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에지 방향의 누적분포함수에 기반한 차선인식

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Lane Detection Based on a Cumulative Distribution Function of Edge Direction

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Abstract - This paper describes an image processing algorithm capable of recognizing the road lane using a CDF (Cumulative Distribution Function), which is designed for the model function of the road lane. The CDF has distinctive peak points at the vicinity of the lane direction because of the directional and positional continuities of the lane. We construct a scatter diagram by collecting the edge pixels with the direction corresponding to the peak point of the CDF and carry out the principal axis-based line fitting for the scatter diagram to obtain the lane information. As noises play the role of making a lot of similar features to the lane appear and disappear in the image we introduce a recursive estimator of the function to reduce the noise effect and a scene understanding index (SUI) formulated by statistical parameters of the CDF to prevent a false alarm or miss detection. The proposed algorithm has been implemented in a real time on the video data obtained from a test vehicle driven in a typical highway.

1. INTRODUCTION

We introduce a novel algorithm to recognize the lane in monocular gray-level road images using a low level image processing. Recently, the analysis of a road traffic scene has been a prosperous topic to the scene understanding and required a strict reliability in accordance with the increasing interest about traffic safety. Although various researches have been done, most of them have shown some limited success in their performance and produced unexpected erroneous results due to dynamically changing illumination, unpredictable weather condition as well as the complexity of the road traffic scene. While segmenting moving vehicles [1, 2] and recognizing the road lane have been classified into two major tasks in the field of computer vision for the road scene understanding, the advent of a robust algorithm has remained as a hard and open problem.

In this paper, we bring into focus on the presentation of a robust algorithm to recognize the road lane for the captured image from a CCD camera mounted in a test vehicle as shown in Fig. 1.

(a) Test vehicle (b) Lane recognition

Fig. 1. Lane recognition

2. OVERVIEW

Generally, the proposed algorithm is based on the following three evidential facts of the road lane. *1) Directional continuity : The direction of lane boundary does not change abruptly. 2) Positional continuity : The position of lane boundary also does not change abruptly. 3) The lane boundary lies at the border between two regions with the different intensity distribution.* The essence of the algorithm is to infer these three evidential facts by low-level image processing. As the fundamental image primitive for the inference, we choose the edge because edge pixels from the lane boundary have a large magnitude and form a group along the lane boundary. While the edge is sensitive to the noise it leads to different consequences depending on how to reprocess the edge information. Here, we assume that noisy pixels are randomly occurred and scattered and expect that the summation of edge pixels reduces the noise effect. Based on the three evidential facts and the expectation we design a CDF (Cumulative Distribution Function) of edge direction as the model function of the road lane. The function accumulates the edge magnitude for the edge direction. It provides a peak value at the vicinity of the lane direction because there seldom exists a mark or a feature satisfying the three evidential facts simultaneously and continuously except for the lane boundary. Now what makes the CDF worthy of note is the fact that it reflects well the properties of the three evidential facts of the road lane. The CDF has figured out a way to connect the edge information with the lane information.

On the way of driving, a human driver effectively uses not only the three evidential facts but also other information such as the direction of heading of other vehicles, objects on the road, geographical features and an intuition from experience and learning. However, it has still considered as the difficult problem to extract those factors by image processing. Unlike the human driver, the proposed algorithm can not be worked well at the situation where the lane boundary is scarcely visible. The CDF constructed with the image captured in this situation does not provide a sharp peak value. Eventually it may result in a false alarm or miss detection. Therefore, the algorithm at least should identify whether the hard situation to extract the subject feature is occurred or not to prevent the false alarm or miss detection. For this purpose, we introduce an index for scene understanding called SUI (Scene Understanding Index). It is the ratio of mean and standard deviation of the CDF. The SUI plays the role of judging whether the algorithm can find features for lane boundary or not.

The proposed algorithm is organized as shown in Fig. 2. First, edge detection and the CDF construction are carried out for each input frame. Second, for successive N images, we construct an ACDF (Averaged CDF) by averaging the N CDFs. There is no difference between the CDF and ACDF except for smoothing effect of the ACDF. Third, we compute the SUI of the ACDF to judge that the proposed algorithm can detect lane or not. Fourth, we search for the local maximum points of the ACDF. Fifth, among the local maximum points we select two points $\hat{\theta}_1$ and $\hat{\theta}_2$ as the estimates of the lane direction on the right and left sides and form two scatter diagrams by collecting the edge pixels with the estimated lane directions. Sixth, the principal axis-based line fitting is performed for each scatter diagram to obtain the position and direction of the lane.

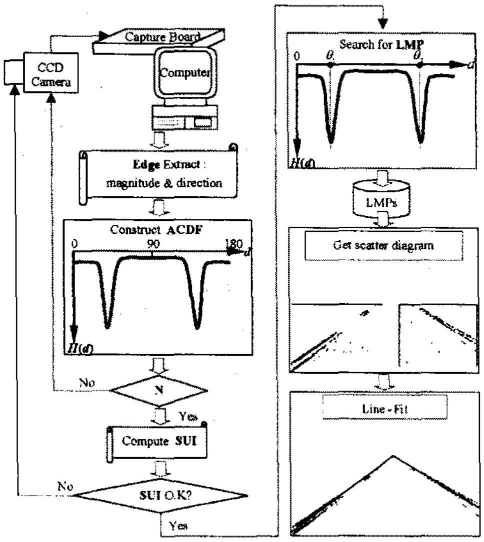


Fig. 2. Organization of algorithm

3. CDF

3.1. Edge detection

An edge is theoretically defined by the gradient of an intensity function. [3] At location (x,y) of an image $f(x,y)$, the gradient is represented by the vector as

$$\nabla \mathbf{f} = \begin{bmatrix} G_x & G_y \end{bmatrix}^T = \begin{bmatrix} \frac{\partial f}{\partial x} & \frac{\partial f}{\partial y} \end{bmatrix}^T \tag{1}$$

and the vector has two important physical quantities which are magnitude and direction as

$$\nabla f(x,y) = \sqrt{G_x^2 + G_y^2} \approx |G_x| + |G_y| \tag{2}$$

$$\alpha(x,y) = \tan^{-1}\left(\frac{G_y}{G_x}\right) \tag{3}$$

We set the range of $\alpha(x,y)$ as $0°$ to $180°$ and express the direction of edge pixel in terms of $1°$ in order to construct a CDF, which will be explained in the next section.

There are many pixels with small magnitude in the road image. Therefore, we get rid of pixels with small magnitude to leave the pixels belonged to the lane boundary. Determining the threshold for edge magnitude has been a difficult problem in the edge detection. We provide an adaptive method to determine the threshold without endowing a heuristic value. The adaptive method utilizes simple statistics such as a mean and a standard deviation of pixels in a small rectangle $\Im$ fixed at the center of lower part on the image. The mean and standard deviation for the edge magnitude in $\Im$ are computed as $\mu_0 = \frac{1}{\|\Im\|}\sum_{(x,y)\in\Im}\nabla f(x,y)$ and $\sigma_0 = \left\{\frac{1}{\|\Im\|}\sum_{(x,y)\in\Im}(\nabla f(x,y)-\mu_0)^2\right\}^{1/2}$, in which $\|\Im\|$ is the size of the rectangle $\Im$. Then, the threshold is determined as $\tau_0 = \mu_0 + \sigma_0$ for the initial frame. For the successive images, the threshold $\Im$ is updated recursively by taking the exponentially weighted average of mean and standard deviation as $\hat{\mu}_{k+1} = (1-\lambda)\hat{\mu}_k + \lambda\mu_{k+1}$ and $\hat{\sigma}_{k+1} = (1-\lambda)\hat{\sigma}_k + \lambda\sigma_{k+1}$ in which λ is experimentally determined to 0.6. $\hat{\mu}_k$ and $\hat{\sigma}_k$ are updated values of the previous frame, and μ_{k-1} and σ_{k-1} are mean and standard deviation of the current image. We use μ_0 and σ_0 as the initial values of $\hat{\mu}_0$ and $\hat{\sigma}_0$. Then, the threshold value is updated by $\hat{\tau}_{k+1} = \hat{\mu}_{k-1} + \hat{\sigma}_{k-1}$. Even though this method has no theoretical background it makes great contribution to the algorithm because it prevents human intervention.

3.2. CDF

We design a model function to describe the characteristics of the road lane through the edge information. As the function of edge direction, it is constructed by accumulating the edge magnitude as follows

$$F(d) = \sum_{n(d)} \nabla f(x,y) \tag{4}$$

Where n(d) is the number of edge pixels with the direction $\alpha(x,y) = d$ in which the range of angle d is that $d \in (0°, 180°)$. This means that if we accumulate the edge magnitude of the pixels with the direction d then we obtain an one-dimensional function as shown in Fig. 3. It represents the distribution of edge direction. So, we call it CDF (Cumulative Distribution Function).

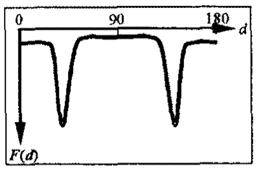


Fig. 3. CDF

If we carefully look at the shape of the CDF we can notice it provides two important properties. One of them is it has distinct two distinctive local maximum points and the other one is it has symmetric property centering around $90°$. The local maximum points of the CDF become the estimates of lane direction because they may correspond to the lane direction. In particular, since the CDF shows the symmetrical shape we can utilize the symmetric property to the vehicles lateral position control problem.

In general, the edge pixels from the lane boundary satisfying the three evidential facts make the CDF have distinct peak points. However, unlike our expectation the CDF of Eq. (4) often produces unclear peak points due to corrupted images. Therefore, it is risky to estimate the directional information of lane from the CDF constructed by single or short frames. To solve the problem we take into account for the fact that there seldom exists a mark or a feature on the road satisfying the three evidential facts continuously and simultaneously except for the lane boundary. Based on this fact, we construct an ACDF (Averaged CDF) by adding and averaging the CDFs obtained from a sequence of successive images to prevent the wrong estimation of the lane direction due to the noise effect as

$$H_k(d) = \frac{1}{N}\sum_{i=k-N+1}^{k} F_i(d),\ k \ge N \tag{5}$$

where subscript k represents the current frame and N means the consecutive N image frames.

3.3. Estimator

We propose two types of estimators of the ACDF. At first, we derive a simple one-dimensional recursive filter. When an additional measurement becomes available to Eq. (5) we have, as the new estimate $H_{k+1}(d) = \frac{1}{N+1}\sum_{i=k-N+1}^{k+1} F_i(d)$. It needs to store past measurements. We can change the expression into a recursive, linear estimator by some manipulation to evidence the prior estimate and to eliminate the storing of past measurements as follows :

$$\hat{H}_{k-1}(d) = \hat{H}_k(d) + \frac{1}{N+1}(F'(d) - \hat{H}_k(d)) \tag{6}$$

where $F'(d)$ is a measurement function defined by

$$F'(d) = \frac{1}{2}(F_k(d) + F_{k-1}(d)) \tag{7}$$

and $\frac{1}{N+1}$ is a gain factor. Subscript in Eq. (6) and Eq. (7) represents the time sequence. The new estimate $\hat{H}_{k+1}(d)$ is given by combining two terms : a prediction term and a correction term. The quantity $F'(d) - \hat{H}_k(d)$ is called the measurement residual. As the measurement function we specially use the average of two CDFs obtained from the latest two images. Duplication of the two images provides a good effect when a broken line forms the road lane, because the overlap decreases the broken range of the lane. More than two images, however, takes time to process and may cause a bad effect when a quick response is required. The Nth ACDF $H_N(d)$ becomes the initial value of the recursive filter. By using the recursive filter it does not need to keep the past data except for the CDF $F_k(d)$ of the previous frame because all previous information is embodied in the prior estimate.

At second, we derive a new estimator based on the moving summation. It overcomes the weak points of the recursive filter of Eq. (6). The estimator has similar form to the ACDF of Eq. (5) as follows :

$$\hat{H}_k(d) = \sum_{i=k-N-1}^{k} F_i(d),\ k \ge N \tag{8}$$

where N is the same one to the Eq. (5). We do not take the average to reduce the processing time and to save the memory. Without averaging, this equation can be expressed as a recursive form as

$$\hat{H}_k(d) = \hat{H}_{k-1}(d) - F_{k-N}(d) + F_k(d),\ k \ge N+1 \tag{9}$$

Except for computing the initial value $\hat{H}_N(d)$ we do not use the Eq. (8) any more. While the recursive estimator of Eq. (6) holds the past information to the prior estimate, it throws away old measurement and takes new measurement at every step. So, it produces the reliable estimate as soon as the normal state is recovered from a transition state like the lane change. Therefore, we regard the estimator of Eq. (9) as the more suitable one to the general traffic scenario than the recursive filter of Eq. (6) and carry out the lane recognition with the estimator.

3.4. SUI

The CDF has sharp peak value at the vicinity of the direction corresponding to the lane direction as shown in Fig. 4. However, when the lane mark becomes scarcely visible due to noises the CDF does not provide a distinct peak value. In this situation, the proposed algorithm leads to a miss detection or false alarm. To notify the occurrence of the difficult situation in advance we derive an index called as a SUI (Scene Understanding Index). The SUI plays the role of judging whether the algorithm can find the features for the lane boundary or not.

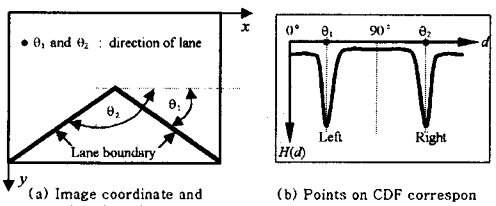
We can guess when a function has a distinct peak value the variance of the function is larger than when a function has not such a distinct peak value. Based on this idea, we derive the SUI as :

$$\Re = \frac{\mu}{\sigma} \tag{10}$$

where μ is the mean value and σ is the standard deviation of the function. We can apply this concept to the CDF. If the ratio is great the CDF has larger possibility not to have distinct peak value than the opposite case. According to the symmetric property we divide the CDF into right and left sides centering around 90° as shown in Fig. 4(b) and reformulate the ratio of Eq. (10) for both sides as follows :

$$\Re_l = \frac{\mu_l}{\sigma_l} \text{ and } \Re_r = \frac{\mu_r}{\sigma_r}. \tag{11}$$

where $\Re_l$ and $\Re_r$ are SUIs, and μ_l, σ_l and μ_r, σ_r are mean and standard deviation of the left and right sides of the CDF, respectively.



(a) Image coordinate and lane boundary

(b) Points on CDF correspon ding to lane direction

Fig. 4. Lane direction and its corresponding points on the CDF

4. RECOGNITION

4.1. Lane direction

As shown in the Fig. 4 of the previous section, it can be supposed that the local maximum point (LMP) of the CDF $\hat{H}_k(d)$ corresponds to the direction of the road lane. According to the Luenberger [4] we introduce a definition for the local maximum point of a function f over Λ as follows :

__Definition__ LMP :

If there is an $\varepsilon > 0$ such that $f(x) < f(x^*)$ for all $x \in \Lambda$ within a distance ε of x^*, then x^* is said to be a strict relative maximum point of f over Λ.

Based on this definition we search for positions of local maxima on both sides of the estimated CDF $\hat{H}_k(d)$. Similar approach was utilized at the reference of Lee and Kweon [5]. The local maximum point from the left side of the CDF corresponds to the direction of the right lane boundary and the local maximum point from the right side of the CDF corresponds to the direction $\hat{\theta}_2$ of the left lane boundary as shown in Fig. 4. We let the two local maximum points as the estimates of lane direction $\hat{\theta}_1$ and $\hat{\theta}_2$.

4.2. Scatter diagram

We construct two sets Γ_l and Γ_r by collecting edge pixels with the estimated lane directions $\hat{\theta}_1$ and $\hat{\theta}_2$ as follows :

$$\Gamma_l = \{(x,y) | \alpha(x,y) = \hat{\theta}_1\} \text{ and } \Gamma_r = \{(x,y) | \alpha(x,y) = \hat{\theta}_2\} \quad (12)$$

where $\alpha(x,y)$ is the edge direction defined in Eq. (3). Each set forms a scatter diagram. We apply a line fitting to these sets to obtain the lane information. If the size of scatter diagram is too small to apply the line fitting we reconstruct the set by using a range instead of single value as follows :

$$\Gamma_l = \{(x,y) | \alpha(x,y) = \hat{\theta}_1 \pm \delta\} \text{ and } \Gamma_r = \{(x,y) | \alpha(x,y) = \hat{\theta}_2 \pm \delta\} \quad (13)$$

where δ is experimentally selected. As the reconstruction makes higher possibility to include outlier pixels in the set, we solve the problem by outlier removal.

4.3. Lane information

We consider the least squares based line fitting (LSBLF) and the principal axis based line fitting (PABLF) to extract lane information in the sets Γ_l and Γ_r. As experimentally proved by Lee and Kweon [5], the PABLF is less affected by locally grouped pixels than the LSBLF. Thus, we apply the PABLF to extract lane information composed of the location and orientation.

At first, using the (p+q)th order moments [3] we compute the center of mass $(\bar{x},\bar{y})$ of each set by

$$\bar{x} = \frac{m_{10}}{m_{00}}, \quad \bar{y} = \frac{m_{01}}{m_{00}} \quad (14)$$

where m_{pq} is the (p+q)th order moment. The center of mass for each scatter diagram plays the role of representing the location of lane. For set Γ_l, $(\bar{x}_l,\bar{y}_l)$ and for set Γ_r, $(\bar{x}_r,\bar{y}_r)$ are obtained by using Eq. (14). Next, the principal axis ϕ is computed by the well known equation [3]

$$\phi = \frac{1}{2}\tan^{-1}\frac{2u_{11}}{u_{20} - u_{02}} \quad (15)$$

where u_{pq} is the (p+q)th order central moment defined by $u_{pq} = \sum_x\sum_y (x-\bar{x})^p(y-\bar{y})^q$ in which $(\bar{x},\bar{y})$ is the center of mass. Principal axes ϕ_l for set Γ_l and ϕ_r for set Γ_r are obtained by using Eq. (15). The principal axis represents the orientation for the lane to be recognized.

5. EXPERIMENTAL RESULTS

We have conducted on-road tests at highways paved with asphalt and cement and rural roads. The driver drove the test vehicle at the average velocity of 100 km/h during the test. We also carried out laboratory test by recording the video sequences of road scene using a VCR to facilitate the test. In the evaluation, image size was 320×240 and 3×3 Sobel operator [3] was used as the edge operator. Experimental results proved the algorithm to be robust with the images of highway and suburban road at a wide variety of conditions.

In this example, road appearance varies due to heavy shadows, letters and arrow mark. Besides, the broken lane marks make the invisible part large. The Fig. 5 showed that the proposed algorithm successfully recognized the lane in this situation.

Fig. 5. Lane recognition in heavy shadows, letters and arrow mark on road surface

Next, we provided the test result in rural settings on undivided, two-lane asphalt roads. According to the D. Pomerleau and T. Jochem [6], nearly 70% of roadway departure crashes occurs in these roads. Therefore, we can not help taking a view of the rural settings seriously. As shown in Fig. 6, noises in the images caused the lane boundary to blur and make the recognition hard. However, the proposed algorithm led to favorable result. We conducted the test as done in highway without a change of parameters.

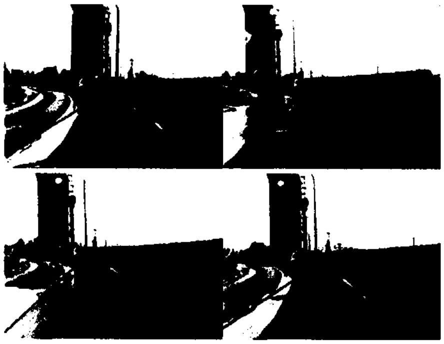


Fig. 6. Lane recognition in rural settings

The following two experiments were performed to show the proposed algorithm could be applicable to a rainy day shown in Fig. 7 and nighttime shown in Fig. 8. We accompanied the recognized lane expressed by a line superimposed on the image with the CDFs to show the close relationship between the recognized result and the CDFs. The graphs in the rectangles of the second and fourth columns of the figures present the ACDF estimated from the previous frame and the CDF constructed from the current frame, respectively. In each rectangle, the upper graph is for the ACDF and the lower graph is for the CDF. If we look at the CDF we can guess whether the lane marks come into view or not on the image. If the lane mark is little visible, the CDF has no distinct peak value. Even if the proposed algorithm successfully performed in a rainy day there was larger possibility to obtain a false alarm or miss detection than a fine day because the third condition of the three evidential facts of the road lane often unsatisfied in a rainy day.

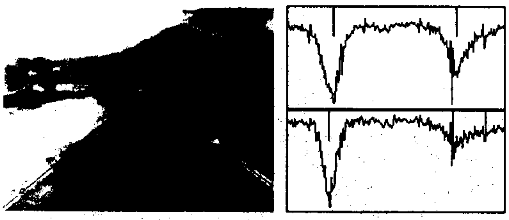


Fig. 7. Lane recognition in a rainy day

If we look at the CDF in the nighttime experimental result shown in Fig. 8 we found that the CDF was rough and uneven. It was caused by weak illumination, which makes lane boundaries indistinct and reduces the visible range of the lane. However, since the weak illumination also prevents to disclose other noise sources the proposed algorithm provided reliable results in a nighttime experiment.

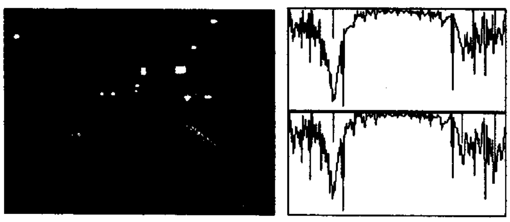


Fig. 8. Lane recognition in a nighttime

6. CONCLUSION

The keynote of the proposed algorithm was to connect the edge information to the evidential facts of the road lane by means of the CDF. As the three evidential facts of the road lane are viewed to the perceptual constraints, the CDF is, in fact, considered as the road model. Besides the role of model function, the CDF eliminates the noise effect in the intensity image and edge. By estimating the CDF by the moving sum we can consistently keep the shape of the CDF and overcome the noise effect appeared in a short time. Even if it is not enough, the newly introduced SUI. provides a clue for the scene understanding.

We carried out successful experiments at a wide variety of conditions without a change of parameter value or human intervention. In addition, the algorithm minimized the use of heuristic parameters, assumptions and constraints. We now develop an algorithm to estimate the curved direction of road by dividing the processing area in the vertical direction of image and constructing the CDF for each zone. The most important thing in the lane recognition by the image processing is to maintain the robustness. To realize this goal we improve the scene understanding function and tracking performance of the lane geometry between frames. In the long run, we will develop a practical system available for autonomous driving system as well as several warning systems.

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