An Integrated Approach to Recognition of Lane Marking and Road Boundary

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Abstract

An integrated vision method was proposed for intelligent vehicles to synchronously recognize the lane marking and road boundary in direct or curve road environment. Firstly, with region connectivity analyzing, the method extracted the brightness features of lane markings on input images by self-adaptive threshold segmenting. Not only the gradient magnitude but also the gradient direction features of the road boundary were extracted by the Sobel operator method. Secondly, the 2-D models of road shape were acquired and the features above were matched to them by least-squares fit. With the circular calling of detecting and tracking program block, the whole process showed a fast and exact capability. The experiments have been conducted with the videos captured from real road scenes, and the results proved that it is a real time and robust method to recognize the road for the vision-based navigation of intelligent vehicles.

1. Introduction

When 21st century is coming, the technique of Intelligent Vehicles becomes an emphasis of Intelligent Traffic System. It is significant and popular to use machine vision on automatic driving and auxiliary navigation for Intelligent Vehicles currently. When the vehicles are driving on highway, vision-based road recognition is applied to control the vehicles in cross direction. At present, the position and the shape of the road are identified mainly by detecting the lane markings [1-4]. However, the line marker usually fades because of the abrasion, so the recognition of road boundary is another safeguard against driving accidents especially when the vehicle is steering on the lane, which is near the roadside. In this case, one side of the lane is the marking and the other side is the road boundary. Both of them must be detected at the same time for the accurate orientating of Intelligent Vehicles.

In [1] and [2], Stereo-vision system was adopted to recognize lane markings. Although this method was comparatively precise, it had disadvantages such as matching difficulty, costly hardware and computation. Another neural network and fuzzy logic techniques in [3] needed to input samples collection beforehand for studying and training. It was quite difficult to fit the complex road environment. Moreover, the methods based on statistic [5] and multicolor [6] had too many computations to satisfy the real-time request of Intelligent Vehicles. Whereas former researches, the paper uses OTSU self-adapted threshold segmentation and edge gradient information detection to extract the feature of line marker and road boundary. The lane image sequences are processed and analyzed with calling the detecting block and tracking block. As a result, the speed of whole processing is increased.

2. Lane detecting

The dividing line between the road surface and background can be found through the brightness feature of image. The average gray value of each row is calculated, so that the horizontal projection is

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formed. In the projection figure (Fig.1), the row of the first minimum is the dividing line. The part under the line on the image is defined as the region of interest (in Fig.2).

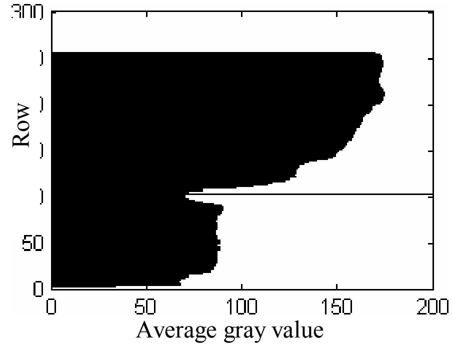
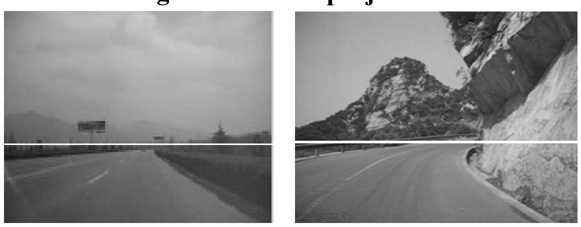


Fig.1 Horizontal projection



(a) Straight road (b) Curve road

Fig.2 The division of the road surface and background

2.1 Feature extracting of lane marking

The gray levels in some row that is including pixels of both road boundary and lane marking are shown in Fig.3. It can be seen that there is a peak of white lane marking on the curve of gray levels and the column is around 40. According to the peculiarity and the image connectivity, the pixels in the lane marking region are divided into two following kinds: on the line and on the others.

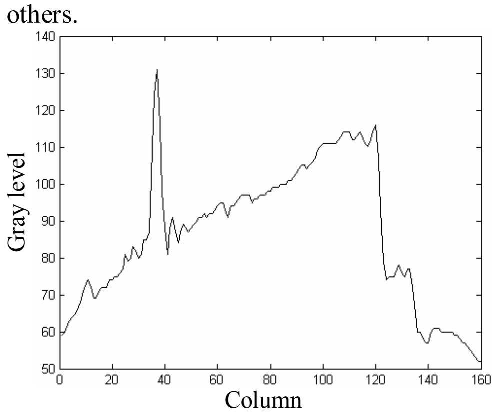


Fig.3 Sampled gray level in a row

The above course is carried out by the OTSU segmenting method, which is a preferable self-adapted thresholding technique. Supposing the gradation of gray levels on an image is L. The number of pixels with the gray level equal to i is n_i. Then the total number of pixels on the image is $N=\sum_{i=1}^{L} n_i$. Afterwards, the pixels are divided into two kinds: C_0 and C_1. The gray levels of C_0 are from 1 to k and the gray levels of C_1 are from k+1 to L (1<k<L). Their appearing probabilities ω and average gray levels μ are as follows:

$$\omega_0=\sum_{i=1}^{k} n_i / N=\sum_{i=1}^{k} p_i=\omega(k)$$

$$\omega_1=\sum_{i=k+1}^{L} n_i / N=\sum_{i=k+1}^{L} p_i=1-\omega(k)$$

$$\mu_0=\sum_{i=1}^{k} n_i i / \sum_{i=1}^{k} n_i=\sum_{i=1}^{k} p_i i / \omega_0$$

$$\mu_1=\sum_{i=k+1}^{L} n_i i / \sum_{i=k+1}^{L} n_i=\sum_{i=k+1}^{L} p_i i / \omega_1$$

The variance between two groups is obtained:

$$\sigma_B^2=\omega_0 \omega_1(\mu_1-\mu_0)^2 \tag{1}$$

The best threshold k^* (k $=k^*$) is the gray level which makes σ_B^2 achieve the maximum. Through reserving the characteristic pixels whose gray levels exceed the threshold k^*, the best effect of image segmentation is obtained. The following step is region connectivity analyzing and connected pixels labeling. It can remove many noisy points and blocks in the segmented image.

2.2 Feature extracting of road boundary

In Fig.3, there is a downward fluctuation on the curve of gray levels with the column around 120. This fluctuation is resulted from a jump, which is from brightness to darkness at the road boundary. The fluctuation is more obvious in the vertical direction of road boundary. Basing on this characteristic of road boundary, the feature points are searched on the image.

An operation manner like convolution is adopted here. Through the horizontal template and vertical template ($\begin{bmatrix}-1 & 0 & 1\\ -2 & 0 & 2\\ -1 & 0 & 1\end{bmatrix}$ and $\begin{bmatrix}1 & 2 & 1\\ 0 & 0 & 0\\ -1 & -2 & 1\end{bmatrix}$) of Sobel operator moving on the image, the gradient vector of each central pixel is calculated ($\nabla f(x,y)=[\Delta_x f(x,y) \quad \Delta_y f(x,y)]^T$). In this way, the horizontal and vertical edges stand out from the image. The gradient amplitude and gradient angle are also received.

Considering the actual situation, there are often discontinuous edge and short interferential edge segments, hence following and searching the edge points is much needed. According to the similarities among the pixels on their gradient amplitude and angle, we judge whether the pixel (x, y) and its neighborhood pixel (i, j), which is near the gradient direction of (x, y), are fitting the two equations:

$$|G(x,y) - G(i,j)| \leq G_{thresh} \tag{2}$$

$$|\Phi(x,y) - \Phi(i,j)| \leq \Phi_{thresh} \tag{3}$$

Here, $G(x,y) = \sqrt{\Delta_x{}^2 f(x,y) + \Delta_y{}^2 f(x,y)}$,

$$\Phi(x,y) = \arctan\left[\frac{\Delta_y f(x,y)}{\Delta_x f(x,y)}\right],$$

G_{thresh} is amplitude threshold and Φ_{thresh} is angle threshold. If the two pixels meet (2) and (3), they will be marked as the characteristic points in the same way and their coordinates will be recorded. Such judgment and connection for road boundary points can not only avoid the disturbance from noises, but also advance the recognition precision and robustness of the whole algorithm.

2.3 Model matching of road boundary and lane marking

Reference [5] defined the quadratic and cubic curve as the road geometrical model and resulted in a mass of computation. Usually, since the curvature of structural roads is very little, linear lane model can describe the true environment much better. It also has the advantages of less computation and better real-time capability to control intelligent vehicles more easily. But in special situation, take the curve road coiling mountains for example, the curvature is so large that the curve model is needed. The quadratic curve is used here to make sure the precision and speed of intelligent vehicles.

The linear geometrical equation of the lane model is $Y = \alpha + \beta x + \varepsilon$, and ε is the noise. A group of extracted characteristic points which are (Y_i, x_i) (i=1,2,…,n) should fill this equation. We try to find the least square estimation ($\hat{\alpha}$, $\hat{\beta}$) of the unknown parameter (α, β) to make sure $\sum_{i=1}^{n}(Y_i - \hat{\alpha} - \hat{\beta}x_i)^2$ = $\min_{\alpha,\beta} \sum_{i=1}^{n}(Y_i - \alpha - \beta x_i)^2$. Through defining $Q(\alpha,\beta)$ = $\sum_{i=1}^{n}(Y_i - \alpha - \beta x_i)^2$ and making $\frac{\partial Q}{\partial \alpha}|_{(\alpha,\beta)=(\hat{\alpha},\hat{\beta})} = 0$, $\frac{\partial Q}{\partial \beta}|_{(\alpha,\beta)=(\hat{\alpha},\hat{\beta})} = 0$, the above formula can be wrote as the following equation:

$$\left.\begin{aligned} \hat{\alpha} + \bar{x}\hat{\beta} &= \bar{Y}, \\ n\bar{x}\hat{\alpha} + \sum_{i=1}^{n} x_i^2 \hat{\beta} &= \sum_{i=1}^{n} x_i Y_i, \end{aligned}\right\} \tag{4}$$

$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$, $\bar{Y} = \frac{1}{n}\sum_{i=1}^{n} Y_i$. After analyzing the coefficient determinant of the equation, equation (4) has a unique solution, that is

$$\begin{cases} \hat{\alpha} = \bar{Y} - \hat{\beta}\bar{x}, \\ \hat{\beta} = \dfrac{\sum_{i=1}^{n}(x_i - \bar{x})(Y_i - \bar{Y})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \end{cases} \tag{5}$$

The variance min $Q(\alpha,\beta)$ = $Q(\hat{\alpha},\hat{\beta})$ is then calculated. If the result is not in the allowable range, the lane is confirmed as crooked road. And the lane model will be changed into the quadratic curve $Y = \alpha + \beta x + \gamma x^2 + \varepsilon$. $(\hat{\alpha},\hat{\beta},\hat{\gamma})$ can be solved by using the family of orthogonal function.

3. Lane tracking

Lane tracking is used to reduce the searching range of characteristic pixels on the image. The positions of road boundary and lane marking on the past frame are regarded as the forecasted positions on the current frame. New feature points are searched in its left and right horizontal neighborhoods, which are 20-pixels wide. Thus, the searching range is reduced from rectangular region in lane detecting to narrow zonal region in lane tracking (Fig.4). A lot of computing time is then saved.

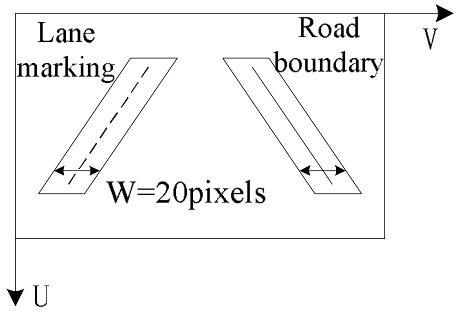


Fig.4 Lane-tracking zonal region

The block diagram of whole algorithm is shown in Fig.5. Every 20 frames make up a processing period. Lane-detecting module is invoked for the first frame and the lane-tracking module is for the remanent 19 frames. The tracking result is verified by the prior knowledge of lane. If the deviation is too big to locate new lane correctly, the current frame will inherit the position of the lane on last frame. And if the lane can not be located newly in two consecutive frames, the lane-detecting module will be called over again.

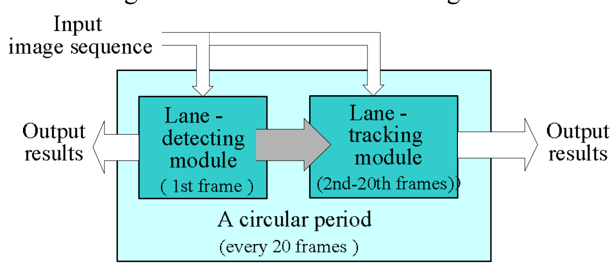


Fig.5 Lane-recognizing process design

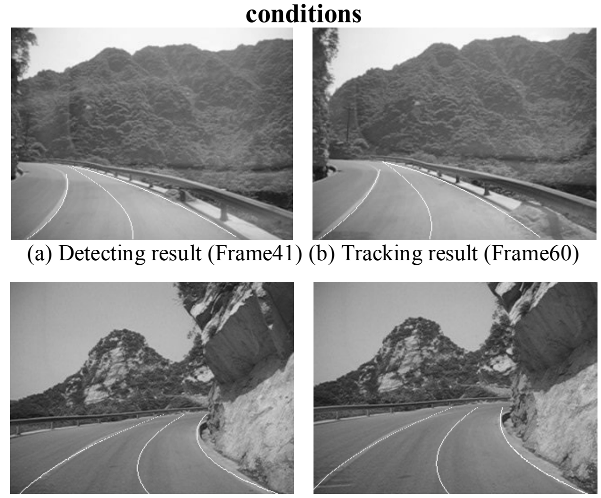
After recognizing the position and shape of the lane, the referenced path for the driving car can be found out through midpoints of the roadway. When the height H , the depression angle θ and the focal distance f of vehicle camera have been known, the deviation displacement s and deviation angle γ of the vehicle can be calculated in 3-D real world. They are quite useful in the transverse and longitudinal navigation for intelligent vehicles.

4. Experimental results

A large number of experiments have been done to the algorithm above. The following images are some results of test sequence which is from the monocular camera on the car. In the Fig.6 and Fig.7, (a) and (c) are the results of calling the detecting block to recognize the road boundary and lane marking. (b) and (d) are the results of calling the tracking block. The white line in the middle of roadway is the referenced path.

(a) Detecting result (Frame141) (b) Tracking result (Frame159)

Fig.6 Results of the straight road in cloudy conditions



(a) Detecting result (Frame41) (b) Tracking result (Frame60)

(c) Detecting result (Frame861) (d) Tracking result (Frame880)

Fig.7 Results of the curve road coiling mountains

Using the gradient information of the edge pixels, the recognition of discontinuous road boundaries is still precise (Fig.8). Furthermore, the algorithm has self-adapted adjusting ability for the lane-tracking error. As shown in Fig.8, the fitting error of the far road boundary in 519th frame is eliminated in 632nd frame.

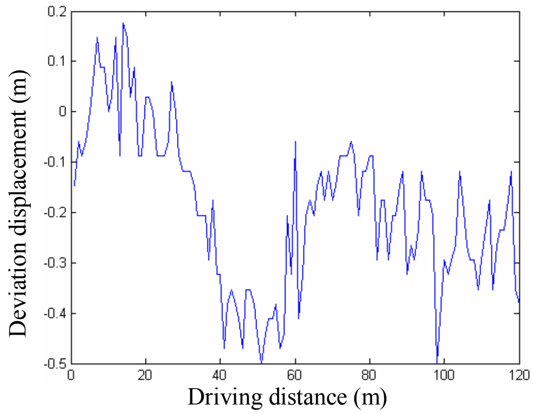
(a) Frame 519 of sequence (b) Frame 632 of sequence

Fig.8 Results on the discontinuous road boundary

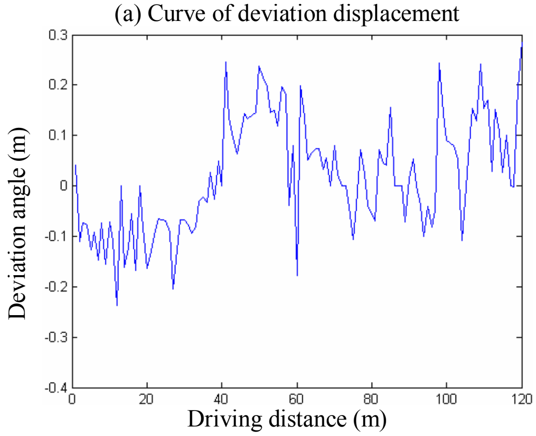
The tested results of lane width from some frames are given in Table I. These data are contrasted with real values. The curves in Fig.9 (a) and (b) separately denote the deviation displacement s and deviation angle γ about the driving car. All negatives indicate left avertence, and the positives are opposite. It can be known from Fig.9 (a) that the car always drove near the left of lane after going ahead about 40 meters.

TABLE 1 THE TESTED DATA OF LANE WIDTH

Frame	141	159	268	274	519	632
Tested lane width (m)	4.438	4.592	4.562	4.647	4.472	4.63
Average tested value (m)	4.557					
Real lane width (m)	4.5					
Average error rate	1.26 %					



(a) Curve of deviation displacement



(b) Curve of deviation angle

Fig.9 The position and direction of driving vehicle

5. Conclusion and perspectives

The paper has described a method designed to recognize the road boundary and lane marking. Firstly, the region of interest is dynamically partitioned from the image. Secondly, the feature pixels of road boundary are extracted by using the gradient vectors of pixels. And the feature extraction of lane marking is finished by self-adapted threshold segmenting. Finally, the least-squares fit technique is applied to match lane model with the feature pixels. The processing course is optimized by calling the lane detecting and tracking module circularly. The whole algorithm shows good robustness and high efficiency. The next task is to recognize unstructured road in special situations such as shadow or ponding. It is another difficult problem for both the domestic and foreign researchers.

6. References

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