Effective lane detection and tracking method using statistical modeling of color and lane edge-orientation

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***Abstract*— This paper proposes an effective lane detection and tracking method using statistical modeling of lane color and edge-orientation in the image sequence. At first, we will address some problem of classifying a pixel into two classes(lane or background) and detecting one exact lane. Generally, the probability of a pixel classification error conditioned on the distinctive feature vector can be decreased by selecting more distinctive features. A proposed pixel classifier model(Bayes decision rule for minimizing the probability of error) uses two distinctive features, lane color and edge-orientation, for classifying a lane pixel from background image. By estimating PDFs of each feature and continuously updating the estimated PDFs, we can effectively adapt the various road conditions and the different types of lane. The histogram of edge magnitudes with respect to edge-orientation will be used as the PDF for the lane edge orientation feature. Similarly, the color histogram of the HSV color model will be used as the PDF of the color feature. And, for the postprocessing, we will use the LMS algorithm in order to exclude misclassified pixels and decide one optimal lane position. Various comparative experimental results show that the proposed scheme is very effective in the lane detection and can be implemented in real-time.**

Keywords-lane detection; tracking; Bayes Rule; LMS fitting; edge orientation

I. INTRODUCTION & RELATED WORKS

Lane detection is one important process in the vision-based driver assistance system and can be used for vehicle navigation, lateral control, collision prevention, or lane departure warning system. Various road conditions make this problem become very challenging including different type of lanes (straight or curvilinear), occlusions caused by obstacles, shadows, lighting changes (like night time), and so on. Therefore, in the literature and recently, there have been many approaches [1]-[11] proposed for solving the above problems in lane detection. For example, in [1], He et al. proposed a color-based vision system to detect lanes from urban traffic scenes. Cheng et al. [2] used the color feature to detect lane lines and utilized the size, shape and motion for false lane region elimination. In [3], Yim and Oh combined three features including the starting position, intensity, and direction for lane detection. In addition to the feature-based scheme, the model-based scheme is more robust in lane detection when different lane types with occlusions or shadows are handled. Kang and Jung [4] proposed a searching framework to group edges with similar directions as a road lane. However, when complicated roads were handled, their method tended to detect false candidates of lane. In [7], Tsai et al. proposed lane detection using directional random walks based on Markov process in order to link components of lane. They showed that edge-feature can be tracked by position estimator for the lane detection. In [8], Lee and Lee et al. in [9], proposed EDF(Edge Distribution Function) to recognize the lane departure of vehicle. However, they still have some problem to detect exact lane under various environments, such as highly cluttered shadows obscuring lane marking, different weather conditions and noises caused by various obstacles.

This paper presents a novel approach to detect exact lane lines from various road in real-time. In Section II, some problem for lane detection will be discussed and we will show some simulation results. In Section III, lane detection and tracking method using statistical modeling is devised. Next, in Section IV, we will evaluate the proposed method. Finally, in Section V, we will conclude and discuss real applications.

II. PROBLEM STATEMENT

Many lane detection approaches[1, 2] use color model in order to segment the lane line from background images. However, the color feature is not sufficient to decide an exact lane line in images depicting the variety of road markings and conditions, as shown in Figure 1. If there are many lanes or obstacle which is similar to lane color, it will be difficult to decide an exact lane. Similarly, some lane detection method uses only edge information[4, 5]. Figure 1 shows some lane detection results using color or edge information. Figure 1(b) and (c) show the results of lane detection based on color and edge features, respectively.

Road-marking extraction is a key component to lane detection. Road and lane markings can vary greatly, making the generation of a single feature-extraction technique difficult. Color and edge-based techniques can work well with solid and segmented lines. However, even though misclassified pixels can be excluded using a proper postprocessing, the above features can often fail in situations such as those in Figure 1(b) and (c) which contain similar color or many extraneous lines.

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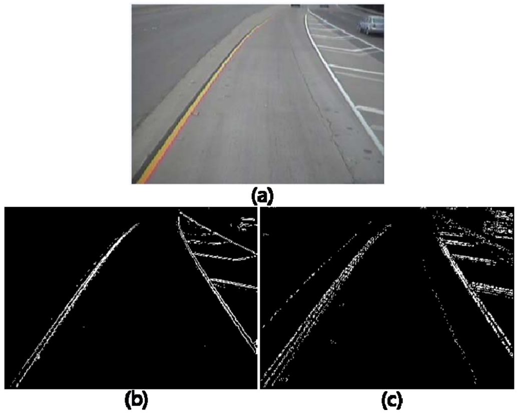

Figure 1. Example of lane detection based on each features. (a) Input image. (b) Lane segmentation using color feature. (c) Lane segmentation using edge feature.

Postprocessing is also one of the most important steps as it ties together the feature-extraction stage with the tracking stage by generating a robust estimate of actual lane detection based on the extracted features. One of the most common techniques used is the Hough transform[10, 11]. Figure 2 shows the final result of lane detection using Hough transform as a postprocessing. As shown in right-side region of Figure 2 (a), a couple of lanes are merged into a right lane. Even though outer lane is not our concern, Hough transform will determine other lane. To overcome these problems, we will use both of lane color and edge-orientation. And, we will continuously update the lane color and edge-orientation features. Additionally, we will use the LMS algorithm for postprocessing in order to generate a robust estimate of actual lane position.

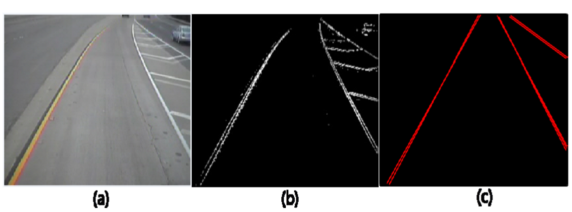

Figure 2. Example of lane detection using Hough transform under mergence of lanes environment. (a) Input image. (b) Lane segmentation using color feature. (c) Result image.

III. Proposed Lane Detection and Tracking Method Using Statistical Modeling

The overall procedure of proposed lane detection and tracking based on statistical modeling is shown in Figure 3. The overall procedure consists of four main processes: Initialization, Lane segmentation, Postprocessing and Adaptive parameter updating process.

In the initialization step, we will estimate the initial PDFs based on conventional color or edge-based lane segmentation method. After initialization, we segment lane pixels by the statistical Bayes decision rule in the lane segmentation process and exclude the misclassified lane pixels using the LMS algorithm for the postprocessing.

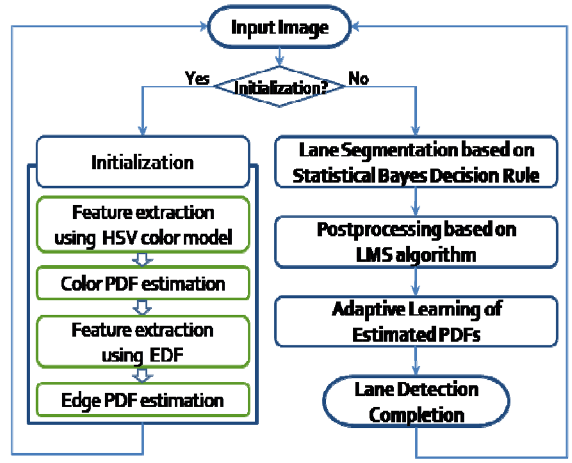

Figure 3. Overall procedure of proposed method.

Finally, each PDF of color and edge-orientation should be updated using the current detected lane pixels.

A. Lane segmentation based on statistical Bayes decision rule

A proposed lane segmentation method uses two distinctive features when there is an input image $f(x,y)$, $Z=[z_1\ z_2]^T$ for classifying lane pixels: lane HSV color feature z_1 and lane edge-orientation feature z_2, which can be defined as:

$$Z=\begin{bmatrix} z_1 \\ z_2 \end{bmatrix}=\begin{bmatrix} I^{HSV}(x,y) \\ \alpha(x,y) \end{bmatrix} \tag{1}$$

where, $I^{HSV}(x,y)$ means the HSV color model and $\alpha(x,y)$ denotes the orientation of edge pixels.

Color of Lane has higher saturation value (white, yellow, blue color) than saturation value of the road. Our HSV color model based on color feature is defined as followings:

$$I^{HSV}(x,y)=w_1H(x,y)+w_2S(x,y)+w_3V(x,y) \tag{2}$$

where w_1, w_2, w_3 are weighted values of each HSV channel. And, to extract edge-orientation feature, we use Sobel edge operator. Then edge of a pixel (x,y) in image $f(x,y)$ as followings:

$$\nabla f=[G_x, G_y]^T=\left[\frac{\partial f}{\partial x}\ \frac{\partial f}{\partial y}\right]^T \tag{3}$$

It can be represented by magnitude and edge-orientation.

$$\begin{aligned} \nabla f(x,y) &= [G_x{}^2, G_y{}^2]^{\frac{1}{2}} \approx |G_x|+|G_y| \\ \alpha(x,y) &= \tan^{-1}\left(\frac{G_y}{G_x}\right) \end{aligned} \tag{4}$$

We let ω denote the class of a pixel, with $\omega = \omega_1$ for the lane pixel and $\omega = \omega_2$ for the background pixel in the segmentation region. Because the state of a pixel is unpredictable, we consider ω to be a random variable.

Also assume that a *priori* probabilities, $P(\omega_1)$ and $P(\omega_2)$ are known. Let $p(Z \mid \omega_i)$ be the state-conditional probability density function for the feature vector Z given that the state of nature is ω_i. Therefore, there is a new binary image $B(x, y)$ by the Bayes decision rule for minimizing the probability of error:

$$\text{Decide} \quad B(x,y) = \begin{cases} 1\,(\text{lane pixel}), & \text{if } \; p(\omega_1 \mid Z) > p(\omega_2 \mid Z) \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

We can express the rule in terms of the conditional and a *priori* probabilities.

$$\text{Decide} \;\; B(x,y) = \begin{cases} 1(\text{lane pixel}), \; \text{if } \; p(Z \mid \omega_1)\cdot P(\omega_1) > p(Z \mid \omega_2)\cdot P(\omega_2) \\ 0, \quad \text{otherwise} \end{cases} \tag{6}$$

We consider the elements of the feature vector $Z = [z_1 \;\; z_2]^T$ to be continuous random variables. A random variable is described by its probability density function. If we assume that the feature variables are independent each other, we compute the conditional probabilities using the estimated probabilities as followings:

$$\begin{aligned} p(Z \mid \omega_1) &= p(z_1 \mid \omega_1)\cdot p(z_2 \mid \omega_1) \\ p(Z \mid \omega_2) &= p(z_1 \mid \omega_2)\cdot p(z_2 \mid \omega_2) \end{aligned} \tag{7}$$

The computation of a posteriori probabilities $p(\omega_i \mid Z)$ and a *priori* probabilities lie at the heart of Bayesian classification. The Bayes rule allows us to compute these probabilities from the a *priori* probabilities $P(\omega_i)$ and the state-conditional densities $p(Z \mid \omega_i)$. So, the *priori* probabilities and the state-conditional densities should be properly estimated.

B. Estimation of state-conditional densities for lane color and edge-orientation features

1) Color feature, z_1 : As shown in Figure 4(e), we confirmed that HSV color feature can be a feature candidate which expresses lane to decide exact lane in general roads. To estimate the PDF of color feature, we can use histogram information. Let $H_{color}(z_1)$ denotes the color histogram of lane pixels as followings:

$$p(z_1 \mid \omega_1) \cong \frac{H_{color}(z_1)}{\Sigma_{z_1} H_{color}(z_1)} \tag{8}$$

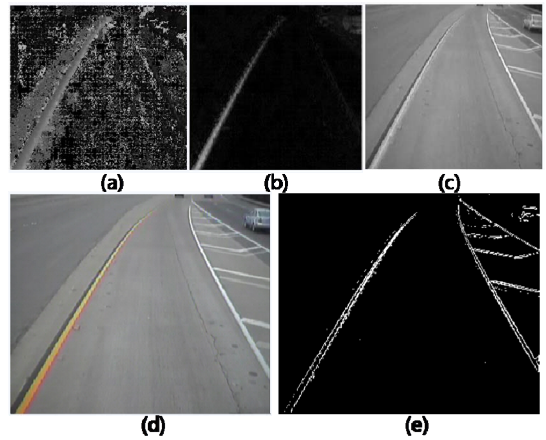

Figure 4. Example of lane detection based on HSV color model. (a) H in HSV. (b) S in HSV. (c) V in HSV. (d) Input image. (e) Segmentation result image.

$p(z_1 \mid \omega_1)$ is normalized to the probability interval [0, 1]. This one provides good estimates of the probability density function of color feature z_1. The PDF of $p(z_1 \mid \omega_2)$ can be approximated as followings:

$$p(z_1 \mid \omega_2) \cong 1 - p(z_1 \mid \omega_1) \tag{9}$$

2) Lane edge-orientation feature, z_2 : Assume that camera is mounted on the center of vehicle, then each lane of left and right side will be distributed with constant edge-orientation. In general straight roads, the shape of EDF theoretically will have the maximum value at each side(left and right)based on an axis of symmetry as shown in Figure 5. The maximum value of the left and right lane should be in the range of $0^o \le \alpha(x,y) \le 90^o$ and, $90^o \le \alpha(x,y) \le 180^o$ respectively.

The edge-orientation is a feature which distinguishes lane edges from other background edges.

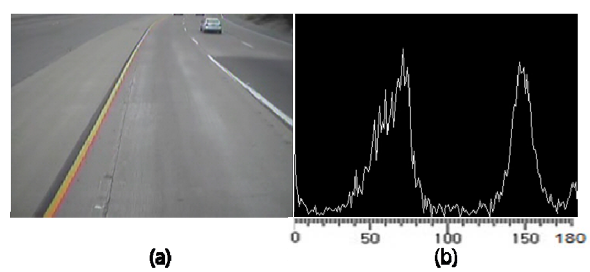

Figure 5. Example of EDF. (a) Input image. (b) Histogram of EDF.

As mentioned Eq. (3) and (4), we can define 1-dimenstion edge-orientation distribution function(0° ~180°, EDF). Figure 5 shows an example of EDF for an input image.

Let $H_{edge}(z_2)$ denotes the edge-orientation histogram of lane pixels.

$$p(z_2 \mid \omega_1) = \frac{H_{edge}(z_2)}{\Sigma_{z_2} H_{edge}(z_2)} \tag{10}$$

Then, $p(z_2 \mid \omega_1)$ is normalized to the probability interval[0, 1]. This one also provides a good estimate of the probability density function of edge-orientation feature z_2. Similarly, the PDF of $p(z_2 \mid \omega_2)$ can be approximated as followings:

$$p(z_2 \mid \omega_2) \cong 1 - p(z_2 \mid \omega_1) \tag{11}$$

C. Postprocessing

In vision-based lane detection, postprocessing is positively necessary to improve estimates based on a priori knowledge of the road and extracted features for estimation of lane position, generally it is determined by Hough transform[10, 11]. In cases of real-time application it may be critical problem caused by time-complexity of Hough transform($O(\Theta N)$), where Θ is a range of edge-orientation and N is an amount of target.

It is necessary to exclude misclassified pixels for improving designed classifier and it will provide better results than before.

Proper lane model can greatly increase the overall lane detection performance by helping to eliminate false positives via outlier removal. A variety of different lane models have been used. In this paper, we will use a set of linear lane model as shown in Figure 6.

If we assume that lane consists of a set of straight lines, we can easily approximate each line using the LMS algorithm in order to find out the linear coefficients, a and b in the following Eq. (12).

$$\begin{aligned} y_{l\,i} &= \hat{f}_{l\,i}(x) = a_{l\,i}x + b_{l\,i}, \quad l = left, \quad i = 1,2,3 \\ y_{r\,i} &= \hat{f}_{r\,i}(x) = a_{r\,i}x + b_{r\,i}, \quad r = right \end{aligned} \tag{12}$$

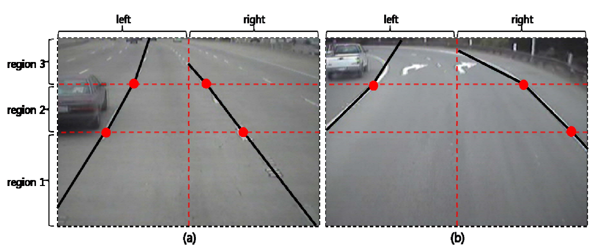

Figure 6. The concept of lane position decision based on a set of linear lane model in sub-regions.

Figure 6 shows the concept of optimal lane position decision based on a set of linear lane model. In Figure 6, the LMS algorithm estimates each optimal lane at right and left side(in time-complexity $O(N)$) of each region.

Also, the line coefficients will be calculated in recursively using the LMS algorithm in order to exclude misclassified pixels. Figure 7 shows the concept of excluding misclassified pixels based on the LMS algorithm.

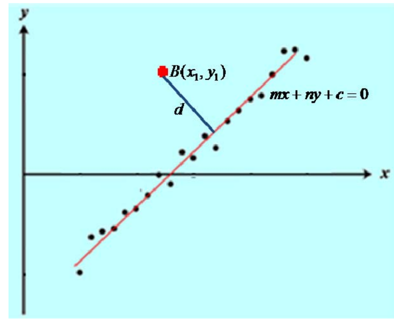

Figure 7. Example of the LMS algorithm for postprocessing.

Based on the point-line distance such as Eq. (13), the detected lane error pixels can be excluded from the exact ones as followings:

$$d = \frac{|mx_i + ny_i + c|}{\sqrt{m^2 + n^2}}, \quad i = 1 \cdots N \tag{13}$$

$$\begin{aligned} &\text{If} \quad |d - \mu_{dis}| > \sigma_{dis}, \quad \text{exclude the lane pixel } B(x_i, y_i) \\ &\qquad\qquad\qquad\qquad \text{from the set of lane pixel.} \end{aligned} \tag{14}$$

where, μ_{dis} is the mean value, σ_{dis} is the standard deviation value of the point-line distance.

D. Adaptive learning of estimated PDF

It should be noted that PDFs of each feature have to be updated, because we utilize the sampled histograms on frame-by-frame basis to obtain learned estimates of the probability density function for lane and background pixels. Having frame-by-frame estimates of lane and background density functions, a linear estimator is used to establish learned estimates of the density function.

We let $p_{k|k}(z_i \mid \omega_j)$ denote the learned density estimates of the density functions for the k th using the sampled density functions $p_k(z_i \mid \omega_j)$ up to $_m$ th frame, our linear estimator as followings:

$$p_{k|k}(z_i \mid \omega_j) = \mu \cdot p_{k|k-1}(z_i \mid \omega_j) + (1-\mu) \cdot p_k(z_i \mid \omega_j) \tag{15}$$

where, $i = 1,2$ and $j = 1,2$. The weighting factor μ is a learning rate associated with the environmental change.

We presented an experimental results(Figure 8) of how each PDF is updated over frame.

IV. EXPERIMENTAL RESULTS

A number of examples were evaluated with real image sequences and have been used for determining the efficiency of the proposed method. Among them, we experimented the video clips(320x240) from IEEE Trans. ITS(http://path.berkeley.edu/~zuwhan/lanedetection). The average processing frame rate is about 21~25 fps under a PC with Intel Core2 CPU of 2.4GHz with 512M memory.

At first, we initialize each PDF using a detected lane frame based on HSV color model and EDF function. Figure 8 shows the estimated PDFs at each frame.

Figure 9 shows the results of lane detection under various lane type and environments. Considering the experimental results of 5th frame, there are many lane-like pixels in the input image. But, our method can segment only the exact lane.

In Figure 9(c) and (d), the vehicle are changing current lane from left to right. Even though movement of vehicle may cause false detection, our method continuously detects exact lane. In normal road-environment(Figure 9(e)), lane color model may detect all lane of the road, but our method can deal with this environment by detecting the exact lane.

As shown in the experimental results, the proposed method works well irrespective of various lane conditions.

V. CONCLUSION & DISCUSSION

An adaptive lane-detection method using statistical modeling of lane color and edge-orientation is proposed at the consecutive images. The proposed lane classifier based on estimated PDFs is adaptive to various environments with low computational complexity for the real-time application. Only using the color feature model or the edge feature model, we can't detect exact lane from the complex background image. However as shown in the experimental results, the proposed method(lane color and edge - orientation) is useful to exclude other lane-like pixels. Also, we proposed the LMS algorithm for postprocessing based on a set of linear lane model and it finds an optimal position of lane in real-time.

The proposed method has low computational complexity for real-time applications compared with other complex feature-based methods. The proposed learning method must be tightly controlled if the algorithm is to be useful in the practical system. The results of the lane classification are used to develop the color and edge-orientation histograms. These histograms are then used to define the lane classification; hence, this algorithm is circular, i.e., the decision depends on itself. Generally, it is known that the buildup of error in a circular algorithm must be tightly controlled if the algorithm is to be useful in the practical car system

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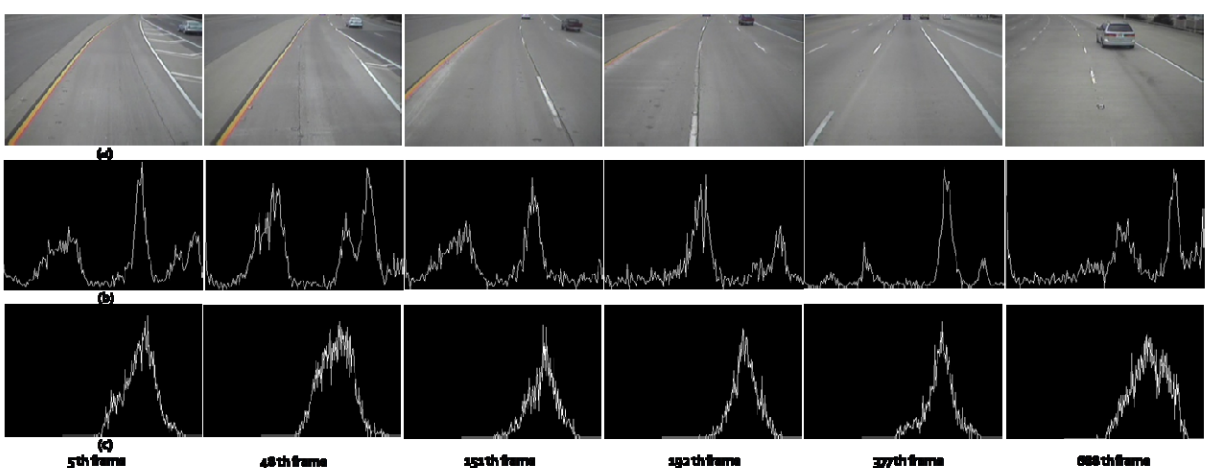

Figure 8. An example of how histograms are updated over frame. (a) Input image. (b) Histogram of edge-orientation feature. (c) Histogram of color feature.

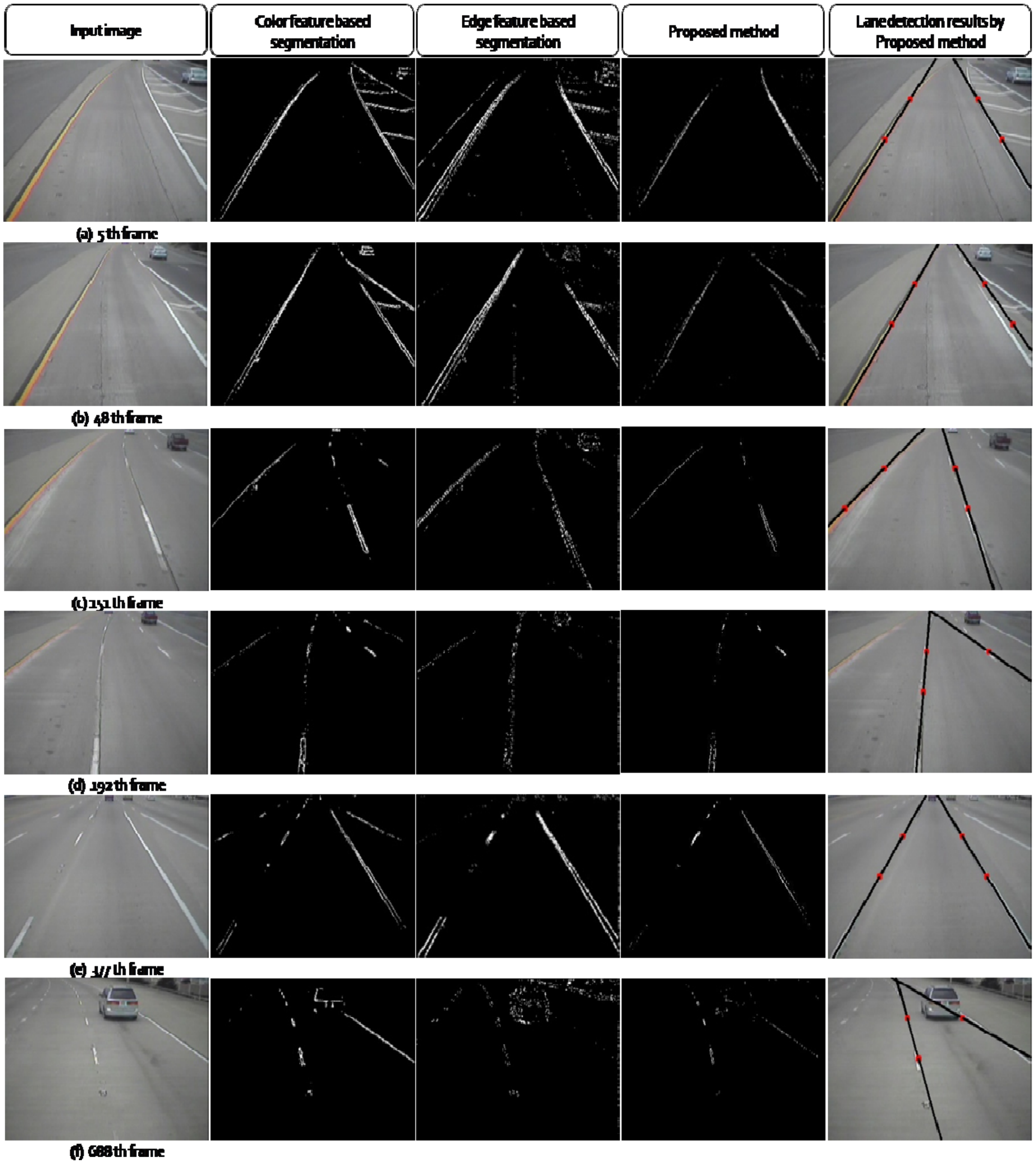

Figure 9. Experimental results.