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A lane detection approach based on intelligent vision ☆

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ABSTRACT

This paper proposes driver assistant system architecture based on image processing techniques. A camera is mounted on the vehicle front window to detect the road lane markings and determine the vehicle's position with respect to the lane lines. A modified approach is proposed to accelerate the HT process in a computationally efficient manner, thereby making it suitable for real-time lane detection. The acquired image sequences are analyzed and processed by the proposed system, which automatically detects the lane lines. The experimental results show that the system works successfully for lane line detection and lane departure prediction.

1. Introduction

Traffic accidents have become one of the most serious modern problems. The reason is that most accidents occur due to driver negligence. Rushed and careless driving can push other drivers and passengers into danger on roads. Many accidents can be avoided if dangerous driving conditions are detected early and other drivers are warned. Cameras and speed detectors are used on most roadways today to monitor and identify drivers that exceed the permitted speed limit. This is a primitive approach because there are limitations. If the drivers slow down before the speed detectors they will not be detected, even though they had exceeded the permitted speed earlier.

There were 13,954 fatal crashes in Taiwan because of failure to stay in the proper lane or running off the road in 2004. Table 1 shows the numbers and percentages of total drivers as more than one factor may be present for the same driver [1].

Failure to stay in the proper lane occurs in 24% of all fatal crashes. This is the most important precursor event in car accidents.

Side impact collision is one of the common types of car accidents. Side impact collisions occur when drivers carelessly change road lanes or merge onto the highway. These accidents are mainly due to the approaching vehicle driver moving into the rear mirror blind-spot of the vehicle in the adjacent lane or the driver loses concentration. Lateral vehicle detection and distance measurement will help drivers control their cars safely. Many studies [2,3] have investigated driving-assistance systems to improve driving safety.

Over the past few years more researches have been conducted on intelligent transportation systems (ITS). A research community [4] has been devoted to the lane departure warning topic (LDW) [5–7]. A significant portion of highway fatalities

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each year are attributed to vehicle lane departures. Many automobile manufacturers are developing advanced driver-assistance systems, many of which include subsystems that help prevent unintended lane departure. A consistent approach among these systems is to alert the driver when an unintended lane departure is predicted. A vision system mounted on the vehicle detects the lane markings on the road and determines the vehicle's orientation and position with respect to the detected lane lines.

Lane detection is a vital operation in most of these applications as lanes provide important information like region-of-interest, for further processing. In most cases lanes appear as well-defined, straight-line features in the image (especially in highways), or as curves that can be approximated by smaller straight lines. The linear HT (Hough transform), a popular line detection algorithm, is widely used for lane detection [8]. The HT [9] is a parametric representation of points in the edge map. It consists of two steps, i.e., "voting" and "peak detection" [10].

In the voting process every edge pixel $P(x,y)$ is transformed into a sinusoidal curve by applying the following:

$$\rho = x\cos\theta + y\sin\theta \tag{1}$$

where ρ is the length of the perpendicular from the origin O to a line passing through (x,y), and is the angle made by the perpendicular with the x-axis, as shown in Fig. 1. The resulting values are accumulated using a 2-D array with the peaks in the array indicating straight lines in the image.

The peak detection involves array accumulation analysis to detect straight lines [11,12].

The high computational time incurred by conventional Hough voting, attributed to the trigonometric operations and multiplications in (1) applied to every pixel in the edge map, makes it unsuitable for direct use in lane detection, which demands real-time processing. Hierarchical pyramidal approaches were proposed in [13,14,6] to speed up the HT

Table 1
Related factors for drivers involved in fatal crashes.

Factors	Number	Percent
Failure to keep in proper lane or running off road	13,954	24.0
Driving too fast for conditions or in excess of posted speed limit or racing	11,818	20.3
Under the influence of alcohol, drugs, or medication	7072	12.2
Failure to yield right of way	4611	7.9
Operating vehicle in erratic, reckless, careless, or negligent manner	3905	6.7
Inattentive (talking, eating, etc.)	3671	6.3
Swerving or avoiding due to wind, slippery surface, vehicle, object, nonmotorist in roadway, etc.	2666	4.6
Failure to obey traffic signs, signals, or officer	2607	4.5
Overcorrecting/oversteering	2466	4.2
Vision obscured (rain, snow, glare, lights, building, trees, etc.)	1679	2.9
Drowsy, asleep, fatigued, ill, or blackout	1653	2.8
Making improper turn	1537	2.6
Driving wrong way on one-way traffic way or on wrong side of road	936	1.6
Other factors	9420	16.2
None reported	20,216	34.8
Unknown	780	1.3
Total drivers	58,080	100.0

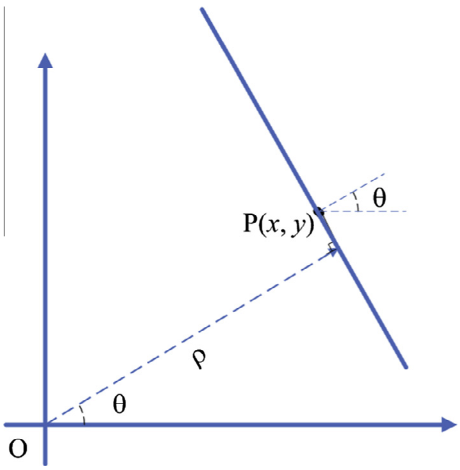

Fig. 1. The relation of lane line and Hough transform.

computation process through parallelism. These hierarchical approaches in [13,14,6] filter candidates to be promoted to the higher hierarchy levels using a threshold of accumulation spaces. For each candidate that qualifies, a complete HT computation is performed again using (1). Hence, although the hierarchical approaches speed up the HT by parallelizing the process, additional costs are incurred for re-computing HT at every level. These increased computational costs are not desirable in embedded applications like lane detection in vehicles, where computational resources are limited.

This paper presents a modified approach proposed to accelerate the HT process in a computationally efficient manner, thereby making it suitable for real-time lane detection. The proposed method is applied for straight lane detection and is shown to give good results with significant computation cost savings. The algorithm is a modified Hough Transform algorithm. The proposed method can be integrated with a driving video recorder (DVR) without burdening the DVR performance.

Section 2 describes the proposed algorithm. The experimental results are presented in Section 3. Section 4 presents the conclusions.

2. Algorithm of the lane detection

Fig. 2 shows a flowchart of the proposed algorithm. A well-suited algorithm is proposed to perform the Hough transform.

The main idea is to randomly select two points in the image space in every step. These points are plugged into the formula and solved simultaneously to obtain a point in parameter space; the corresponding unit accumulators are then set to zeros in the parameter space *P*. If the points exist in parameter space the corresponding accumulators count plus 1, if not, the points are inserted into parameter space. When a certain unit of accumulators achieves a certain threshold, the corresponding accumulator is identified as the detected line parameters. Changing from HT to RHT is shown in Fig. 2.

2.1. Hough transform

According to the HT (Hough Transform) additive property as shown in Fig. 3, the HT of point A with respect to the image origin "O" is equal to the sum of the HT of A with respect to any intermediate point B, and HT of B with respect to O, i.e.

$$\mathrm{HT}(\mathrm{A},\mathrm{O}) = \mathrm{HT}(\mathrm{A},\mathrm{B}) + \mathrm{HT}(\mathrm{B},\mathrm{O}) \tag{2}$$

where HT(x,y) represents the HT of point x with respect to point y. In other words, the HT of a point A with respect to a global origin O can be broken into two parts: the HT of that point A with respect to a local origin B and the HT of the local origin B with respect to the global origin O.

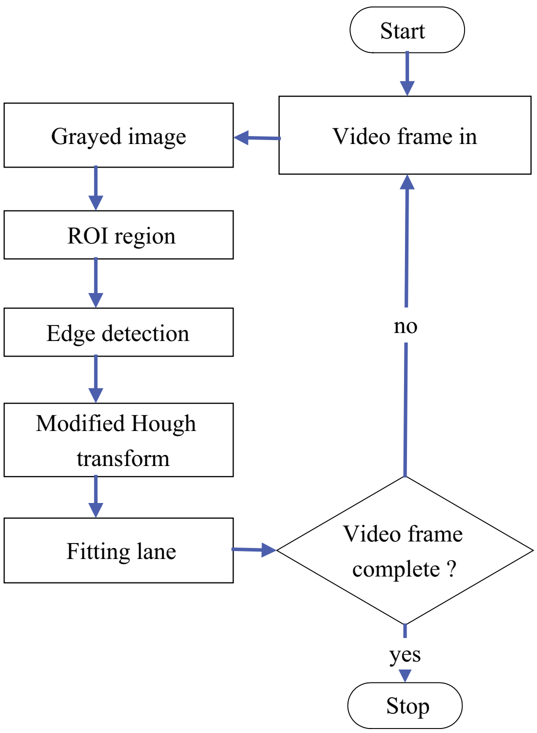

Fig. 2. The flow chart of the lane detection.

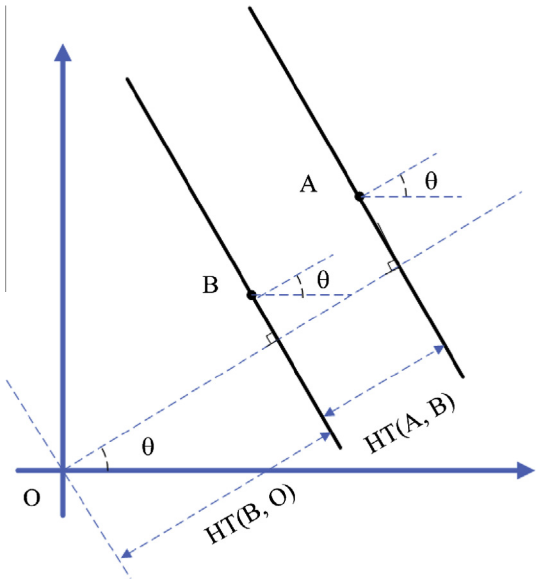

Fig. 3. The additive property of Hough Transform.

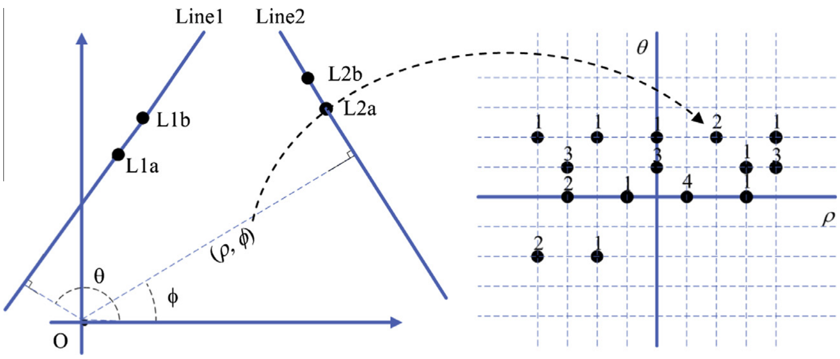

Fig. 4. The transform procedure from image space to parameter space. The count is increased from 1 to 2.

2.2. Fitting lane

Some researches [15–17] used a similar quantization approach to merge vicinal lines. The approach used in [15–17] computed *dis*1 and *dis*2, then according to threshold for discretizing *dis*. This procedure is similar to the quantization of ρ in our approach. However, our approach uses another quantization parameter θ.

The proposed approach computes ρ and θ of each line. The procedure normalizes each number pair and extracts their characteristics only once. The approach transforms the (x,y) space into the (ρ,θ) space and discretizes the (ρ,θ) coordinate space. The discretizing procedure slightly eliminates the CPU computing effort.

After the edge detection process the lane line identification process is as follows:

There are parameter arrays that store two types of parameters, ρ_i and θ_i, where *i* equals the pixel number of each ROI Region of Interest (ROI) which is a selected subset of pixels for processing. Only the ROI of each frame is processed such that the computational complexity is significantly reduced. The ROI is about 1/3 of a full frame from the bottom up.

Step 1: Clear all parameter arrays empty, i.e., Para$(\rho,\theta) = 0$ for ρ and θ belong to real numbers.

Step 2: Read in all pixels (x_i,y_i) from random places of ROI. Randomly select two points in Line1 and Line2, respectively.

Step 3: Select two points L1a(x_i,y_i) and L1b(x_{i+1},y_{i+1}) randomly from Line1, as shown in Fig. 4. Solve two parameters ρ and θ from the two points L1a(x_i,y_i) and L1b(x_{i+1},y_{i+1}). The number pair $N_i(\rho_i,\theta_i)$ is a combination of the above solution.

The same procedure is repeated for Line2. The parameter space points $N_i(\rho_i,\theta_i)$ bases on the following equations:

$$\theta_i = \tan^{-1}((x_i - x_{i+1})/(y_{i+1} - y_i)) \quad (3)$$

$$\rho_i = x_i \cos(\theta_i) + y_i \sin(\theta_i) \quad (4)$$

Step 4: According to the N_i from step 3, Search $||N_i(\rho_i, \theta_i) - \text{Para}(\rho, \theta)|| \leqslant \varepsilon$, where $||A||$, $\text{Para}(\rho, \theta)$ and ε are the norm of A, all the parameter space and a default little value, respectively.

If (ρ_C, θ_C) exists in the parameter space such that $||N_i(\rho_i, \theta_i) - \text{Para}(\rho_C, \theta_C)|| < \varepsilon$, the value of $\text{Para}(\rho_C, \theta_C)$ will be in increments of 1.

If the norm between $N_i(\rho_i, \theta_i)$ and $\text{Para}(\rho_C, \theta_C)$ more than ε, insert and initialize $\text{Para}(\rho_i, \theta_i)$ to 1, i.e., $\text{Para}(\rho_i, \theta_i) = 1$. ε is the pixel number and depends on the frame size. Choosing $\varepsilon = 2^k$, k is integer for efficiently computing. $\varepsilon = 16$ is used for $640 * 480$.

Step 5: After all points in Line1 and Line2 are traversed from step 3 to step 4, all of the elements in the parameter space are already setup.

If the value of $\text{Para}(\rho_i, \theta_i)$ is more than the threshold after parameter space setup, the road line exists. The pair (ρ_i, θ_i) will be kept for the next step to draw the corresponding lane.

If the value of $\text{Para}(\rho_i, \theta_i)$ is less than the threshold, the road line does not exist.

Step 6: According to the $\text{Para}(\rho_i, \theta_i)$ got from step 5, a straight line will be draw on the frame. The parameter space is used for lane predicting.

2.3. Lane departure prediction

The lane position deviation obtained from two or more initial detecting processes is small. So the positions of the lanes are predictable. After the lane recognition process the lane departure prediction starts to work.

The departure prediction is only made in even frames for computation reduction. If the θ of the left lane line is more than a departure threshold value for 10 continuous even frames, the departure starts. If the θ of the right lane line is less than a departure threshold value for 10 continuous even frames, the departure also starts.

3. Experimental results

The experiment was run under the OpenCV environment. The identification process is shown in Fig. 2.

The application first reads in the color video frame. It transforms the color image into gray images for every frame as shown in Fig. 5a. Only the pixels in ROI were extracted edge image. The ROI was about 1/3 of a full frame. The calculation complexity can be reduced only in the ROI.

The local difference in neighboring pixels is used to look for the edge. This is an image gradient processing method. It accurately locates the edge and applies image segmentation to the obvious edge. Fig. 5b depicts the edge line image in ROI.

The modified Hough transform algorithm was applied in the parameter space setup. Draw the lane lines to the original frame as shown in Fig. 5c.

Fig. 5a. After gray image process in ROI.

Fig. 5b. After edge detection process in ROI.

Fig. 5c. Road lane line prediction at night.

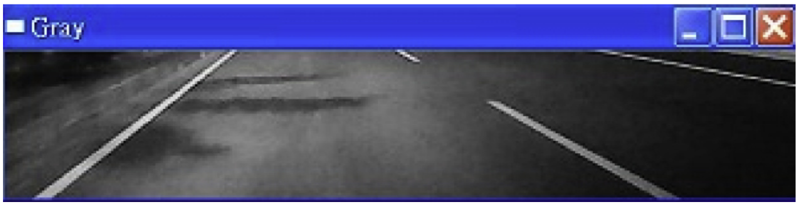

Fig. 6a. After gray image process in ROI at night.

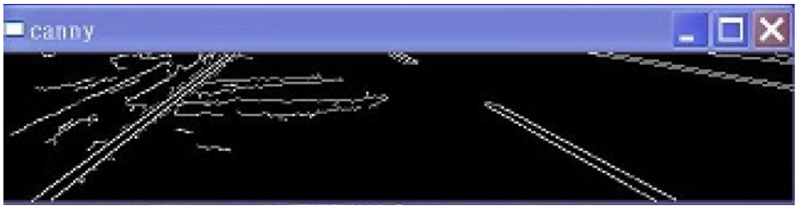

Fig. 6b. After edge detection process in ROI at night.

Fig. 6c. Road lane line prediction at night.

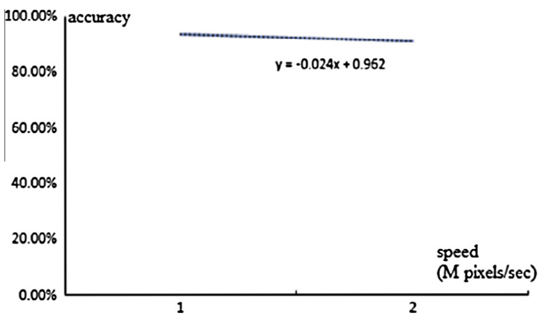

Fig. 7. The relation of accuracy versus speed.

Figs. 6a–6c depict the algorithm operated at night. The algorithm shows good performance at night.

The experiment detected 2620 frames. The accuracy rate reached 93.8%. The speed of the proposed algorithm is about 0.18 s/frame for frame size $640 * 480$. The speed was greatly improved with the same accuracy. The accuracy rate reached 91.4% for $320 * 240$. The speed is about 0.065 s/frame.

Fig. 7 shows the speed versus accuracy chart. As each frame size is different from different video sources. The speed is normalized to pixels per second, for example, frame size $640 * 480$ divided by 0.18 s/frame. The accuracy is relative to the resolution. The relation of accuracy versus speed is modeled as follows:

From the above equation, the correlation is weak between accuracy and speed. The proposed algorithm has great significance for real-time applications.

4. Conclusions

The paper presented a lane detection and lane departure method. High computational time is required by the conventional Hough transform owing to the trigonometric operations and multiplications. In order to meet real-time environment requirements the proposed lane detection algorithm uses a modified Hough Transform combined with a prediction algorithm to extract the lane. These experiments were run under the OpenCV environment.

These experiments showed that the proposed approach can easily locate the corresponding lane parameter space. Two thousand six hundred and twenty frames were accurately detected in these experiments. The accuracy rate reached 93.8%. The proposed algorithm speed is about 0.18 s/frame for $640 * 480$ frame size. The application processing speed was greatly improved while maintaining the same accuracy level. From the experimental results it is obvious that the proposed approach successfully provides real-time lane detection and departure prediction using a personal computer.

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