Check for updates

Surface Features Classification of Airborne Lidar Data Based on TerraScan

Maohua Liu[1(✉)], Xiubo Sun[2], Yue Shao[1], and Yingchun You[1]

[1] School of Civil Engineering, Shenyang Jianzhu University, Shenyang, China
liumaohua1115@126.com
[2] Liaoning Nonferrous Geological Exploration General Institute Co., Ltd., Shanghai, China

Abstract. This paper focuses on the classification of airborne lidar (LiDAR) data using TerraScan software. At first, the composition of the airborne lidar system and the organization and characteristics of the point cloud data are analyzed. Then, the basic principles of classification by TerraScanare analyzed based on the airborne lidar data in the urban. First, noise points such as blank and low points are removed, next, implement point cloud filtered according to the macro commands provided by TerraScan, and finally further classify and point cloud are thinned, included that classify ground points, vegetation points, building points, and model key points, this operation is generated mainly by program implementation; In order to ensure the accuracy of the classification, manual classification must be carried out. Consequently the classification results of TerraScan are summarized, involving the advantages and disadvantages of the classification, and the technical development requirements of classification using TerraScan are proposed.

Keywords: Airborne lidar · TerraScan · Point cloud filtering · Point cloud classification

1 Introduction

With booming of Earth observation technology, it is possible to acquire high-precision geographic information using the new airborne laser radar system rapidly. The main content of post-processing of airborne lidar measurement data is filtering and classification. The filtering removes the features and vegetation foot points in the point cloud data, and extracts the Digital Elevation Model (DEM); It is necessary to classify the laser foot point data to distinguish artificial points and vegetation data foot points definitely data classification for carrying out ground object extraction and 3D reconstruction. John Secord uses aeronautical imagery to segment LiDAR point cloud data based on the similarity between LiDAR data points and points [1]. Cui et al. proposed a method of building extraction based on edge detection by Lidar data. This method firstly generates different scale DSM depth images from LiDAR point cloud data, and then extracts the edge of the building according to the edge detection operator [2]; Antonarakis et al. classify nine types of features on the three river meanders of the Garonne and Allier rivers in France through an object-oriented supervised taxonomy.

Y. Xie et al. (Eds.): GSES 2018, CCIS 980, pp. 185–190, 2019.
https://doi.org/10.1007/978-981-13-7025-0_19

Six surface models for classifying target features were generated from LiDAR point cloud data during the experiment: vegetation height model, canopy percentage model, average intensity model, intensity difference model, probability distribution skewness and kurtosis model [3]; Ren Zizhen et al. proposed a LiDAR building extraction method based on contour shape analysis. The method firstly uses the LiDAR data to generate the DSM contour, then extracts the building contour according to the contour shape feature parameters, and finally extracts the building according to the topological relationship and the geometric characteristics of the building outline [4]. This paper focuses on the denoising of raw airborne radar data based on TerraScan, classification of ground, low vegetation, medium vegetation, high vegetation and buildings. The experimental data selected in this paper is point cloud data of a one city, with an area of about 1.5 km^2, containing 7055604 points, and the data format is *.las.

1.1 Point Cloud Data Filtering

Firstly, the thinning and denoising of the point cloud data is carried out. Every 10 points is extracted and thinned. Denoising processing removes the point below the normal ground height by 0.5 m within 5 m from the reading point to achieve low-point separation by setting the parameters, meanwhile the distance of the points within 5 m radius and the high-order error is greater than 5 times standard deviation is removed [5]. The separation of the air points the denoising of the point cloud is realized.

According to the characteristics of the research area, in the paper, TIN-based filtering method is carried out. The parameter including the iteration angle, the iteration distance and the maximum building size is repeat lysetted, showed in Fig. 1 are established. The filtering result is shown in Fig. 2. The yellow represents the ground point and the black represents the feature point.

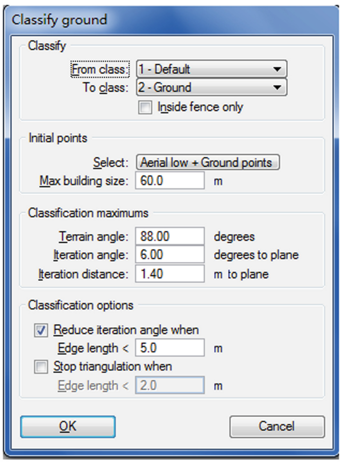

Fig. 1. The parameter of the filter

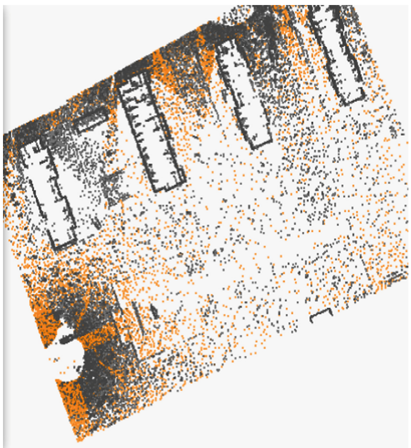

Fig. 2. The result of the filter (Color figure online)

2 Point Cloud Classification

2.1 Vegetation Point Classification

Vegetation points can be classified into three categories based on elevation values: low vegetation, medium height vegetation, and high vegetation. For example, low vegetation is set to a point below 0.5 m [6, 7]. The specific algorithm is a temporary triangle model established at the ground point, and then other points are compared with the elevation values of the triangle model. If it is less than 0.5 m, this point can be classified into the classification of low vegetation. According to the same algorithm, medium-height vegetation and high vegetation can be distinguished. The results obtained in the experiment according to the above method are not satisfactory, therefore, the points above 0.25 m above the ground point are divided into medium vegetation points. Similarly, the points in the middle vegetation point that are 2 meters above the ground are divided into high vegetation points [8, 9]. This method also classifies the building points into the vegetation, and provides a data foundation for the next building point classification. After the building classification is completed, the remaining is the vegetation data. The classification result is shown in Fig. 3.

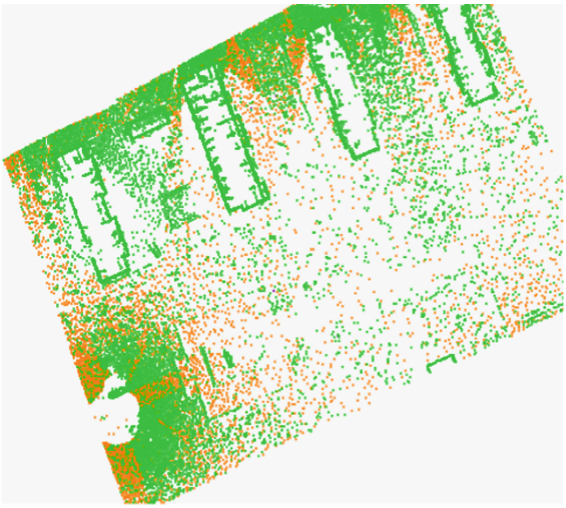

Fig. 3. The result of classification of vegetation

2.2 The Classification of Buildings

The classification of buildings is based on the high of vegetation, thus the separation of buildings must rely on manual classification, The automatic classification results of buildings are not ideal. This problem is mainly overcome by manual classification. The manual classification is carried by means of the sectional view, and the angles need be cut in the original data to ensure the accuracy of the classification. As shown in Figs. 4 and 5.

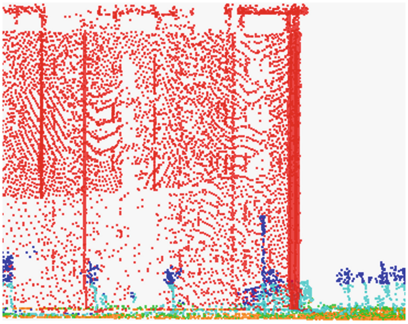

Fig. 5. The sectional view of the building

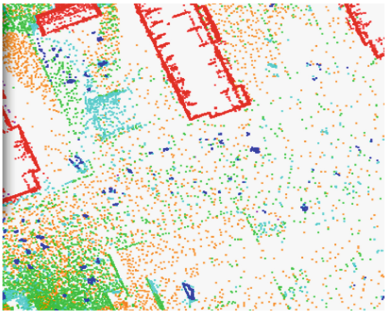

Fig. 4. The separation of buildings

3 Laser Point Cloud Data Classification and Accuracy Assessment

After the automatic classification by TerraScan, it is necessary to manually process some position which exist shortcoming processed by macros. The macro processing is only automatic preliminary classification, and the process exist error. Therefore there is a step of manual classification. Due to the deviation of the parameter settings by macro during the classification, some point surround the house will not be right, even there may be some error points which do not belong to the building. This situation needs to be paid more attention to some in post processing. Therefore, the parameter setting by macros is very important and determined by several test (Figs. 6 and 7).

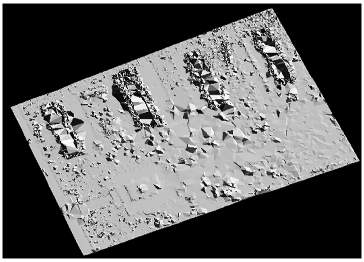

Fig. 6. The data before classification

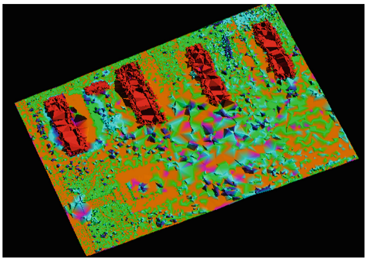

Fig. 7. The data after classification

In this paper, the accuracy of TerraScan classification is determined according to the error classification rate of laser point cloud, which can obtain good filtering effect and preserve the integrity of terrain features. The original point-to-point spatial structure is related, however, in the actual operation of the classification method, this structural connection is not known, therefore the spatial connection between the points cannot be well used, resulting in some error in the process. If only the LiDAR point cloud data is classified into two types of feature data and ground data, the classification error can be divided into two species, the first type of error is classifying the ground point as the feature point incorrectly and the second type of error is in contrast. In general, it is considered to remove the feature points as much as possible, the parameters are set according to this standard, even at the expense of eliminating some topographic features, which causes too many second errors in the classification results. The results of this experiment classification are shown in Table 1.

Table 1. The result of the classification

		The data after filtering			
		Number of ground points	Number of non-ground points	Sum	Proportion
Reference data	The number of real ground points	89165	2152	91317	12.94%
	The number of real non-ground points	53827	560279	614106	87.06%
	Sum	142992	562431	705423	
	Proportion	20.27%	79.73%		

The accuracy of the classification results is: the first error is 2.36%, the second error is 8.77%, and the total is 7.94%. It can be seen from the experimental results that first error is small, which means that there are fewer ground points that are mistakenly divided into ground points, and more points are mistakenly divided into ground points. The classification result is affected by the low local point, this condition leads to the increase of the second error. Especially when the classification elevation of low plants is less than 0.1 m, it is easy to increase the second error.

4 Conclusion

(1) The classification method of this paper is based on the theory of polygons, This method assumes that the calculated value of the target point of the classification process is related to the points within a certain rang. It is more suitable for the distribution of actual points, because the spatial points are not independent and are related to the surrounding points, revealing the structural connection between the spatial points. Therefore the ideal results have been achieved.

(2) In the process of vegetation classification, the conditions of distinguishing the small protrusions and the low vegetation are unreasonable. In the actual situation, the elevation of the low vegetation is less than 0.1 m, and the ground feature elevation is more than 0.1 m, thus this could increase the classification error;

(3) In the process of building separation, the conditions for distinguishing building information from raised ground information are unreasonable. If the gradient of the ground information changes greatly, it is easy to judge it as building and eliminated, which requires a certain amount of manual intervention.

References

1. Secord, J., Zakhor, A.: Tree detection in Urban regions using aerial lidar and image data. IEEE Geosci. Remote Sens. Lett. **4**(2), 196–200 (2007)
2. Cui, J.-J., Sui, L.-C., Xu, Z.-H., et al.: Building extraction from LiDAR data based on edge detection. J. Surveying Mapp. Sci. Technol. **25**(2), 98–100 (2008)
3. Antonarakis, A.S., Richards, K.S., Brasington, J.: Object-based land cover classification using airborne LiDAR. Remote Sens. Environ. **112**(6), 2988–2998 (2008)
4. Ren, Z., Cen, M., Zhang, T., et al.: Building extraction from LIDAR data based on shape analysis of contours. J. Southwest Jiaotong Univ. **44**(1), 83–88 (2009)
5. Zhang, K., Chen, S.-C., et al.: A progressive morphological filter for removing non ground measurements form airborne LiDAR data. IEEE Trans. Geosci. Remote Sens. **419**(4), 872–882 (2003)
6. Vosselman, G., Maas, H.G.: Adjustment and filtering of raw laser altimetry data. In: OEEPE Workshop on Airborne Laser scanning and Interferometric SAR for Detailed Digital Elevation Models, Stockholm, 1–3 March 2001, Official Publication OEEPE no. 40, 2001, pp. 62–72 (2001)
7. Sithole, G., Vosselman, G.: Experimental compasion of filter algorithms for bare-Earth extraction from airborne laser scanning point clouds. ISPRS J. Photogrammetry Remote Sens. **59**(1–2), 85–101 (2004)
8. Samadzadegana, F., Bigdelia, B., Hahnb, M.: Automatic road extraction from lidar data based on classifier fusion in urban Area. Int. Arch. Photogrammetry Remote Sens. Spat. Inf. Sci. **38**(3), 81–87 (2009)
9. Shan, J., Sampath, A.: Urban DEM generation from raw lidar data: a libeling algorithm and its performance. Photogram. Eng. Remote Sens. **71**(2), 217–226 (2005)