Lane Change Detection and its Application to Suspicious Driving Behavior Analysis

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Abstract

This paper presents a novel edge labeling scheme for detecting lanes from videos in real time. Firstly, pairs of edge pixels with different edge types are grouped using the labeling technique. Then, different lane hypotheses can be generated for lane modeling. Then, a lane geometrical constraint is derived from the pinhole camera geometry for filtering out impossible lane hypotheses. Since the constraint is invariant to shadows and lighting changes, each desired lane can be robustly detected even though different occlusions and shadows are included in the analyzed scenes. After filtering, a kernel-based modeling technique is then proposed for modeling different lane properties. With the modeling, different lanes can be effectively detected and tracked even though they are fragmented into pieces of segments or occluded by shadows. The proposed scheme works very well to analyze lane conditions with night vision. With the lane information, different dangerous driving behaviors like lane departure can be directly analyzed from road scenes. Experimental results show that the proposed scheme is powerful in lane detection. The average accuracy rate of vehicle detection is 95%.

1. Introduction

Lane detection [1] is one important component in the vision-based driver assistance system and can be used for vehicle navigation, lateral control, collision prevention, or lane departure warning. There are three major problems in lane detection; that is, (1) lighting, especially in night time; (2) shadows, producing unusual patterns on the road surface; and (3) object occlusions, reducing the visibility of lane. Therefore, in the literature, there are many approaches [1]-[10] proposed for tackling the above problems in lane detection. Usually, a lane has a special color and high contrast (or high edge responses) to the background for attracting the driver's attentions. Thus, the features used in lane detection can be color, edge, texture, or hybrid of them. For example, Crisman and Thorpe [2] proposed a SCARF(Supervised Classification Applied to Road Following) system which used adaptive color classification and a voting technique for lane localization. In [3], He *et al*. proposed a color-based vision system to detect lanes from urban traffic scenes. However, color is easily influenced by light changes and becomes especially unclear at night. Thus, there are more edge-based approaches proposed for lane detection. For example, in [4], Broggi and Berte proposed a real-time vision-based system to detect well-painted lanes according to their edge features. In [6], Kreucher and Lakshmanan proposed a LANA to extract different edge features for lane detection from frequency domain. In addition to edge, texture is also another important feature for lane detection in unstructured images. In [7], Rasmussen used a set of multi-scale Gabor wavelets filters to detect road directions from an ill-structure image. In [9], Jeong and Nedevschi combined edge and texture features to form a classifier for segmenting lane regions from the background. Usually, multiple features will perform better than single one. Thus, in [1], McCall and Trivedi incorporated lane markings, lane texture, and vehicle state information to generate robust estimates of lane curvature.

In addition to the feature-based scheme, the model-based scheme performs more robustly in lane detection when different lane patterns, occlusions or shadows are handled. For example, Kluge *et al*.[10], proposed a deformable template to model and detect different lane types (including straight line or curve). Furthermore, in [5], Wang *et al*. used *B*-snake to model curve and straight lanes from their edge features so that poorly-painted lanes were extracted from videos. In [11], Tsai proposed a fuzzy inference system to model lane properties for overcoming the existence of shadow. To more robustly detect lanes, many advantages can be benefited from 3D data or stereo vision. In [12], Bertozzi and Broggi proposed a GOLD system which uses an inverse perspective mapping to removing perspective effects and then detect lane markings and obstacles using stereo vision. In addition, in [13], Nedevschi *et al.* proposed a 3D lane detection method for lane detection, pitch angle analysis, and roll angle estimation from videos. Although 3D information can significantly reduce the perspective effects for lane and obstacle detections, the inherent correspondence problem makes it unfeasible for real-time applications.

This paper presents a novel edge labeling scheme to detect lanes from videos in real time. Even though the analyzed videos contain various occlusions, shadows, or lane patterns, the proposed method still performs very well to detect each desired lane. Fig. 1 shows the flowchart of our system. First of all, different edge points are extracted using Gaussian differential operators. Then, an edge labeling technique is proposed for finding all pairs of edge points as lane candidates. After that, a lane geometrical constraint is derived for filtering out impossible lane candidates. Due to the filtering, only few lane hypotheses should be generated and verified. With the set of lane hypotheses, a kernel-based modeling scheme is then proposed for finding all missed lane segments. Based on this lane model, different lanes can be detected and tracked even though the analyzed road scene includes different shadows, occlusions, and light changes. Experimental results have proved the superiority of the proposed method in lane detection.

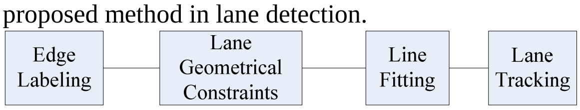


Fig. 1 Flow-Chart of the proposed system

2. Lane Candidate Extraction Using Edge Labeling

To detect lanes from the front view of a moving vehicle, the most challenging task to be overcome is lighting change. In the past, most approaches use color features to detect lane lines from videos. However, color will change under different lighting conditions. Compared with color, edge is a most stable feature for lane detection. Thereby, an edge labeling technique is proposed for detecting lanes more robustly.

2.1 Edge Labeling

Let $I(x, y)$ denote the input image. This paper uses the Gaussian derivative filter $G_x(x, y, \sigma)$ for extracting vertical edge points from the convolution of $I(x, y)$ with $G_x(x, y, \sigma)$ by the form $I_x(x, y, \sigma) = G_x(x, y, \sigma)$ $*$ $I(x, y)$, where $*$ is the convolution operation. Then, given a point *p(x,y)* in I, it is classified as "positive" or "negative" according to the following rule:

$$map(p) = \begin{cases} +, \text{ if } & I_x(p) > T_{edge}; \\ -, \text{ if } & I_x(p) < -T_{edge}; \\ 0, & \text{otherwise.} \end{cases} \qquad (1)$$

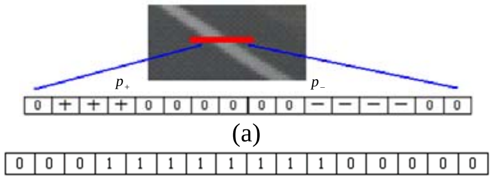
After edge labeling, we can horizontally scan each pixel in *I* line by line to find any pair of pixels p_+ and p_- which satisfy the following rules:

(a). p_+ is at the left side of p_-;

(b). p_+ is "positive" and p_- is "negative;

(c). Only "0" pixels appear between p_+ and p_-.

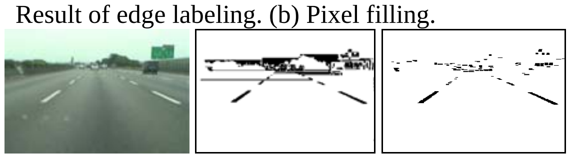
Fig. 2 shows the result of edge labeling. In (a), after edge labeling, two critical points p_+ and p_- can be detected. Then, after resetting, a line segment of lane can be obtained like Fig. 2(b). After scanning the input image *I* line by line, different lane segments can be then obtained through a connected component analysis. Like Fig. 3, (a) is the original image and (b) is the result after edge labeling and a connected component analysis. However, there are many noisy lane regions also to be extracted. In what follows, a width constraint will be derived for filtering out impossible lane candidates.



(a)

(b)

Fig. 2 Example of edge labeling and filling. (a) Result of edge labeling. (b) Pixel filling.



(a) (b) (c)

Fig. 3 Result of edge labeling and filtering. (a) Original image. (b) Result of edge labeling. (c) Result after filtering using a width constraint.

2.2 Width Constraint

This section will use a camera model to estimate the width changes of a lane when it is observed along the *y* coordinate. Then, different lane segments can be more accurately verified from videos for lance detection.

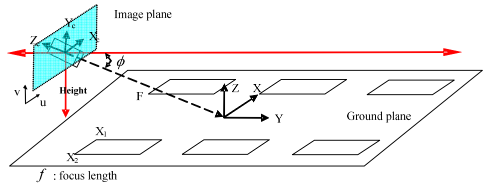


Fig. 4. The perspective geometries between the camera and road.

Let (X_c, Y_c, Z_c) denote the camera's coordinate system and (*X*, *Y*, *Z*) the ground plane coordinate system. Given a focal length *f*, the perspective projection of points in the pinhole camera's coordinate (X_c, Y_c, Z_c) onto the image coordinate (*u*, *v*) can be described by the following two equations:

$$u = -f\frac{X_c}{Z_c} \text{ and } v = -f\frac{Y_c}{Z_c}. \qquad (1)$$

Assume that the camera is placed at the height h above the ground plate with the tilt-down angle ϕ. Like Fig. 4, the relations between (X_c, Y_c, Z_c) and (X, Y, Z) can be described by the following equations:

$$X_c = X \quad , \quad Y_c = Y\sin\phi + Z\cos\phi \quad , \quad \text{and} \quad Z_c = -Y\cos\phi + Z\sin\phi - h\csc(\phi)\,. \tag{2}$$

Plugging Eq.(2) into Eq.(1) and using the fact that the ground plane Z is 0, we get

$$u = \frac{fX}{Y\cos\phi + h\csc(\phi)} \text{ and } v = \frac{fY\sin\phi}{Y\cos\phi + h\csc(\phi)}\,. \tag{3}$$

Let W be the width of this lane on the ground plane. Then, the lane width w on the image plane is the form:

$$w = \frac{fW}{Y\cos\phi + h\csc(\phi)}\,. \tag{4}$$

The Y value in Eq.(4) can be solved from Eq.(3):

$$Y = \frac{-h\csc(\phi)v}{v\cos\phi - f\sin\phi}\,. \tag{5}$$

The lane width w will change along the v coordinate. Plugging Y into Eq.(4), the relation between w and v can be then obtained as follows:

$$w = \frac{W}{h}(f\sin\phi - v\cos\phi)\,. \tag{6}$$

Then, according to Eq.(6), a width constraint can be formed for filtering out impossible lane candidates.

2.3 Lane Candidate Extraction

After edge labeling, different lane regions can be formed. Like Fig. 3, (c) is the result of edge labeling and filtering with the width constraint from (a). Each lane region will be a possible lane. Thus, a connected component analysis is first applied to the result of edge labeling for obtaining different lane candidates. Let l_i denote the remained lane region which includes different lane segments $s_{i,k}$. Each segment $s_{i,k}$ is a horizontal line with the central point $cp_{i,k}$. The set of central points $cp_{i,k}$ will form a line l_i.

Assume l_i has N central points $(x_{i,k}, y_{i,k})$ and will be fitted to a straight-line model: $y = m_i x + b_i$. Then, the parameters m_i and b_i can be obtained by minimizing the error function:

$$E(b_i, m_i) = \sum_{k=1}^{N}(y_{i,k} - b_i - m_i x_{i,k})^2\,. \tag{7}$$

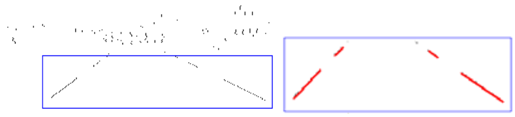
After line fitting, a re-projection technique will be used for finding all isolated points which locate in l_i. Given a point p, the distance between p and l_i can be defined as follows:

$$d(p, l_i) = \frac{|y_p - m_i x_p - b_i|}{\sqrt{1 + m_i^2}}\,. \tag{8}$$

For each point in l_i, if it does not satisfy the following condition:

$$d(p, l_i) < 5\,, \tag{9}$$

it will be filter out. Fig. 5 shows the result of line fitting and re-projection.



(a) (b)

Fig. 5 Result after line fitting.

3. Lane Detection Using Edges and Colors

In addition to edge, color is another feature for lane detection. Therefore, this section uses a kernel-based method for modeling different lanes.

3.1 Lane Modeling

When a vehicle moves along a lane, the pixels on this lane will have similar colors. For the ith lane l_i, we use (μ_R, μ_G, μ_B) and (ρ_R, ρ_G, ρ_B) to denote the color means and variances of all pixels in l_i in the (R, G, B) channels, respectively. In addition, ρ_d is used to denote the variance of distances $d(p, l_i)$ (see Eq.(9)) for all pixels p in l_i. Then, the Gaussian model to model the lane l_i is defined by:

$$G_{l_i}(p) = \exp\left(-\frac{(R_p - \mu_R)^2}{\rho_R^2} - \frac{(G_p - \mu_G)^2}{\rho_G^2} - \frac{(B_p - \mu_B)^2}{\rho_B^2}\right)\exp\left(-\frac{d^2(p, l_i)}{\rho_d^2}\right).$$

Then, we can judge whether a point p locates on this lane if

$$G_{l_i}(p) < 0.75\,. \tag{10}$$

3.2 Lane Tracking

In practice, a lane will not always be clear and keep continuous on each video frame. To tackle the above problem, a lane tracking technique should be proposed for robustly detecting lane positions. The tracking technique takes advantages of Eq.(10) to find out all the missed lane points. When a lane disappears on the current frame I_t, we will search each pixel p in I_t whether it satisfies Eq.(10). If the answer is yes, p will be collected to be a lane candidate appearing in l_i. After the scanning, even though l_i is missed in the current frame, it still will be well recovered.

3.3 Lane Change Detection

When the driver drives his car across the lane line, the lane poison will change along the horizontal direction. The case "lane change" can be considered as an unusual event. This unusual event can be easily detected if the lane moves across the center of bottom line of the observed frame.

4. Experimental Results

Fig. 6 Detection result of lanes with different types.

Fig. 7 Detection result of lanes with different colors.

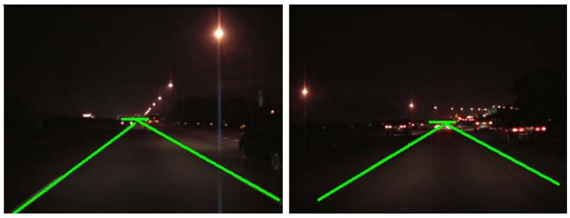


Fig. 8 Results of lane detection at night time.

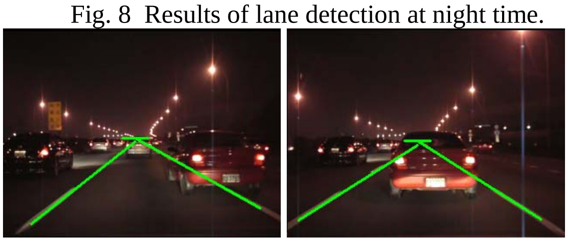


Fig. 9 Results of lane detection when cars moved on the road.

Fig. 10 Lane departure detection.

To examine the performance of our proposed to detect lane lines, different videos captured under different lighting conditions, weathers, day or night time were collected for the test. Fig. 6 shows the results of lane detection when lanes had different types. Fig. 7 shows the results when lanes had different colors. Our proposed method also performs well to detect lanes at night time. Fig. 8 shows the results of lane detection at night time. Fig. 9 shows the results of lane detection when cars moved on the road. However, our method still worked well to detect all desired lanes. Fig. 10 shows the result of lane departure detection. When this unusual event happened, a warning message was sent to the driver. The average accuracy of our method is 95%.

5. References

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