SEGMENTATION-BASED GROUND POINTS DETECTION FROM MOBILE LASER SCANNING POINT CLOUD

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Commission VII, WG VII/6

KEY WORDS: Filtering, Mobile Laser Scanning, Point Cloud, Point Cloud Segmentation

ABSTRACT:

In most Mobile Laser Scanning (MLS) applications, filtering is a necessary step. In this paper, a segmentation-based filtering method is proposed for MLS point cloud, where a segment rather than an individual point is the basic processing unit. Particularly, the MLS point cloud in some blocks are clustered into segments by a surface growing algorithm, then the object segments are detected and removed. A segment-based filtering method is employed to detect the ground segments. Two MLS point cloud datasets are used to evaluate the proposed method. Experiments indicate that, compared with the classic progressive TIN (Triangulated Irregular Network) densification algorithm, the proposed method is capable of reducing the omission error, the commission error and total error by 3.62%, 7.87% and 5.54% on average, respectively.

1. INTRODUCTION

In the last decade, mobile laser scanning (MLS) is a quite new technology in which environment are mapped by laser distance measurements from moving vehicles, and transformed into a georeferenced 3D point cloud using GPS/IMU data. As a state-of-the-art technology for mapping and remote sensing, MLS can serve as an effective solution for surveying complex environment, such as urban environment and road corridors (Lin et al., 2013). Many mature MLS systems can be found from the market (Kaartinen et al., 2012), and widely used for various purposes such as road inventory (Pu et al., 2011), map update (Hwang et al., 2013), façade extraction (Yang et al., 2013; Jochem et al., 2011), building reconstruction (Frueh et al., 2005; Becker et al., 2009), road marking extraction (Yang et al., 2012), window extraction (Wang et al., 2012), tree extraction (Wu et al., 2013), object extraction and recognition (Yang et al., 2012; Yu et al., 2013; Golovinskiy et al., 2009, etc).

In fact, among various applications, detection of ground points is a necessary step. Because the ground points probably make up the largest percentage of entire points and the objects of interest are usually located on the ground surface (Pu et al., 2011; Golovinskiy et al., 2009; Elhinney et al., 2010). However, the existing ground detection methods for airborne LiDAR point cloud are also employed for MLS point cloud, and they are faced with the following problems:

The huge amount of points (Pu et al., 2011; Yang et al., 2013) causes heavy computational burden. Thus, object points should be partially removed before filtering.

Existence of outliers, especially low outliers, may lead to many errors (Elhinney et al., 2010). Thus, the outliers should be eliminated at first for most filtering methods.

There are variable point densities (Yang et al., 2013) and data gap, which may make the ground surface not well sampled.

A point cloud is normally composed of various types of complex and incomplete scene structures (Yang et al., 2013), and the lower parts of off-terrain objects (such as vehicle, façade, tree trunk, etc.) are attached on the ground surface, thus the points belonging to the lower parts are likely to being classified as ground measurements.

Urban ground surface itself is not smooth and continuous enough, because there are lots of break lines such as road edges and curbstones (Zhou et al., 2012). However, the points around the break lines may be misclassified.

Practices suggest filtering of LiDAR data can be strengthened by analyzing segments rather than individual points (Filin et al., 2006). Moreover, once a point cloud has been segmented, segment attributes can be collected to classify the segments (Vosselman et al., 2010). As a result, similar to object-based image analysis (Blaschke et al., 2010), a segment-based classification is more reliable than a point-based classification (Vosselman et al., 2010; Zhang et al., 2013; Rutzinger et al., 2008) for point cloud. Thus, a segment-based method for ground measurement detection from MLS point cloud is proposed herein. The main contribution of our method consists of two parts. The first one is a knowledge-based method (Pu et al., 2011) is employed to detect the off-terrain objects. The second one is a segment-based method for point cloud filtering is proposed to remove the lower parts of objects and retain the points around break lines.

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2. METHOD

Our proposed method is composed of four core steps, namely data partition, point cloud segmentation, object segments detection, and segment-based progressive TIN densification (PTD). Moreover, the classic point-based PTD method (Axelsson, 2000) is widely employed in filtering of point cloud, and it is improved by our segment-based method.

2.1 Data partition

Processing MLS point cloud is a challenging task due to the huge point data volumes. Instead of processing the whole point cloud directly, the raw MLS point cloud are partitioned into multiple blocks, and then information of interest is extracted from the points in each block,. The geometrical shape of each block is manually specified, and the overlapping zones between neighbouring blocks can be permitted. After data partition, each dataset in a block is taken as an independent point cloud taking part in the following processing.

2.2 Point cloud segmentation

Point cloud segmentation is the process to partition a point cloud into coherent and connected point clusters. Specifically, points on a certain geometric feature are coherent points, such as co-plane, co-surface, and co-line points; whilst connected points are a group of points in which every point has at least one neighbouring point within a certain distance.

The surface growing algorithm proposed by Vosselman and Klein (2010) is used herein. After data partition, the laser point cloud in each block is segmented into planar segments with a surface growing algorithm. After segmentation, the ground surface is clustered into several large segments, each building façade may be clustered into one segment, and the vegetation has many small segments. Moreover, the surface growing method supposes that some points are outliers, thus they are not labeled in segmentation. These outliers are eliminated from the point cloud, and only the planar segments are used for the following operations.

2.3 Object segments detection

Geometric features of a segment and topological relations between segments have been widely employed in information extraction from point cloud (Pu et al., 2011). Generally, most building façade segments are very large and aligned vertically (Yang et al., 2013; Jochem et al., 2011), and most vegetation segments are small (Zhang et al., 2013; Rutzinger et al., 2008) and scattered in 3D space (Yang et al., 2013; Zhang et al., 2013).Two features about orientation and scatterness are selected to detect object segment herein. A method to calculate the orientation and the scatterness of a planar segment was proposed in (Zhang et al., 2013), where the scatterness is calculated based on the principal components analysis (Yang et al., 2013). Based on visual evaluation of the histograms of orientation and scatterness, two thresholds about orientation O and scatterness S for distinguishing the façade and non-faced, vegetation and non-vegetation can be determined in a try-and-error way. In our proposed approach, the potential building façade segments and vegetation segments are first detected and labeled as “object”; and they are eliminated from the following processing, which will reduce the volume of points for the subsequent step.

2.4 Segment-based PTD

This step is similar to the PTD filter, but the basic processing unit is a segment rather than a single point. It is composed of five core steps, and details of five steps refer to Section 3.4 in (Lin et al., 2014).

3. EXPERIMENTS AND PERFORMANCE EVALUATION

3.1 Test data and the relevant parameters

Two test datasets were acquired using the SSW mobile mapping system. The SSW mobile laser scanning system is developed and made by Beijing 4D Vision Information Technology Co. Ltd, China. The hardware of the SSW consists of a laser scanner, a CCD camera system, a portable control unit box, a GNSS/INS unit etc. The laser scanner collects data at a rate of 200,000 measurements per second with a field of view (FOV) of 360°. The first data has 2,000,173 points, with an average point density of 110 points/m^2; while the second data has 2,000,055 points, with an average point density of 160 points/m^2. The first data covers an area in Beijing City, China, with approximate 350m length and 500m width. The second data covers an area in Sanxia City, China, with approximate 330m length and 220m width. Moreover, both datasets have various types of artificial objects and the ground surfaces are not smooth enough.

The shared five parameters m , t , θ , d , l are set to the same values for both filters applied on the two datasets, as shown in Table 1. Moreover, our proposed method needs more parameters. Specifically, in the surface growing segmentation, the orientation threshold, o , and scatterness threshold, s are set to 45° and 0.2 respectively for both two data.

3.2 Results and Performance Evaluation

With the specified parameters in Table 1, we perform the filtering on the two datasets using the two methods.

Visual inspection suggests that the surface growing method yields good results, and there is less under-segmentation and over-segmentation. Some statistics about the filtering results refer to Table 2. For the PTD method, there are 57 outliers and 718 outliers in the two test datasets, respectively. 64 points and 60 points are selected as seed points in the two test datasets; there are 1,035,516 ground points and 1,155,869 ground points in the final filtered results. For our proposed method, there are 974,043 object points and 1,205,793 object points detected by the step in the Section 3.3 in the two test datasets; there are 535,226 points and 900,949 points selected as seed points in the two test datasets; there are 994,760 ground points and 1,135,437 ground points in the final filtered results. The statistics in Table 2 suggest that our method does not need outlier removal step, it is capable of detecting most of the object measurements, and it is capable of selecting many more seed ground points.

Quantitative assessment follows the method proposed in ISPRS filter test (Sithole et al., 2004). Three kinds of errors are calculated, namely, type I errors (i.e., omission errors), type II errors (i.e., commission errors), and total errors. Moreover, the reference results of the two datasets are produced in a way of combination of automatic filtering and manual editing. The three types of errors of the two filters for the two datasets are listed in Table 3. For our proposed method, the three types of errors are 0.07%, 0.39% and 0.23%for the first test dataset; the three types of errors are 4.74%, 0.09% and 2.86% for the second test dataset. For the PTD method, the three types of errors are 3.23%, 7.55% and 5.40% for the first test dataset; the three types of errors are 8.85%, 8.66% and 8.77% for the second test dataset. The statistics in Table 3 suggest that our proposed approach achieve better results than the classic PTD method. On average, compared with the PTD algorithm, the type I error, the type II error and total error of our method are reduced by 3. 62%, 7.87% and 5.54%. Moreover, in both cases, the three types of errors of our method are quite low, which shows that our filtered results are very close to the ground truth data.

Parameters	m (m)	t (°)	θ (°)	d (m)	l (m)
Threshold value	60	88	6	0.5	1.0

Table 1. Input five shared parameters of the two filters in the two datasets

Indices / Scene	Total number of points (points)	Classic PTD method			Our method		
		Number of outliers (points)	Number of seed points (points)	Number of ground points (points)	Number of object points (points)	Number of seed points (points)	Number of ground points (points)
Data set 1	2,000,173	57	64	1,035,516	974,043	535,226	994,760
Data set 2	2,000,055	718	60	1,155,869	1,205,793	900,949	1,135,437

Table 2. Statistics about the filtered results of the two filters

The experiments indicate that our proposed method has quite better performances than the classic PTD method. Our method's advantages come from the embedding of point cloud segmentation, which makes the judging in a segment-wise manner. In the segment-based judging, the lower parts of the off-terrain objects are less possible being detected as ground, while the points around the road edges are more possible being detected as ground.

Dataset NO.	Type of error	PTD(%)	Our method(%)
Data set 1	I	3.23	0.07
	II	7.55	0.39
	T	5.40	0.23
Data set 2	I	8.85	4.74
	II	8.66	0.09
	T	8.77	2.86

Table 3. Three types of errors of the two filters in the two test datasets

4. CONCLUSIONS AND DISCUSSION

Filtering is one of the core post-processing steps for MLS point cloud. However, the classic PTD filter fails to remove the lower parts of the objects and preserve the ground measurements in steep terrain areas. Thus, a segment-based filtering method is proposed by integrating the PTD framework and surface growing segmentation method. The experiments are performed on two datasets to verify our proposed method; moreover, two ground truth datasets are produced to calculate the accuracies. The results suggest that, our proposed approach is better than the classic PTD method in removing vehicle measurements and preserving ground measurements. Moreover, our approach solves the five problems of the PTD method listed in Section 1. Particularly, it has significantly lower type I errors, type II errors and total errors than the PTD algorithm. The future work will focus on the improvement of the proposed filter to reduce the type II error, and parallel computing is going to be implemented to promote the efficiency.

ACKNOWLEDGEMENTS

This research was funded by the General Program sponsored by the National Natural Science Foundations of China (NSFC) under Grant 41371405.

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This contribution has been peer-reviewed.
doi:10.5194/isprsarchives-XL-7-W4-99-2015