Dynamic Programming and Curve Fitting Based Road Boundary Detection

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Abstract: - This paper presents a vision based road boundary detection based on the combination of dynamic programming and 2nd order polynomial approximation. The initial estimate of the most likely road boundaries are obtained by a modified dynamic programming on a cost field defined on the edge image. A second order polynomial is fit to the initial coarse estimate of road boundaries to obtain a refined estimate of the road boundaries. The second order approximation of the road boundaries allows the estimation of the curved segments in addition to the straight segments of the road boundaries. Experiment results for road images taken under various non-ideal scenarios with shadow, unmarked lane segments and curvatures are presented.

Key-Words: - lane detection, dynamic programming, curve fitting

1 Introduction

Increasing safety concerns on the road have led to the investigation and deployment of many Intelligent Vehicle Assistant Systems (IVAS) in vehicles. Accurate road lane and boundary line detection is one of the key tasks of the IVAS. Vision based approaches have been widely used in the literatures for road lane detection [2-10].

The vision based techniques can be broadly divided into the feature based and model based lane detection. The feature based techniques [2-5] extract the low level image features like color or edges to estimate the road lines. The model based techniques [6-10] employ a linear or quadratic lane model for lane representation and are more robust against noise and missing data. GOLD system [2] uses edge based lane boundary detection. LOIS system [3] uses edge magnitude and orientation as features and a parabolic approximation for road lanes. LANA algorithm [4] is based on a set of DCT coefficients for diagonally dominant edges and parabolic approximation for the road model. A road boundary extraction based on dynamic programming and Randomized Hough transform is presented in [10] and a system based on a hyperbola–pair approximation is presented in [7][8].

In this paper we propose a combination of the feature based and the model based method for robust performance. A similar approach for road boundary detection is proposed in [10], but the current work differs in that it accounts for the near as well as the far field and unlike [10] is suitable for curved road segment estimation. The rest of the paper is organized as follows: Section II presents the details of the proposed method; section III provides the experimental results and section IV concludes the paper.

2 Proposed Method

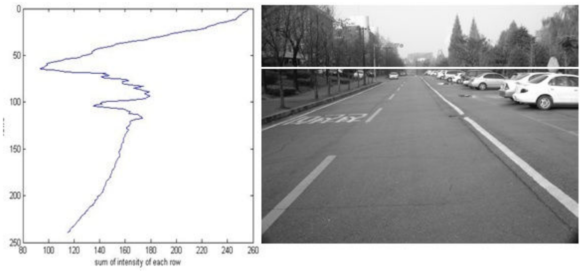
The algorithm presented in this paper is different from others as it uses a combination of dynamic programming [1] and second order polynomial approximation of the road lane. In addition to finding the trivial straight lane segments, the cost field and neighborhood in the dynamic programming is modified to accommodate for curved road lane.

2.1 Horizon Line Detection

To limit the ROI for the search of the most likely road lane segments, a horizon line is separating the road region from the background is found initially. The horizon line is estimated by using a horizontal intensity profile [9]. For an image of size MxN, The horizontal intensity profile ($H_{profile}$) is given as,

$$\underset{i \in \{1,2,..,M\}}{H_{profile}(i)} = \sum_{j=1}^{N} I(i,j) \qquad (1)$$

The horizon line is marked by a significant difference in intensity above and below it, usually the sky region being brighter than the road region. The first minimum of $H_{profile}$, Fig.1 (a), assuming the top left corner of the image, Fig. 1(b), as origin gives the position of the horizon line.



(a) (b)

Fig.1. (a) Horizontal intensity profile with first minimum at x=64; (b) The horizon line superimposed in the original image.

2.2 Edge Extraction

The most distinctive edge pixels appear along the road boundaries due to sharp contrast between the road surface and painted lines or some type of non-pavement surface. In addition edge pixels also provide directional information. The Sobel operator is used to extract the edge image. Since the road boundaries are parallel on the ground plane and not parallel to the image plane, they appear to converge in the image plane. So the edge pixels with near vertical and horizontal orientation are filtered out from the edge image, Fig.2, as they are more likely to be related to other structures rather than the road lane.

Fig.2. Edge image (threshold=0.3) with the near horizontal and near vertical edges filtered out.

2.3 Road boundary selection by Dynamic Programming

Dynamic programming is a global optimization algorithm to compute the optimal path by taking the local minimum at each node. Let $D(i,j)$ and $D(k,l)$ be the shortest distance to the goal from node (i,j) and node (k,l) respectively. Assuming $d_{ij,kl}$ is the shortest distance from node (i,j) to its neighboring node (k,l), then $D(i,j)$ can be expressed in terms of $D(k,l)$ and $d_{ij,kl}$ by the following equation

$$D(i,j) = \min\left\{d_{ij,kl} + D(k,l), (k,l) \in R(i,j)\right\} \qquad (2)$$

Here, $R(i,j)$ is the set of neighboring nodes of node (i,j). Eq. (2) is repeatedly applied locally until all the corresponding nodes have their minimum distance to the goal obtained. An optimal path is defined as the path that has the lowest cost from a starting point to the goal point. For each node on the possible path, the next node among $R(i,j)$ is the one with the minimum cost to the goal line. This process is repeated until the goal point is reached. To accommodate for the curves in the road lane the search neighborhood for dynamic programming is modified as,

$$(k,l) \in R(i,j) \forall k = i-1, l \in \{j-2, j-1, j, j+1, j+2\} \quad (3)$$

The link cost $d_{ij,kl}$ from node (i,j) to all neighboring nodes (k,l) is assumed to be 1 and a cost on the nodes themselves is defined using the intensity of the image pixels $I(x,y)$ conditioned on the edge image $I_{edge}(x,y)$ as,

$$nodecost(i,j) = \begin{cases} (1 - I(i,j))\, if \ I_{edge}(i,j) = 1 \\ \eta_1 (1 - I(i,j)) \ if \ I_{edge}(i,j) = 0 \end{cases} \qquad (4)$$

where η_1 >1. For the experiments η_1 =20 is taken. The horizon line is set as the goal line on the road image as the road lane is not visible beyond the horizon line. The distance initialization on the cost field is done as,

$$pathcost(i,j) = \begin{cases} 0 \text{ if } i = horizon\ line \\ \eta_2 \qquad elsewhere \end{cases} \qquad (5)$$

where η_2 >>1. =1000 is taken for the experiments. The road lane is then found in two phases. In the first phase, the minimum cost from the goal line to every node is accumulated towards the starting line using Eq. (2). Once the cost field is computed, Fig 3(a), the second phase is to trace along the minimum cost path towards the goal line, starting from the two start points. For an image of size MxN, the two starting points are set at the bottom left and bottom right of the image as given by Eq. (6)

$$\begin{aligned} S_l(M,j) &= \min\{pathcost(M,j); j \in \{1:N/6\} \\ S_r(M,j) &= \min\{pathcost(M,j); j \in \{5N/6:N\} \end{aligned} \qquad (6)$$

Fig. 3(b) shows the two lane boundaries traced by dynamic programming.

2.4 Second Order Polynomial Approximation

Let $\{(x,y_l)\}$ and $\{(x,y_r)\}$ be the set of data points for the left and right lane returned by dynamic programming. These data points give a coarse estimate of the road boundaries which at times seem unrealistic.

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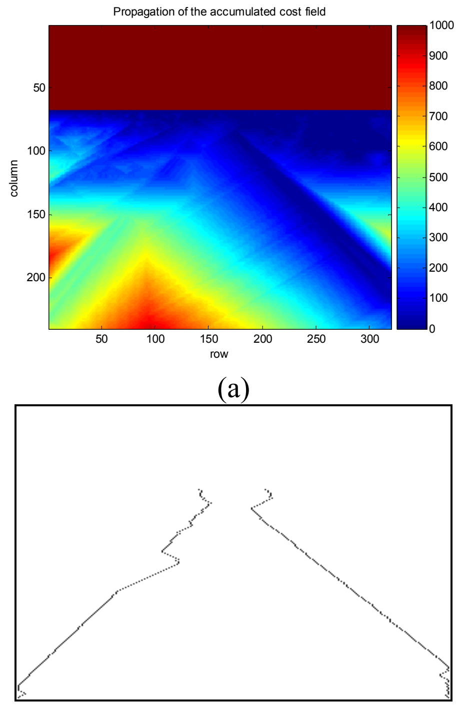


(a)

(b)

Fig.3. Optimal path finding using dynamic programming; (a). Propagation of the accumulated cost field. (b) The optimal path generated by backtracking from the starting points to the goal line in the cost field.

As road boundaries are simple curves which can be safely approximated by a second order polynomial, we fit these data points to a polynomial of the form $y = ax^2 + bx + c$. The data points are fit to the curve by minimizing the sum of the squares of the offsets of the points from the curve. The best fitting curve $f(x)$ has the least square error, i.e.,

$$\Pi = \sum_{i=1}^{n}[y_i - f(x_i)]^2 = \sum_{i=1}^{n}[y_i - (ax_i^2 + bx_i + c)]^2 = \min \quad (7)$$

where a, b and c are unknown coefficients and x_i are the known row positions and y_i the corresponding column positions. To obtain the least square error, the unknown coefficients a, b and c must yield zero first derivatives.

$$\begin{cases} \dfrac{\partial \Pi}{\partial a} = 2\sum_{i=1}^{n} x_i^2[y_i - (ax_i^2 + bx_i + c)] = 0 \\ \dfrac{\partial \Pi}{\partial b} = 2\sum_{i=1}^{n} x_i[y_i - (ax_i^2 + bx_i + c)] = 0 \\ \dfrac{\partial \Pi}{\partial c} = 2\sum_{i=1}^{n}[y_i - (ax_i^2 + bx_i + c)] = 0 \end{cases} \quad (8)$$

Expanding the above equations, we have

$$\begin{cases} \sum_{i=1}^{n} x_i^2 y_i = a\sum_{i=1}^{n} x_i^4 + b\sum_{i=1}^{n} x_i^3 + c\sum_{i=1}^{n} x_i^2 \\ \sum_{i=1}^{n} x_i y_i = a\sum_{i=1}^{n} x_i^3 + b\sum_{i=1}^{n} x_i^2 + c\sum_{i=1}^{n} x_i \\ \sum_{i=1}^{n} y_i = a\sum_{i=1}^{n} x_i^2 + b\sum_{i=1}^{n} x_i + c\sum_{i=1}^{n} 1 \end{cases} \quad (9)$$

The unknown coefficients can be obtained by solving the linear equations of Eq. (9). Once the coefficients of the polynomial are estimated, we can have a smooth and realistic estimate for the road boundaries.Fig.4 shows the refined estimate of road lane.

Fig.4. Smooth road boundaries extracted after fitting a second order polynomial to the data of Fig 3(b).

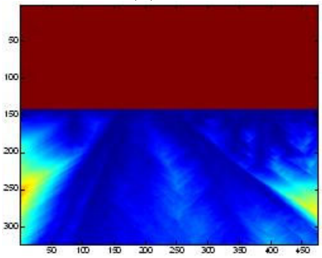
3 Experimental Results

The proposed method is evaluated on different road images containing the near and far field. Typical cases, Fig.5 (a-e), with shadow, unmarked lanes, non-ideal road textures and curved roads are considered to test the robustness of the proposed method. Fig 5 (a) shows a typical road with non-ideal texture and missing lane markings. The lane detection problem becomes challenging due to many noisy edge segments and the missing lane markings. Fig 5(a_p) shows the propagation of the cost field and Fig. 5(a') shows the detected road line boundaries after a second order polynomial is fit to the lane data points found by dynamic programming. The coefficients of the approximated polynomials for the left and right boundary are given in Table 1. Fig. 5(b) shows a road with discontinuous lane markings. The propagated cost field and the detected road boundaries are shown in Fig. 5(b_p) and Fig. 5(b') respectively. Fig. 5(c) shows a road with oil stains and shadow and the cost field and detected road boundaries are presented in Fig. 5(c_p) and 5(c') respectively. Fig. 5(d) shows a curved road segment with continuous lane markings and the propagated cost field and the detected road boundaries are presented in Fig. 5 (d_p) and Fig. 5 (d'). Further evaluation on a curved road with discontinuous lane markings is presented in Fig.5 (e), Fig.5 (e_p) and Fig. 5(e').

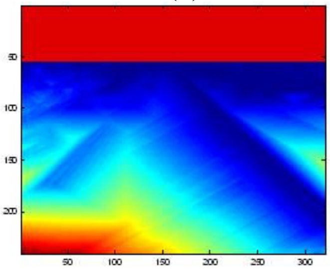
The simulation results presented in Fig.5 show that road boundaries under varying conditions can be detected using the proposed algorithm.

(a)

(b)



(a_p)



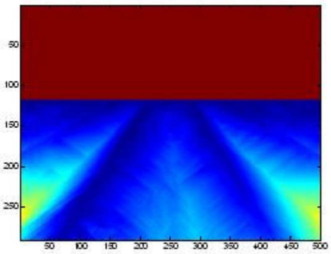
(b_p)

(a')

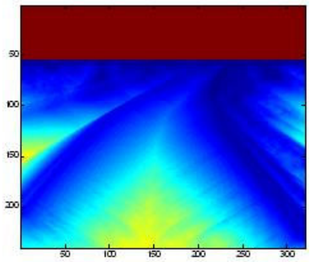
(b')

(c)

(d)



(c_p)



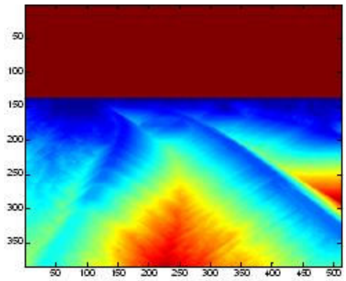
(d_p)

(c')

(d')

(e)

(e')



(e_p)

Fig. 5 Road lane detection under various road conditions (a). Road with non-ideal texture and missing lane paint.(b) Road with discontinuous lane markings. (c) Road with oil marks and shadow. (d) curved road segment .(e) curved road segment with discontinuous markings.(ap-ep) Propagation of the accumulated cost field of the corresponding images. (a'-e') The detected road boundaries of the corresponding road images.

Table 1. The coefficients of the polynomials fit to the data from dynamic programming for the left and right lane in each image.

Coefficients->		a	b	c
Image (a)	left	-0.00071597	-0.1127	197.29
	right	-0.00046705	1.5836	23.58
Image (b)	left	-0.00026592	-0.4634	146.54
	right	-0.0016232	1.4468	75.469
Image (c)	left	-0.0005526	-0.6621	300.8
	right	-0.00034163	0.95654	173.49
Image (d)	left	0.0050482	-2.5507	322.65
	right	0.0033708	-0.3913	232.19
Image (e)	left	-0.0030766	1.0752	51.383
	right	-0.0035368	3.095	-148.2

4 Conclusion

In this paper a robust method for road boundary detection is proposed. The horizon line is extracted to limit the search space for the road boundary. Edge candidates are extracted and dynamic programming is employed to obtain the optimal road boundaries. The search neighborhood in dynamic programming is modified so as to accommodate the curved segments of the road lane along with the straight segments. At the final stage a second order polynomial is fit to the road lines extracted from dynamic programming to have

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more realistic and refined road boundaries. The experiments carried out show that the proposed method has good performance and is robust under non-ideal road conditions also.

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