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Night curve recognition algorithm based on K-means clustering and improved Hough transform

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Abstract. In order to solve the problem of poor robustness and real-time performance of existing lane line recognition algorithms in night curve recognition, a fast night curve recognition algorithm based on K-means clustering and improved Hough transform is proposed and implemented. The algorithm firstly intercepts the lower two thirds of the image as the region of interest (ROI), then binarizes the ROI image by using the block local optimal threshold method, and then obtains the starting point of the lane line by using the improved Hough transform. Finally, based on the starting point, the lane line in the image is calibrated by using the K-means clustering algorithm. The experimental results show that the method can detect the lane lines of roads turning at night, and is suitable for other roads at day and night, with good real-time performance and robustness.

1. Introduction

Lane recognition is an important part of the automatic driving system and plays an important role in the autonomous navigation system and lane departure warning system of a vehicle. Lane line identification includes straight track and curve recognition. Hough Transform [1] is now used in straight track recognition to detect lanes by identifying straight lines. It has good real-time performance and strong robustness, but it is not accurate enough for corner recognition, especially at night. Many scholars at home and abroad have carried out a lot of research on curve recognition and proposed various models, including concentric circle model, quadratic curve model, hyperbolic pair model and variable lane model [2], which all has their own advantages and disadvantages. Chu et al. [3] proposed a curve recognition algorithm based on the piecewise line model, which uses Hough Transform for multiple times, making it failing to meet the requirements of real-time. Chen et al. [4] proposed a lane detection algorithm based on B-spline, which needs multiple iterations to achieve convergence, making the system complex. Recent years saw some scholars adopt the methods of cyclotron curve, neural network, and deformation template [5-7], but they were all, to some extent, restricted by robustness and real-time performance. Taking into consideration the weak robustness and real-time performance of the above models and algorithms in nighttime corner detection, this paper proposes a nighttime curve recognition algorithm based on improved Hough Transform and K-means clustering.

2. Image Preprocessing

Generally, road images contain useless information such as sky, trees, and guardrails. In order to improve the real-time performance of the algorithm and reduce the amount of calculation, it is necessary to extract and process only the useful part of the image. According to the parameters of the focal length, horizontal angle and elevation angle of the vehicle camera and experience, this paper selects the lower two-thirds of the road image for processing. Figure 1 (a) is the original road map; Figure 1 (b) is the intercepted region of interest.
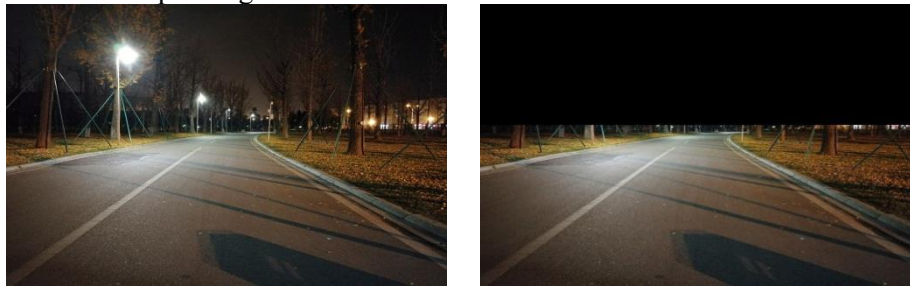
(a) Original image   (b) Two-thirds of the original image

Figure 1 Original image and lower two-thirds of the image

2.1. Color image graying

The original pixel color is RGB, and the processed pixel gray value is Gray, then it can be grayed out according to the following formula:

$$Gray = R \times 0.299 + G \times 0.587 + B \times 0.144$$

Figure 2 is a grayscale image.

Figure 2 Grayscale image

2.2. Binarization using local optimal threshold

Image binarization, the key to which is reasonable selection of the threshold separates the lane line from the surface. Due to the interference of street lights, lights, shadows, etc., the light distribution in the night driving image is uneven [8]. In order to reduce that impact, this paper adopts binarization using local optimal threshold. Firstly, the road image is equally divided into a finite number of small rectangular images, in which the light is relatively distributed. Then each rectangular image is binarized using the local optimal threshold method.

Local optimal threshold method extracts distribution characteristics of the gray value of each rectangular image, uses the category variance as the criterion, selects the maximum value of the variance between the classes as the selected threshold, and sets a rectangular image into the level M, the number of pixel the gray value i is n, then total number of pixels is N:

$$N = \sum_{i=1}^{M} n_i$$

The probability of each pixel value P_i is

$$P_i = \frac{n_i}{N}$$

Select an integer K to divide it into two groups, namely C_0, C_1

$$C_0 = \{1,2,3,\cdots,K\}$$
$$C_1 = \{K+1, K+2, \cdots, M\}$$

Then the probability of C_0 occurrence is

$$\omega_0 = \sum_{i=1}^{K} P_i = \omega(K)$$

Its corresponding mean μ_0 is

$$\mu_0 = \frac{\sum_{i=1}^{K} iP_i}{\omega_0} = \frac{\mu(K)}{\omega(K)}$$

The probability of C_1 occurrence ω_1 is

$$\omega_1 = \sum_{i=K+1}^{M} P_i = 1 - \omega(K)$$

Its corresponding mean μ_1 is

$$\mu_1 = \frac{\sum_{i=K+1}^{M} iP_i}{\omega_1} = \frac{\mu - \mu(K)}{1 - \omega(K)}$$

$\mu = \sum_{i=1}^{M} iP_i$ is the statistical mean of the grayscale of the overall rectangular image, then

$$\mu = \omega_0\mu_0 + \omega_1\mu_1$$

Then the variance between groups C_0 and C_1 $\sigma^2(K)$ is

$$\sigma^2(K) = \omega_0(\mu_0 - \mu)^2 + \omega_1(\mu_1 - \mu)^2$$

Changing the value of K between $1,2,3,\cdots,M$ to make the value of the optimal threshold $\sigma^2(K)$ is the maximum variance of K. From the segmented formula, this paper joints all binarized rectangular image.

$$f(x) = \begin{cases} 0 & x < K \\ 255 & x \geq K \end{cases}$$

Figure 3 compares the effects of ordinary binarization and local optimal threshold binarization.
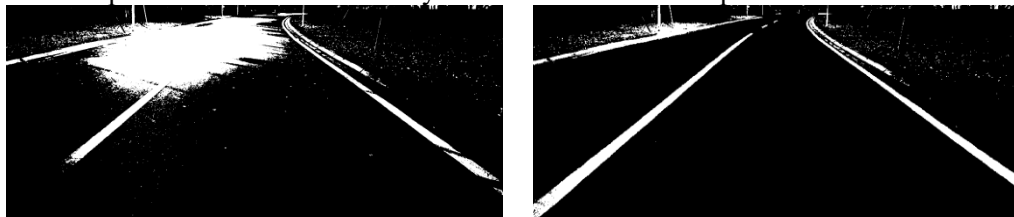
(a) Ordinary binarization   (b) Local optimal threshold binarization

Figure 3 Chart of binary comparison

3. Curve Recognition Based on K-Means Clustering Algorithm

Cluster analysis is an unsupervised observational learning [9]. Its basic principle is to perform clustering categorization by calculating similarities or differences between samples according to certain features based on the sample's own attributes but not any mode that can be referenced or followed or priori information, using mathematical methods, following certain common points or different points. K-means algorithm has good scalability and high efficiency when dealing with large amounts of data. When the sample cluster is approximated as Gaussian, the classification effect is

more significant [10-11]. K-means algorithm, taking k as the parameter, divides n samples into k clusters, so that the clusters are highly similar while the similarity between clusters is lower. It uses Euclidean distance as the similarity measure, which corresponds to optimal classification of the original cluster center. The algorithm uses the error squared criterion function and the criterion function as the function of the clustering criterion. In this paper, the white pixels in the binarized image are used as samples to cluster. The steps are as follows:

(1) Initial setting of k centroids: $\mu_1, \mu_2, \cdots \mu_k$

(2) Mark each sample pixel as the category closest to the center, i.e.

$$label_i = \arg \min_{1 \le j \le k} \| x_i - \mu_j \|$$

(3) Update each category center to the mean value of all sample pixels belonging to the category

$$\mu_j = \frac{1}{|c_j|} \sum_{i \in c_j} x_i$$

(4) Repeat the last two steps until the change in the category center is less than a certain threshold, that is, then clustering is completed.

3.1. Average centroid distribution

K-means clustering analysis algorithm needs to manually preset the number of clustering categories and appropriately increase the number of clustering categories. In most cases, it makes the final clustering result more accurate. But if the number of clustering categories is too large, not only it is not helpful to the recognition effect, but add extra calculation, degrading the real-time performance of the image processing; but if the number of cluster categories is too small or the initial centroid distribution is uneven, for the application scenarios with strong randomness such as road recognition, It does not make sense even after clustering. This paper chooses to divide the ROI image into a total of 240 small square images (hereinafter referred to as "map domain"), and then divide each map into a total of 9 squares. In each square, there is an initial centroid at the center. Then K-means clustering process with k value of 9 is performed in each map field. The experiment shows that the above-mentioned average centroid distribution and map selection can better reflect the clustering characteristics of the image of ensuring the real-time image processing.
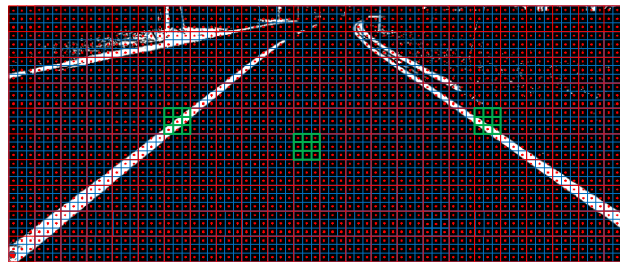

Figure 4 Map of initial centroid

3.2. Clustering process

Take the three consecutive fields in the upper image as shown in the figure below. Cluster each of the fields separately. In the clustering process, if the number of white pixels in the small square of the centroid is less than δ, then delete this centroid; once the clustering is completed, the centroid is recalculated for each category region. Figure 5(b) shows the centroid distribution after the first clustering operation; Figure 5(c) shows the centroid distribution after the third clustering operation. According to Figure 5, the lane line can be determined after three iteration operations. Since the road image in the upper area is narrower while that of the road line in the lower area is wider in general, this paper divides the ROI area equally into upper and lower areas. The upper and the lower area undergo three clustering operations, and then an average centroid merging. Figure 5(d) shows the results of the average centroid merging of all the centroids of a row in (c) according to the following

formula.

Assume that there are i centroids in the horizontally consecutive 9 squares in a row composed of small squares after three clusters, the number of white pixels in each square in which the centroid is located is the centroid coordinate us n_i, and the merged average centroid coordinate is (x, y), then:

$$x = (n_1 * x_1 + n_2 * x_2 + \cdots + n_i * x_i)/(n_1 + n_2 + \cdots + n_i)$$

$$y = (n_1 * y_1 + n_2 * y_2 + \cdots + n_i * y_i)/(n_1 + n_2 + \cdots + n_i)$$
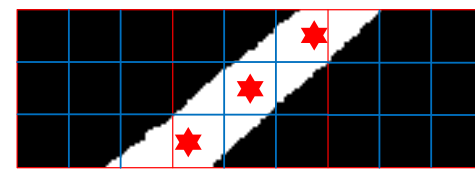
(a) Initial centroid distribution map
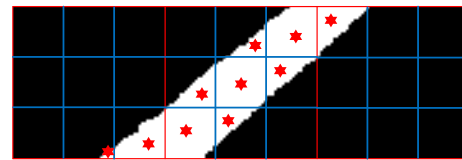
(b) Primary cluster centroid distribution map

(c) Cubic cluster centroid distribution map

(d) Calculation of average centroid distribution

Figure 5 Process of centroid calibration

After the whole ROI image is processed by the above clustering shown in Figure 6, all the white pixel point regions, including the non-lane line portions are distributed with centroids, wherein the lower half of the image is sparsely distributed while the upper half of the region is densely distributed, thus making calibration of the lane line accurate. Improved Hough Transform is used to identify the starting point of the lane line, and then fits all the centroids on the lane line to complete the lane line identification at night.
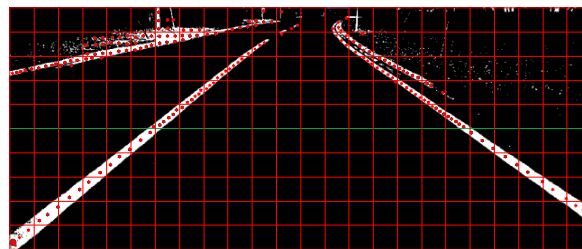
Figure 6 Results of calibrating lane line using centroids

4. Road Starting Point Recognition Based on Improved Hough Transform

4.1. Improved Hough Transform

For the lane line at the corner, the curve taken by the camera near the bottom of the ROI area can be approximated as a straight line. The area is first detected using the Sobel operator [12]. For results, see Figure 7. Improved Hough Transform is then used to detect the approximate straight lines. Improved Hough Transform is fast in calculation and makes the lane line detection more accurate.

Figure 7 Sobel edge detection results

Each feature point on the line feature is represented by the feature quantity $v = (x, y, \theta, s)$, where (x, y) is the lane line position, θ is the direction of the lane line method, and s is the characteristic strength of the lane line. The algorithm steps for detecting straight lines based on line features of improved Hough transform are as follows:

Step 1: Assume the parameter space $(\rho, \theta) \in [\rho_{min}, \rho_{max}] \times [\theta_{min}, \theta_{max}]$, quantize the parameter space into $m \times n$ cells, set the accumulator matrix, save the accumulated value $Q_{m \times n}$, set the initial value to 0, and calculate the quantization step size.

$$S_\rho = (\rho_{max} - \rho_{min})/m, \, S_\theta = (\theta_{max} - \theta_{min})/n$$

Step 2: Take the feature vector $\upsilon_i = (x_i, y_i, \theta_i, s_i)(i = 1,2,\cdots,l)$, $\theta_{ij} = \theta_i + j \times S_\theta$. Let j take value in turn in the integer interval $[-k, k]$ ($k = 5$ in this paper) and perform the following loop calculation.

Substitute (x_i, y_i, θ_{ij}) into $\rho = x \cos\theta + y \sin\theta$.

$$\rho_{ij} = x_i \cos\theta_{ij} + y_i \sin\theta_{ij}$$
$$r = [(\rho_{ij} - \rho_{min})/S_\rho + 0.5],$$
$$t = [(\theta_{ij} - \theta_{min})/S_\theta + 0.5],$$
$$w = 1 - |j|/k ,$$

(r, t) is the corresponding cell in the accumulator; w is the weight of the current cell accumulator. Finally, conduct the following accumulative calculation:

$$Q_{m \times n}(r, t) + = ws_i$$

Step 3: take the value of v_i and conduct sequential calculation based on step 2 until all the feature quantities are taken. Take the line parameters corresponding to the cells with the largest cumulative value as the final detection result.

After completing the line detection of the lower quarter image of ROI using the improved Hough Transform, look for the starting point of the lane line. In order to accurately determine the starting position of the lane line, take the starting positions of the two approximate straight lines as the normal lines of the two straight lines and the intersection of the two perpendicular lines as the starting point of the actual lane line. Figure 8 shows line detection using Hough Transform and the starting point of the road determined by the intersection of the perpendicular line.
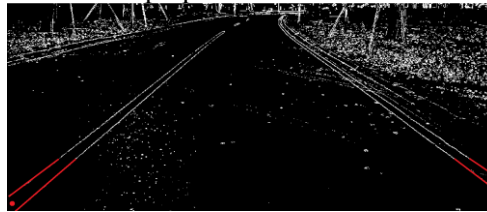

Figure 8 Detect the starting point of the road using Hough Transform

4.2. Fit the lane line
Take the starting point of the road identified in Figure 8 as the starting point, find the first centroid in

the square above the starting point, and connect the starting point to the first centroid using a straight line to determine the slope of the line k_0 between the starting point and the first centroid. Then, find the second centroid in the upper slope range $[k_0 - 0.1, k_0 + 0.1]$ with the first centroid as the origin point, and then connect the first and second centroids with a straight line to determine the slope of the second centroid k_1 between the first and the second centroid. Take the second centroid as the origin, and find the third centroid in the upper range $[k_1 - 0.1, k_1 + 0.1]$. Then, fit all the centroids to the lane line to complete night corner recognition. Figure 9(a) shows the lane line fitting result; Figure 9(b) shows the identified night corner region filling result.
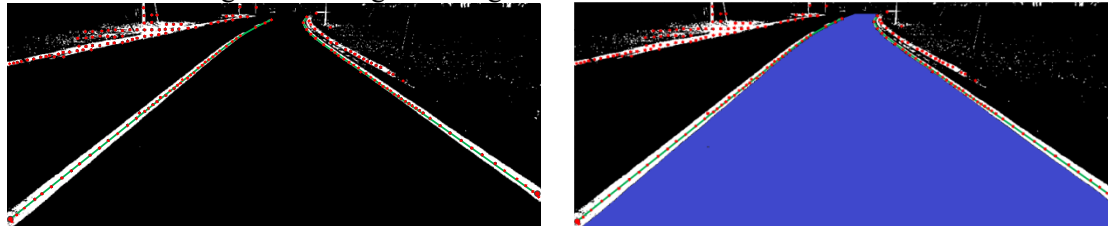

| (a) Lane line fitting results | (b) Road area filling |

Figure 9 Results of night corner testing

5. Result

Acquire the nighttime and daytime lane video images of the pixels from the car camera, extract 3000 frames at a rate of 25 frames per second perform a test on a computer with an Inl(R) 2.27 GHz CPU and a RAM of 4 GB. Randomly select four pictures respectively at day, night, corner and straight road. The results are as follows: Figure 10(a) shows the daytime straight track recognition, Figure 10(b) shows the daytime curve recognition, Figure 10(c) shows the night straight track recognition and Figure 10(d) shows the nighttime curve recognition.
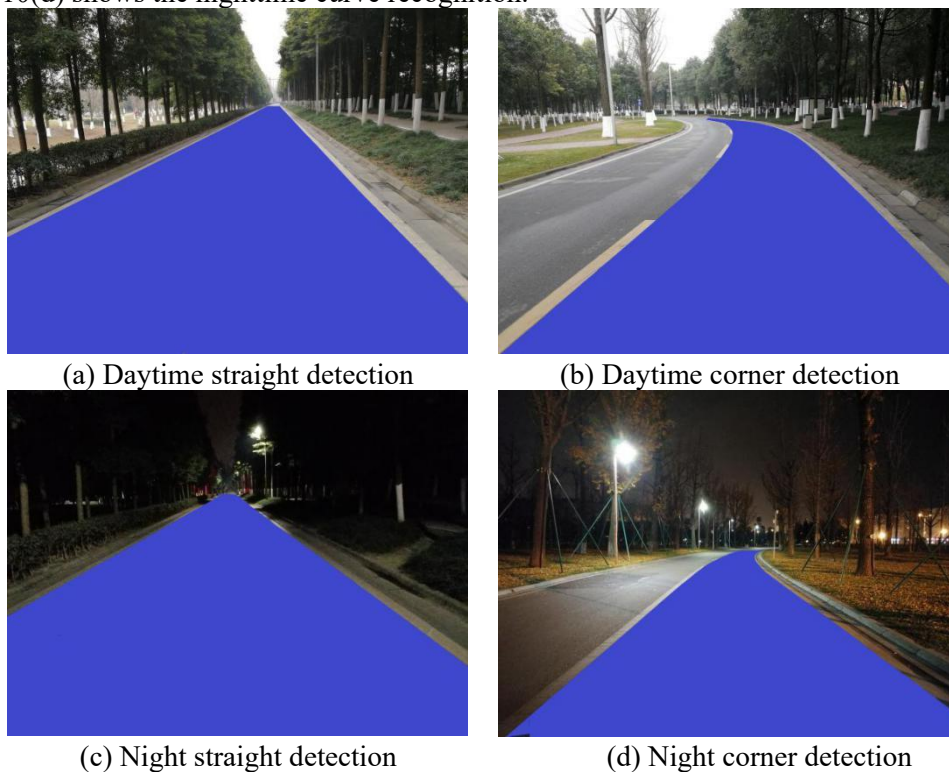
| (a) Daytime straight detection | (b) Daytime corner detection |

| (c) Night straight detection | (d) Night corner detection |

Figure 10 Experimental results in four scenarios

It can be seen from the above results that the curve recognition algorithm in this paper has strong

robustness. It not only has good recognition effect on night corners, but also applies to night straight roads and daytime corners and straight roads. The lane detection time in each frame of the image is within 150ms, so it has good real-time performance.

6. Summary

In nighttime corner recognition, curve recognition algorithm based on K-means clustering and improved Hough Transform can better describe the characteristics of the lane line compared with curve model, neural network and segmented line detection of curves. It also has lower algorithm complexity, good recognition of straight lines and curved roads, and good adaptability to different lighting conditions during day and night, which can better meet the requirements of real-time performance and robustness. However, when there are obstacles in front or the lane lines are covered, the algorithm is not accurate enough. Relevant research work will be carried out in this aspect later on.

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