Parallel-Snake with Balloon Force for Lane Detection

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SUMMARY  Lane detection plays an important role in Driver Assistance Systems and Autonomous Vehicle System. In this paper, we propose a parallel-snake model combined with balloon force for lane detection. Parallel-snake is defined as two open active contours with parallel constrain. The lane boundaries on the left and right sides are assumed as parallel curves, parallel-snake is deformed to estimate these two boundaries. As lane regions between left and right boundaries usually have low gradient, snake will lose external force on these regions. Furthermore, inspired by balloon active contour model, the balloon force is introduced into parallel-snake to expand two parallel curves from center of road to the left and right lane boundaries. Different from closed active contour, stretching force is adopted to prevent the head and tail of snake from converging together. The experimental results on three different datasets show that parallel-snake model can work well on images with shadows and handle the lane with broken boundaries as the parallel property.

key words: lane detection, parallel-snake, planar homography

1. Introduction

Lane detection is a process to estimate lane region in road scene images. The images can be depth maps from radars or other sensors. Vision-based lane detection uses computer vision technologies to locate lane regions in road images which are captured from a moving camera. According to [1], vision-based lane detection techniques can be classified into three categories: region-based methods employ image segmentation algorithms to locate the area of road, feature-driven approaches tend to organize edges into a meaningful shape and model-based approaches match a template defining some characteristics of lanes to the observed image.

In the last decade, various models have been proposed for lane description with different assumptions. Lane boundaries were modeled to be straight in [2]–[4], while researchers in [5] described lanes as piecewise lines to achieve better accuracy. Moreover, parabolas were used in [6], [7] and B-snake was proposed in [8], [9] with the best flexibility. Most of them described each sides of lane boundaries separately, but only [10], [11] took the parallel property of two boundaries into consideration. In [11], Marcos et al fitted features into parallel arcs with the same center as lane boundaries on the perspective rectified image while Qiang et al fitted them into parallel lines in [10]. Parallel-arc model cannot represent lane boundaries with large curves accurately, meanwhile parallel lines cannot handle lane boundaries with curves.

The B-snake model proposed in [8], [9] described lane boundaries as B-spline and snake was employed to estimate the parameters of B-spline. Compared with other models, B-snake model is robust to shadows as the external force for snake is based on the gradient of image instead of individual features. Even so, snakes will lose force on lane regions with small intensity variation, and it is common on structured road. This makes snake model hard to convergence to the lane boundaries. For B-snake initialization, wang et al used CHEVP algorithm to initialize B-spline, but CHEVP algorithm is sensitive to the line detection results on lane boundaries. The fault estimation of knots will produce totally different snake.

In this paper, we model lane boundaries as parallel parabolas to avoid the initialization of B-spline, although B-spline is the most flexible model. Considering the efficiency and accuracy of lane model, we only model lane boundaries in mid-section of captured image as parabola. Since the captured image cannot retain the parallel property of lane boundaries on left and right sides as perspective distortion, we transform perspective image into bird-view image to retrieve parallel property by using planar homography. Parallel-snake is deformed on bird-view image to estimate the parallel lane boundaries, and balloon force is introduced to expand the parallel snakes from center of road to the left and right boundaries to guarantee the snake will not lost force on regions with small gradient.

The rest of paper is organized as follows. Section 2 elaborates lane model using parallel parabolas and method to estimate parallel parabolas with least square. Section 3 present parallel-snake model for lane boundaries estimation combined with balloon force. Finally, experimental results and conclusions are given in Sect. 4 and Sect. 5, respectively.

2. Lane Model

Lane model is important for lane detection. The captured image from moving camera cannot retain the parallel property of lane boundaries as the perspective distortion. Therefore, perspective image as shown in Fig. 1 (a) is transformed into bird-view image as illuminated in Fig. 1 (b) to retrieve parallel property. Planar homography [12] is used to perform this transformation. In this paper, we assume lane boundaries on the left and right side are parallel, and the part of lane boundary in the mid-section is described as parabola, the selection of mid-section is determined by the pitch of camera.

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DOI: 10.1587/transinf.E97.D.349

Manuscript received June 5, 2013.
The lane model $L$ is denoted as $(L_{\text{mid}}, L_{\text{sid}})$, where $L_{\text{mid}}$ is the parabola of mid-curve, and $L_{\text{sid}}$ is the offset of the right and left boundaries to mid-curve, exhibited in Fig. 1 (b). The left and right boundaries are regarded as shift of the mid-curve $L_{\text{mid}}$. The parabolas for right and left lane boundary are expressed as:

$$y_{r} = ax_{m}^{2} + bx_{m} + c_{r}$$

and

$$y_{l} = ax_{m}^{2} + bx_{m} + c_{l}$$

where $(a,b,c_{l})$ and $(a,b,c_{r})$ are coefficients of parallel parabolas $y_{l}$ and $y_{r}$, respectively. $x_{m}$ is sampled at $x$ coordinate of mid-section with constant interval on bird-view image. Thus, lane model $L_{\text{mid}}, L_{\text{sid}}$ is defined as:

$$L_{\text{mid}} = ax_{m}^{2} + bx_{m} + \frac{c_{l} + c_{r}}{2}$$

and

$$L_{\text{sid}} = \frac{|c_{l} - c_{r}|}{2}$$

The parameters $(a,b,c_{l},c_{r})$ of lane model are estimated by solving (5) with least square method.

$$\begin{bmatrix} x_{m}^{2} & x_{m} & 1 & 0 \\ x_{m}^{2} & x_{m} & 0 & 1 \end{bmatrix} \begin{bmatrix} a \\ b \\ c_{l} \\ c_{r} \end{bmatrix} = \begin{bmatrix} y_{l} \\ y_{r} \end{bmatrix}$$  \hspace{1cm} (5)

### 3. Parallel snakes

Parallel-snake extends traditional snake into a pair of open snakes with parallel constraint. Energy function $E_{\text{snake}}$ of snake $v(s)$, $s \in [0,1]$, is defined as (6). The estimation of snake is to find snake $v'(s)$ which minimize $E_{\text{snake}}$.

$$E_{\text{snake}} = \int_{0}^{1} E_{\text{int}}(v(s)) ds + \int_{0}^{1} E_{\text{ext}}(v(s)) ds$$  \hspace{1cm} (6)

The internal energy force $E_{\text{int}}$ given in (7) defines constraints of snake by using first and second order derivatives of $v(s)$ with weight $\alpha(s)$ and $\beta(s)$. The first order derivative punishes stretching and prevents the curve from deforming excessively, while the second order derivative describes the curvature of snake, and penalizes bending.

$$E_{\text{int}} = \frac{1}{2} \left( \alpha(s) \| v'(s) \|^2 + \beta(s) \| v''(s) \|^2 \right)$$  \hspace{1cm} (7)

The external energy force $E_{\text{ext}}$ deforms snake by using information from image rather than snake itself. As the definition in (8), $E_{\text{ext}}$ composes of image energy function $E_{\text{img}}$ and stretching energy function $E_{\text{str}}$ for the head and tail of snake. $E_{\text{img}}$ is the Gaussian blurred intensity value of points which push snake to the center ridge of region. Meanwhile, different from traditionally closed snake model, $E_{\text{str}}$ function presented in [13] is adopted to prevent the head and tail of snake from getting together and thus, it produces an open curve. The gradient of $E_{\text{str}}$ is defined in (9), the magnitude of stretching force $F(v(s))$ is given in (10). Where $I(\cdot)$ is the intensity of image, $\bar{I}$ is the mean intensity of whole image, $I_{f}$ and $I_{b}$ represent the mean intensity of foreground and background according to the snake model.

$$E_{\text{ext}} = E_{\text{img}}(v(1)) + E_{\text{img}}(v(2)) + k_{\text{str}} \cdot E_{\text{str}}(v(s))$$  \hspace{1cm} (8)

$$\nabla E_{\text{str}} = \begin{cases} \frac{\partial \bar{I}}{\partial x} \cdot F(v(s)), & s = 0 \\ \frac{\partial \bar{I}}{\partial y} \cdot F(v(s)), & s = 1 \\ 0, & \text{otherwise} \end{cases}$$  \hspace{1cm} (9)

$$F(v(s)) = \frac{I(v(s)) - \bar{I}}{I_{f} - I_{b}}$$  \hspace{1cm} (10)

The balloon force for snake firstly presented in [14] is used to dilate a closed active contour. We use balloon force here to expand two parallel snakes from center of road to boundaries, as shown in Fig. 2 (a). As elaborated in [15], the minimization of energy function is obtained by using Euler-Lagrange equation. The solution of Euler-Lagrange equation is approximated by finite differences, which can be expressed as two equations formed as:

$$Ax + f_{x}(x,y) = 0$$  \hspace{1cm} (11)

$$Ay + f_{y}(x,y) = 0$$  \hspace{1cm} (12)
By removing cyclic boundary condition for open active contour, the penta-diagonal banded matrix $A$ is defined in (13).

$$A = \begin{bmatrix}
C_0 & C^*_+ & C^*_2 & 0 & \cdots & 0 & 0 & 0 & 0 \\
C^-_1 & C^*_0 & C^*_+ & 0 & \cdots & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & \cdots & C^-_2 & C^-_1 & C^*_0 & C^*_+ \\
0 & 0 & 0 & 0 & \cdots & C^*_2 & C^*_1 & C^*_0 & 0 \\
\end{bmatrix}$$

with

$$C^*_+ = C^*_2 + C^-_2$$
$$C^*_0 = C^*_1 + C^-_1$$
$$C^*_0 = C_0 + C^-_2$$
$$C^*_1 = C_1 + C^-_2$$
$$C^*_2 = C^*_2 + C^-_2$$

The $f_x(x,y)$ and $f_y(x,y)$ are formed as:

$$f_x(x,y) = \frac{\partial E_{ext}}{\partial x}$$

$$f_y(x,y) = \frac{\partial E_{ext}}{\partial y}$$

The expanding behavior using balloon force can be achieved by adding the normal vector to $f_x(x,y)$ and $f_y(x,y)$, which can be expressed as:

$$f_x(x,y) = k_{bal} \cdot \vec{n}(s) - \frac{\partial E_{ext}}{\partial x}$$

$$f_y(x,y) = k_{bal} \cdot \vec{n}(s) - \frac{\partial E_{ext}}{\partial y}$$

where $k_{bal}$ is a weighting factor used to control normal vector’s contribution to expansion.

The stretching force $E_{str}$, illustrated in Fig. 2 (b), pulls the head and tail of filament along first order derivative and its magnitude is determined by intensity difference between the foreground and background. The stretching force guarantees to produce a longest filament with similar intensity.

As illustrated in Fig. 3, balloon force expands parallel curves from inside to outside while the $E_{imag}$ guarantees the snake converge to a uniform area based on gradient of image. The combination of $E_{imag}$ and $E_{bal}$ will make a pair of parallel snakes dilate to outside until the gradient force equal to balloon force.

4. Results

The parallel-snake based lane detection algorithm has been implemented with Matlab and verified on Caltech, CMU and Run2a lane datasets. Some detection results from different datasets are given in Fig. 4. Structured roads with lane markings are shown in Fig. 4 (a) while unstructured roads without lane markings are given in Fig. 4 (b-g). Figure 4 (c) (d) (g) give some results on roads with heavy shadows. Furthermore, the parallel-snake can work well on images with lane boundaries inconspicuous shown in Fig. 4 (d) (g), and road with broken lane region given in Fig. 4 (f).

In [16], Mohamed et al located lane boundaries by employing a lane marking detector, and it achieved 96.34% correct rate on Caltech lane dataset which has more than 1000 structured road images captured from two different cities. Compared with [16], our proposed method gained 97.2% correct rate, meanwhile parallel-snake model can handle both the structured roads and unstructured roads as it based on the gradient of lane regions, but lane marking detector based methods can only process structured roads with lane markings.

B-snake based lane detection method proposed in [9] achieved 95% correct rate on Run2a dataset which consisted of just 56 road images with lane markings, our proposed method got 98% on this dataset. As parallel-snake and B-snake in [9] both are based on snake model, the comparison of these two methods indicated that the introduction of IPM gave the benefit of snake estimation, in the other words,
snake model can be deformed better in bird-view image than in perspective image.

Caltech and Run2a datasets are captured from structured roads with lane markings. In order to verify the performance of our proposed method on unstructured roads, we tested parallel-snake model on CMU dataset which consists of hundreds of country road images, as shown in Fig. 4 (b-g). The lane images in CMU dataset have different illumination varying and some lane images have broken lane boundaries which can verify the benefit of our parallel-snake model. We achieved 89% correct rate on this dataset, the error came from the fault estimation of vanishing points which led to error estimation of IPM. There is no more comparison with other works, because no standard dataset is defined and researchers usually verified on their own dataset, especially for the unstructured road datasets.

5. Conclusion

In this paper, a parallel-snake model with balloon force for lane detection is proposed. The experimental results show that parallel-snake model can handle both the structured and unstructured lanes, and it is robust to shadows and illumination changing and shadows. Even part of lane boundaries and lane regions are broken, parallel constrain can guarantee parallel-snake model giving correct results. There are two contributions in this paper. Firstly, parallel-snake model is proposed for lane detection. Secondly, balloon force is introduced into parallel-snake to expand parallel-snake from the center of road to the left and right boundaries.

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