Road-Lane Detection Based on a Cumulative Distribution Function of Edge Direction

Un-Kun Yi, Joon-Woong Lee and Kwang-Ryul Baek

Abstract - This paper describes an image processing algorithm capable of recognizing road lanes by using a CDF (cumulative distribution function). The CDF is designed for the model function of road lanes. Based on the assumptions that there are no abrupt changes in the direction and location of road lanes and that the intensity of lane boundaries differs from that of the background, we formulated the CDF, which accumulates the edge magnitude for edge directions. The CDF has distinctive peak points at the vicinity of lane directions due to the directional and the positional continuities of a lane. To obtain lane-related information a scatter diagram was constructed by collecting edge pixels, of which the direction corresponds to the peak point of the CDF, then the principal axis-based line fitting was performed for the scatter diagram. Noises can cause many similar features to appear and to disappear in an image. Therefore, to reduce the noise effect a recursive estimator of the CDF was introduced, and also to prevent false alarms or miss detection a scene understanding index (SUI) was formulated by the statistical parameters of the CDF. The proposed algorithm has been implemented in real time on video data obtained from a test vehicle driven on a typical highway.

1. Introduction

This paper introduces a novel algorithm that recognizes lanes in monocular gray-level road images. The algorithm uses low-level image processing. Recently, the analysis of road traffic environments has been a useful topic to the scene understanding and required strict reliability in accordance with the increasing interest in traffic safety. Although various studies have been conducted, most of them have only shown limited success in their performance and produced unexpected erroneous results due to dynamically changing illumination, unpredictable weather conditions and the complexity of road traffic environments. While segmenting moving vehicles [4, 15] and recognizing road lanes have been classified into two major tasks in the field of computer vision for understanding road scenes, the advent of a robust algorithm has remained as a hard and open problem. This paper focuses on the presentation of a robust algorithm that recognizes road lanes for images taken from a CCD camera mounted on a test vehicle as shown in Fig. 1.

Much research about road-lane recognition by image processing has been conducted. Of such research there are feature-based methods [1, 5, 9, 10, 12], model-based methods [3, 13, 14], neural network-based methods [8, 11], probabilistic methods [20], etc. Most research share and combine some principles from each of these methods. One common issue of these methods is how to provide a reliable algorithm even in the noisy sources because all these methods are strongly influenced by noise.

(a) Test vehicle (b) Captured image (c) Lane recognition

Fig. 1 Lane recognition

The well-known Hough transform [8, 16] and other line approximation techniques [2, 10] are typical approaches of the feature-based method. The Hough transform, however, has inherent problems such as a quantization error for Hough space and a lengthy processing time. Bimbo et al. [8] combined the Hough transform and a neural-net application for recognizing road lanes. They divided an input image into multiple tiles and extracted line segments for each tile by using the Hough transform and took advantage of a neural network to estimate road boundaries by using extracted line segments. Liou and Jain [1] presented a vanishing point-based road-following algorithm. Unlike most approaches that attempt to control vehicles by finding the road center, their approach utilizes the displacement between the previous vanishing point and the current point to determine the steering angle. Bertozzi and Broggi [12] assumed the road lane mark to be the region of a vertical bright line of a constant width surrounded by a darker region in the top view-image, which is obtained by inverse perspective mapping. Such an assumption is not true for unpainted roads. Their method would apply well to white-painted lane marks. However, roads cannot always satisfy the condition of being white-painted due to sources

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of noise such as wear, shadows and occlusion by sandy trash. In addition, to take top-view images their method requires data that describe the geometric relationship between the road and the camera. Even though the top-view image is in the spotlight of the lane recognition, it requires geometric data for inverse perspective mapping and the interpolation of transformed image to obtain an even-sized image, as done in the RALPH [9]. In the SCARF [20], Crisman and Thorpe combined feature-based lane recognition with probabilistic modeling. The SCARF, however, does not determine the initial road location automatically. Because the probabilistic modeling in the SCARF classifies the pixels into "road" and "off-road", the classification may be degraded in white-painted paved roads. Taylor et al. [6] relied on a template-based correlation matching to look for similar patterns on the road. While the RALPH [9] and ALVINN [11] had the common goal of generating the steering command for the lane keeping system, their approaches were different. The RALPH, based on the scan-line intensity profile from low-level image processing, estimates the road curvature and computes the lateral vehicle location. In the RALPH, several hypothesized models are used to determine the appropriate road curvature, and an adaptation process is also required whenever the geometric information about driving lanes changes. The RALPH does not take into account vehicles passing other vehicles. On the other hand, the ALVINN is based on a neural-net application, which requires time for learning and needs human intervention. Dickmanns et al. [14] and Takahashi [13] described a model of road geometry and the relative structure between the road lane and the camera mounted on a vehicle. Because of its great dependency on the model, the efficiency of the model-based method is degraded when the accuracy of the model worsened. However, compared to the feature-based method this method is less sensitive to noise.

2. Overview

An algorithm in this paper is based on the following three assumptions about road lanes. *1) Directional continuity: The direction of lane boundaries does not change abruptly. 2) Positional continuity: The position of lane boundary does not change abruptly. 3) Lane boundaries lie at the border between two regions with different intensity distributions.* The essence of the algorithm is to infer such assumed facts by low-level image processing. As the fundamental image primitive for the inference, we chose the edge because edge pixels from lane boundaries have a large magnitude and form a group along boundaries. While the edge is sensitive to noise it leads to different consequences depending on how the edge information is reprocessed. In this paper, we assume that noise-filled pixels occur randomly and are scattered, and expect that the summation of edge pixels reduces the effects of noise. Based on the three assumptions and the expectation we designed a CDF (cumulative distribution function) of edge directions as the model function of road lanes. The function accumulates the edge magnitude of edge directions. It provides a peak value at the vicinity of the lane directions because except for the lane boundaries there seldom exists a mark or a feature satisfying the three assumptions simultaneously and continuously. The CDF is noteworthy because it reflects well the properties of the three assumptions of road lanes. The CDF has enabled the edge-related information and the lane-related information to be connected.

While driving, a human driver effectively uses not only the three assumptions but also other information such as the traveling direction of other vehicles, objects on the road, geographical features, and an intuition based on experience and learning. However, it is still considered a difficult problem to extract such factors by image processing. Unlike a human driver, the proposed algorithm cannot work well in situations where lane boundaries are difficult to detect. The CDF constructed with images captured under poorly visible conditions does not provide a clear peak value. Eventually, the algorithm may result in a false alarm or a missed detection. Therefore, to prevent a false alarm or a missed detection the algorithm should at least identify whether or not a situation in which it is difficult to extract subject features has occurred. For this purpose, we introduce an index for understanding a scene called the SUI (scene understanding index). The SUI is the ratio of the mean and the standard deviation of the CDF. The SUI judges whether or not the algorithm can find features for lane boundaries.

In addition to the SUI, this paper introduces a moving summation-based recursive estimator. The estimator gradually adapts itself to new circumstances such as lane changes.

The proposed algorithm is organized as shown in Fig. 2. First, edge detection and the construction of the CDF were performed for each input frame. Second, for successive N images, an ACDF (averaged CDF) was constructed by averaging the N CDFs. There is no difference between the CDF and the ACDF except for the smoothing effect of the ACDF. Third, the SUI of the ACDF was computed to judge whether or not the proposed algorithm could detect lanes. Fourth, the local maximum points of the ACDF were searched for. Fifth, among the local maximum points, two points, $\hat{\theta}_1$ and $\hat{\theta}_2$, were selected as the respective estimates of the lane directions on the right and left lane boundaries, and two scatter diagrams were formed by collecting the edge pixels with the same values of $\hat{\theta}_1$ and $\hat{\theta}_2$. Sixth, the principal axis-based line fitting was performed for each scatter diagram to obtain the position of lanes.

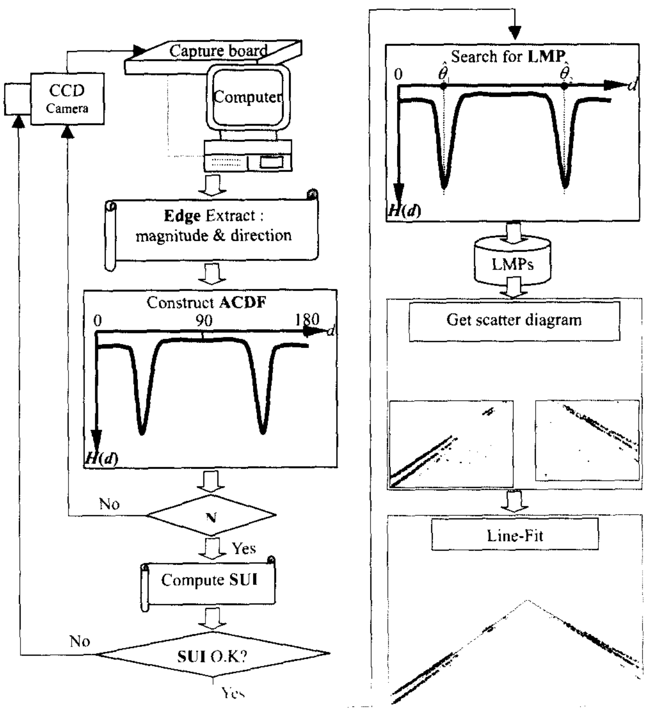


Fig. 2 Organization of the algorithm

3. The CDF

3.1 Edge detection

An edge is theoretically defined by the gradient of an intensity function [7]. At location (x,y) of an image $f(x,y)$, the gradient is represented by the vector, as follows:

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

The vector in turn has two important physical quantities, magnitude and direction, as respectively shown below:

$$\nabla f(x,y) = \sqrt{G_x^2 + G_y^2} \approx |G_x| + |G_y|, \quad \alpha(x,y) = \tan^{-1}\left(\frac{G_y}{G_x}\right).$$

To construct a CDF we set the range of $\alpha(x,y)$ as 0 to 180 , and express the direction of the edge pixel in terms of 1 .

In the detection of edges, one serious problem is reducing the processing time. We used two approaches to reduce the time. One of them limits the processing area above the vanishing point [19]. Because lanes visible in a road image generally lie in this area, it is believed that this approach will reduce the processing time. The other approach utilizes a look-up table to compute the edge direction, as done by Kahn et al [10].

In a road image, There are many pixels of a small magnitude. Therefore, to leave the pixels belonged to the lane boundaries we eliminated pixels that have a small magnitude. Determining the threshold for edge magnitude has been a difficult problem in the detection of edges. We provide an adaptive method for determining the threshold without endowing a heuristic value. The adaptive method utilizes simple statistics such as the mean and the standard deviation of pixels in a small rectangle $\Im$ fixed at the center of the lower part of an image. The mean and the standard deviation for the edge magnitude in $\Im$ are respectively computed as follows:

$$\mu_0 = \frac{1}{\|\Im\|} \sum_{(x,y)\in\Im} \nabla f(x,y) \text{ and } \sigma_0 = \left\{ \frac{1}{\|\Im\|} \sum_{(x,y)\in\Im} (\nabla f(x,y) - \mu_0)^2 \right\}^{1/2},$$

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 τ is updated recursively by taking the exponentially weighted average of the mean and the standard deviation, as follows:

$$\hat{\mu}_{k+1} = (1-\lambda)\hat{\mu}_k + \lambda\mu_{k+1} \text{ and } \hat{\sigma}_{k+1} = (1-\lambda)\hat{\sigma}_k + \lambda\sigma_{k+1},$$

in which λ is experimentally determined to be 0.6, $\hat{\mu}_k$ and $\hat{\sigma}_k$ are the updated values of the previous frame, and μ_{k+1} and σ_{k+1} are respectively the mean and the standard deviation of the current image. We used μ_0 and σ_0 as the respective initial values of $\hat{\mu}_0$ and $\hat{\sigma}_0$. Then, the threshold value is updated as $\tau_{k+1} = \mu_{k+1} + \hat{\sigma}_{k+1}$. Even though this method has no theoretical background, it makes a significant contribution to the algorithm because it eliminates the need for human intervention.

3.2 The CDF

Based on edge information, we designed a model function to describe the characteristics of a road lane. The function is constructed by accumulating the edge magnitude, as follows:

$$F(d) = \sum_{n(d)} \nabla f(x,y) \qquad (1)$$

where n(d) is the number of edge pixels of the direction $\alpha(x,y) = d$, in which the range of angle d is $d \in (0^\circ, 180^\circ)$. We expect that if the edge magnitude of the pixels of the direction d is accumulated, then one-dimensional function can be obtained, as shown in Fig. 3. The function represents the distribution of edge direction. So, we call it CDF (cumulative distribution function).

If the shape of the CDF is examined carefully, it can be noticed that it has two important properties. One is that it has two distinct local maximum points, and the other is that it has a symmetric property centering around 90 if the optical-axis of the CCD camera mounted on a test vehicle is at the center of a lane. The local maximum points

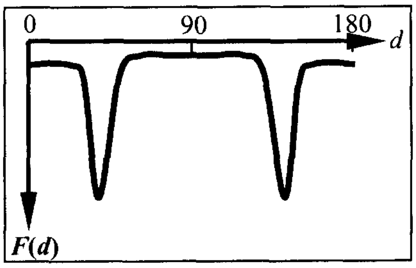


Fig. 3 CDF

become the estimates of the lane direction because they are likely to correspond to the lane direction. In particular, because the CDF shows a symmetrical shape, the symmetric property can be used to solve a vehicle's lateral position control problem.

Contrary to our expectations the CDF of Eq. (1) often produces peak points that are unclear due to corrupted images. Therefore, it is risky to estimate the directional information of a lane based on the CDF constructed by single or short frames. To solve the problem, we took into account the fact that except for lane boundaries there seldom exists a mark or a feature on a road satisfying the three assumptions simultaneously. Based on this fact, to prevent an incorrect estimation of lane directions due to noise effects we constructed an ACDF (averaged CDF) by adding and averaging the CDFs obtained from a sequence of successive images. The ACDF is formulated as follows:

$$H_k(d) = \frac{1}{N} \sum_{i=k-N+1}^{k} F_i(d), \quad k \geq N \tag{2}$$

where the subscript k represents the current frame and N denotes the consecutive N image frames. According to Gelb [18], the mean value is known to be an unbiased and minimum variance estimator. Generally, on a highway, the road environment is exposed to much noise, the road curvature is relatively small, and lane marks are painted by broken lines. Therefore, a larger N is more effective to noisy environments. However, a larger N does not quickly reflect a change because of a larger smoothing effect. Eventually, we can not help determining N experimentally because advantages and disadvantages exist at the same time.

3.3 The Estimator

We propose an estimator for the ACDF. The estimator is derived based on the moving summation. It is similar in form to the ACDF of Eq. (2). This estimator is formulated as follows:

$$\hat{H}_k(d) = \sum_{i=k-N+1}^{k} F_i(d), \quad k \geq N \tag{3}$$

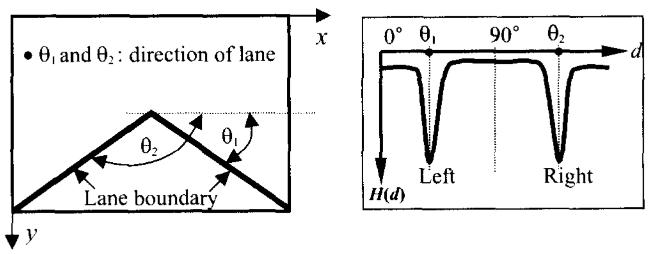
where N is the same as the N in Eq. (2). To reduce the processing time we did not take the average as done in Eq. (2). Without averaging, this equation can be expressed as a recursive form, as follows:

$$\hat{H}_k(d) = \hat{H}_{k-1}(d) - F_{k-N}(d) + F_k(d), \quad k \geq N+1 . \tag{4}$$

Except for computing the initial value $\hat{H}_N(d)$, Eq. (3) is no longer used. The estimator discards old measurements and takes new measurements at every step. So, it produces a reliable estimate as soon as the normal state is recovered from a transition state such as a lane change. Therefore, we regard the estimator shown in Eq. (4) as being suitable for estimating the general traffic scenario.

3.4 The SUI

When lane marks become poorly visible due to noises, the CDF does not provide a distinct peak value, and the proposed algorithm may lead to a missed detection or a false alarm. To note the occurrence of such situation in advance, we derived an index called an SUI (scene understanding index). The SUI judges whether or not the algorithm can find features for lane boundaries. It is believed that when a function has a distinct peak value, the variance of the function is larger than when it does not have such a distinct peak value. Based on this fact, we derived the SUI as follows: $\Re = \mu/\sigma$ where μ is the mean value, and σ is the standard deviation of the function.



(a) Image coordinate and lane boundary

(b) Points on CDF corresponding to lane direction

Fig. 4 Lane directions and their corresponding points on the CDF

We can apply this concept to the CDF. If the SUI is high, the CDF has a relatively larger possibilty of not having a distinct peak value than when the SUI is low. We divided the CDF into right and left sides, centering around 90°, as shown in Fig. 4(b), and reformulated the SUI for both sides, as follows:

$$\Re_l = \frac{\mu_l}{\sigma_l} \quad \text{and} \quad \Re_r = \frac{\mu_r}{\sigma_r}, \tag{5}$$

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

When the lane recognition procedure is initially performed, if either of the SUIs exceeds an experimentally determined threshold value, the procedure skips over the initial frame and proceeds to the next frame because the initial information about the recognized lane is utilized in the subsequent recognition process. The basic application scheme of the SUIs is summarized as follows:

- For the initial processing :
  if ($\Re_l \geq \kappa$ or $\Re_r \geq \kappa$), goto next frame
  else do lane recognition
- For the subsequent processing :
  if ($\Re_l < \kappa$ and $\Re_r < \kappa$), do lane recognition
  elseif ($\Re_l \geq \kappa$ and $\Re_r \geq \kappa$) lane information = previous lane information
  elseif ($\Re_l \geq \kappa$) right-side lane information = previous right-side lane information
  else left-side lane information = previous left-side lane information

where κ is the experimentally determined threshold value of the SUIs.

4. Lane-Related Information

4.1 Lane direction

As shown in Fig. 4, it can be supposed that the local maximum point (LMP) of CDF $\hat{H}_k(d)$ corresponds to the direction of a road lane. Following to Luenberger[17], we introduced a definition for the LMP 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 the above definition, we searched for the positions of local maxima on both sides of the estimated CDF $\hat{H}_k(d)$. As shown in Fig. 4, the LMP from the left-side of the CDF corresponds to the direction θ_1 of the right-lane boundary and the LMP from the right-side of the CDF corresponds to the direction θ_2 of the left-lane boundary. We set the two LMPs as the estimates of the lane directions $\hat{\theta}_1$ and $\hat{\theta}_2$.

4.2 Scatter diagram

We constructed two sets, Γ_l and Γ_r, by collecting edge pixels of $\hat{\theta}_1$ and $\hat{\theta}_2$, as follows: $\Gamma_l = \{(x,y) | \alpha(x,y) = \hat{\theta}_1\}$ and $\Gamma_r = \{(x,y) | \alpha(x,y) = \hat{\theta}_2\}$, where $\alpha(x,y)$ is the edge direction. Each set forms a scatter diagram. We applied a line fitting to these sets to obtain the lane-related information.

4.3 Lane-related information

To extract the lane-related information from the sets Γ_l and Γ_r, we considered the least squares-based line fitting (LSBLF) and the principal axis-based line fitting (PABLF). As experimentally proved by Lee and Kweon [2], the PABLF is less affected by locally grouped pixels than the LSBLF is. Thus, we applied the PABLF to extract the lane-related information consisting of locations and orientations.

First, by using the (p+q)th-order moments [7], we computed the center of the mass of each set by the following calculation: $\bar{x} = m_{10}/m_{00}$, $\bar{y} = m_{01}/m_{00}$ where m_{pq} is the (p+q)th-order moment. The center of mass for each scatter diagram represents the location of a lane. By using Eq. $(\bar{x},\bar{y})$, $(\bar{x}_l,\bar{y}_l)$ is obtained for set Γ_l, and $(\bar{x}_r,\bar{y}_r)$ is obtained for set Γ_r. Next, the principal axis ϕ is computed by the well-known equation:

$$\phi = \frac{1}{2}\tan^{-1}\frac{2u_{11}}{u_{20} - u_{02}},$$

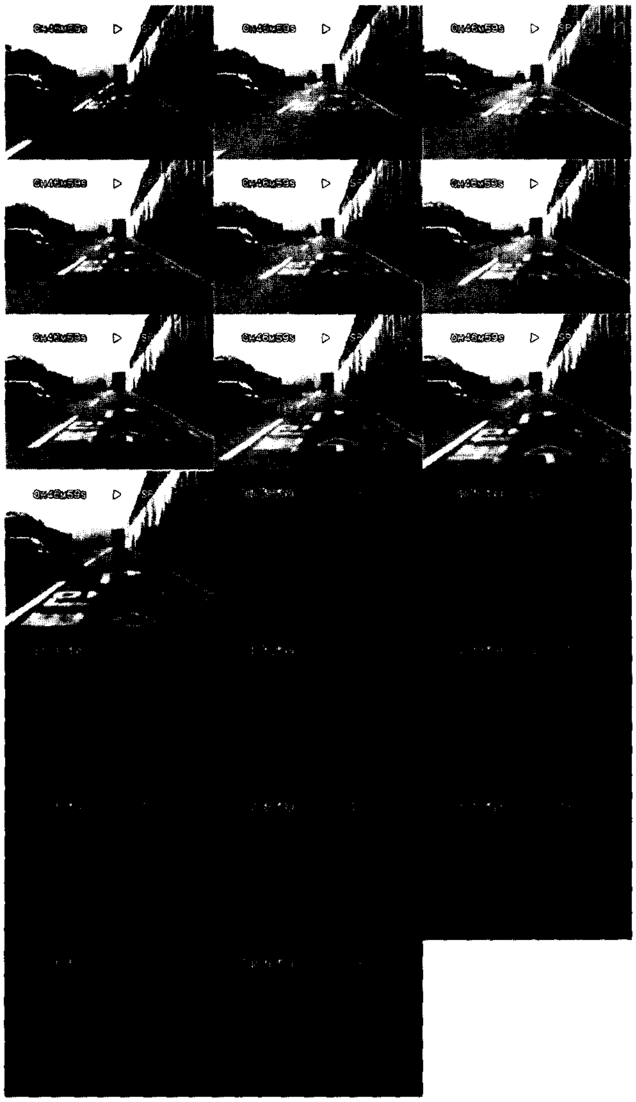
where u_{pq} is the (p+q)th-order central moment by $u_{pq} = \sum_x \sum_y (x-\bar{x})^p (y-\bar{y})^q$, in which $(\bar{x},\bar{y})$ is the center of mass. Principal axes ϕ_l for set Γ_l and ϕ_r for set Γ_r are obtained. A principal axis represents the orientation for the lane to be recognized.

5. Experimental Results

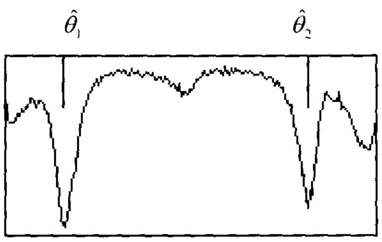
We have conducted on-road tests at highways and rural roads. A driver drove the test vehicle at the average velocity of 100 km/h during the test. In the evaluation, the size of the image was 320×240 pixels and a 3×3 Sobel operator [7] was used as the edge operator. Experimental results proved the algorithm to be robust with images of highways and suburban roads under a wide variety of conditions.

In the experiment, we dealt with the initial lane recognition problem. When the algorithm is performed to extract a lane, there is initially no information except for a video signal. So, we newly constructed an ACDF by Eq. (2). To obtain the initial lane-related information, the symmetric property of the ACDF centering around 90° was used.

The initial lane recognition process is presented in Fig. 5. First, the ACDF, shown in Fig. 5(b), was constructed by using ten successive image frames and their edges as shown in Fig. 5(a). That is, N in Eq. (2) is ten, which has been experimentally determined. Second, the SUIs of Eq. (5) were computed to be $\Re_l$ =1.1029 and $\Re_r$=1.2540, which satisfy the experimentally determined threshold of κ=2.0. The ACDF also satisfied the symmetric property centering around 90°. Third, for the new input image, shown in Fig. 5(c), we constructed the CDF by Eq. (1), as shown in Fig. 5(d). Then, the ACDF was estimated according to Eq. (4), as shown in Fig. 5(e). Fourth, the LMPs $\hat{\theta}_1$ and $\hat{\theta}_2$ were found according to the scheme in section 4.1, then a scatter diagram was onstructed as shown in Fig. 5(g). For the construction of the scatter diagram, to

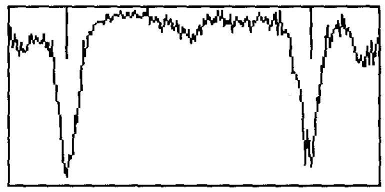


(a) Ten successive gray-level images and their edges



(b) The construction of the ACDF

(c) A new input image and its edges

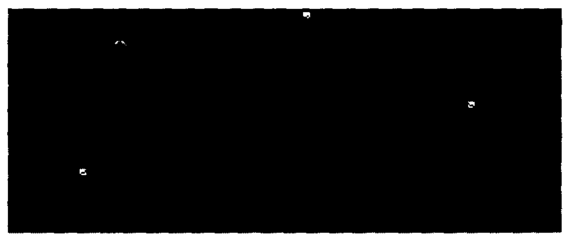


(d) The CDF for the new input image

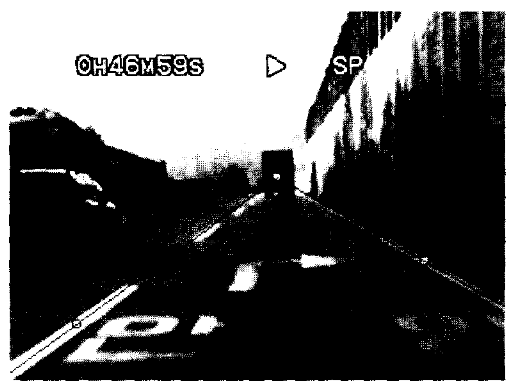
(e) An estimated ACDF

(f) An overlap of $\nabla f_k(x,y)$ and $\nabla f_{k-1}(x,y)$

(g) A scatter diagram



(h) A fitted line calculated following PABLF



(i) A fitted line on a raw image

Fig. 5 Initial lane recognition process increase the number of pixels in the diagram, we used the latest two successive images. The approach improved the results of the PABLF. Finally, we applied the PABLF to the scatter diagram and obtained the lane-related information. The fitted line was displayed on the edge and raw image, as shown in Figs. 5(h) and 5(i), respectively.

Further tests mainly dealt with the environmental contexts, which greatly affect the appearance of the road. The following experiment is an extension of the previous initial recognition problem. The subsequent procedure is almost the same as the initial procedure, except that there now exist lane-related information and an estimated ACDF. In this example, the appearance of the road varies due to heavy shadows, letters, broken lane marks and arrow marks. Fig. 6 shows that the proposed algorithm successfully recognized a lane under the adverse conditions.

Fig. 6 Lane recognition with heavy shadows, letters, and arrow marks on the road surface

Next, we provided test results for rural settings on undivided, two-lane asphalt roads. According to Pomerleau and Jochem [9], nearly 70% of roadway departure crashes occur on such roads. Therefore, such rural settings must be seriously examined. As shown in Fig. 7, noises in the images causes lane boundaries to become blurred and make the lane recognition difficult. However, the proposed algorithm led to favorable results. We conducted the test as done on highways without changing parameters.

The next two experiments were performed to show that the proposed algorithm could be applied on a rainy day (Fig. 8) and in nighttime (Fig. 9). The graphs in the rectangles of the figures respectively present the ACDF estimated from the previous frame (the upper graph) and

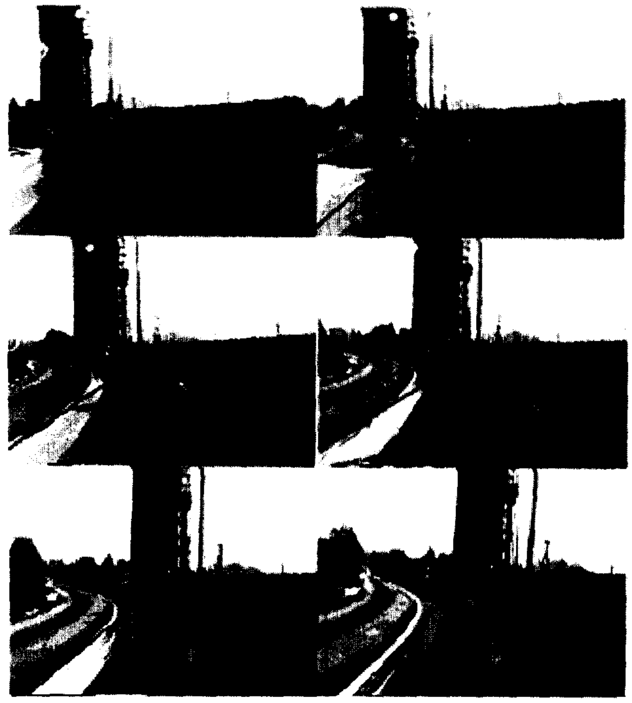


Fig. 7 Lane recognition in rural settings

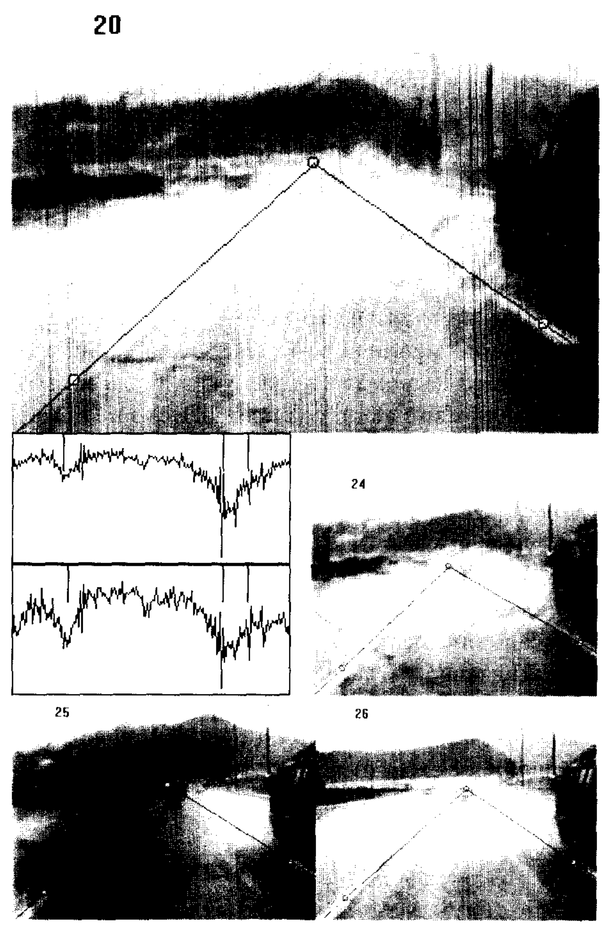


Fig. 8 Lane recognition on a rainy day

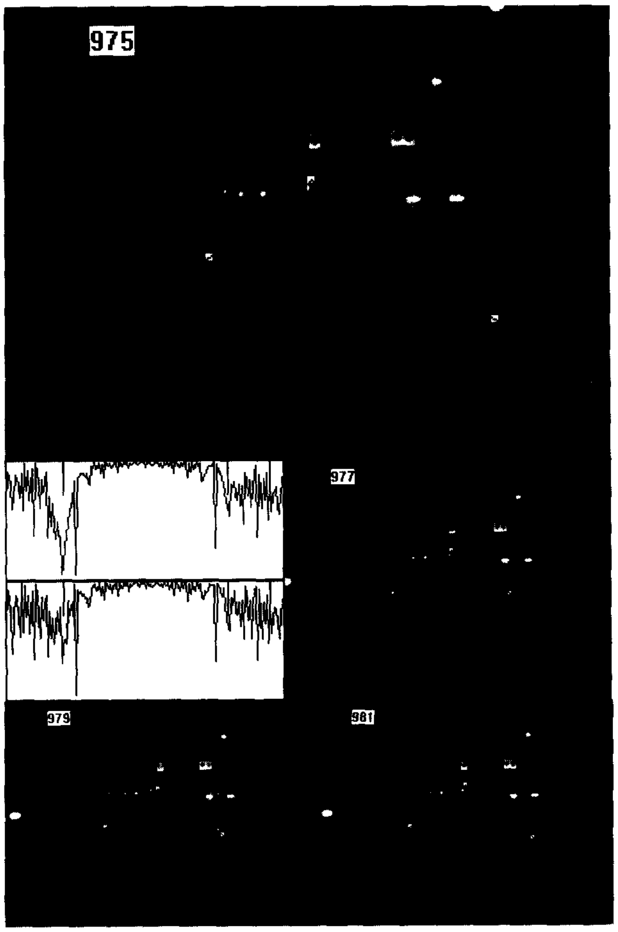


Fig. 9 Lane recognition in nighttime

the CDF constructed from the current frame (the lower graph). The CDFs provide clues whether or not the lane marks come into view on the image. If the lane marks are not very visible, the CDF has no distinct peak value. Even if the proposed algorithm performs successfully in a rainy day, compared to a clear day, there is a higher possibility of obtaining a false alarm or a miss-detection. On a rainy day, road lanes are often not satisfied the assumption that lane boundaries lie at the border between two regions with different intensity distributions.

In reviewing the CDFs for the nighttime experimental results, as shown in Fig. 9, it can be seen that the CDFs were rough and uneven due to weak illumination, which causes lane boundaries to become indistinct and reduces the visible range of lanes. However, because the weak illumination also prevents the disclosure of other sources of noise, the proposed algorithm provided reliable results in the nighttime experiment.

6. Conclusion

The main purpose of the proposed algorithm is to connect the edge-related information to the three assumptions of road lanes by means of the CDF. Because the three assumptions of road lanes are viewed to be perceptual constraints, the CDF is, in fact, considered to be a road model. In addition, the CDF eliminates noise-related effects in intensity images and edges. By estimating the CDF with the use of the moving sum, the shape of the CDF can be consistently maintained and the noise effects can be overcome in a short time. The newly introduced SUI provides a clue for understanding scene.

We successfully performed experiments under a wide variety of road conditions without changing parameter values or adding human intervention. In addition, the algorithm minimized the use of heuristic parameters, assumptions, and constraints. The most important goal in lane recognition by image processing is maintaining robustness. To realize this goal, we are now improving the scene-understanding function and the tracking performance of lane geometry between frames. The proposed algorithm was coded by MFC Visual C++ and evaluated on a Pentium PC (330MHz) and a frame grabber of Meteor-II with the speed of 10 frames per second.

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