Finding and Tracking Road Lanes using "Line-Snakes"

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Abstract : *This paper presents a method for finding and tracking road lanes. The method extracts and tracks lane boundaries for vision-guided vehicle navigation by combining the hough transform and the "active line model (ALM)".*

The hough transform can extract vanishing points of the road, which can be used as a good estimation of the vehicle heading. For the curved road, however, the estimation may be too crude to be used for navigation. Therefore, the hough transform is used to obtain an initial position estimation of the lane boundaries on the road. The line snake - ALM - then improves the initial approximation to an accurate configuration of the lane boundaries. Once the line snake is initialized in the first image, it tracks the road lanes using the external and internal forces computed from images and a proposed boundary refinement technique.

Specifically, an image region is divided into a few sub-regions along the vertical direction. The hough transform is then performed for each sub-region and candidate lines of road lanes in each sub-region are extracted. Among candidate lines, a most prominent line is found by the ALM that minimizes a defined snake energy. The external energy of ALM is a normalized sum of image gradients along the line. The internal deformation energy ensures the continuity of two neighboring lines by using the angle-difference between two adjacent lines and the distance between the two lines. A search method based on the dynamic programming reduces the computational cost. The proposed method gives a unified framework for detecting, refining and tracking the road lane. Experimental results using images of a real road scene are presented.

1. Introduction

Lane detection and tracking are two main tasks for vision-guided vehicle navigation. Lane markings extracted from input images are commonly used to calculate the vehicle heading on highway. Reliable detection of the markings depends on a local edge operator and a line extraction algorithm which converts edges into image lines corresponding to road lane.

There have been many classical lane extraction methods such as the hough transform or straight line approximation[1][2], curve detection based-on simulated annealing[3], and line acquisition from support regions using gradient directions[4][5]. But, classical line extraction methods suffer from noises such as cluttered edge or missing of middle lane, intermittent, shadows in extracting exact lane boundaries from noisy edges. Reviews for previous works for lane edges from noise edges are well denoted in [3].

For sequential tracking of road lane for car traveling, as another problem, previous techniques use prior knowledge of the road geometry and temporal constraints which make easy the tracking. Lane tracking is thus treated as an easier problem than lane detection. Many conventional methods concentrate on the development of reliable lane boundary detection techniques in noisy images. In this paper, we present a unified method for finding and tracking road lanes. The method extracts and tracks lane boundaries by combining the hough transform[9] and an active line model that is extended from the active contour model(snakes) [6][7][8]. A smaller threshold for the edge gradient produces many false edges as well as the true edges corresponding to lane boundaries. Therefore, extracted lines from the noisy edge elements include many noisy line fragments. Among the noisy line fragments, the probability of the detection of lane boundary is very high as long as a threshold for the edge gradient is kept low. This assumption forms a search problem in which a linked line chain, that well describes lane boundary, is searched among short line fragments. The proposed algorithm, based on this assumption, combines the local hough transform to find candidate lines in the local sub-regions on the given image and an active line model(ALM) to find an optimally linked line chain of the lines. Therefore, our method primarily allows the existence of noisy line candidates.

In addition, ALM is combined with a lane refinement technique which refines initial detected lines of ALM for exact lane boundaries. The same technique is used as a simple tracking method as well. ALM is thus a unified technique which performs lane detection, refinement, and tracking simultaneously.

Section 2 details the proposed ALM. Section 3 shows the method which uses snakes model and the hough transform for lane detecting and refining even in cases where there are incomplete lane markings and noisy edges. Section 4 denotes the tracking method in sequential frames. Section 5 describes conclusions.

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2. Active line model

The method for finding and tracking road lanes consists of the hough transform and the active line model(ALM). For curved or straight lane boundary, snake model combined with the hough transformation gives a unified framework for vehicle guidance. ALM is motivated from the active contour model(ACM)[4][5], originated by Kass, etc. ACM offers a solution to a variety of tasks in image analysis and machine vision. It's a minimum energy contour that depends on its shape and location within the image. ACM can move from current location to the local neighborhood location on the image plane. Position of ACM control points depends on both internal energy, which gives thin-plate constraints of the contour, and external energy which draws the contour curve to the image edge. ACM is very sensitive to image noise or cluttered background by the local property of the contour spline. When background edges having the object or image noise exists, the deviation from the object boundary position appears. The proposed active line model uses linked control-lines as another form of original snakes based on edge force of a single control point on the active contour.

The hough transform is performed for each sub-region and candidate lines of road lanes in each sub-region are extracted. Among candidate lines, a most prominent line is found by the ALM that minimizes the following energy :

$$E_{ALM} = E_{\text{int}} + E_{ext} \qquad (1)$$

$$\begin{aligned} E_{\text{int}} &= \alpha \cdot d(L_i^e, L_{i+1}^s) + \beta \cdot \theta(L_i, L_{i+1}) \\ &= \alpha \cdot (L_{i+1}^s - L_i^e)^2 + \beta \cdot \cos^{-1}\left(\frac{(L_i^e - L_i^s)\cdot(L_{i+1}^e - L_{i+1}^s)}{\left|L_i^e - L_i^s\right| \cdot \left|L_{i+1}^e - L_{i+1}^s\right|}\right) \end{aligned} \qquad (2)$$

$$E_{ext} = \gamma \cdot \sum_{i=s}^{i=e} \left|\nabla G(\sigma) * I(i)\right| \qquad (3)$$

where the superscripts, s and e, on L denote the starting and ending point of a line. The external energy of ALM is a normalized sum of image gradients along the line. The internal deformation energy ensures the continuity of two neighboring lines by using the angle-difference between two adjacent lines and the distance between the two lines(see Fig.1). Normalization of the internal energies is needed as well.

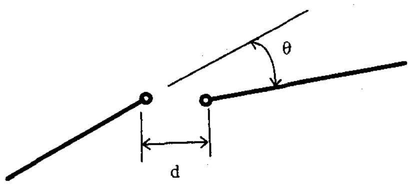


Fig. 1 Definition of internal energy; d is the distance between two neighboring lines and θ is the angle-difference

3. Lane detection

3.1 Initial Estimation by the local Hough transform.

The hough transform can extract vanishing points of the road, which can be used as a good estimation of the vehicle heading. For the curved road, however, the estimation may be too crude to be used for navigation as shown in Fig.2. Therefore, the hough transform is used to obtain an initial estimation of the lane boundaries on the road. The line snake then improves the initial approximation to an accurate configuration of the lane boundaries. Once the line snake is initialized in the first image, it tracks the road lanes using the external and internal forces computed from subsequent images.

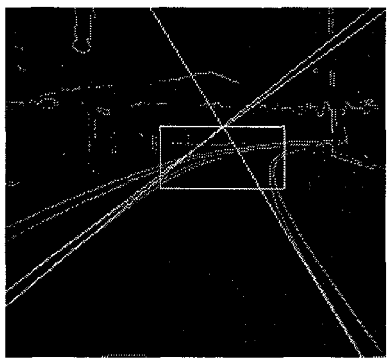
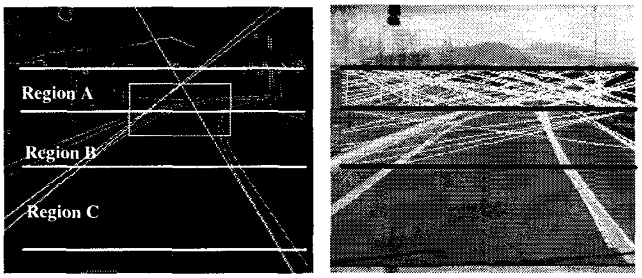


Fig.2 Two lines found by hough voting the whole image region.

First, an image region is divided into a few sub-regions in Fig.3(a), the number of sub-regions is three. The hough transform is then performed for each sub-region and candidate lines of road lane in each sub-region are extracted as shown in Fig.3(b).

For example, in Fig.3(a), the region height is gradually narrower as we move to the upper part of image. In region (C), which is near to the vehicle, the lane boundary is clear and can be detected with a high reliability. But, in region (A), which is far from the vehicle, extracted. It's then assumed that a linked line-chain from the 3 sub-line sets exists on the lane boundary.



(a) (b)

Fig.3 Region partition of road lane for local hough transforms; (a) 3 sub-regions;(b) line subsets obtained by local hough transform

We use the dynamic programming[7] to find a set of connected lines among the line candidates of the neighboring sub-regions.

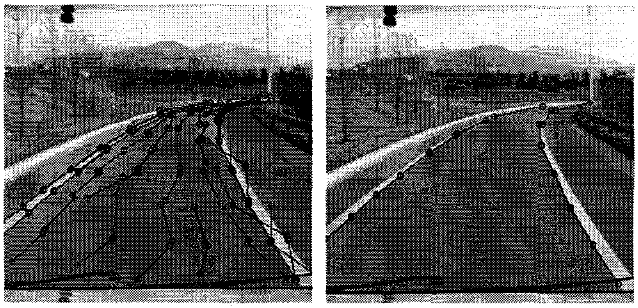
The problem of minimization for defined ALM function can be represented in the following form :

$$\begin{aligned} E(v_1, v_2, \ldots, v_n) \\ &= E_1(v_1, v_2) + E_2(v_2, v_3) + \ldots \\ &\quad + E_{n-1}(v_{n-1}, v_n) \end{aligned} \tag{4}$$

where each variable is allowed to only take on m possible values. One way to find the minimum of the above function is by exhaustive enumeration. A more efficient method is via discrete dynamic programming, with v_i corresponding to the state variable in the i th decision stage. For a function having the form of (4), with $n = 5$,

$$\begin{aligned} s_1(v_2) &= \min_{v_1} E_1(v_1, v_2) \\ s_2(v_3) &= \min_{v_2} s_1(v_2) + E_2(v_2, v_3) \\ s_3(v_4) &= \min_{v_3} s_2(v_3) + E_3(v_3, v_4) \\ \min_{v_1,\ldots,v_5} E(v_1,\ldots,v_5) &= \min_{v_4} s_3(v_4) + E_4(v_4, v_5) \cdot \end{aligned} \tag{5}$$

The total search number of exhaustive search is m^5. The time complexity for ALM is $O(5 \cdot m^2)$, where n is the number of ALM and m is the number of possible choices at each sub-region stage. In general, the time complexity for the ALM is $O(n \cdot m^2)$



(a) (b)

Fig.4 Simulation test for lane detection of ALM(7 linked line case); (a) multiple lines selected by an human operator using a mouse; (b) two line-chains denoting both lanes detected by dynamic programming.

To test the reliability of ALM, many lines are manually placed on arbitrary positions by user as shown in Fig.4(a). The number of sub-regions is seven and each region has ten candidate lines. When starting from the bottom row, we can obtain two linked-line-chains having minimum snakes energy as shown in Fig.4(b). It is apparently on the exact lane boundaries and have smoothly connected line form. In this experiment, the only assumption we use is that the distance between two neighboring lines must be smaller than 20 pixels.

As a real scene test, in Fig.5, multiple lines in a local sub-region are extracted by using a low threshold for edge gradient value. In the figure, we can see that a few line fragments among many multiple lines exactly overlap with the lane boundary.

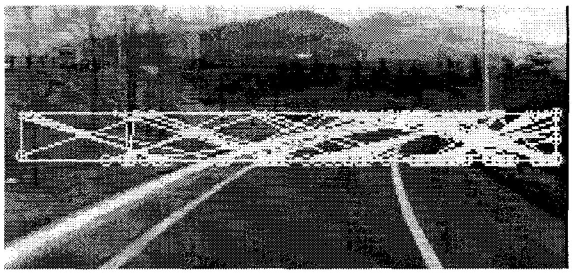
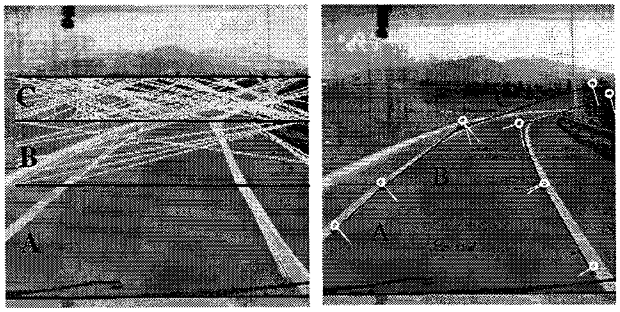


Fig.5 The local hough transform and detected multiple lines for a sub-region; denoted by a rectangle in white.

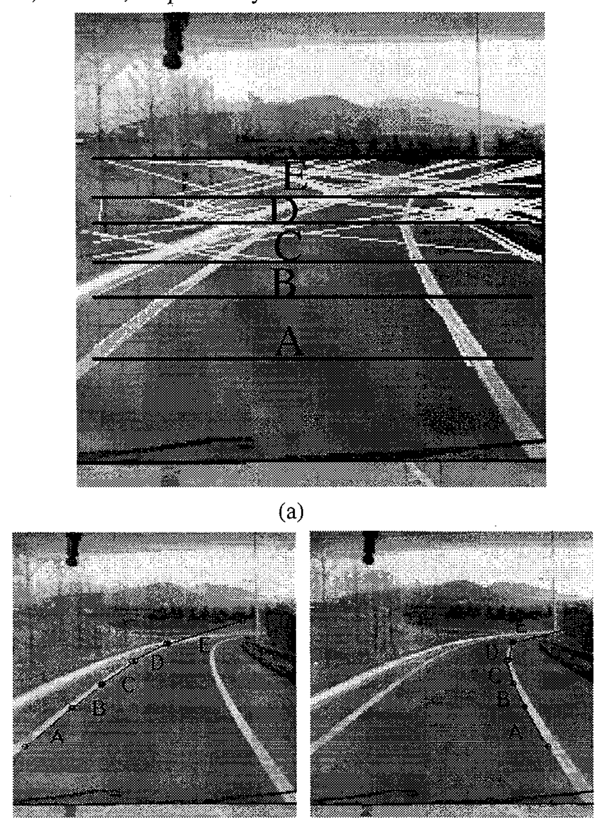
Finally, we obtain the left and right linked-line minimizing the ALM energy as shown in Fig.6(b). In this case, the number of obtained hough lines is 13 in region (A), 30 in region(B), and 86 in region (C), respectively. White lines in Fig.6(b) indicate the normal directions of detected lines for lane refinement, which is explained in the next section.



(a) (b)

Fig.6 Lane detection of ALM from line candidates of hough transform; (a) multiple line detection by hough transform in the each 3 sub-regions; (b) lane detection, which is a combined line-chain indicating the minimum snake energy, white lines are normal direction of detected lines.

For 5 sub-regions in Fig.7(a)~(c) to justify reduced computational cost comparing to exhaustive search, the local hough transform and the ALM gives multiple lines and optimal line chain for each sub-region as well. Energy coefficients α, β, γ of ALM in eq.(2),(3) are set as 1.0, 1.0, and 1.2, respectively.



(a)

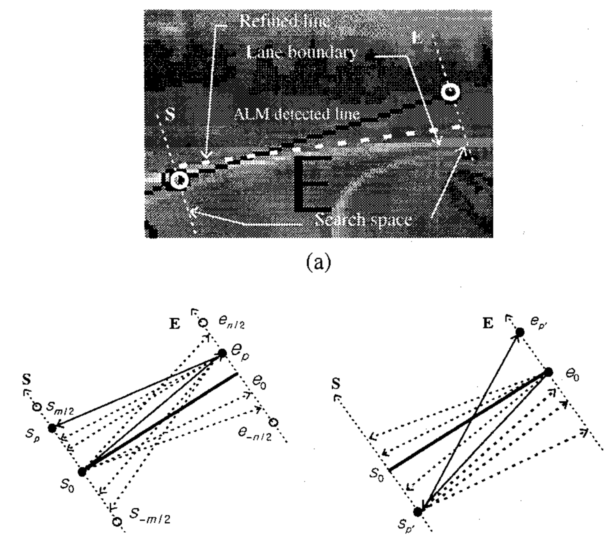
(b) (c)

Fig.7 Lane detection for 5 sub-regions; (a) multiple line detection by the hough transform; (b) left lane detection; (c) right lane detection.

In above experiments, we can see that ALM is an efficient method to find the curved road lane. If the local hough transform gives lines partially overlapping on the lane despite of cluttered or noisy image, robust lane boundary detection is possible.

3.2 Lane refinement

ALM is a line combination of the minimum snake energy which approximately represents the lane boundary of neighboring sub-regions. Because results for curved lane do not exactly represent the lane boundary, for example, line segment E in Fig.7(b), lane refinement is needed. If a detected line by ALM partly overlaps with the lane boundary, a local refinement constraint translates and rotates the detected line from the current line position to a neighborhood position while searching for image gradients.



(a)

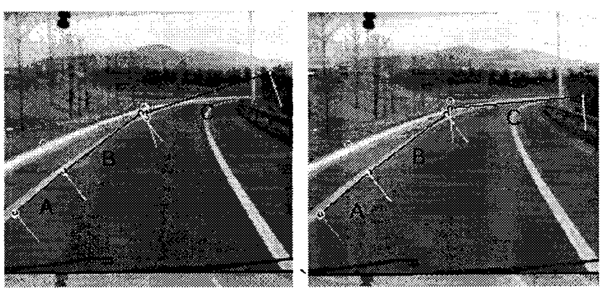
(b) (c)

Fig.8 Finding ALM candidates (a) local configuration of a sub-region; (b)(c) 4-candidate lines refining road lanes that are search candidates.

In Fig.8(a), a thick line in black, which is extracted by the Hough transform and ALM, does not correspond to the curved lane boundary. For a normal search on the line to refine the lane, consider two lines S and E which are perpendicular to the line at two ends. S_i and e_i are possible starting and ending positions for the normal direction of the line and S_0, e_0 is the position of ALM detected line(in Fig.8(b)). If the number of points on S, E for refinement are m and n respectively, we can obtain $m \times n$ line candidates. Because a full line-search to find a maximum edge value has high computational cost, a few lines are only searched. Those lines refining edges are again used as candidates for the ALM minimization.

As shown in Fig.8(b), consider the n lines $(s_0, e_{-n/2}), (s_0, e_{-n/2+1}), \ldots, (s_0, e_{n/2})$. Among n lines, a line with the maximum image gradient value becomes a candidate line (s_0, e_p) for the ALM optimization in the current sub-region. We can similarly obtain a set of m lines, $(s_{-m/2}, e_p)$, $(s_{-m/2+1}, e_p), \ldots, (s_{m/2}, e_p)$ which are linked from e_p to the normal position S. We can obtain a line (s_p, e_p) having the maximum edge value as well. On the line E, we start from e_0 and can get $(s_{p'}, e_0)$ and $(s_{p'}, e_{p'})$ as well(Fig.8(c)). Hence, we obtain 4 candidate lines $(s_0, e_p), (s_p, e_p)$, $(s_{p'}, e_0)$, and $(s_{p'}, e_{p'})$ to refine the lane boundary in a sub-region.

In a similar way, we can obtain 4 candidate lines for the other sub-regions. The ALM then performs the search for finding a minimum energy line chain connecting all the sub-regions. For a real image with curved lanes, the proposed method successfully extracts the current lane by refining the detected lines as shown in Fig.9. The detailed view is shown in Fig.8(a) in which a dotted line in white represents a refined line.

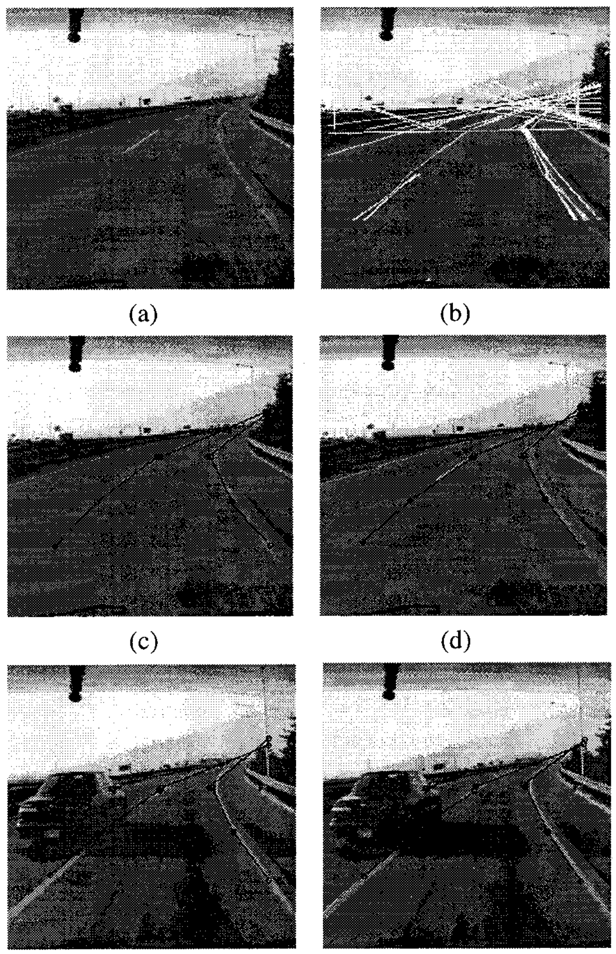


(a) (b)

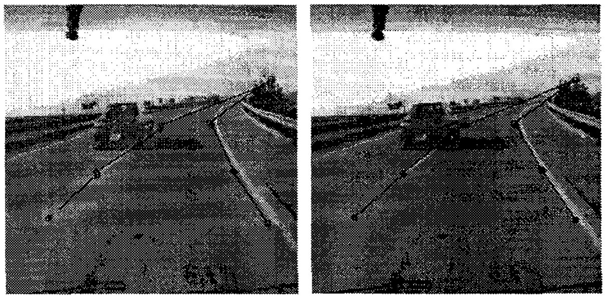
Fig.9 Lane refinement of detected line by ALM: (a) ALM detects a 3-line chain; (b) ALM can find a minimum energy line consisting of ones among 4 candidate lines refining to edge in each sub-region.

4. Lane tracking

Lane tracking uses the same lane refinement method described in the previous chapter. Assume that the displacement of lane boundary between inter-frames is relatively small. Then, extracted road lanes of the previous frame are used as initial candidates of road lanes in the current frame. Starting from the hypothesized line locations, the lane refinement method searches for a minimum energy line set. As a real experiment for noisy images, Fig.10(a),(b) shows the first image and detected multiple hough lines. Fig.10(c) shows, detected lines by the ALM and the local hough transform for 3 sub-region. Obtained lines are refined on lane boundary by using the lane refinement technique of the previous chapter(Fig.10(d)). Refined line position is then used as an initial ALM position for the next frame as shown in Fig.10(e). We can see that tracking and refinement of lane for the frame is reasonable in Fig.10(f). In Fig.10(g),(h), the tracking and refinement processes for the following frames are repeated.



(a) (b) (c) (d) (e) (f)



(g) (h)

Fig.10 Lane tracking in the sequential image frames; (a) first frame having missing and intermittent lanes; (b) hough lines in 3 sub-regions; (c) lane detection by hough transform and ALM; (d) lane refinement by local line candidates and energy minimization of ALM; (e)initial tracking position for a following frame; (f) lane refinement of initial position; (g) initial tracking position for next frame; (h) refinement.

5. Conclusions

We observe that vanishing points by the classical hough transform do not predict well the moving direction of the vehicle for the curved road because of the curved edge and the projective projection on the image plane. Our proposed method, which consists of the local hough transform and the active line model(ALM), overcomes the limitation under the assumption that the curved lane can be decomposed into a set of line segments.

The method first finds multiple line-candidates in adequately partitioned sub-regions using the hough transform. The ALM, as a next process, then detects a set of line segments, which correspond to the road lanes, by minimizing a total energy of the ALM through dynamic programming. Using the detected line-chain and the image gradient, lane refinement is performed to give more exact lane position by only a local search. Refined lines are tracked in the following sequential frames. By ALM, we can do lane detection, refinement and tracking in a unified framework.

The proposed method, as a reliable method for finding and tracking road lane, has shown a good performance with images of the real road scene, in which many false road lanes exist due to shadows and occlusions by other passing cars.

In future, the current method will be combined with Kalman filter for sequential tracking while solving local occlusion of lanes by other cars. It will endow an energy that pull the ALM candidates toward a predicted position of the filter.

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