A RECOGNITION METHOD FOR AIRPLANE TARGETS USING 3D POINT CLOUD DATA

Mei Zhou*, Ling-li Tang, Chuan-rong Li, Zhi Peng, Jing-mei Li

Academy of Opto-Electronics, Chinese Academy of Sciences, No.9, Dengzhuang Nanlu, Beijing, China
zhoumei@aoe.ac.cn

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ABSTRACT:

LiDAR is capable of obtaining three dimension coordinates of the terrain and targets directly and is widely applied in digital city, emergent disaster mitigation and environment monitoring. Especially because of its ability of penetrating the low density vegetation and canopy, LiDAR technique has superior advantages in hidden and camouflaged targets detection and recognition. Based on the multi-echo data of LiDAR, and combining the invariant moment theory, this paper presents a recognition method for classic airplanes (even hidden targets mainly under the cover of canopy) using KD-Tree segmented point cloud data. The proposed algorithm firstly uses KD-tree to organize and manage point cloud data, and makes use of the clustering method to segment objects, and then the prior knowledge and invariant recognition moment are utilized to recognise airplanes. The outcomes of this test verified the practicality and feasibility of the method derived in this paper. And these could be applied in target measuring and modelling of subsequent data processing.

1. INTRODUCTION

LiDAR (Light Detection and Ranging) is an active remote sensing system which can quickly provide three dimensional information of earth surface and object. Currently it has been used in many fields, such as 3D city models, urban planning, design of telecommunication networks, vegetation monitoring and disaster management, etc. Based on the characteristic of LiDAR that can penetrate vegetation cover, this paper in particular focuses on the research on the method of target extraction by using multi-echo point cloud data of LiDAR.

Considering the application of three-dimensional target recognition using LiDAR data, it mainly focuses on airplane, building, power lines, etc. So far many methods were proposed but there are still some problems. The first one is about how to express and recognize objects of arbitrary shape while most of the recognition methods restrict the objects' shape at present. Secondly, objects are usually in complex background while many methods can only apply to a single object without considering surrounding. Thirdly, it's difficult to recognize object with uncompleted information. Due to the limitation of the current equipment, the distance between point clouds is fairly long, so we could only get information on large objects without details. Considering there are many kinds of object with a complex background in one area, artificial interpretation would cost a lot of time and work. So, it's necessary to design reasonable algorithm on targets recognition.

Currently, bare objects orientated recognition and abstraction based on LiDAR point data mainly focus on building, road and power line abstraction. A relative smaller body of literatures address disguised objects abstraction, also mainly concentrating on camouflage net disguised objects detecting (Marino et al., 2005; Buck et al., 2007). In general, most of those recognition methods are based on region, outline or feature points (Prokhorov, 2009; Golovinskiy et al., 2009). Considering the airplane targets in LiDAR point cloud data, the direction of airplanes may be arbitrary, even the outline or size is different, while their shapes have certain similarities, so the method must consider both deformation and scale invariance. The moment invariants are suitable to solve the problem mentioned above.

Automatic recognition of aircrafts based on moment invariants from binary television image was described (Sahibsingh et al., 1977). In this paper, the profile and boundary of targets was extracted from binary television images before the moment transformation, and then classification experiments were carried out base on a Bayes decision rule and a distance-weighted k-NN rule. Zhongliang et al. (1992) proposed a new method for automatic ship classification using superstructure moment invariants. In those papers, the classification methods of aircrafts or ships extracted from images by moment could be also applied on LiDAR point cloud data, but point cloud data is discrete, there are some differences between the distance image and binary image, especially in the detail of the target outline.

Hans-Gerd et al. (1999) worked on invariant moments in raw laser altimetry data to extract model parameters of standard gable roof type houses, such as location, length, width and height of a building as well as its orientation, roof type and roof slope. Jinhui et al. (2009) proposed a new approach of target recognition based on LiDAR point cloud data by affine invariable moment, the experiment was based on data acquired by terrestrial laser scanner. Firstly the target images were generated by distance value of point cloud data, and then through the process of filtering, thresholding and region labelling, the affine moments of target region were extracted as features, finally BP network and SVM algorithm were used for target classification and recognition. There would be still

* Corresponding author.

further research of this method on the application of airborne LiDAR point cloud data.

In addition, the experiment of hidden targets extraction was not mentioned in these papers. This method is based on LiDAR point cloud data organized by KD-tree, after target segmentation, Hu invariable moments and flight characteristics could be also combined to improve the airplane target recognition, even hidden airplanes mainly under the cover of canopy.

The first step of hidden targets detection is target segmentation. Compared to other image segmentation methods, the segmentation based on KD-tree can deal with 3D point cloud data directly. The proposed algorithm firstly uses KD-tree to organize and manage point cloud data, and then utilizes clustering method to segment objects. Based on the result of segmentation, the prior knowledge and invariant recognition moment is utilized to identify target of interest.

The outcomes of this test verified the practicality and feasibility of the method derived in this paper. The accuracy rate is 0.937, error ratio is 0.063. The approach in this paper could also be applied in other kinds of covered targets extracting. These could be applied in target measuring and modelling of subsequent data processing.

2. SEGMENTATION BASED ON KD-TREE

In data processing, target segmentation is to classify points have same properties (such as height, intensity, etc.) into one class, and it is also the premise of target recognition, fitting and measurement. The proposed algorithm firstly uses KD-tree to organize and manage point cloud data, and then uses clustering method to segment objects.

2.1 KD-tree

This paper employs KD-tree to store and manage LiDAR point cloud data. In this way, each point's neighbour-finding could be queried by KD-tree which is actually a K-dimensional binary tree of every node (Moore, 1991). In this section, KD-tree is three dimension, and built as follows: choose the splitting dimension as the longest dimension of the current hyperrectangle, and then choose the point closest to the middle of the hyperrectangle along this dimension. This strategy gives consideration to both tree's balance and segmented units' regularity. Moreover, in order to avoid empty branch, the tree's top floors could still follow the standard rules.

2.2 Targets Clustering

After organizing point cloud data by KD-tree, query to search points within effective distance among neighbourhood has been established. Aiming at target segmentation, points in certain distance are classified into one class. We adopt the nearest neighbor query method since finding proximal points to create local surface patch rapidly is the key step (Bin, 2008). When given point ***p*** and query distance ***d***, the nearest neighbour query method is to lookup points in the sphere with ***p*** as center and ***d*** as radius. Obviously, the core algorithm is to find all units intersecting with the sphere. The unit of KD-tree is called hyperrectangle (as rectangle in two-dimensional, rectangular parallelepiped in three-dimensional), and can be defined with two arrays: the minimum and maximum of coordinate value of each point. On purpose of estimating whether there is an intersection between the hyperrectangle ***hr*** and the sphere, the point ***t*** in ***hr*** nearest to ***p*** must be found, its expression is:

$$t_i = \begin{cases} hr_i^{\min} & p_i \le hr_i^{\min} \\ p_i & hr_i^{\min} < p_i < hr_i^{\max} \\ hr_i^{\max} & p_i \ge hr_i^{\max} \end{cases} \tag{1}$$

where $hr_i^{\min}$ and $hr_i^{\max}$ is the minimum and maximum value of ***hr*** in the *i*th dimension. Hyperrectangle satisfies condition that distance between ***p*** and ***t*** no more than ***d*** would be looked up, and the range query terminates when all points are checked.

In the clustering method, the choice of a reasonable distance threshold has an important influence on the results of target segmentation. Therefore, in this paper, the distance threshold is set to 1-1.5 times point spacing.

3. MOMENT INVARIANTS

Considering that the feature of airplane is distinct when overlooked, so the target recognition method in image is used for airplane recognition in LiDAR data. Moment is usually used to characterize the distribution of random quantity in statistics. If we take binary image or gray image as two-dimensional density distribution function, the moment method can be applied to image analysis.

3.1 Basic Concept of Moment

For digital image $f(i, j)$ of two-dimensional (N×M), moment with p+q order can be defined as (Zhongliang et al., 1992):

$$m_{pq} = \sum_{j=0}^{M-1}\sum_{i=0}^{N-1} i^p j^q f(i, j) \tag{2}$$

where *i*, *j* is the coordinate in the image, and the central moment of $f(i, j)$ with p+q order is:

$$u_{pq} = \sum_{j=0}^{M-1}\sum_{i=0}^{N-1} (x-\bar{x})^p (y-\bar{y})^q f(x, y) \tag{3}$$

It's easy to prove central moment u_{pq} is translation invariance, if making it with scale invariance, normalized central moment $\bar{u}_{pq}$ should be used and defined as:

$$\bar{u}_{pq} = \frac{u_{pq}}{(u_{20}+u_{02})^r} \quad \text{or} \quad \bar{u}_{pq} = \frac{u_{pq}}{(u_{00})^{(p+q+2)/2}} \tag{4}$$

where $r = (p+q+2)/4;\ p+q = 2, 3, \ldots$.

3.2 Hu's Moment Invariants

Lower order moment could express a certain distribution or target's basic geometric properties. Main regular moments are zeroth order moment, first-order moment, second-order moment, third-order moment. Hu's moment invariants theory (Hu, 1962) is a nonlinear combination of 7 parameters by normalized central moments, defined as:

Moment invariant 1:

$$\phi_1 = u_{20} + u_{02} \tag{5}$$

Moment invariant 2:

$$\phi_2 = (u_{20} - u_{02})^2 + 4u_{11}^2 \tag{6}$$

Moment invariant 3:

$$\phi_3 = (u_{30} - 3u_{12})^2 + (3u_{21} - u_{03})^2 \tag{7}$$

Moment invariant 4:

$$\phi_4 = (u_{30} + u_{12})^2 + (u_{21} + u_{03})^2 \tag{8}$$

Moment invariant 5:

$$\begin{aligned}\phi_5 &= (u_{30} - 3u_{12})(u_{30} + u_{12}) \times [(u_{30} + u_{12})^2 - 3(u_{21} + u_{03})^2] \\ &+ (3u_{21} - u_{03})(u_{21} + u_{03}) \times [3(u_{30} + u_{12})^2 - (u_{21} + u_{03})^2]\end{aligned} \tag{9}$$

Moment invariant 6:

$$\begin{aligned}\phi_6 &= (u_{20} - u_{02})[(u_{30} + u_{12})^2 - (u_{21} + u_{03})^2] \\ &+ 4u_{11}(3u_{30} + u_{12})(u_{21} + u_{03})\end{aligned} \tag{10}$$

Moment invariant 7:

$$\begin{aligned}\phi_7 &= (3u_{21} - u_{03})(u_{30} + u_{12}) \times [(u_{30} + u_{12})^2 - 3(u_{21} + u_{03})^2] \\ &+ (3u_{21} - u_{03})(u_{21} + u_{03}) \times [3(u_{30} + u_{12})^2 - (u_{21} + u_{03})^2]\end{aligned} \tag{11}$$

Semi-major axis *a*:

$$a = [\frac{u_{20} + u_{02} + [(u_{20} - u_{02})^2 + 4u_{11}^2]^{1/2}}{\mu_{00} / 2}]^{1/2} \tag{12}$$

Semi-major axis *b*:

$$b = [\frac{u_{20} + u_{02} - [(u_{20} - u_{02})^2 + 4u_{11}^2]^{1/2}}{u_{00} / 2}]^{1/2} \tag{13}$$

Based on the above parameters, ratio φ of semi-major axis and semi-minor axis is:

$$\varphi = a / b \tag{14}$$

Radiometric *F* of ellipse is:

$$F = u_{00} / \pi ab \tag{15}$$

As the same with Hu's 7 moment invariants, in actual data processing, φ and *F* should be expressed by normalized central moments.

4. AIRPLANE RECOGNITION METHOD

In LiDAR data, the direction of airplane is arbitrary, the outline and size are usually different, but they are similar in appearance, so the method must consider deformation and scale invariance. We use prior knowledge and invariant recognition moment to recognise airplanes (even hidden targets mainly under the cover of canopy). Figure 1 shows the processing procedure as follows:

1. Filter and classify point cloud data into ground points and non-ground points;
2. Organize non-ground points by KD-tree;
3. Cluster the organized point cloud data and calculate the different targets;
4. Transfer each object into depth image. Assign the minimum and maximum of the targets' height as 0 and 255, so the height range can be extended to 0-255;
5. Refine depth image;
6. Remove the incorrect results based on prior knowledge such as the targets' length, width, height and the ratio of length to width;
7. Calculate seven invariant moments of airplanes;
8. Identify target by Euclidean distance between the target and template which was built before.

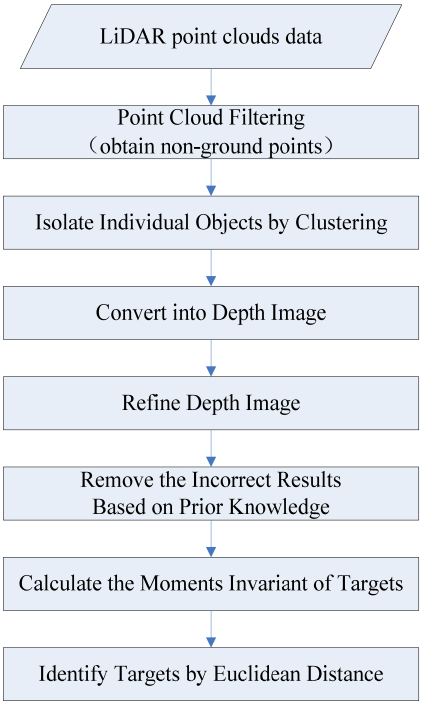

Figure 1. Flowchart of airplane recognition

5. EXPERIMENTAL RESULTS AND ANALYSIS

In this section, we experimented on the LiDAR point cloud data to confirm the recognition method for airplane targets proposed in this paper. The point cloud data to be identified is shown in Figure 2 (the red and green points respectively represent ground and non-ground points), which contains 23128 points and with a density of 2.4 points/m^2, and the results of target recognition are shown in Figure 3 (the green and red points respectively represent airplane target and other target points).

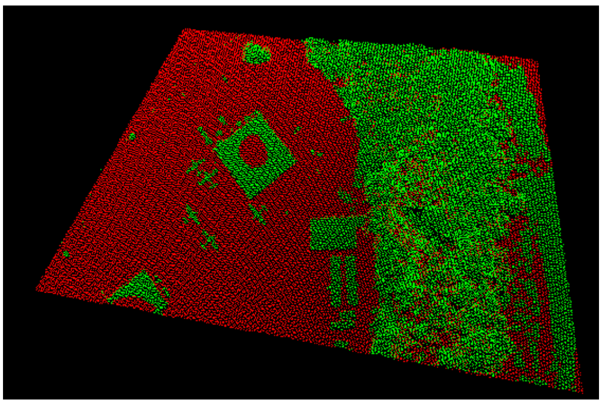

Figure 2. Point cloud data to be identified

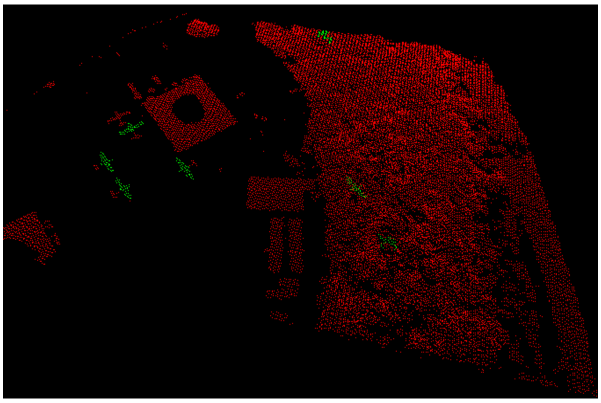

Figure 3. Result of airplane recognition

In order to demonstrate the precision and robustness of the proposed method, another LiDAR point cloud data is shown in Figure 4 (the red and green points respectively represent ground and non-ground points), which contain 64954 points and with a density of 1.7 points/m^2, and the results are shown in Figure 5 (the green and red points respectively represent airplane target and other target points).

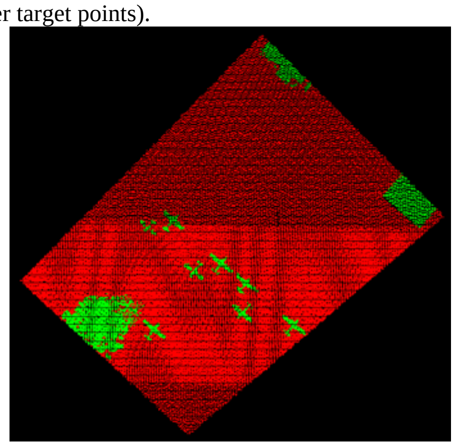

Figure 4. Another point cloud data to be identified

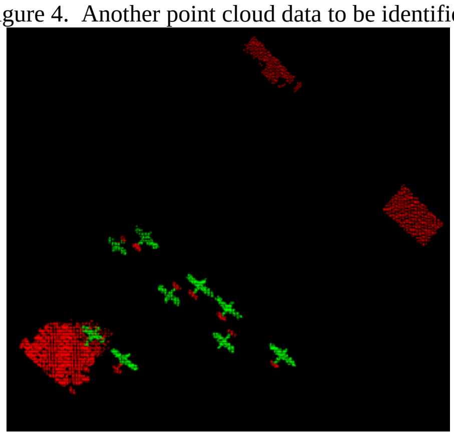

Figure 5. Result of airplane recognition

In this paper, we firstly use KD-tree to organize and manage point cloud data, and make use of the clustering method to segment objects, and then the prior knowledge and invariant recognition moment are utilized to recognise airplanes. Some of depth images obtained from results of the clustering method are shown in Figure 6 (for displaying, in the depth images, the grey range is 127-255, and the points of no value are set to 0). The results in top row are correct, while the ones in below row are incorrect, but can be eliminated by the invariant recognition moment.

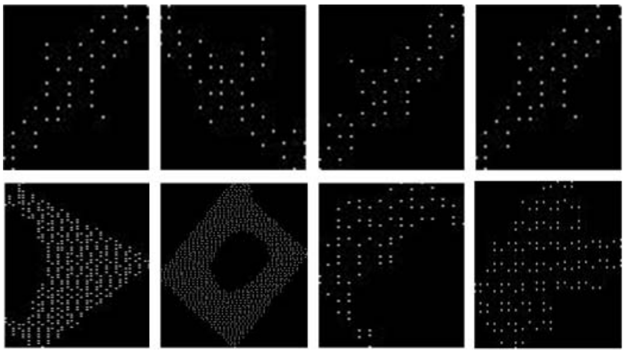

Figure 6. Depth images of the clustering results

In addition, in order to verify the effectivity of moment invariants, we carried out an experiment utilizing the match template method (Bin, 2008) to recognize airplanes in the same depth image. Table 1 lists the performance comparison. The results show that the moment invariants used in this paper is superior to the other.

	Result of this paper	Result of paper (Bin, 2008)
Total number of targets	16	16
Number of correct results	15	13
Number of incorrect results	1	4
Number of miss targets	1	3
Accuracy rate (%)	93.75	81.25
False alarm rate (%)	6.25	23.53

Table 1. Performance comparison

6. CONCLUSIONS

Airplane recognition based on LiDAR point cloud data is a brand new application domain. Taking advantage of KD-tree and Moment Invariants, this paper presents a novel method to recognize airplane targets. And by carrying out tests we validated its feasibility and practicality. Considering many other factors, e.g. canopy density, canopy thickness, and LiDAR hardware properties, could influence the effect of disguised objects detecting by using point cloud data, the further research work should be considered the above issues.

In addition, the approach of this paper could also be applied to other kinds of targets (even hidden targets) recognition. And we are now working on the algorithm evaluation and perfection, as well as analyzing the factors that affect targets recognition and researching the better method for neighbour targets segmentation.

7. REFERENCES

Bin, X., 2008. Research on object extraction and measurement based on LiDAR data, Master Thesis, Academy of Opto-Electronics, Chinese Academy of Sciences, Beijing, China.

Buck, J., Malm, A., Zakel, A., Krause, B., Tiemann, B., 2007. High-resolution 3D coherent laser radar imaging. Laser Radar Technology and Applications XII. Proc. of SPIE, Vol. 6550, pp. 655002.

Golovinskiy, A., Kim, V., Funkhouser, T., 2009. Shape-based recognition of 3D point clouds in urban environments.

Computer Vision, 2009 IEEE 12th International Conference on, Kyoto, Japan, pp. 2154-2161.

Hans-Gerd, M., George, V., 1999. Two algorithms for extracting building models from raw laser altimetry data. ISPRS Journal of Photogrammetry & Remote Sensing 54, 1999, pp. 153-163.

Hu, M., 1962. Visual pattern recognition by moment invariants. Information Theory, IRE Transactions, 8(2), pp. 179-187.

Jinhui, L., Zhuoxun S., 2009. New Approach of Imagery Generation and Target Recognition Based on 3D LIDAR Data. The Ninth International Conference on Electronic Measurement & Instruments, 2009, pp. 612-616.

Marino, R. and W. Davis, 2005. Jigsaw: a foliage-penetrating 3D imaging laser radar system. Lincoln Laboratory Journal, 15(1).

Moore, A., 1991. An intoductory tutorial on kd-trees. PhD Thesis, Efficient Memory-based Learning for Robot Control, Computer Laboratory, University of Cambridge, Cambridge, England.

Prokhorov, D.V., 2009. Object recognition in 3D LiDAR data with recurrent neural network. Computer Vision and Pattern Recognition Workshops 2009, California, USA, pp. 9-15.

Sahibsingh, A., Kenneth, J., Robert, B., 1997. Aircraft Identification by Moment Invariants. IEEE Transactions on Computers, Vol. C-26, No. 1. 1977, pp. 39-46.

Zhongliang, Q., Wenjun, W., 1992. Automatic ship classification by superstructure moment invariants and two-stage classifier. Singapore ICCS/ISITA '92, 1992, pp. 544-547.

8. ACKNOWLEDGEMENTS

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