A Fast Segmentation Method of Sparse Point Clouds

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Abstract: In this paper, we present a fast segmentation algorithm based on the geometric characteristics of the objects and the attribute of medium. This algorithm is not only suitable for sparse point clouds, but also for dense point clouds. It is built up of three stages: First, the range image is established from the Velodyne VLP-16 laser scanner data, which changes the sparse characteristic of data in the original space and determines the close relationship between the data points. Then, according to the geometric relation of the adjacent data points and point clouds edges distribution analysis, a region growing method is used to complete the fast segmentation of point clouds data, obtaining a series of mutually disjoint subsets. Finally, based on the laser intensity, refined segmentation of the under-segmentation subset is addressed using the K-means clustering method. The point clouds of an indoor corridor scene are used to verify the superiority of our method and compared with three typical algorithms. Experimental results prove that our method can fastly and accurately segment objects in the scene, and is not sensitive to noise and satisfactory in anti-noise performance.

Key Words: Sparse point clouds, Range image, Point clouds segmentation, Laser intensity

1 INTRODUCTION

The accuracy and real-time performance of objects detection in the surrounding environment is the key factor for the perception and decision of an unmanned system. Laser range sensors, also called LIDARs, are often used for environment perception and object detection because of their many advantages, such as, high anti-interference ability, measuring accuracy and real-time performance, etc. Currently, object classification and recognition for point clouds obtained by LIDAR has become a hotspot in 3D visual field [1]. In the process of point clouds, the segmentation of 3D laser range data is a critical pre-processing step in intelligent navigation of unmanned vehicles, ground measurement, three-dimensional reconstruction, obstacle detection, environment awareness tasks, etc. The fast segmentation of the same object point clouds has become a relatively well-researched topic [2].

In the last couple of decades, a set of segmentation algorithms for various types of point clouds had been proposed (e.g. 2D laser data, the dense 3D data form Riegl scans or Kinect, the sparse 3D data from Velodyne). Those published segmentation algorithms can be briefly divided into the following groups: feature-based segmentation method [3] [4], grid-based segmentation method [5], range image-based segmentation method [6] and intensity image-based segmentation method [7]. KE Yinglin *et al*.[8] proposed a new grid-based segmentation method that divides measured points into many 3D grids and estimates the grid's curvature by the maximum principal curvature of the point nearest to the grid center. Based on the grid's curvature the edge-grids are detected, and the point clouds are partition into several regions based on the connectivity of 3D grids. However, it requires a uniform distribution of point clouds since every 3D-grid should contain some scattered points. Therefore, this method is not suitable for segmenting sparse point clouds with uneven spatial distribution. In [9], a segmentation algorithm is proposed for the problem that the edge is uneasy to position when dealing with the point clouds. In this algorithm, the regional distribution property of point clouds is taken as the basis, and a regional growth approach is used to accurately segment the point of the plane. M.Himmelsbach *et al*. [10] proposed a 2.5D occupancy grid model that records the estimated height of objects above the ground. Above these methods, however, ignore the intensity information that can distinguish different surface media. In the paper [11] researchers establish a linear laser intensity correction model based on the laser range equation and the radiation mechanism of laser scanner systems, where the intensity value is modified to eliminate the influence of the laser incident angle and measurement distance. However, this corrected intensity-based approach is only applicable to the segmentation of object cloud with the large difference of reflectivity. Another interesting segmentation approach was addressed in [12], where different types of media intensity calibration experiments were conducted in order to obtain calibrated intensity. After that, the segmentation is done according to the location of the point clouds and the laser calibration intensity information. Igor Bogoslavskyi *et al*. [13] presented a fast method that segments 3D range data into different objects and runs online, where the computation directly runs on a 2D range image that was generated from raw 3D point clouds. However, when it is applied to the large-scale scenes (e.g. the wall, the building exterior surface, etc.) will produce serious over-segmentation.

In this paper, we propose a fast segmentation algorithm based on the Igor Bogoslavsky's method, which makes full use of the geometric and attribute features of the object points. First, this algorithm maps the raw point cloud

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data to the range image by the LIDAR measurement principle and takes the spatial geometric angle constraint and the distance constraint as the segmentation criteria. Then, the region growing method is used to segment the raw point cloud. Finally, according to the intensity of objects, the under-segmentation with a relatively large difference in reflectivity are refined, so that two or more objects that are close to each other or even inter-connected are segmented into separate objects. This algorithm, noise-immune as it is, can obtain relatively accurate segmentation results.

2 FAST SEGMENTATION

2.1 The Mathematical Description of Segmentation

Assuming that 3D point clouds obtained from the laser scanner can be represented by the universal set *S* as follows:

$$S = \{(X_i, Y_i, Z_i, I_i), i = 1,2,\cdots,n\} \tag{1}$$

Where (X_i, Y_i, Z_i) and I_i denote the 3D coordinates in the Cartesian coordinate system and laser intensity of the reflected beam, respectively, and *i* is the serial number of the data points. The aim of segmentation is to spatially group points with similar properties into one region. In other words, point clouds segmentation is the process of obtaining a set of mutually disjoint subsets $R = \{S_0, S_1, \cdots, S_m\}$ which belongs to the universal set *S*, where $S_i(i \geq 0)$ is a subset which contains the points that belong to the same object, and *m* is the number of independent objects. If the subset *R* satisfies the following conditions, then, *R* is called an effective segmentation of the universal set *S*.

1) $\bigcup_{i=1}^{m} S_i = S$, which means that the union of the subsets is the universal set *S*, that is, each data point is belongs to a specific subset.

2) $S_i \cap S_j = \phi, \forall i, j \in \{0,1,\cdots,m\} \text{and} i \neq j$, which means that each data point can't belong to two different subsets at the same time.

3) The data points in each subset $S_i(i \geq 0)$ have the same characteristics, such as the normal vector, mean curvature and Gaussian curvature, and any two different sub-sets have different characteristics.

4) Each sub-set $S_i(i \geq 0)$ is a connected region, that is, the point in every subset is inter-connected in the space.

2.2 Fast Segmentation Based on Geometric Characteristics of Point Clouds

Most raw data provided by laser range scanners is described by spherical coordinates, and a coordinate vector in the spherical coordinate system is defined as $P = [r, \theta, \phi]^{\mathrm{T}}$, where *r*, θ , and ϕ denote the range, azimuth and elevation component, respectively. The range image generated from the universal set *S* can be expressed as $R(\theta, \phi)$, where the range image pixel value is the range at the angle（θ, ϕ）. Fig.1 is a range image generated from the raw 3D point cloud and the intensity image $I(\theta, \phi)$ can be obtained similarly. If the raw data measured from different laser scanner is not in the form of (r, θ, ϕ) , we still can obtain the range image through projection. Then, the segmentation can still be done using the proposed algorithm in this paper.

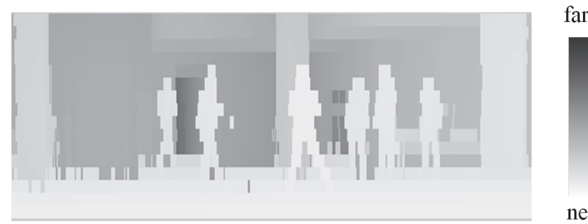


Fig.1 Range image from raw point clouds

Fig.2a shows an illustration of two adjacent points *A* and *B* measured from the VLP-16 located at *O* with the laser beams *OA* and *OB*. We assume the *y*-axis is oriented along the further of two adjacent points, where α is the angle between adjacent laser beams, d_1, d_2 are the laser distance from the target point *A*,*B* respectively, and *H* is the projection of point *B* on *OA*. The angle between *A* and *B* is defined as β between the straight line passing through the two points *A*, *B* and the line connecting the point that is further away from the scanner and the laser center, and $0^\circ < \beta < 90^\circ$.

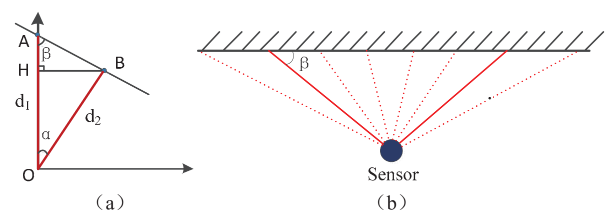


Fig.2 Geometric relationship of the scan time

Fig. 3 illustrates the pedestrian point cloud and the top view on the pedestrians, where the red line indicates the connection between two adjacent points belonging to different objects, and the green line vice versa. Intuitively, if the two adjacent points belong to the same object, β is large and vice versa. So the angle β can be used as the key parameter of the segmentation cloud. The theoretical formula is derived as follows:

$$\beta = \arctan\frac{\|BH\|}{\|AH\|} = \arctan\frac{d_2 \sin\alpha}{d_1 - d_2\cos\alpha} \tag{2}$$

Where α is the known angle between adjacent laser beams, which is either horizontal or vertical, and usually provided in the user guide manual.

From the theoretical formula of the angle β can be known, its value is determined by the range from the adjacent object point to the laser center, and it can be used as an important parameter of the segmentation. Assuming β_D is the threshold of β, we can make a decision about whether to divide any two points in the range image into separate clusters or merge them into one by this threshold. However, there is a failure case when we segment a multi-planar scene point clouds by this parameter alone. As shown in Fig.2b, the laser is scanning the wall in front of it from left to right, and angle β enlarges gradually and then becomes smaller. No matter what threshold value β_D we choose, it results in an over-segmentation of successive wall .

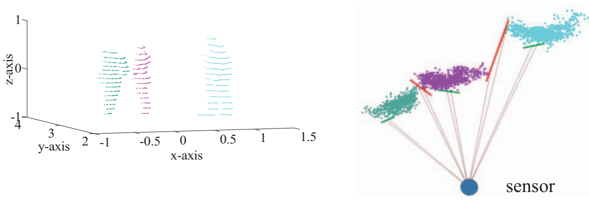


Fig.3 The pedestrian point clouds from Velodyne

In order to overcome the serious over-segmentation phenomenon caused by a single angle parameter, we introduce the distance constraint D between adjacent data points. The Euclidean distance between adjacent data points belonging to the same object is almost equal to the arc length formed by the short side and vice versa, so the distance threshold D can also be used as the parameter of point cloud segmentation. The formula is as follows:

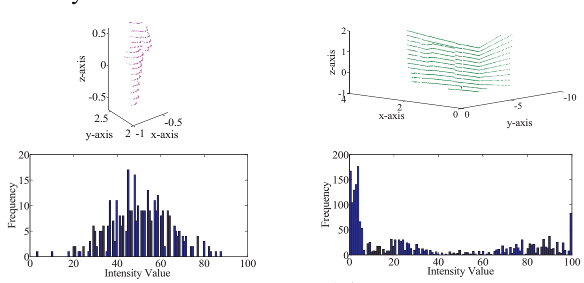
$$D = K * L * \alpha \quad (3)$$

Where K is the correction coefficient, and $L = \min(d_1, d_2)$ represents the distance that is closer to the laser center.

2.3 Refined Segmentation Based on The Attributes of Point Cloud

The laser intensity reflects the reflectivity of the object material. Intuitively, the reflection intensity value can be used as a key parameter to distinguish different media. However, the reflection intensity can be affected by the laser incident angle and measuring distance in application. For exploiting the laser intensity, we firstly correct it, taking the influence factor into account [14] [15].

In our experiments, the reflection intensity value of the 16-beam LIDAR was calibrated by internal unit. It can be directly used to refine the segmentation of the under-segmentation subject to large difference in reflectivity.



（a）The intensity histogram of a single object

（b）The intensity histogram of double objects

Fig.4 The intensity histogram of point cloud

The intensity histogram of single object and double object are shown in Fig.4, Repeated experiments indicate that the multi-peak structure characteristics of the intensity histogram is derived from the hybrid point cloud consisting of different media. The process of refined segmentation is as follows: First of all, according to the specific application scenario, we set the minimum point threshold P_{num} that is the minimum number of the under-segmented subset for initial screening. Then, the retained under-segmented subsets can be selected by the variance and the multi-peak structure of the intensity histogram. Finally, we refine segmentation of under-segmented subsets with large difference in medium property using the K-means clustering method.

3 SEGMENTATION ALGORITHM

In this paper, we assumed that the terrain is flat and the orientation of the LIDAR with respect to robot is known a priori. Thus, according to height difference threshold in the direction Z, we can quickly filter out the ground point cloud by calculating each column of the range image, leaving the object point clouds collection S. The basic algorithm flow is shown in Fig. 5

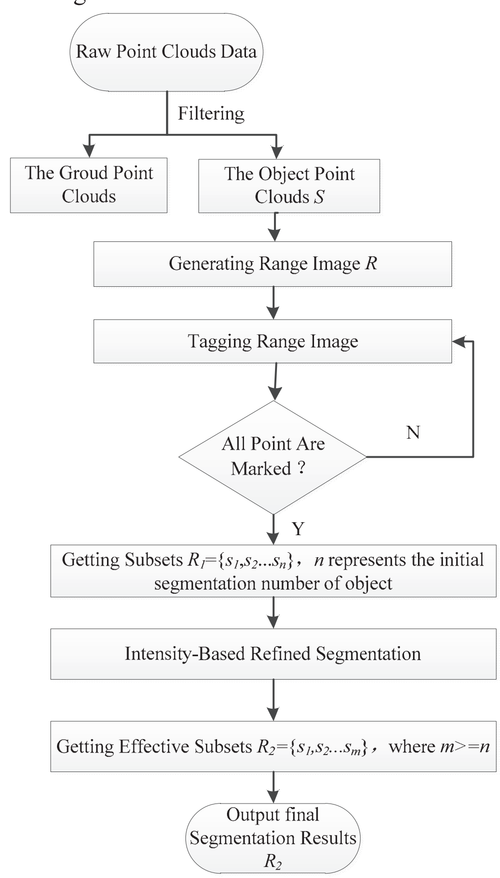


Fig.5 The basic flow chart of point clouds segmentation algorithm

The procedure of the algorithm and the basic steps are described as follows:

Step 1 On the basis of the assumed ground model, the ground point clouds are filtered out by the height difference threshold of the data in the direction *Z*, leaving the object point clouds collection *S*.

Step 2 The range image *R* is generated from the object point clouds collection *S* based on the map $R(\cdot)$.

Step 3 Based on the proposed angle constraints and distance constraints, the initial segmentation of the point cloud is accomplished by the region growing method. The pseudo code is shown in Tab.1.

Table1. The Pseudo Code of the Tagging Range Image

Algorithm 1 Tagging Range Image

Tag ⟵ 1，R ⟵ Range Image
L ⟵ zeros(R_{rows}×R_{cols})
for r=1 …R_{rows} **do**
 for c=1 …R_{rows} **do**
  if L(r,c)==0 **then**
   RegionGrowFun(r,c,Tag)
   Tag=Tag+1
Fun: RegionGrowFun(r,c,Tag)
region.push({r,c})
while(size(region)!=0)
 {r,c} ⟵ region.top()
 R(r,c)=0
 L(r,c) ⟵ Tag
for {r_n,c_n} ∈ NeighborhoodFour{r,c} **do**
 d1 ⟵ max(R(r,c),R(r_n,c_n))
 d2 ⟵ min(R(r,c),R(rn,cn))
 D=K*d2*α
if $\beta \ge \beta_D \,\|\, |d_1 - d_2| \le D$ **then**
  region.push({rn,cn})
region.pop()

Step 4 According to the statistical properties of the reflection intensity value, the set of initial segmentation $R_1 = \{S_0, S_1, \cdots, S_n\}$ is filtered, leaving the potential under-segmented subsets with the large difference in medium property. Then, the subsets are refined using the K-means clustering method.

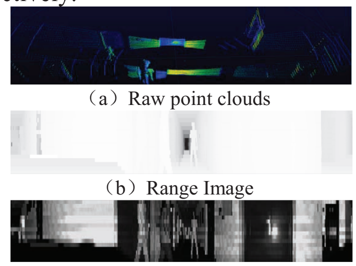
Step 5 Output the final point clouds segmentation results.

From the description of Algorithm 1, we can see that the algorithm guarantees visiting each point in the range image at maximum twice. Thus, the maximal complexity of this algorithm is equal to 2**N*, where *N* is the number of pixels in the range image. The computation complexity of this algorithm is linear with the number of point clouds. So, Algorithm 1 can accomplish fast segmentation of point clouds.

4 EXPERIMENTL RESULTS

In this paper, we focus on fast and effective segmentation for offline processing on a ground mobile robot that is equipped with a 16-beam laser scanner, as shown in Fig.6. In the experiment, we set the scanning frequency of the 16-beam scanner to be 10Hz and arbitrarily select a frame of data for comparative experiment. The original data of the 360° indoor corridor point cloud, the visual range image and the intensity image are shown in Fig.7, respectively.

Fig.6 Velodyne VLP-16 scanner



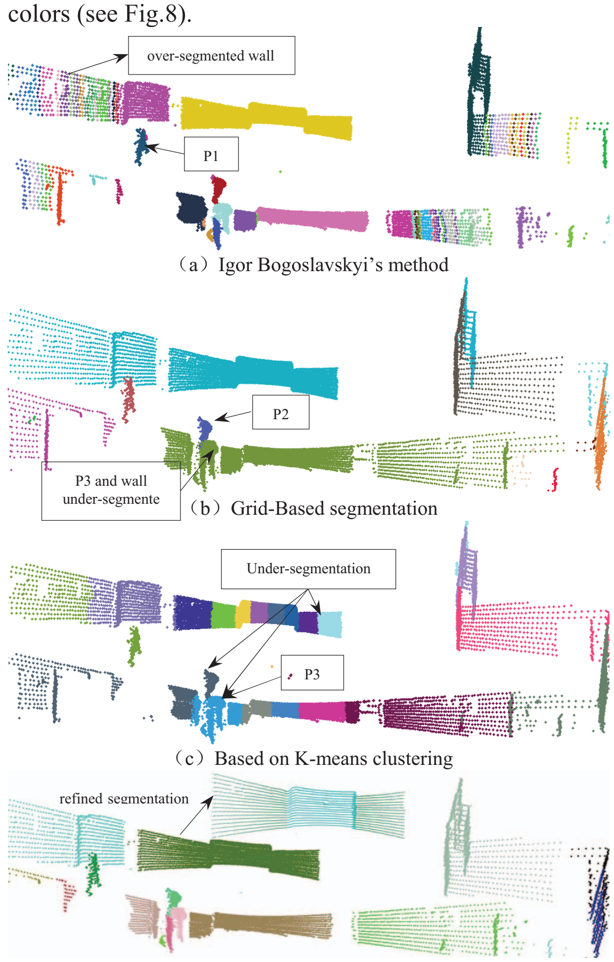
（a）Raw point clouds

（b）Range Image

（c）Intensity Image

Fig.7 Visualization of data

In order to objectively evaluate the superiority of the algorithm proposed in this paper, we use three different methods to segment the same scene point clouds data and the segmentation results are displayed in different random colors (see Fig.8).



（a）Igor Bogoslavskyi's method

（b）Grid-Based segmentation

（c）Based on K-means clustering

（d）Our approach

Fig.8 The comparison of experimental results of four different segmentation algorithms.

As shown in Fig.8, there are three pedestrians in this scenario, where P1, P2, P3 denote the pedestrians. In this experiment, three different segmentation methods are compared, including the method of Igor Bogoslavskyi [13], the grid-based method in [16] and the classical K-means clustering. The method of Igor Bogoslavskyi brings a severe over-segmentation of the continuous wall (see Fig.8a), resulting in a rapid increase of the number of subsets of the universal set *S*. The segmentation result is harmful to the 3D feature extraction and recognition in the following process. Fig.8b shows the segmentation effects at the best appropriate mesh size, however, P3 is still not completely separated from the wall. Generally speaking, the grid-based method has a slight tendency to under-segment the point clouds, and its effect is determined by the grid discretization. Therefore, this method does not apply to the separation of objects that are close to each other. The segmentation results based on K-means clustering is subject to greater uncertainties, so that the result is affected by the initial position of the clustering center and the number of cluster centers. According to the result of this method as shown in Fig. 8c, P2 and P3 are not well segmented from this scenario. The algorithm proposed in this paper generates satisfying segmentation effects (see Fig.8d), as it can accurately segment three pedestrians in the scene, and refine the point clouds of the wall and the door with the large difference in medium property.

5 CONCLUSIONS AND FUTURE WORK

In this paper, we propose a fast and accurate segmentation method of 3D Spare point clouds for the Velodyne VLP-16 laser scanner. Our method solves two major problems in point clouds segmentation: 1) how to establish a relationship between sparse data points; 2) how to reduce the interference of noise points. This method exploits the neighborhoods relation given by the range image and the reflection intensity of object to successfully segment 3D spare point clouds and it can be applied to a variety of different applications and scenes. Our future work will focus on integrating additional image information and the result of segmentation to recognize and classify the objects.

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