Real-time extraction method of road boundary based on three-dimensional lidar

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Abstract. The problem of road boundary extraction in the structured road environment where there are discontinuities, occlusions and dynamic vehicles is critical to autonomous driving, but a solution to this problem has remained elusive. In this paper, a new straight-line method for real-time extraction of road boundary is proposed. Three-dimensional (3D) lidar is used to recognize road boundary with random sampling consensus algorithm (RANSAC) and certain filters. First of all, the boundary point cloud data are extracted with the method by calculating curvature change and height difference for each laser layer, then RANSAC algorithm is used to fit the extracted boundary points, then get the straight-line equation of the road edge. Finally, the Amplitude-Limiting filter and the Kalman filter are applied synthetically to the obtained boundary equation, remove unreasonable line equation and smooth the boundary line jitter. The real vehicle test proves that this algorithm can accurately and robustly perceive the curb boundary under a variety of road conditions mentioned above. The operation time of the on-board industrial computer is 26.7ms which fully meets the real-time requirements of unmanned vehicle.

1. Introduction

In recent years, with the great potential of unmanned driving technology in areas like traffic safety, environmental protection and traffic pressure, countries all over the world have paid more and more attention to the research of related technologies. Accessible area detection is an important perception task for autonomous driving, where there are boundary detection and semantic segmentation [1-4]. Semantic segmentation is of higher precision while is also kind of time consuming and demands high computing power. Subject to the restrictions of onboard hardware, this paper mainly focuses on the extraction of road boundary to detect accessible area. Accurate and real-time road boundary extraction is the basis of perception tasks in autonomous driving system and is also the key technology to autonomous navigation for intelligent vehicles.

At present, the existing road boundary extraction methods are mostly based on gray scale or color images [5-8]. Considering that the visual sensor is a passive sensor, vision is easy to be constrained by the conditions of night, fog, road water, etc., leading to that vision is difficult to fully meet the practical application needs. Luckily, with the widespread application of lidar in the field of unmanned driving, the usage of lidar for boundary detection has been also gradually developed. The lidar used in automatic driving can be divided into 2D and 3D according to its vertical field angle. Among them, the number of scanning points obtained by 2D lidar is relatively scarce, thus its characteristics are relatively low, which limits the robustness of the road boundary detection algorithm [9-11].
On account of the huge point cloud data obtained by 3D lidar, researchers have begun to use 3D lidar to extract road boundaries. Liu et al. [12] obtained the scanning points by comparing the height of adjacent scanning points to fit the line, while they did not consider dynamic obstacle and the mutation of the scanning point. Zhao et al. [13] first fitted the road surface as a plane, then obtained the boundary points on the basis of the plane. However, the quality of the boundary points was heavily affected by the plane fitting effect, resulting in that the algorithm is not robust. Huang et al. [14] detected the curb based on ground segmentation, whose boundary could also be influenced by segmentation result and is unstable too. Zhang et al. [15] used sliding windows to extract road boundary points layer-by-layer and used parabola to fit road boundaries. However, the topological structure of the graph and the time complexity of the algorithm were over limitation. It took too long to deal with the point cloud data of the 3D lidar, which is difficult to meet the requirements of real-time on the boundary detection algorithm.

In order to solve the above problems, the method proposed by this paper uses 3D lidar velodyne HDL-64 SE3 and extracts the boundary points directly from the original lidar point cloud, and then a combination of the straight-line fitting based on RANSAC algorithm and certain filters are used to obtain the road boundary robustly. The proposed method in this paper could fit the straight-line road boundary in real-time and also in high precision. With the usage of Amplitude-Limiting filter and Kalman filter, the method eliminates the influence of dynamic obstacles very well when detecting the road boundary.

This paper is organized as follows. Section 2 introduces the lidar we used and the structured road model. Section 3 presents the road boundary fitting method. Section 4 discusses and reports the qualitative and quantitate results of road boundary fitting. Concluding remarks are given in Section 5.

2. Lidar and road model

The HDL-64 SE3 lidar has 64-layer rays, scanning the surrounding area in 360 degrees horizontally with its own mechanical rotation in high resolution less than 0.02m, which means that lidar could detect the details of pedestrians, trees and cars. Lidar’s vertical field of view is 26.9 degrees, receiving up to 2.2-million scanning points per second. Therefore, processing such a large amount of point cloud data imposes high requirements on the real-time performance.

All point cloud obtained by scanning a whole circle are called one frame data. During driving, the unmanned vehicle will distinguish accessible area and the inaccessible area when processing each frame data. In the experiment, we have noticed that there is usually a distinct road edge between the accessible area and inaccessible area, whether it is an urban road or highway. For example, the curb of an urban road, the fence at a highway, therefore, it is feasible to divide the accessible area and the inaccessible area by reasonably utilizing the height information and curvature of road curb. Based on the above discussions, the urban roads or highways studied in this paper can be simplified as the model shown in figure 1. There is an obvious height jump between the accessible area and the inaccessible area.

![Figure 1. The road model used in experiment.](image-url)
3. **Road boundary extraction method**

In this paper, a new road boundary extraction algorithm for structured road is proposed. First of all, 64 layers lidar is stratified according to laser layers to collect boundary points by curvature and elevation difference; secondly, the RANSAC algorithm is applied to conduct straight line fitting on the boundary points collected; finally, the Amplitude-Limiting filter and Kalman filter are used to remove the abnormal line equations and smooth linear jitter.

3.1. Extraction boundary points by sliding pane

Ideally, when an unmanned vehicle runs on a sufficiently large pavement, the lidar scanning points collected will be concentrically distributed. The point cloud data collected in such case are shown in figure 2. By collecting the point cloud reflected by the objects around lidar, precise location information relative to the lidar coordinate system of the objects could be got.

![Figure 2. Lidar point cloud chart.](image)

When an unmanned vehicle runs in a structured road environment, the lidar receives environmental information by point cloud data. Taking the point cloud of layer I in figure 1 as an example, it is not difficult to conclude that height information changes continuously in the section OA; when lidar scans from accessible area to inaccessible area, there are obvious height jumps because of the curb. Meanwhile, the curvature of the point cloud will also change significantly, forming typical boundary features, as shown in section AB. The characteristics of curb scanning points can be summarized as following two conclusions:

1. The height difference between adjacent points of same laser layer will obviously increase along the road curb;
2. The curvature of the laser point cloud in the same laser layer will also change significantly along the road curb.

Based on the two features summarized above, the algorithm starts with the sliding pane moving from point O to point O’ in figure 1 to search the height jump and curvature jump layer by layer. the moving step L and the point cloud size S of the pane would be determined previously. We slide the pane from the very beginning (point O) to somewhere far to the right (point O’) and calculate the height difference and the curvature in every pane to find out the most possible boundary points. During the pane sliding process, the largest height difference $z_{diff}$ and curvature $r$ obtained by the last three points were calculated every pane, if both $z_{diff}$ and $r$ is over setting thresholds, the last point of this pane would be collected as boundary point, then we would redo this process in the next lidar layer. The formulas could be written as follows, $z_i (i = 1, 2 \ldots s)$ represents the z coordinate value of every lidar points in the pane:

$$
\begin{align*}
    z_{\text{min}} &= \min(z_1, z_2, z_3 \ldots z_s) \\
    z_{\text{max}} &= \max(z_1, z_2, z_3 \ldots z_s) \\
    z_{\text{diff}} &= z_{\text{max}} - z_{\text{min}}
\end{align*}
$$

(1)
For curvature \( r \) in every pane, the curvature could be calculated as follows:

\[
r = \sqrt{\frac{(y_3-y_1+k_1(x_2-x_1)-k_2(x_2+x_3-2x_1))^2+(k_1(y_2-2y_1)+k_2(y_3+y_1-y_2)-k_1k_2(x_3-x_1))^2}{2(k_1-k_2)}}
\]  

(2)

\((x_1, y_1), (x_2, y_2), (x_3, y_3)\) are x and y coordinate values of last three points in the pane, \(k_1\) and \(k_2\) can be written as follows:

\[
k_1 = -\frac{x_1-x_2}{y_1-y_2}, \quad k_2 = -\frac{x_3-x_2}{y_3-y_2}
\]  

(3)

3.2. Road edge straight line fitting based on RANSAC algorithm

After all the road boundary points extracted by sliding pane method, next step is to select suitable model to fit the points. Considering: 1) during driving, the unmanned vehicle will shake around, resulting in that the coordinate values of scanning points are inaccurate; 2) the pavement will not be in an ideal smooth state, and there may be convex hull in the middle of the road, which could be mistaken as curbs by sliding pane method.

The RANSAC algorithm, based on the idea of random sampling consistency, estimates the optimal mathematical model from the selected data set (local point), and iterates continuously until the fitted mathematical model satisfies the selected local points as much as possible. And maximum exclusion is carried out for outbound points, which is, the noise. Therefore, the straight line fitting method based on RANSAC algorithm can effectively eliminate the influence of noise points. The road edge line model under the vehicle coordinate system is as follows:

\[
y = kx + b
\]  

(4)

Wherein, \(k\) represents the slope of the curb line in the vehicle coordinate system, and \(b\) represents the linear intercept in the vehicle coordinate system.

3.3. Kalman filter based on Amplitude-Limiting filter

The road line obtained by RANSAC algorithm is a reflection of the current road condition, which wobbles a lot, so it is necessary to use the Kalman filter to smooth the jitter of the boundary line.

Before Kalman filter, Amplitude-Limiting filter is used to remove the interference detection, like the case that running car between the lidar and curb would be identified as boundary by mistake. This paper solves this problem by continuously storing five freshest \(k\) of boundary equation, and as shown in formula (5) and (6), mean values \(k_{\text{mean}}\), as well as variances \(\delta_k\) are calculated for storing \(k\) data when fresh boundary equation slope \(k\) is collected. Only if both \(k_{\text{mean}}\) and \(\delta_k\) meet threshold requirement of Amplitude-Limiting filter settings, the current linear equation is considered to be effective and can be input to the next step of Kalman filtering.

\[
k_{\text{mean}} = \frac{k_1+k_2+\cdots+k_5}{5}
\]  

(5)

\[
\delta_k = \frac{(k_1-k_{\text{mean}})^2+(k_2-k_{\text{mean}})^2+\cdots+(k_5-k_{\text{mean}})^2}{5}
\]  

(6)

The value of the slope \(k\) and the intercept \(b\) value of the boundary equation after Amplitude-Limiting filter are taken as the observation values into the Kalman filtering equation. In a very short period of time, the change of slope and intercept can be regarded as a model of uniform velocity. And the changes of \(k\), \(b\) can be written as formulas (7) and (8):

\[
k(n) = k(n-1) + c_k \cdot \Delta t
\]  

(7)

\[
b(n) = b(n-1) + c_b \cdot \Delta t
\]  

(8)
Wherein, \( c_k, c_b \) are the variation values of slope and intercept set in the filter, \( c_k \) is taken as 0.01, \( c_b \) is taken as 0.1. \( \Delta t \) means time difference between the two Kalman filter process. Formulas (7) and (8) can be combined to formula (9) as state prediction equation of Kalman filter.

\[
x(n) = Ax(n - 1) + Bu(n - 1)
\]

(9)

Wherein, \( x(n) = \begin{pmatrix} k \\ b \end{pmatrix} \) means state vector at current time, that is, the slope and the intercept value obtained after Amplitude-Limiting filter. \( u(n) = \begin{pmatrix} c_k \\ c_b \end{pmatrix} \) is input control variable, the derived state transition matrix and input control matrix can be written as:

\[
A = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad B = \begin{bmatrix} \Delta t & 0 \\ 0 & \Delta t \end{bmatrix}
\]

(10)

The co-variance prediction equation of Kalman filtering equation can be written as follows:

\[
p(n|n - 1) = A \cdot p(n - 1) \cdot A^T + Q
\]

(11)

The matrix Q in the matrix represents a process noise co-variance matrix, which is assumed to be independent of each other in the algorithm, resulting in that only the elements on the diagonal line in the Q matrix are non-zero values, its expression in the experiment is shown as formula (12):

\[
Q = \begin{bmatrix} 0.25 & 0 \\ 0 & 0.49 \end{bmatrix}
\]

(12)

The renewal equation of the Kalman equation can be written as follows:

\[
k(n) = p(n|n - 1) \cdot H^T \cdot (H \cdot p(n|n - 1) \cdot H^T + R)^{-1}
\]

\[
x(n) = x(n - 1) + k(n)(x(n) - H \cdot x(n|n - 1))
\]

(13)

\[
p(n) = (I - K(n)) \cdot p(n|n - 1)
\]

(14)

(15)

The variable R in the formula (14) represents the covariance matrix of the measurement noise. And the R matrix determined by the parameter adjustment process in the experiment is:

\[
R = \begin{bmatrix} 1.96 & 0 \\ 0 & 2.25 \end{bmatrix}
\]

(16)

4. Experimental verification

By using the algorithm described above, the HDL-64 SE3 lidar of Velodyne company is installed at the top of the unmanned vehicle, which is tested in the actual scene and the real-time display is implemented by ROS. The vehicle is equipped with industrial computer, and the CPU model is Intel core i7-6200. To test the robustness and the effectiveness of the proposed method in this paper, the experiment was conducted on two parts for both qualitative and quantitate evaluation.

4.1. Qualitative analysis of the road boundary extraction algorithm

The first part of the experiment was divided into three scenarios. Test scenario one and two are campus roads whose surface is smooth, only a small number of pedestrians and vehicles passed through, and there are obvious road edge features between accessible area and inaccessible area; Scenarios three is urban road, while there are vehicles parked on the roadside and passing through, obstructing the detection of the boundary.

In the test scenario one, the vehicle runs through a campus road with continuous boundary features; in the second scene, the vehicle runs through a campus road with two intersections in front of the right roadside, causing the road boundary to be cut and discontinuous. The detection effect of scenario 1 is shown in figure 3, and the detection effect of scenario 2 is shown in figure 4. In both figure 3 and figure 4, (a) shows the road image captured by the front camera on the vehicle. The comprehensive display of extracted boundary points and the boundary line is shown in (b). In figure 3(b) and figure
4(b), boundary points extracted by the algorithm are represented by white squares, and the fitting road boundary lines are displayed by red lines.

Figure 3. (a) Road image of scenario 1 and (b) Comprehensive display of fitting effect.

Figure 4. (a) Road image of scenario 2 and (b) Comprehensive display of fitting effect.

In the third scenario, the vehicle runs through a dynamic urban road with dense traffic, and there are often disturbing vehicles on both sides of the unmanned vehicle. The filtering effects are shown in figure 5. Figure 5(a) shows a dynamic vehicle passing through the right back of the experimental vehicle, figure 5(b) displays several dynamic vehicles passing on the right side of the experimental vehicle. It can be seen that the fitting effect of road boundary is very stable. The filtering method greatly reduces the interference phenomenon caused by buses or cars passing by the unmanned vehicle, enhances the robustness of the boundary extraction algorithm.

Figure 5. (a) dynamic cars approaching gradually under scenario 3 and (b) dynamic cars drives away.
4.2. Quantitate experiment of the road boundary extraction algorithm

In order to quantitatively analyze the reliability of the algorithm, we compare the proposed method with two state-of-the-art methods which are Haar Wavelet Transformation method [16] and Hough Transformation [17]. The comparison is conducted under the method used by Zhang et al. [15]. The proposed method is evaluated based on a sequence of 92 frames (approximately 70m straight road) in the dataset including discontinuities, occlusions and dynamic vehicles. The data are running offline on the industrial computer, the average processing time of the whole extraction algorithm is 26.7ms per frame data as shown in figure 6. For the common working frequency of 10HZ in practice, the time consuming fully meets the real-time requirements.

![Figure 6. The processing time of proposed algorithm in 92 frames.](image)

The evaluation method draws on [15]. We measure the distance between the fitting boundary line and the road curb in the lidar point cloud chart and set the criterion as 0.1m to judge if the boundary is good or bad just like the parameters set by [15]. The statistical results are shown in the table 1. From table 1, Hough Transformation is too time-consuming though it has a relative high accuracy, while Haar Wavelet Transformation method runs fast with the lowest precision. The proposed method here reaches a good balance on precision and real-time performance.

| Methods          | Average period | Precision rate |
|------------------|----------------|---------------|
| Proposed         | 26.7ms         | 88.04%        |
| Haar Wavelet     | 16.4ms         | 78.91%        |
| Hough            | 73.2ms         | 83.22%        |

5. Conclusions

The road boundary extraction algorithm based on 3D lidar is composed of the extraction of road boundary points based on point cloud geometry information, the fitting of the roadside line based on the RANSAC algorithm, Amplitude-Limiting filter and the Kalman filter. The real vehicle experiment proves that this algorithm leads to accurate and robust road boundary extraction, and the fitting effect is still good under dynamic obstacle conditions. At the same time, the algorithm takes a short time(26.7ms), completely meeting the requirements of real-time performance. Compared with two state-of-the-art methods, the proposed method in this paper achieves a good balance between the real-time performance and boundary detection precision, solves the problem of discontinuities, occlusions and dynamic vehicles by filtering.

However, the method in this paper also needs to be further improved. The RANSAC algorithm can perfectly remove the influence of the noise point and fit the road along straight line. When it comes to that the road itself is curved, this fitting method cannot meet the actual engineering requirements. Curve-fitting method should be further researched in the next step.
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