Road boundary detection algorithm based on multi-line 3D laser radar

Zhi Wei-Zhong, Peng Fei-Wang, Ze Peng-Zhang, Zheng-Yang, Hui-Zhang

***Abstract*— A road boundary detection algorithm based on multi-line 3D lidar is proposed for urban structural road boundary detection. The principle of this algorithm is that the point cloud data is extracted from a certain height road environment based on the existence of a certain elevation transition between the structured road area and the non-road area. Then, the region of interest is divided into four parts based on the radar coordinate system. According to the different regions, the point cloud data with obvious gradient (increasing and decreasing) are extracted by using the data gradient analysis. Finally, the least square method and the uniform non-periodic B - spline curve method are used to fit the road boundary of the straight and the curve respectively. The experimental results show that the algorithm can meet the task of real-time detection of intelligent vehicle road boundary for obstructing whether the road boundary is obstructed and whether the road boundary is continuous with high accuracy and robustness.**

***Index Terms*— intelligent vehicle; lidar; data gradient analysis; uniform non-periodic B-spline curve; road boundary detection**

I. INTRODUCTION

Intelligent vehicle on the surrounding driving environment perception, detection, identification is an important part of its autonomous navigation research. The purpose of road boundary detection is to distinguish between road area and non-road area, to provide a more secure traffic area for mobile robots, and to provide accurate road information for mobile robot autonomous navigation in order to plan its travel path accurately.

The field-based boundary detection system based on visual passive sensors has a narrow field of view and cannot provide more depth information in the surrounding environment and is susceptible to environmental factors. Based on the lidar active sensor is not only a wide range of detection, higher resolution and less affected by the environment. The road boundary detection algorithm based on visual passive sensor is mainly divided into feature-based method and model-based method. In [1], a real-time road detection algorithm based on neural network is proposed. The algorithm in the existing road environment can be more accurate detection of the road, but does not apply to the new road environment, and the algorithm is less accurate when the road route is changed to a curve. In [2], an algorithm based on road color and texture is proposed to detect urban roads by multiple artificial neural networks. However, because the road color and texture are susceptible to light and large cracks, and thus affect the accuracy and robustness of the algorithm. In [3], the method of road boundary recognition based on single line radar is proposed by defining idealized road model. The experimental results show that the method can identify the straight road environment more accurately, but for the corners and the branched road environment, the algorithm has low accuracy and low applicability. In [4], the geometric characteristics of the road edge are associated with the brightness information of the image, and an algorithm for detecting and accurately locating the road boundary is proposed. The experimental results show that the algorithm can detect the road boundary more accurately and the real-time performance is better, but it is easy to be influenced by environmental factors. In [5], a road boundary recognition algorithm based on the light intensity and azimuth information obtained by stereoscopic vision sensor is proposed. The experimental results show that the algorithm can identify the road boundary more accurately, but the robustness and accuracy are reduced when there are obstructions with similar brightness on the road or shadow masking. In [6], an algorithm based on LIDAR for real-time detection of road boundary is proposed. However, the algorithm based on the vertical path of adjacent roads and sidewalks is based on quadratic polynomials, and applicability also has some limitations.

In a structured road environment, the road boundary is based on the shoulder, and the geometric characteristics of the shoulder are important information for road boundary detection. The multi-line 3D laser radar collects the point-point cloud data with obvious elevation changes relative to the road area. The change of the elevation is located in the different position of the target vehicle, stratified gradient gradient with regular gradient, and the lidar is the active sensor, subject to external factors less interference. Therefore, this paper combined with HDL-32E laser radar for road boundary detection.

II. STRUCTURED ROAD BOUNDARY DETECTION ALGORITHM

1.1 Algorithm flow

This paper detects the road boundary algorithm is divided into the following steps: 1. The extraction of road boundary points is divided into the following three parts: (1) Based on the height of the radar in the target vehicle roof, the point - rough point of the road surface point cloud data is less than a certain height threshold in the cloud area of the target vehicle. (2) Based on the radar coordinate system, the target car is divided into four parts: a. $x>0, y>0$; b. $x<0, y>0$ c. $x>0, y<0$ d. $x<0, y<0$ In the different regions, data gradient analysis method is used to extract the cloud points with obvious gradient (increasing and decreasing). (3) Calculate the distance between two adjacent points, determine the number of clustering targets, and finally extract the point cloud data with the number of internal point

cloud data of the cluster target greater than a certain threshold; The road boundary is fitted by the least squares method, and the road boundary of the curve model is fitted by the uniform non-periodic B-spline curve. The process of road boundary recognition algorithm is shown in Figure1.

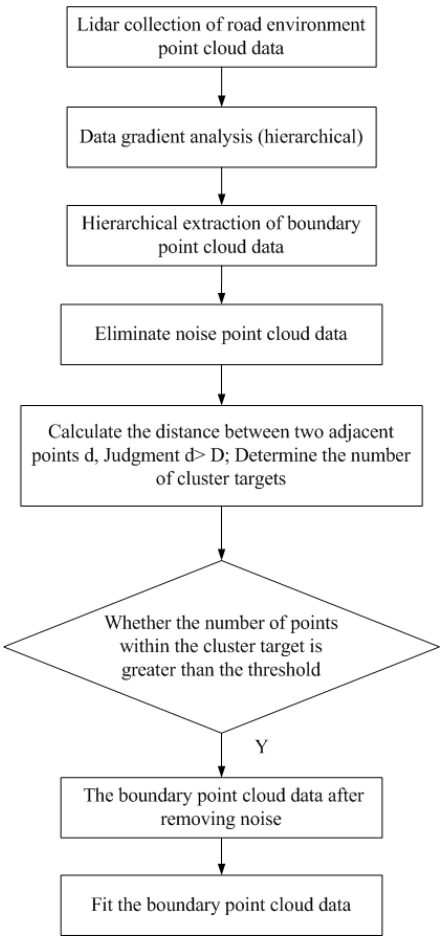


Fig. 1 Algorithm flow chart

1.2 Extraction of road boundary points

Based on the HDL-32E laser radar, the boundary data of the road boundary point has obvious characteristics of hierarchical gradient (increasing and decreasing), In this paper, we propose a hierarchical extraction of road boundary point cloud data based on the data gradient analysis method in different regions of the target vehicle. Considering that there is a problem of gradient (increment and decrement) of the cloud data with a small amount of point cloud data in a certain point cloud data of the non-road boundary area collected by the HDL-32E lidar, there is a lot of noise points in the extracted road boundary point cloud data. In this paper, we use K-means clustering method to eliminate noise. By comparing the distance d_i of the adjacent two points with a gradient (increasing and decreasing), the K value is determined. Finally, the clustering target interior point cloud data with the number of internal point cloud data of the clustering target is larger than a certain threshold. K value determination method:

$$d_i = |p_i - p_{i+1}|, (i = 1, 2, ...n) ; d_{threshold} = m \ ;$$

$$for \ i = 1 : n$$

$$if \ d_i > d_{threshold}$$

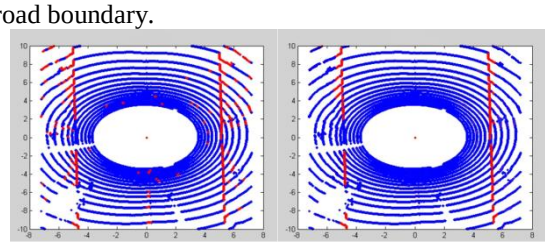
$$K = i \ ;$$

$$end$$

$$end$$

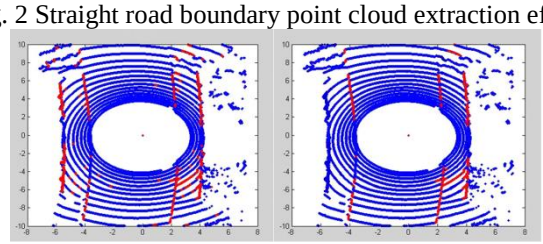
Where p_i is a point cloud data with gradient (increment, decrement) characteristics of a layer of road boundary collected by the extracted lidar; m is a gradient (increasing, decreasing) characteristic of the adjacent layer at two points of distance d_i Threshold value; K is the number of clusters that determine the K value in the clustering method.

In Figure 2 (a), the blue dots cloud is a point in the lidar scanning and a point cloud information of the target car's area of interest in a certain height range. The red dot cloud is the road boundary point cloud projection before the denoising . In Figure 2 (b), the red point cloud is a method to determine the number of clustering targets (values) in the clustering method based on the comparison of the adjacent two points of the gradient (ascending and decreasing) characteristics of a certain layer. The clustering target internal point cloud data The number of less than a certain threshold of the cluster target to remove the noise after the road boundary point cloud projection. From the figure we can see that many noise has been deleted, the red point cloud can be clearly on behalf of the road boundary. In Figure 3 (a), the blue point cloud is a point cloud of the laser radar scanning and the point cloud information of the target area of the vehicle is in a certain height range. The red point cloud is the road boundary point cloud projection before the denoising , In Figure 3 (b), the red dot cloud for clustering method denoising after the road boundary point cloud projection. Obviously a lot of noise has been removed, the red point cloud can be clearly on behalf of the road boundary.



（a）Before removing noise（b）After removing noise

Fig. 2 Straight road boundary point cloud extraction effect



（a）Before removing noise（b）After removing noise

Fig. 3 Corner road boundary point cloud extraction effect

III. ROAD MODELING AND SOLVING

1. B-spline curve definition

$n+1$ control points $p_i (i = 0, 1, \cdots n)$, M -order B-spline curve of the expression:

$$C(u) = \sum_{i=0}^{n} P_i N_{i,m}(u) \quad , \quad (1)$$

In the formula, $N_{i,m}(u)$ is a harmonic function, also called a basis function, which can be defined as a recursive formula:

$$N_{i,m}(u)=\frac{u-t_i}{t_{i+m-1}-t_i}N_{i,m-1}(u)+\frac{t_{i+m}}{t_{i+m}-t_{i+m}}N_{i+1,m-1}(u) \quad (2)$$

When $u\in[t_i,t_{i+1})$, $N_{i,1}=1$; In other cases, $N_{i,1}=0$. Where t_i is the node value, Constitute a M -order B-spline function of the node vector, where the node is a non-reduced sequence. Combined with the geometric characteristics of the shoulder in the curve model on the urban structured road, this paper uses the cubic B-spline curve to carry out the road boundary fitting of the curve model. The cubic B-spline curve is a smooth and continuous second-order derivative curve. The matrix of the cubic B-spline curve is expressed as follows:

$$C(u)=\frac{1}{6}[u^3,u^2,u,1]\begin{bmatrix}-1 & 3 & -3 & 1\\ 3 & -6 & 3 & 0\\ -3 & 0 & 3 & 0\\ 0 & 4 & 1 & 0\end{bmatrix}\times\begin{bmatrix}p_{i-1}\\ p_i\\ p_{i+1}\\ p_{i+2}\end{bmatrix},u\in[0,1] \quad (3)$$

2. The determination of the key points of the fitting curve

Some of the key points in the extracted cloud boundary data will have an effect on the shape of the approximation curve, which is called the curve fitting key. The curvature distribution of these points can reflect the overall and local characteristics of the extracted road boundary points. Therefore, this paper adopts the curvature distribution curve fitting method.

First, the curvature of the cloud data of the extracted road boundary point is solved. In this paper, the following method is used to solve the curvature radius ρ_i of the i th data point: 1) extract any two adjacent data points a, b, c in any two adjacent two points; 2) to do the vertical line, find two vertical intersection, namely: the center; 3) Calculate the center of the circle and the length d_i of any point is the curvature radius of the i -th data point ρ_i. So the curvature of the i -th data point is obtained, and the curvature distribution of the road boundary point is shown in Figure4.

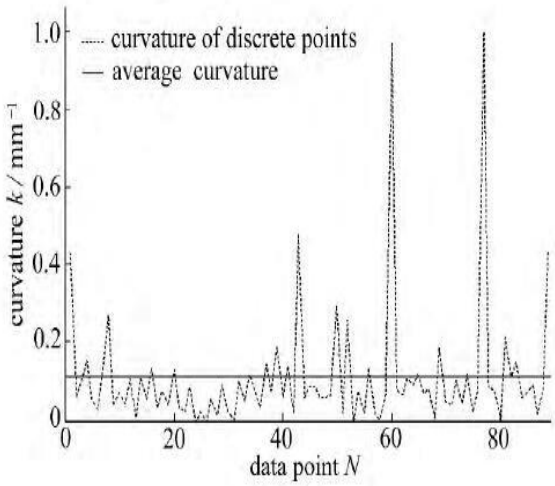


Fig.4 Curvature distribution of road boundary points

The number of key points is smaller than half of the total number of road boundary data points by $[k]=k_{avg}$, and the number of vertices can be effectively controlled because the curvature value of the road boundary contour is occasionally irregular. In the following, we use the method of [7] to construct the cubic B-spline curve interpolated at the key point.

3. Parameterization of key points

In order to make the fitting curve fully reflect the distribution of road boundary points, the centripetal parameterization method is adopted.

For $n+1$ key point $Q_k(k=0,1,\cdots,n)$, remember as $l=\sum_{k=1}^{n}\sqrt{|Q_k-Q_{k-1}|}$, then $\overline{u_0}=0,\overline{u_1}=1$, and $\overline{u_k}=\overline{u_{k-1}}+\sum_{k=1}^{n}\sqrt{|Q_k-Q_{k-1}|}/l$.

4. Node vector calculation

Use the mean method to solve the middle node vector by the formula (5) In [13]: $u_{j+p}=\frac{1}{p}\sum_{i=j}^{j+p-1}\overline{u_i}, j=1,2,\cdots,n-p$, (5)

5. Inverse control node

The basis function $N_{i,p}(\overline{u_m})$ is obtained by the parameter $\overline{u_m}$ and the node vector U. In the equation (3), the control node is the only unknown quantity, and is solved by the method [8].

IV. EXPERIMENTAL VERIFICATION AND DISCUSSION

In order to verify the effectiveness of this algorithm, the Tang Jun electric vehicle EV02 is loaded with the HDL-32E lidar as the experimental platform, as shown in Figure 5.

Fig.5 Experiment platform with lidar

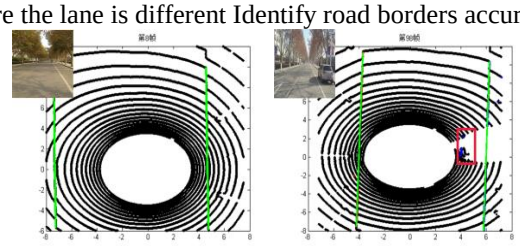
In order to compare the accuracy and robustness of the algorithm, the algorithm is used to deal with 670 frame cloud data and compare it with the idea of using the linear discriminant analysis (LDA) classification method proposed in [9]. The successful detection rate of this algorithm is 96%, of which 90% is the minimum boundary deviation of the fitting road, 6% is the larger boundary deviation of the fitting road, but has little effect on the road boundary detection, and can still provide accurate for the autonomous navigation of the mobile robot Road boundary information. In order to verify the accuracy and robustness of the proposed algorithm, the 3D data of the 310-point environment point in the structured road environment collected by the radar are processed. Compared with the proposed algorithm

performance and the performance of the proposed algorithm [9], as shown in Table 1:

Table 1 Algorithm performance

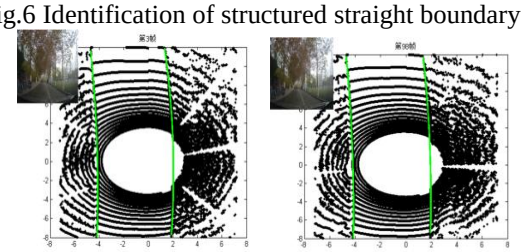
Road environment	The accuracy of the algorithm proposed in this paper（%）	The accuracy of the algorithm proposed in Document [9]（%）
Straight road boundaries	95.7	91.3
Corner road boundaries	82.5	73.8

The traditional image recognition algorithm can only recognize the incomplete straight or corners of the curve, and the robustness is poor due to the unavoidable introduction of noise interference in the camera's shooting condition, camera viewing angle and image transmission. The algorithm based on Matlab platform simulation results shown in Figure 6 and Figure 7, the green curve for the different roads, lighting and other conditions identified under the structural road boundaries. Figure 6 is a structured straight boundary identification map of different interval frame data (28th, 96th frame). Figure 7 shows the structured corners of the different frame data (36th, 87th frame) under low light conditions. It can be seen that the algorithm can be completed even in different road conditions (straight, corners), different road widths (actual road conditions: about 13 m, about 6 m), and where the lane is different Identify road borders accurately.



（a）28th frame （b）96th frame

Fig.6 Identification of structured straight boundary



（a）368th frame （b）87th frame

Fig.7 Identification of structured curve boundary

V. CONCLUSION

In view of the different urbanization and structured road environment, there is no obstacle to block the road boundary whether the road environment is continuous, this paper presents a better accuracy and robust road boundary detection algorithm. The key of the algorithm is two parts: first: According to the different regions of the target vehicle, the data of the point cloud with obvious gradient (increasing and decreasing) are extracted by data gradient analysis method. Second, based on different road models, adaptive selection of different road boundary point cloud data fitting method. However, in the unstructured road environment, the algorithm will be greater deviation, and real-time to be further improved. In the future research, will further combine the different road environment, improve the adaptability of the algorithm. (1) This algorithm only applies to structured straight road environment, in order to improve the accuracy of road boundary and vehicle target recognition, we should further integrate the multi - sensor information fusion.

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