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Adaptive Segmentation Algorithm based on LiDAR Point Cloud

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Abstract

Point cloud segmentation is of great significance in point cloud data processing, and the algorithms proposed in recent years can segment the whole outline, but many details are missing. In order to improve the precision of high point cloud segmentation, an adaptive algorithm based on LiDAR point cloud is proposed. First, the point cloud data are denoised, and the random sampling consistency algorithm (RANSAC) is used to detect and eliminate the plane points. Secondly, octree is used to establish the topology structure, calculate the adaptive distance, obtain the appropriate value of each detection distance, and carry out Euclidian clustering. Then, appropriate seed points are selected from the clustering results for regional growth. Finally, a threshold is set to further optimize the over-segmented and under-segmented point clouds. The method is verified by equipoint cloud data of intermountain overhead lines. Experimental results show that the segmentation results of this method are superior to the European clustering and octree based regional growth algorithm in both overall and detail.

Keywords

Point Cloud Segmentation; Lidar Technology; Regional Growth; Euclidean Cluster.

1. Introduction

LiDAR (Light Detection And Ranging) is an important way to obtain 3D geographic information, which has high efficiency and strong anti-interference, and can obtain large-scale high-precision point clouds [1], providing a brand-new technical means for power grid planning and measurement. Point cloud segmentation is to divide the messy point cloud data in space into sets with the same attributes[2], which provides important information for subsequent surface reconstruction and other processing, and is the basis of realizing object recognition. However, due to the high dimension, large scale, disorder and lack of organizational structure of point cloud data[3], the difficulty of point cloud segmentation is increased, so point cloud segmentation has always been one of the hot spots and difficulties in research.

At present, point cloud segmentation is mainly divided into two directions: one is the classical algorithm widely used in feature extraction and object segmentation, which is mainly divided into three categories. 1) Based on the segmentation algorithm of region growth, select the appropriate seed points in the point cloud, and divide the discrete points around each seed point according to the similarity parameters such as curvature and correlation coefficient. In 2012, Wang[4] implemented a fast plane segmentation algorithm based on region growth, which can be used for indoor obstacle detection. 2) Attribute-based segmentation algorithm, which classifies points according to their characteristic attributes. In 2010, Zhan[5] realized a point cloud segmentation algorithm combining normal vector and color information. Zhan[6] et al,also improved the traditional Euclidean clustering algorithm, which established feature vectors by considering a number of similarity parameters, and divided them according to similarity in the neighborhood of selected points. 3) Based on graph segmentation algorithm, the graph structure is constructed for segmentation. Schoenberg [7] et al, realized a segmentation algorithm based on Markov random field model, which mainly deals with depth images after data fusion. In 2015, Yang [8] and others used the graph model to fuse regions, and obtained RGB-D image segmentation results with clear boundaries by minimizing the energy function.

Second, point cloud segmentation methods based on deep learning are mainly divided into three categories. 1) Based on projection and view method, 3D data is transformed into 2D image, and then processed[9]. Qin[10]et,al, realized a segmentation method based on multi-view, and proposed the first network architecture to apply multi-view CNN to the classification of large-scale building point clouds. 2) The method based on point cloud is characterized in that the initial data is directly input, and the point cloud is not processed before input. PointNet[11] is the first network to realize this method,Later, Qi et al,put forward PointNet [12], which is mainly composed of feature extraction blocks composed of Pointnet, and uses feature propagation to improve the network architecture. 3) Unsupervised learning method, which is a new trend of deep learning development, makes use of the characteristics of self-encoder, and can realize different types of leapfrog generation without relying on data annotation. Li et al,proposed SO-Net network [13], which can extract features from each node of self-organizing graph by using self-organizing map to input point cloud.

These methods have their own advantages, but they all have some shortcomings. Point cloud segmentation based on deep learning has greatly improved in detail processing, but it needs to train a large amount of data and build a complex environment, which consumes a lot of time and has a limited scope of application. However, the classical algorithm has fixed functions, and the segmentation of point cloud is not fine enough. In order to reduce the time complexity and improve the segmentation accuracy of point cloud, in this paper, the related algorithms are improved, and the adaptive Euclidean clustering and the optimized region growing algorithm are used for segmentation in two steps, and experiments are carried out on multiple point cloud data sets. Experimental results show that the method adopted in this paper has a great improvement compared with the related algorithms, and has achieved good segmentation results.

2. Point Cloud Preprocessing

In the process of collecting data by using LiDAR technology, this technology does not actively screen laser points, but scans and records all targets in the visual range, so the obtained point cloud data contains some noise points. At the same time, because the measurement error will produce random and disorderly outliers, and the point cloud obtained after scanning the overhead line scene is complicated, the calculation is heavy. Therefore, it is necessary to preprocess the point cloud data, mainly dealing with noise points, outliers and plane points in the data. On the one hand, it avoids the influence of these useless points on segmentation results, on the other hand, it can reduce the complexity of data and improve the segmentation accuracy.

2.1. Remove Noise Points

In the initial data of point cloud, the number of points is numerous, and there will be a large number of points that are far away from the measured object,These noise points and outliers are not conducive to point cloud segmentation, and will also complicate the calculation of point cloud normals and curvatures, thus affecting the segmentation results of point cloud.

After comparing several methods, Statistical Outlier Removal is selected to remove noise points,By creating a filter to process the neighborhood of points, the points that do not meet the standards are eliminated. Specific steps: 1) For each point, calculate the average distance from it to all adjacent points. Assuming Gaussian distribution, a mean μ and a standard deviation σ can be calculated,2) In this set of neighborhood points, all points whose distance from their neighborhood is greater than (μ+ d * σ) interval are regarded as outliers, which can

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be removed from the point cloud data. D is the threshold of multiple of standard deviation, which is 1 by default in this method. Because of the large scale of overhead line point cloud, the number of adjacent points of each point is set to 100, and D is set to 2, which indicates that if the distance of a point exceeds the average distance plus more than two standard deviations, this point will be marked as an outlier and removed.

2.2. Plane Point Elimination

For the overhead line point cloud, the main segmentation targets are towers and power lines,The noise points are removed in the first step, but the vast ground still occupies a large part, so it is necessary to eliminate these plane points. In this paper, RANSAC algorithm is used to detect plane points and eliminate them, and the main adjustment parameter is distance threshold. Because the ground of overhead line point cloud is high and there are many vegetation influences, it is necessary to adjust the parameters several times, and the appropriate threshold is 15 meters.

3. Euclidean Clustering

3.1. Combined with RANSAC Euclidean Clustering Method

Firstly, the input point cloud is voxelized down-sampled and discrete points removed to simplify the processing of point cloud; Secondly, RANSAC algorithm is used to detect and eliminate plane point clouds, which is convenient for subsequent operations; Finally, European clustering is performed.

3.2. Algorithm Evaluation

This method has good stability, can extract the plane point cloud, is convenient for processing the remaining points, and is suitable for segmenting objects out of plane. However, the segmentation of data is incomplete, and some laser points will be lost, which takes a long time to deal with large-scale complex point clouds.

4. Regional Growth

4.1. Region Growth Algorithm based on Octree

Traditional region growing algorithm has some shortcomings such as difficulty in parameter adjustment and over-segmentation, Anh-Vu Vo [14] and others put forward an improved region growing algorithm based on octree.

4.2. Algorithm Evaluation

Compared with the traditional region growing algorithm, this method combines octree in the traditional algorithm, which improves the segmentation efficiency and makes the segmentation result smoother. However, the segmentation of details is not accurate enough, which will lead to over-segmentation and insufficient segmentation.

5. Improved Algorithm

The above two algorithms have their own advantages, but the segmentation results are still insufficient,Therefore, this paper proposes an improved algorithm, which combines the advantages of the two algorithms and solves the shortcomings of the above algorithms.

Firstly, Euclidean clustering is improved, and an adaptive threshold Euclidean clustering algorithm is proposed. Because the point cloud data is discrete and disorderly, in order to find the neighborhood relationship of each point quickly, the topological relationship of the point cloud needs to be established first.

As a common spatial index strategy, Octree and KD-Tree are widely used in point cloud data organization. The two methods have their own characteristics,Some scholars' experiments indicate that Octree is more suitable for large point clouds. Using Octree method, the point clouds are divided into three-dimensional grids, and the topological relations between the point clouds are established,Then, the adjacent points are searched for each laser point, and the Euclidean distance between each point and the adjacent points is calculated and classified. The specific algorithm flow is as follows:

1) establish octree data structure for input point cloud data P.

2) Establish an empty cluster set R and a queue Q, and each point in Q should perform the following operations.

3) Perform the following steps for each $P_i \in P$

a. Add P_i points to the current queue Q

b. for each point $P_i \in Q$, perform the following operations: firstly, search P_i for k nearest neighbor by using search radius r, and the searched point is P_i^k; Secondly, the euclidean distance between P_i^j and P_i is calculated for each $P_i^j \in P_i^k$, and the two with the smallest distance are classified as one class; Finally, check whether each P_i point performs the above operations, and if not, add the point to the queue Q.

c. when all the points in the list in queue q perform the above operations, add the points in Q to the list of set r, and empty the list of Q.

4) Calculate the Euclidean distance between all clusters in R and the cluster with the smallest Euclidean distance. Repeat this process until the Euclidean distance between all clusters in R is greater than the distance threshold S_d.

$$S_d = a \cdot \left(X_i^2 + Y_i^2\right) + b \cdot \sqrt{X_i^2 + Y_i^2} + c$$

S_d is the most important part to realize adaptive change. X_i and Y_i are the coordinates of the points to be processed, and a, b and c are the adjustment parameters, and their values usually change with the angle accuracy of lidar,The higher the angle accuracy, the smaller the value. When calculating the Euclidean distance between a data point or cluster and its neighboring points or clusters, S_d will adjust its value according to the coordinates of the center point of the point or cluster, so the appropriate value of each detection distance is obtained. This self-adaptive adjustment will select the appropriate clustering threshold according to different point clouds, which overcomes the shortcoming of fixed segmentation scale in the above algorithm and greatly improves the segmentation accuracy.

Then the region growing algorithm is carried out,The traditional region growing algorithm has random selection and fixed interval selection for seeds,Although these methods are simple, the segmentation results are unstable. Because of the adaptive Euclidean clustering in the first step, the point cloud has been divided into several categories, which is beneficial to the selection of seed points,Random selection of seed points in the relatively smooth area of the clustered point cloud cluster can improve the stability of segmentation. In order to solve the problems of over-segmentation and insufficient segmentation in the region growing algorithm based on octree, it is necessary to optimize the segmented point cloud,The specific process is as follows:

1) setting a minimum value min and maximum value max of point cloud clustering;

2) divide all kinds of segmented point cloud values Q_i (i =1,2,3 ...). Compare with that value in step 1 to find out the point cloud clusters which are less than min and lar than max;

3) classifying the point cloud cluster smaller than min and its nearest normal point cloud cluster as a class, and setting a smaller termination condition for the point cloud cluster larger than max for secondary segmentation;

4) Repeat step 2 again until the points of all point clusters are between min and max.

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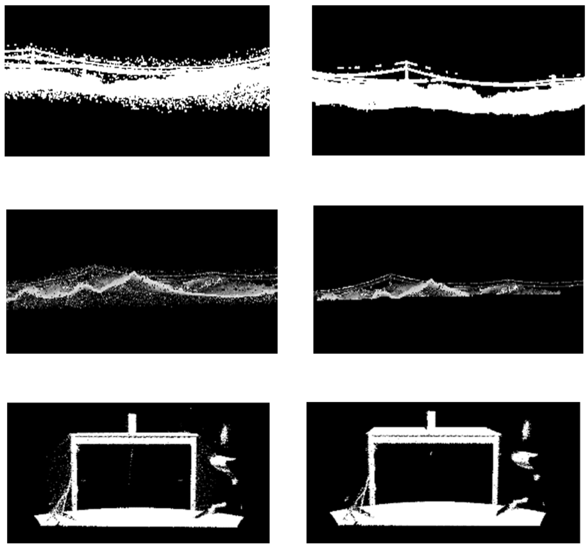
6. Experiment and Analysis

In order to verify the effectiveness and universality of the algorithm, this paper selects table_scene_lms400 point cloud data provided by the mountain overhead line and PCL official website to test the algorithm, and compares the experimental results of this method with those of Euclidean clustering and octree-based region growth algorithm.

6.1. Pretreatment Results

Comparison of the effects before and after denoising using statistical analysis technology is shown in Figure 1.

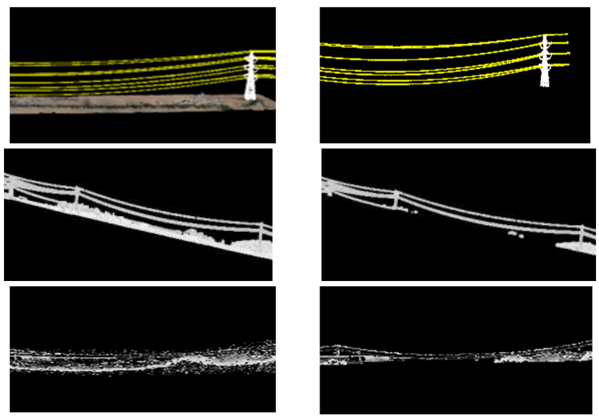


before denoising after denoising

Figure 1. Comparison before and after denoising

By comparing before and after denoising, it can be seen that the unorganized outliers and noise points in the original data have been effectively eliminated, which reduces the amount of data processed, and then presents the segmentation target better.

The effect comparison before and after using RANSAC algorithm to eliminate plane points is shown in Figure 2.



before eliminating after eliminating

Figure 2. Comparison before and after eliminating plane points

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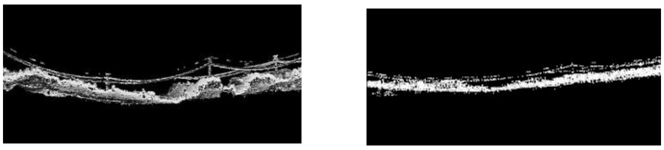
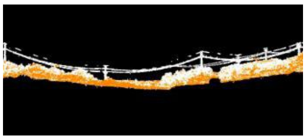
From the comparison before and after elimination, it can be seen that the plane points occupying a large proportion in the original data have been completely eliminated, and the objects above the ground are preserved, which is convenient for the next step of data segmentation.

6.2. Comparison of Segmentation Results

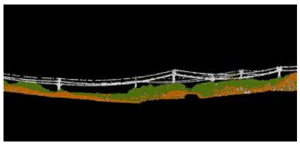
The segmentation results of this method are compared with those of Euclidean clustering and octree-based region growing algorithm as shown in Figures 3 and 4.



(a) original data set 1 (b) Euclidean clustering segmentation result



(c) Region growing algorithm based on octree segmentation result

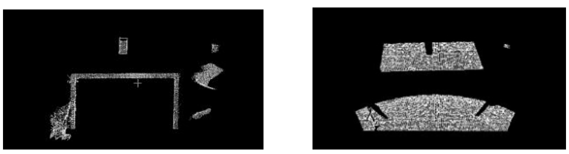


(d) Segmentation result of this method

Figure 3. Segmentation result of data set 1

Data set 1 is a point cloud of mountain transmission lines, which describes long-distance power lines and small towers. By comparing the results, it can be seen that some laser points are still lost in Euclidean clustering, and small towers and a large number of power lines are not completely displayed. The segmentation effect of region growing algorithm based on octree has been improved, but a few power lines are lost, and the power lines are connected with the ground, which leads to insufficient segmentation. This method can separate all towers and power lines, and there is no connection between the power lines and the ground, which solves the shortcoming of insufficient segmentation,The results are more complete and superior to the above two methods in whole and detail.

(a) Original data set 2



(b) Euclidean clustering segmentation result

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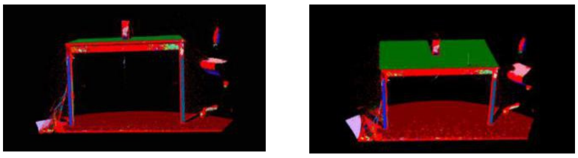
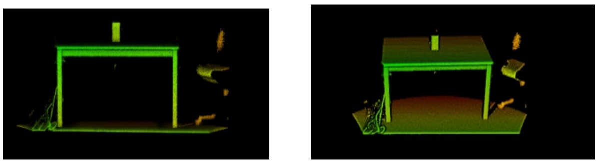


(c) Segmentation results of region growth algorithm based on octree



(d) Segmentation result of this method

Figure 4. Segmentation result of data set 2

Data set 2 is a desktop point cloud, which describes a table and objects on the desktop and beside it. From the comparison of segmentation results, it can be seen that Euclidean clustering displays planes and objects separately, but it is not easy to observe and understand. The region growing algorithm based on octree has a good segmentation effect, which distinguishes different objects with different colors, but different colors exist on the same object (such as table legs), resulting in wrong segmentation. The method in this paper can distinguish all kinds of objects completely, and solve the shortcoming of wrong segmentation,The effect is more intuitive and the contrast is more obvious, which is better than the above two methods in whole and detail.

Generally speaking, this method has greatly improved the whole and details of point cloud segmentation, and has a good segmentation effect for LiDAR point clouds with large data volume.

7. Conclusion

This paper presents an adaptive segmentation algorithm based on LiDAR point cloud. Firstly, the RANSAC algorithm is used to detect ground points and eliminate them, Then, the topological relationship of disordered point clouds is established, and the appropriate value of each detection distance is calculated according to the adaptive distance, and then Euclidean clustering is carried out, Seed points are selected from the clustering results for regional growth, Finally, the segmentation results are further optimized. Experimental results show that this algorithm can improve the accuracy of segmentation, and has good results in the whole and details. But there are still some shortcomings, Because of the combination of RANSAC algorithm, Euclidean clustering algorithm and region growing algorithm, in addition, the large amount of point cloud data increases the computational complexity. How to improve the segmentation accuracy and reduce the computational complexity will be the next research content.

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