduce the amount of time-consuming manual editing (Flood, 2001; Chen et al., 2013).

1.1. Filtering strategies

Various types of filtering methods have been proposed. Based on the filter strategies, these algorithms can be grouped into four major categories (Liu, 2008; Meng et al., 2010): interpolation-based (Kraus and Pfeifer, 1998; Axelsson, 2000; Evans and Hudak, 2007; Mongus and Žalik, 2012; Chen et al., 2013), slope-based

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(Vosselman, 2000; Sithole, 2001), morphological-based (Zhang et al., 2003; Chen et al., 2007; Li, 2013; Pingel et al., 2013) and segmentation/cluster-based filters (Filin, 2002; Sithole and Vosselman, 2005; Zhang and Lin, 2013). For the interpolation-based methods, the initial ground points are selected and then densified iteratively to create a provisional surface that gradually approaches the final ground surface. The slope-based methods are based on the assumption that the gradient of the ground is obviously smoother than that of non-ground objects (Sithole, 2001), and the threshold to distinguish ground from non-ground points is determined by a monotonically increasing kernel function (Vosselman, 2000). For the morphological-based methods, the mathematical morphology operations, e.g., dilation and erosion, are exploited to process the Digital Surface Model (DSM) (Zhang et al., 2003), and the non-ground objects can be removed by using a combination of the basic operations. The methods in the last category generally cluster the dataset in the feature space into some segments, for which normal vector and elevation differences in the neighborhood are two appropriate measurements (Filin, 2002; Zhang and Lin, 2013). Subsequently, the premise that points in the same cluster should share the same label can be used to enhance the classification.

Sithole and Vosselman (2004) presented an experimental comparison of the performance of eight filtering algorithms. The authors concluded that the interpolation-based filters often outperform the other methods in the handling of complex terrain because the sophisticated interpolation methods can partially handle various terrain features. Therefore, the interpolation-based approach is exploited in this study. In the following subsection, we do not provide an exhaustive review of all of these methods but instead highlight only the interpolation-based filters that are directly relevant to our work in the next subsection.

1.2. Interpolation-based filters

The linear prediction approach presented by Kraus and Pfeifer (1998) was an early investigation of an interpolation-based filter used to create a DEM in a wooded area. In the interpolation procedure, a weight, which ranges from 0 to 1.0, is assigned to each point. Starting with a grid surface interpolated with identity weights, the weights are determined by the residual between the elevation of the point and the interpolated surface. A dual truncated decreasing function is adopted, so points with residuals smaller than a lower bound are awarded maximum weights and those higher than an upper bound are penalized with zero weights, which will not contribute to the ground surface. In this manner, the weights and ground surfaces are both iteratively refined. Pfeifer et al. (2001) extended the method to a hierarchic scheme with a data pyramid to accelerate the filtering process. In addition, because the coarse level grids (top-level) in the data pyramid are more likely to be ground points, as they are the local minimum in a larger window, the hierarchical pyramid scheme can offer a more robust ground surface estimation. The data pyramid is commonly built in a quad-tree structure, in which a node in the upper level is linked to four nodes in the lower level, but we have noticed that making the pyramid move slowly to the bottom level will provide more accurate results (*cf.* Section 2.2). The iteration strategy adopted in the method is based on refining the weight assignment. However, other methods that iterate with the densification of ground points have exhibited better performances. Axelsson (2000) provided a groundbreaking report on ALS filtering based on a Triangulated Irregular Network (TIN), also referred to as Progressive TIN Densification (PTD) (Zhang and Lin, 2013). Although the original progressive TIN surface filter has provided promising work with excellent performance (Sithole and Vosselman, 2004), it turns out that optimization details, which were kept proprietary in the original PTD approach by Axelsson (2000), have great impacts on algorithm accuracies (Zhang and Lin, 2013). Most investigations tend to use a gridded surface with more sophisticated interpolation methods, which can also achieve comparable results (Mongus and Žalik, 2012; Chen et al., 2013).

Recently, an interpolation-based method using the Thin Plate Spline (TPS) approach as the interpolant was demonstrated to be experimentally more suitable for ALS filtering compared with other interpolation techniques, e.g., Kriging, Inverse Distance Weighting (IDW) and TIN, according to the work by Evans and Hudak (2007). The authors introduced a multiscale curvature classifying (MCC) algorithm for the filtering of ALS data. In contrast to representing the ground surface with TIN (Axelsson, 2000), MCC employs regular gridded DEM. After selecting the initial ground points, these points were used to interpolate a raster surface with TPS for the first scale, and then, unclassified points were tested against the average elevation of the 3×3 neighbors in the DEM similar to the work by Haugerud and Harding (2001). The points were classified as ground, if the elevation difference was less than a given threshold. The process was repeated until no more points were added into ground points. Then, the process moved on to the next resolution. For a larger resolution, a scale gain (0.1 m) was added to the curvature threshold to address the effect of changes in slope (Chen et al., 2013). Three scales were used in total, and they were determined as $0.5w$, w, and $1.5w$. The curvature threshold was t, $t + 0.1$, and $t + 0.2$, respectively, where w and t are the user-defined initial scale and threshold, respectively. Chen et al. (2013) proposed a similar method with multi-scale TPS interpolation, and by performing tests against the benchmark dataset supplied by the ISPRS Commission, the authors demonstrated the outstanding performance of TPS interpolation in ALS filtering. Although the interpolation-based method with TPS described above (Evans and Hudak, 2007; Chen et al., 2013) adopted three levels of interpolated scale, the points were not prepared in the pyramid structure. At each scale, all points were tested against a curvature threshold instead of processing in the coarse-to-fine sequence. Furthermore, Mongus and Žalik (2012) presented a TPS interpolation-based algorithm without parameter tuning. After building a data pyramid of the point clouds, a surface is interpolated iteratively from the coarsest level toward the finest level. The removal of parameter tuning is achieved based on the statistical information of the elevation residuals between points and DEM. The benchmark tests demonstrated that the method exceeded the performance of the software standard, even with automatically determined parameters.

1.3. The ASF approach

As described above, most of the previous studies have determined the filter threshold using elevation information only, and the threshold remained the same for a single dataset, even with various terrain features. Most algorithms achieve arguably excellent performance when applied to consistent and plain areas, but the filters remain problematic when faced with complex shapes/configurations and significant discontinuities (Sithole and Vosselman, 2004). Multiple factors can account for the problem, with the major factor likely being the complexity of the landform. In fact, the challenge of handling different terrain features bundled into a single dataset has already been explored in previous works (Sithole and Vosselman, 2004; Zhang and Lin, 2013). For example, in an actual filtering problem, the region may contain low objects or vegetation on flat surfaces in addition to sharp ridges or scarps on rough surfaces. The varying features must be handled by different filtering thresholds. A small threshold should be assigned to de-spike the low objects, and a larger threshold should be applied to retain the ground points on the tops of ridges or on the edges of scarps. Sithole and Vosselman (2004) proposed the