Lane Line Edge Detection Based on Improved Adaptive Canny Algorithm

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Abstract. With the development of autonomous driving technology, effective access to information on lane lines is of great significance for the decision-making of unmanned vehicles. The Canny operator is widely used in identifying the edge of the lane line, but the adaptive ability and anti-interference ability of the traditional Canny operator are flawed. In this paper, the lane line edge detection algorithm of the adaptive Canny algorithm is improved, and the adaptive median filtering and morphological closing operation are used to prevent the edge information from weakening while using multiple directions to calculate gradient magnitude. Finally, iterative method is used to improve the OSTU adaptive algorithm to determine its high and low thresholds. The test results show that the improved algorithm can effectively improve the accuracy, speed and anti-interference ability of the detection.

1. Introduction (Heading 1)
The emergence of self-driving cars is an inevitable trend in the development of science and technology and is of great significance for improving urban traffic problems. Similarly, due to the particularity of driverless vehicles, all parties put forward high requirements for driving safety. The safety of driving a driverless vehicle mainly depends on whether the lane keeping is accurate. The lane line is the most direct part of the environment perception of the driverless vehicle. The effective acquisition of the lane line information has a great effect on the decision of the unmanned vehicle. Only when the vehicle has a real-time and accurate understanding of its position relative to the lane line can it operate accordingly.

At present, there are many different methods for lane line edge detection, but basically each method is greatly restricted by environmental factors. In general, the methods of lane line detection are roughly divided into two types: feature-based methods and model-based methods [1]. The feature-based method consists of three parts: image preprocessing, lane line edge detection and lane line fitting. The edge detection is the most important part of the recognition process, and Canny operator [2] is a kind of edge detection operator with good performance, which is widely used in many image processing fields. As for Canny operator smoothing image, bilateral filtering is used in [3] to improve image contrast, but the disadvantage is that it is not adaptive and cannot remove the salt-and-pepper noise that may occur in image collection. In terms of obtaining high and low gradient threshold, [4] uses the OTSU algorithm to solve the problem that the Canny algorithm cannot adaptively determine the high and low thresholds, but it needs to traverse all gradient modulus values, and the real-time performance is poor.

In view of the above shortcomings, this paper improves the lane line edge detection algorithm of the adaptive Canny algorithm. First, adaptive median filtering and morphological closing operations are...
used instead of Gaussian filtering in the Canny algorithm; The horizontal, vertical, 45° and 135° directional templates are used to calculate the image gradient, which reduces the noise sensitivity and improves the edge positioning accuracy. Finally, the iterative method is used to reduce the range of traversing gradient modulus required by OTSU algorithm to speed up the operation. The basic principle of the traditional Canny algorithm

In 1986, Canny deduced the multi-level edge detection algorithm -- Canny algorithm, and proposed three features that a good edge detection algorithm should have:

- Optimum detection: real edges are found to the greatest extent, with the least possibility of missing and error detection.
- Optimal positioning: the position of the detected edge point is basically the same as the position of the real edge point, and the position of the interference edge point is farthest from the position of the real edge point.
- Correspondence only: The detection edge point and the real edge point can maintain a unique correspondence to the greatest extent.

1.1. Image Denoising
The Canny algorithm uses a suitable Gaussian function to convolve with the original image. The Gaussian function is shown as (1):

\[ G(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{x^2}{2\sigma^2}} \]  

where \( \sigma \) represents the filter width, and different degrees of denoising can be achieved by changing the \( \sigma \).

1.2. Calculate the Pixels Gradient
The conventional edge difference operators (Rober, Prewitt, Sobel) are used to calculate the modulus and direction of horizontal and vertical gradients.

The modulus of the gradient is calculated as shown in (2):

\[ G = \sqrt{G_x^2 + G_y^2} \]  

\( G \) represents the gradient modulus of the point, \( G_x \) represents the gradient of the point in the horizontal direction, and \( G_y \) represents the gradient of the point in the vertical direction.

The calculation formula of gradient direction is shown in (3):

\[ \theta = \arctan \frac{G_x}{G_y} \]  

where \( \theta \) represents the gradient direction of the pixel.

1.3. Non-maximal Suppression
After calculating the modulus and direction of the gradient of each pixel, in order to ensure a clearer boundary, only the pixel with the maximum gradient modulus in the neighborhood of fixed radius is retained. It can effectively reduce the number of non-edge points and accelerate the calculation.

1.4. Double Threshold Connection
There is also a large amount of interference after the image is non-maximal suppressed. Canny algorithm sets a high threshold and a low threshold. The boundary larger than the high threshold is
called the strong boundary and must be the real boundary. On the contrary, the boundary smaller than the low threshold must not be the boundary, and the boundary between the two boundaries is also called the weak boundary, whether it is the boundary needs further research [5].

However, there are some disadvantages in the detection of edge points by using the traditional Canny algorithm. Firstly, in the aspect of image smoothing, although Gaussian filtering can suppress some noise, sometimes it will weaken the edge information. In addition, the selection of dual threshold needs manual input. Under some circumstances, the fixed threshold will not only be unable to extract the lane line image due to blurred edges, but also be too low to generate excessive number of useless edges.

2. Traditional Canny algorithm improvement

2.1. Adaptive Smoothing Image
Traditional Canny algorithm chooses Gaussian filter, some edge details will be lost, and more or less wear of the lane line will affect the edge detection in practice. At the same time, salt-and-pepper noise may be generated in the image collection process, which will bring great interference to the lane line identification. In this paper, the median filter is used to replace the Gaussian filter in the traditional algorithm. According to the principle of the median theorem, \( n^2 \) pixels in an \( n \times n \) fixed field in the image are arranged according to the gray value, and the arranged median is assigned to the center pixel of the matrix.

The traditional median filter window size is fixed, which is poor for strong noise suppression, and will lead to serious image detail loss during filtering [6]. Therefore, adaptive median filtering algorithm [7] is adopted, and the algorithm flow is as follows:

Definition: \( Z_{\text{min}} \) is the minimum value of gray in the current window, \( Z_{\text{max}} \) is the maximum value of gray in the current window, \( Z_{\text{mid}} \) is the median value of gray in the current window, \( Z_{xy} \) is the gray value of the center pixel of the current window, and \( S_{\text{max}} \) is the maximum size of the window.

For the first detection, the filter window with fixed initial size is used for traversal.

A:

\[
\begin{align*}
A_1 &= Z_{\text{mid}} - Z_{\min} \\
A_2 &= Z_{\text{mid}} - Z_{\max}
\end{align*}
\]  

(4)

If \( A_1 > 0 \) and \( A_2 < 0 \), go to B; otherwise, the filter window size will be increased by 2. If the window size is less than or equal to \( S_{\text{max}} \), repeat A; otherwise, \( Z_{xy} \) will be output.

B:

\[
\begin{align*}
B_1 &= Z_{xy} - Z_{\min} \\
B_2 &= Z_{xy} - Z_{\max}
\end{align*}
\]  

(5)

If \( B_1 > 0 \) and \( B_2 < 0 \), it is considered that there is no noise in this area, and the output \( Z_{xy} \) is the result; otherwise, the median value \( Z_{\text{mid}} \) is used to replace the original value output.

Then, the morphological closed operation is applied to the median filtered grayscale image to fill the small dark voids in the lane line, which also can smooth the lane line boundary, maintain the continuity of the edge and improve the accuracy of detection.

The closed operation is defined as:

\[
A \bullet B = (A \oplus B) \Theta B
\]  

(6)

Where, \( \Theta \) represents morphological corrosion and \( \Theta \) represents morphological expansion.
The specific noise reduction effect is shown in Fig. 1:

![Figure 1](image1.png)

**Figure 1.** Results of different noise reduction methods: (a) Median filter & Closed operation; (b) Gaussian filtering.

The noise reduction method in this paper highlights the details of the edge and fills in the interference in the target.

2.2. *Multi-direction Calculation of Gradient Amplitude*

Because of the difference in the direction in which the lane lines are presented, only the calculations from the horizontal and vertical directions have limited suppression of noise and will produce false edge. Therefore, the improved Sobel operator [8] is adopted in this paper to extend it to a ladder degree template in the four directions of horizontal, vertical, 45° and 135°. P represents the input grayscale image, the formula is:

\[
G_{45} = \begin{bmatrix}
2 & 1 & 0 \\
1 & 0 & -1 \\
0 & -1 & -2
\end{bmatrix} * P
\]  (7)

\[
G_{45} = \begin{bmatrix}
2 & 1 & 0 \\
1 & 0 & -1 \\
0 & -1 & -2
\end{bmatrix} * P
\]  (8)

The improved gradient magnitude formula is:

\[
G^* = \sqrt{G_x^2 + G_y^2 + G_{45}^2 + G_{135}^2}
\]  (9)

The improved Sobel operator detection and processing results are shown in Fig. 2:

![Figure 2](image2.png)

**Figure 2.** Results of different noise reduction methods: (a) Improved Sobel operator; (b) Traditional Sobel operator.
The improved Sobel operator improves the traditional Sobel operator both in terms of enhancement of lane line edge and anti-interference.

2.3. Adaptive Acquisition of Canny Algorithm High and Low Threshold

The threshold algorithm adopted in [4] was proposed by OTSU in 1978. It is considered that the image can be classified into the target and the background by using the gray information of the image, and the optimal separation point between target and background is the maximum inter-class variance or the minimum intra-class variance under the optimal gradient.

If this concept is applied to Canny algorithm for calculating the high and low threshold, the specific formula is:

The high threshold $T$ in Canny algorithm divides pixel points into target $C_0$ and background $C_1$. There are $N$ pixel points in the image, and the number of pixels corresponding to the gradient value of $i$ is $n_i$. Then, $p_i$ is the probability of taking any pixel whose gradient value is $i$.

$$p_i = \frac{n_i}{N}$$ (10)

The probability of pixel distribution in the target $C_0$ is omega $\omega_0$, and the probability of background $C_1$ is $\omega_1$.

$$w_0 = \sum_{i=T+1}^{T} p_i$$ (11)

$$w_1 = \sum_{i=0}^{T} p_i$$ (12)

It can be obtained that the mean values of the target $C_0$ and the background $C_1$ are respectively $\mu_0$ and $\mu_1$, and the gradient average value of the entire image is $\mu$, and the variances are respectively $\sigma_0$ and $\sigma_1$.

$$\mu_0 = \sum_{i=T+1}^{T} \frac{ip_i}{\omega_0}$$ (13)

$$\mu_1 = \sum_{i=0}^{T} \frac{ip_i}{\omega_1}$$ (14)

$$\mu = \omega_0 \mu_0 + \omega_1 \mu_1$$ (15)

$$\sigma_0^2 = \sum_{i=T+1}^{T} \frac{(i-\mu_0)^2 p_i}{\omega_0}$$ (16)

$$\sigma_1^2 = \sum_{i=0}^{T} \frac{(i-\mu_1)^2 p_i}{\omega_1}$$ (17)

The intra-class variance of target $C_0$ and background $C_1$ is $\sigma_B^2$, and the inter-class variance is $\sigma_A^2$.  

5
\[
\sigma^2_B = \frac{\omega_1 \sigma^2_0 + \omega_1 \sigma^2_1}{\omega_0 + \omega_1} \tag{18}
\]
\[
\sigma^2_A = \omega_0 (\mu_0 - \mu)^2 + \omega_1 (\mu_1 - \mu)^2 \tag{19}
\]

However, in practice, it is difficult to have the maximum inter-class variance and the minimum intra-class variance. In order to take into account both aspects to obtain the optimal solution, this paper takes the ratio of the gradient's inter-class variance and intra-class variance \(\gamma^2\) as the standard. When \(\gamma^2\) is the largest, the threshold is considered as the segmentation threshold.

\[
\gamma^2 = \frac{\sigma^2_A}{\sigma^2_B} \tag{20}
\]

However, the desired maximum \(\gamma^2\) needs to traverse the gradient amplitude of all pixels in the image, so this paper uses iterative method to narrow the range of the optimal threshold so as to reduce the computation.

The specific steps are as follows:

- Since the average gradient value can initially show the distribution of different gradients in the continuous image, \(\mu\) is selected as the initial threshold \(T_0\).
- The threshold \(T_0\) obtained at the first time was used to re-segment the image between the target and the background, and the average gradient value between the target and the background was calculated respectively, and a new threshold \(T_1\) was calculated as (21).

\[
T_1 = \frac{\mu_0^* + \mu_1^*}{2} \tag{21}
\]

- The same method can obtain the optimal threshold \(T_n\) for the \(n\)th time, until the corresponding iteration formula condition is reached. The iteration termination formula is shown in formula (22):

\[
|T_n - T_{n-1}| < 10 \tag{22}
\]

\(n\) represents the number of iterations of the image. In order to meet the requirements of speed and accuracy, it is considered through experiments that the effect is optimal when the gradient value difference between the two iterations is 10.

- Calculate the values of all \(\gamma^2\) in the neighborhood of size 10 around the optimal segmentation threshold \(T_n\), find the gradient \(h_2\) at the maximum of \(\gamma^2\), and use the gradient as the high threshold in the Canny algorithm; Finally, set the low threshold \(h_1\) to half of the high threshold \(h_2\).

3. Experimental results and analysis

The computer configuration used in the algorithm experiment in this paper is as follows: Intel Core i5 processor, clocked at 2.60GHz, 8G system memory, the experimental platform is Visual Studio 2013, the software uses C++ to write and call OpenCV library, and select 1000 actual scenes. A representative image with a resolution of 640 x 480.

The edge detection algorithm in this paper is based on the improvement of the Canny algorithm. Reference [9] proposes A kind of edge detection evaluation method by calculating the number of edge points \(A\), 4-connected components \(B\) and 8-connected components \(C\). The smaller the value of \(C/A\), the better the continuity of edge detection; The smaller the value of \(C/B\), the better the degree of linear
connectivity. The experiment compares the average of the experimental results by comparing the traditional Canny algorithm, the algorithm in [4] and the algorithm in this paper.

Table 1. Statistical table of edge detection effect of different algorithms

| Algorithm                  | Evaluation Parameters | A  | B  | C  | C/A | C/B |
|----------------------------|-----------------------|----|----|----|-----|-----|
| Traditional Canny algorithm|                       | 4831| 1657| 512| 0.106| 0.308|
| Algorithm in Reference [4] |                       | 6716| 1687| 577| 0.086| 0.342|
| Algorithm in this paper    |                       | 7533| 1859| 580| 0.077| 0.312|

According to the statistical data in TABLE I, both the C/A and C/B values of the algorithm in this paper are smaller than the traditional Canny algorithm and the algorithm in the literature [4]. From the continuity of edge detection, the algorithm in this paper has a good effect.

Table 2. Average time consuming statistical table for edge detection

| Algorithm                  | Traditional Canny algorithm | Algorithm in Reference [4] | Algorithm in this paper |
|----------------------------|-----------------------------|---------------------------|-------------------------|
| Time (ms)                  | 20                          | 54                        | 50                      |

According to the statistics in TABLE II, although the traditional Canny algorithm has the shortest average time, the way of setting the threshold is not adaptive. In this paper, the iterative method is used to narrow the range of searching for the optimal threshold, and the average time is 92.6% of the time of the algorithm in [4]. On the premise of maintaining adaptability, the algorithm in this paper has a good effect in real-time.

4. Conclusion and Future Work
In this paper, the shortcomings of the existing Canny adaptive algorithm are improved. Firstly, the edge detection effect is improved by changing the filtering mode, so that the edge detection results are more continuous. The iterative method can save 7.4% time in calculating the high and low threshold of the Canny algorithm using OTSU algorithm.

However, in the case of severe wear on the edge of the lane line, the algorithm in this paper cannot well complete the edge detection, which is also the focus of the next research.

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