Real time mobile lane detection system on PXA255 embedded system

Ming-Jer Jeng, Pi-Chih Hsueh, Chun-Wei Yeh, Pei-Yung Hsiao¹, Chao-Han Cheng, and Liann-Be Chang

Abstract—In this paper, we present a real time mobile lane detection system (LDS) based on PXA255 embedded system. The software with generic 2-D Gaussian smoothing filters includes the power-of-two approximation algorithm for the Gaussian coefficients which is easy to be hardware designed. In the lane detection algorithm stage of an image processing flow, the global edge detection is able to transfer the gray level image into binary pattern and show the edge of the object. Then, we use this binary pattern to find out the traffic lane location with following algorithms like the peak-finding and grouping, edge connecting, lane segments combination, lane boundaries selection. At last, the lane departure warning algorithm detects whether the vehicle is in traffic lanes and judges whether to send out the warning. Experimental results both operated under different circumstances and real image sequences will also be presented.

Keywords—Mobile lane detection system, embedded system, Generic 2-D Gaussian smoothing filters, Lane detection algorithm, Global edge detector, Lane departure warning algorithm.

I. INTRODUCTION

LECTRONIC products built with the CMOS / CCD photosensitivity element in present market is a tendency so that a portable electronic product with driving assistant system would be a feasible application. There are a lot of researchers and vehicle makers figuring out methods that can develop driving assistance system and improve driving safety [1]-[14]. There are many research topics on driver assistance systems mainly focusing on the lane detection technology since it is basic and has many applications, such as autonomous vehicles [1],[4] and the lane departure warning systems[5],[8]-[14]. Most of the researches still implemented on PC platforms and some of the vehicle makers only adopt such driver assistance systems into their concept cars or latest vehicles, so their flexibility may decline. An important step in developing a lane departure warning system is to have a robust lane detector. To realize the lane detection, noise disturbance can greatly affect

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lane distinction. The noise reduction techniques usually involve averaging the value of pixels reside in a local area and generating a blurred or smoothed image. Numerous softwareand hardware-based edge detection algorithms have been proposed. Most algorithms are able to produce acceptable edge results, but fail as the noise signal increases. To reduce such noise signal and ensure the performance of image, we present a generic 2-D Gaussian smoothing filter which can improve noise resistant ability. The Gaussian filter plays an important role in digital image processing tasks such as image segmentation, image blurring, and edge detection. Such filter is usually adopted in the filed of edge detection, and we also present a robust lane detection algorithm which can efficiently reduce noise. In this paper, we present a mobile lane detection system based on PXA255 embedded system. The algorithm we used is divided into two part, the first part is image preprocessing and the second part is lane detection. To enhance portability and flexibility of the Lane departure warning systems, we will develop a portable real-time lane departure warning system which should be cheap, easy to install, and be able to be combined with other vehicular consumer devices, such as digital cameras, cell phones, and PDAs. Further, we are going to discuss our algorithm and related research studies.

II. GENERIC 2-D GAUSSIAN SMOOTHING FILTER AND LANE DETECTION ALGORITHM

Front level processing of the Lane Detection system need to use the lane detection algorithm. For lane detection algorithm applications, image processing tasks are applied to the real-world images. Noise signals may be easily introduced into the original image during the image acquisition stage, image compression stage or even the image transmission stage. To eliminate such noise signals, and to ensure the performance of the overall image processing flow, an additional step of noise reduction is necessarily required. So we present the Generic 2-D Gaussian Smoothing Filter to reduce noise. The Gaussian filter is one of the specialized weighted averaging filters. It has been widely adopted in the field of image processing and computer vision for years, and is known for its image smoothing and noise reduction capability.

A. Generic 2-D Gaussian Smoothing Filter

The values derived from the 2-D Gaussian distribution are mostly complex floating point values, which makes it difficult to implement in hardware. It would perform slowly even if that certain hardware is implemented. The following shows how we derive the original Gaussian smoothing mask. Fig.1 defines the index (x, y) of the center element of a 5x5 mask to

be (0, 0), and the whole mask move to span from (-2, -2) to (2, 2) shown as below.

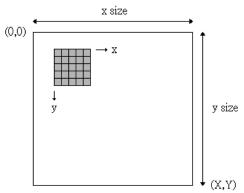


Fig.1 The 5x5 mask, that the x-axis in vertical direction, while the y-axis in horizontal direction.

The value of each element in the 5x5 Gaussian smoothing mask is defined by Gaussian function.

$$G_{\sigma}(x,y) = e^{-(x^2+y^2)/2\sigma^2}$$
 (1)

Where x, $y = \{-2, -1, 0, 1, 2\}$ and $\sigma = [0.1, 5.0]$. The summation of the whole mask should be equal to 1 by the definition of Gaussian distribution. Therefore, we need to sum the whole 25 elements and normalize them.

$$S_{\sigma} = \sum_{x=-2}^{2} \sum_{y=-2}^{2} G_{\sigma}(x, y)$$
 (2)

$$G_{n\sigma}(x,y) = G_{\sigma}(x,y)/S_{\sigma} \tag{3}$$

To derive the digital-approximated 2-D Gaussian mask for hardware implementation, we use the combination of power-of-two terms to approximate each element, and it can be implemented by simply shift operations in hardware. Then the intuitive power-of-two approximation algorithm of each of the 25 elements may be written as shown in Fig.1(a) after each element is determined, we still need to make sure that the sum would still be close to 1. Let the value of each approximated coefficient be denoted as $A\sigma(x\ ,\ y)$, and again the sum of twenty five current approximated coefficients would be

$$S_{A\sigma} = \sum_{x=-2}^{2} \sum_{y=-2}^{2} A_{\sigma}(x, y)$$
 (4)

The power-of-two approximation for $1/S_{A\sigma}$ is also determined using the algorithm shown in Fig.2(a), except for that the range of i is extended from 7 to 15. An example of our digital-approximated Gaussian mask is shown in Fig.2(b).

$$\begin{array}{lll} \operatorname{Approx}(\operatorname{val}) & & & & \\ 1 & & \operatorname{term} \leftarrow 0 & \\ 2 & & \operatorname{rtterm}[\operatorname{term}] \leftarrow \left\{0\right\} \\ 3 & & & \operatorname{for} \ i \leftarrow 0 \ \operatorname{to} \ 7 \\ 4 & & & & \operatorname{if} \ \operatorname{term} < \lambda \\ 5 & & & & \operatorname{then} \ \operatorname{if} \ \operatorname{val} \ > = 2^{(-\mathrm{i})} \\ 6 & & & & \operatorname{then} \ \operatorname{rtterm}[\operatorname{term}] \leftarrow \operatorname{i} \\ 7 & & & & \operatorname{val} \leftarrow \operatorname{val} \ - \ 2^{(-\mathrm{i})} \\ 8 & & & & \operatorname{term} \leftarrow \operatorname{term} \ + \ 1 \\ 9 & & & & \operatorname{return} \ \operatorname{rtterm} \end{array}$$

(a)

	0	2-3	2-3+2-4	2-3	0
	2-3	2 ⁻² +2 ⁻³	2-1+2-3	2 ⁻² +2 ⁻³	2 ⁻³
3+2 ⁻⁶)×	2-3+2-4	2 ⁻¹ +2 ⁻³	2 ⁰ +2 ⁻⁴	2-1+2-3	2-3+2-4
	2 ⁻³	2 ⁻² +2 ⁻³	2-1+2-3	2 ⁻² +2 ⁻³	2 ⁻³
					0
	0		2 +2	2	U
		(b)			

Fig.2 Power-of-two approximation (a) Algorithm and (b) Example of the Gaussian mask for σ = 1.1 and λ = 2.

To describe the errors between the original Gaussian mask and the 2n-approximated Gaussian mask in a formal way, we define each of the approximated normalized elements in the 2ⁿ 2n-approximated Gaussian mask as:

$$A_{n\sigma}(x,y) = A_{\sigma}(x,y) / S_{A\sigma}$$
 (5)

Consequently, the absolute accumulated error is defined as:

$$E_{\sigma\lambda} = \sum_{x=-2}^{2} \sum_{y=-2}^{2} \left| G_{n\sigma}(x, y) - A_{n\sigma\lambda}(x, y) \right| \tag{6}$$

The decision for the acceptable accumulated error affects the algorithm. We adopt to approximate the Gaussian mask. Based on our empirical experiences and cost consideration, we used the two-term's 2ⁿ-approximation 2-D Gaussian mask as the proposed filter.

B. Global Edge Detection

 (2^{-3})

The Global threshold edge detector uses a 3x3 mask to detect the difference between each pixel. It needs to obtain mean value and variance of night pixels to decide the edge points. In order to implement by logic circuit, we modified it as equation (8)-(9), which has a very little differences between the original value and the modified one.

$$\mu_{x,y} = \left(\frac{1}{8} - \frac{1}{64}\right) \sum_{\Delta x = -1, \Delta y = -1}^{\Delta x = 1, \Delta y = 1} g(x + \Delta x, y + \Delta y) \tag{7}$$

Then we use the average difference of a 3x3 mask to replace the variance value of the original algorithm.

$$\delta_{x,y} = \left(\frac{1}{8} - \frac{1}{64}\right) \sum_{i=1}^{9} \left| x_i - \mu_{x,y} \right| \tag{8}$$

Finally, we use the following procedure to make pixels' value in a 3x3 mask become binary.

$$g(x + \Delta x, y + \Delta y) = \begin{cases} 1, \delta_{x,y} \ge Tn \\ 0, \delta_{x,y} < Tn \end{cases}$$
(9)

After we modified the original algorithm, we can easily implement it by logic circuit. Furthermore, although Global threshold edge detector is a threshold value based algorithm, the configuration of Global threshold value, Tn, is much easier

than that of peak finding based algorithm due to the insensitive characteristic. Fig.3 shows the results after Global threshold edge detector in different circumstances.

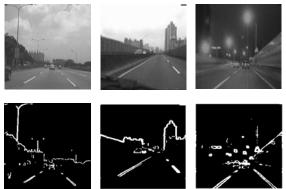


Fig.3 Global edge detection results in different situations.

C. Peak finding and grouping

The processing frame will become a binary image after edge detection procedure, then, the original peak finding algorithm need to be modified. As shown in Fig. 4, we have to define three variables: Ps, Pe, Pp, where star point(Ps) is the position of first climbing up point, end point (Pe) is the position of last climbing down point, and Peak point (Pp) is the middle point between Ps and Pe. After the edge detection procedure, two sides of lane mark may be detected. Therefore, we will combine two close peak point to a new point as shown in Fig.4. After finding peak points in the image, we group the peak points which may locate at the same lane boundaries. We use a 9x11 mask to group peak points. We make every peak point to be the central point of a 9x11 mask, and let other points in the mask to be the same group like as the central point, and then repeat the same operation again and again.

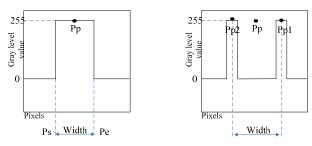


Fig.4 Peak point and combination of two near peak points

D. Edge Connection

The selected peak points are collected and separated as many as line segments by employing the least square method. Each produced line segment is defined as below:

$$L(P_L(X_L, Y_L), P_U(X_U, Y_U), b_0, b_1)$$
 (10)

Where P_L is the top point of line segment, P_U is the bottom point of line segment, b_0 is the intercept of line segment, and b_1 is the slope of line segment. The b0 and b1 are generated by equation (11)-(12):

$$b_0 = \overline{X} - b_1 \overline{Y} \tag{11}$$

$$b_{1} = \frac{n \sum_{i=1}^{n} x_{i} \cdot y_{i} - \sum_{i=1}^{n} x_{i} \sum_{i=1}^{n} y_{i}}{n \sum_{i=1}^{n} y_{i}^{2} - (\sum_{i=1}^{n} y_{i})^{2}}$$
(12)

III. ARCHITECTURE OF LANE DEPARTURE WARNING SYSTEM

In this section we exemplify each state of the lane detection algorithm result and present the software architecture on our platform. The Lane detection application architecture shows in Fig.5. The lower level of the software architecture is portable hardware. Above hand-hold hardware level is board support pocket like bootloader, device drivers, and OEM Adaptation Layer. The intermediate level is the kernel, device manager, GEWS, and service manager of operation system. Then, the middle level between the application API and lane departure warning application is a virtual machine level.

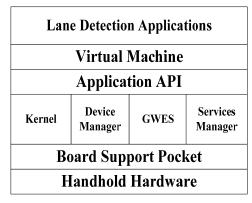


Fig.5 Lane Detection Application software architecture with Pxa255 and Pc.

In the software design, we used standard C program to design the whole lane detection system framework. The software module framework is presented in Fig. 6. In Fig. 6 the C program functions are separated in three groups. The first group is BMP file control operation functions. Those functions are used to open, close, transfer, and save BMP image files in

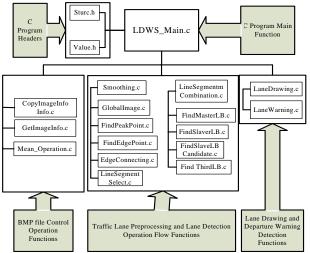


Fig.6 Traffic lane image processing flow chart using lane detection algorithm.

order to support the lane detection system operation flow. The second group is the traffic lane preprocessing and lane detection operation flow functions. Those functions are main operation flow of the lane detection system algorithm. The third group is lane drawing and departure warning detection functions. These functions are drawing out the traffic lane image and detect the vehicle even departure from the lane

IV. EXPERIMENTAL RESULT

The processing results are shown as below. Fig.7 shows traffic lane image when the vehicle is moving to another traffic lane with sufficient lightness in day and Fig.8 also shows clear traffic lane image at night.



Fig.7 Lane detection system exhibits a clear image under sufficient lightness



Fig.8 Results for night traffic lane detection tests.

Figures 9 and 10 show the process in each step of the algorithm. When the input image is without noise addition, it can clearly detect two traffic lanes. Figure 11 shows the lane detection results with noise addition. Figure 11(a) exhibits original traffic lane without noise addition. Figure 11(b) shows the traffic lane image with Gaussian noise addition by variance=0.01. Figure 11(c) shows the traffic lane image with generic 2-D Gaussian smooth filter σ =0.9 and grouping mask 9×11. The presenting algorithm can capture two traffic lines under the input image without noise addition while the input image with Gaussian noise addition misses the correct traffic lines. If we add Gaussian smoothing filter on image processing front level, the algorithm can capture the correct traffic line on the both main sides. Figure 12 shows the processing time during lane detection operation flow which cost almost little time in other stage except global edge detection stage.

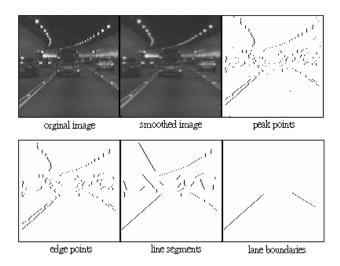


Fig.9 Processing results for lane detection step by step with $(Vx_,V_y) = (150, 80)$ and Tn=10.

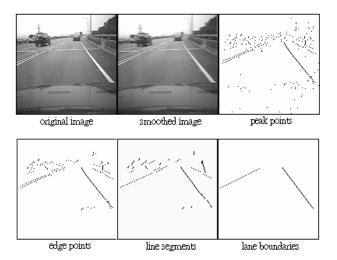


Fig.10 Processing results for lane detection flow and each step images with (Vx, V_y) = (150, 80) and Tn=10..

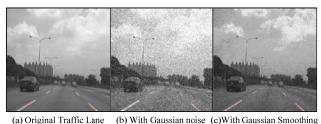


Image and Lane Detection Image, variance=0.01 and filter, σ=0.9 ,mask 9X11and Result Lane Detection Result Lane Detection Result

Fig.11 Lane detection results in different noise addition images. (a) original traffic lane Image. (b) the traffic lane image with Gaussian noise addition by variance=0.01. (c) the traffic lane image processed by generic 2-D Gaussian smoothing filter with σ =0.9 and the grouping mask 9X11.

Figure 12 shows the experiment platform and the concept drawing of the device placement. The platform is PXA255 embedded system. Clearly, correct lane detection is displayed.

The processing time in a single frame is about 70ms. Further investigation to reduce processing time is progressing.



Fig.12 Result for lane detection using PXA 255 CPU as the platform

V. CONCLUSION

In this paper, we present a detailed software handheld lane detection system based on PXA255 embedded system, which can be easily mounted on real vehicle and dramatically improve safety. The software lane detection algorithm can process the calculation very fast and easily set up on PDA device from recent market. The proposed lane departure detection algorithm let us to detect lane departure under a high vehicle departure speed and avoid false alarm situation successfully. At last, the evaluations prove that this system is robust in most situations including Gaussian noise addition.

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