The Detection of Lanes and Obstacles in Real Time Using Optimal Moving Window

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Abstract: In this paper, a method to detect lanes and obstacles from the images captured by a CCD camera fitted in an automobile is proposed, and a new terminology "Moving Window" is defined. Processing the input dynamic images in real time can cause quite a few constraints in terms of hardware. In order to overcome these problems and detect lanes and obstacles in real time using the images, the optimal size of "Moving Window" is determined, based upon road conditions and automobile states.

The real time detection is made possible through the technique. For each image frame, the moving window is moved in a predicted direction, the accuracy of which is improved by the Kalman filter estimation. The feasibility of the proposed algorithm is demonstrated through the simulated experiments of freeway driving.

1. Introduction

Recently, several advanced countries are promoting the construction of Intelligent Traffic System(ITS), the aim of which is to provide traffic service forming a part of national welfare improvement[14]. Hereupon, Korea has established ITS Korea and has been putting spurs to the construction of ITS. Advanced Vehicle System(AVS), which is a part of ITS, is to maximize safety through the improvement of facility and manipulation behind the wheel and ultimately to introduce autonomous driving. It is working under different names , for example, AVCS(Advanced Vehicle Control System) in America, Prometheus in Europe, and ASV(Advanced Safety Vehicle) in Japan[1],[2],[4].

This paper has selected the following procedures to process image information. First, central moment is calculated after detecting the edge using the image within a moving window, whose pixels are distinguished by 256 gray levels. For the central moment, a curve fitting method is applied, considering the information at the previous point of time. The new central moment calculated after the application of a curve fitting method is called "Check Point" in this paper. Based upon this check point, the next position of the moving window can be estimated, using Kalman filter.

The aforementioned process of image information is based upon the moving window technique and the size of a moving window will be determined in this paper, considering the real conditions of road-design. The technique of adjusting the position of a moving window in real time according to a situation will also be addressed.

2. Image Processing

2.1. Edge detection

It is important to perceive a particular value of intensity as a lane among various input images. So information on roads is generally found in vertical elements in the images of driving environment, a vertical detecting mask can be used to find it. It is also possible to detect incorrect edge points, in case there is much noise in the image. To improve this, the expanded Prewitt 5× 5 Operator as (1) is used in this paper, considering more of neighbor pixels[13].

$$H_x = \frac{1}{10}\begin{bmatrix} 1 & 1 & 0 & -1 & -1 \\ 1 & 1 & 0 & -1 & -1 \\ 1 & 1 & 0 & -1 & -1 \\ 1 & 1 & 0 & -1 & -1 \\ 1 & 1 & 0 & -1 & -1 \end{bmatrix} \quad (1)$$

2.3. Optimal size of a sub-block

Consecutive input images have the size of 640× 480 pixel at every sampling time. It can cause the increase of unnecessary computation to apply preprocessing to total image in order to draw some necessary information. Therefore, the research on the decrease of computation time by designating a necessary part as a sub-block is being in progress[5-8].

- Size of a sub-block : When the conditions of road design are considered[3], the location of a lane in an input image can be represented by a curvature radius ***r*** and a gradient. When a vehicle is moving at the maximum admissible speed(max. speed : 100 [km/h]) among the road with has the curvature($690 \sim \infty$ [m]) and gradient($0 \sim 1.718$ [$^\circ$]) that allow maximum safety, the minimum size that does not lose the location of a lane can be designated as a sub-block.
- Size the necessary number, and the initial location of sub-blocks : According to the proposed conditions under which the size of a sub-block is determined, the size of subsequent sub-blocks distantly located from a moving vehicle will be determined. Besides, considering the actual distance(20 [m]) corresponding to the size of a sub-block, the number of subsequent sub-blocks needs to be minimized so that a vehicle moving at the maximum admissible speed(max. speed: 100 [km/h]) can detect the lanes and the obstacles that are located within the minimum safety distance(100 [m]) in front.

Before modelling a driving road, the coordinate system of constituents should be established. Any point in real world corresponds to a point in the image obtained through a CCD camera as shown in Fig. 1.

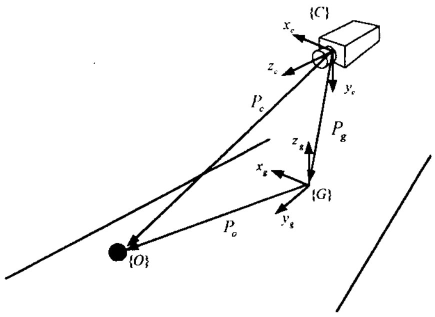


Fig. 1. Coordinate systems between a camera and a point in real world.

$$P_c = {}^cR_g P_o + P_g \tag{2}$$

Assuming that the camera is installed horizontally to the road, and directed to the front from the center of the road, we have ${}^cR_g = R(x, 90°)$, and. $P_G = [0 \quad d \quad 0]^T$

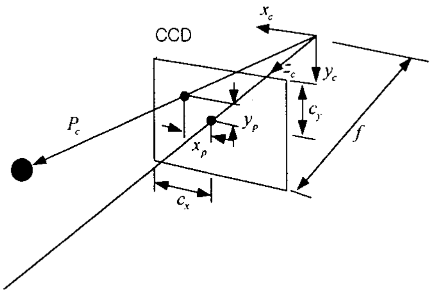


Fig. 2. Perspective model of camera.

Where f means a focal length of the camera, and (x_i, y_i) represents the pixel-coordinate of the image frame yields (3) and (4),

$$x_i = \frac{p_{cx}}{p_{cz}\delta x} f + c_x \tag{3}$$

$$y_i = \frac{p_{cy}}{p_{cz}\delta y} f + c_y \tag{4}$$

Where δx and δy represents the horizontal and vertical length of a CCD element respectively and (c_x, c_y) represents the coordinate of the central point in the CCD image frame. The actual length between the two bottom corners which do not appear in the input image can be computed as (5) and (6)

$$x_h = \frac{\omega_c y_h \delta x}{2f} = \frac{\omega_c \delta x p_{gz}}{h_c \delta y} = \frac{\omega_c \delta x}{h_c} d \ [m] \tag{5}$$

$$y_h = \frac{2f p_{gz}}{h_c \delta y} = \frac{2f}{h_c} d \ [m] \tag{6}$$

Where ω_c and h_c represents the number of the horizontal and vertical pixels in the input image respectively p_{gz} represents the height of the camera from the bottom, and δy is defined as unity to represent the standard size. Fig. 3 shows the modelling of a road into a circular arc to consider the shape of the curvature of a driving road.

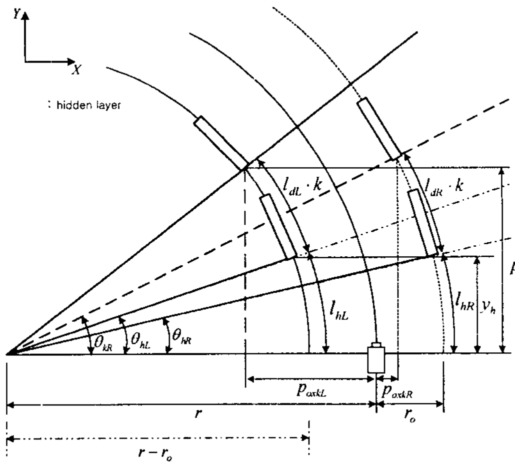


Fig. 3. Modelling of a road after considering the shape of a curvature.

For the right lane, the following two formulas can be derived.

$$\theta_{hR} = \sin^{-1} \frac{y_h}{r + r_o} \tag{7}$$

$$l_{hR} = (r + r_o)\theta_{hR} = (r + r_o)\sin^{-1} \frac{y_h}{r + r_o} \tag{8}$$

Using this, θ_{kR}, which is the arc angle of the kth right lane, can be denoted as follow :

$$\theta_{kR} = \frac{l_{hR} + l_{dR} \cdot k}{r} = r^{-1}\left\{(r + r_o)\sin^{-1}\left(\frac{y_h}{r + r_o}\right) + l_{dR} \cdot k\right\} \tag{9}$$

$$x_{ikR} = \frac{(r + r_o)\cos\theta_{kR} - r}{(r + r_o)\sin\theta_{kR}} \frac{f}{\delta x} + c_x \tag{10}$$

$$y_{ikR} = \frac{d}{(r + r_o)\sin\theta_{kR}} \frac{f}{\delta y} + c_y \tag{11}$$

Based on the above, the starting point of the kth lane appearing in the input image can be also determined as (12)

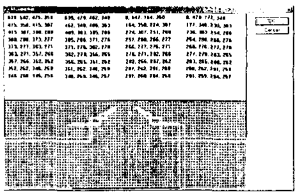
$$W_{pk}(r) = [x_{ik} \quad y_{ik}]^T \qquad 0 \le W_{pk}(r) \le M \tag{12}$$

When r becomes infinite from the minimum radius of rotation 690 [m] on a freeway in case of a rectilinear road, the maximum range of information on a lane being acquired inside a block is defined as the size of a sub-block It is shown in (13).

$$W_{pk}(r) = [x_{ik} \quad y_{ik}]^T \qquad 0 \le W_{pk}(r) \le M \tag{13}$$

The shape of the vertical curvature of a road influences the vertical length of a sub-block. The minimum length of convex curvature per 100 [km/h] corresponds to the gradient of 3 [%]. Therefore, the quantity of change $\delta\theta = \tan^{-1} 0.03 = 1.718[°]$ changes P_{ozk} into $P_{ozk} = P_{oyk} \sin\delta\theta$ It has little effect on the size of a sub-block in (13), so it can be ignored.

The size of a defined sub-block is as Fig. 4 and Fig. 5 where $f = 0.024\,[m]$, $d = 1.2\,[m]$, $\delta x = 8.577 \times 10^{-6}\,[m]$, $\delta y = 8.316 \times 10^{-6}\,[m]$, $l_d = 20\,[m]$, $cx = 320$, and $cy = 240$.



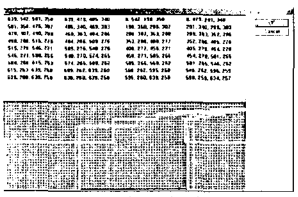


Fig. 4. Simulation for a rectilinear road

Fig. 5. Simulation for a curved road.

3. Recognition of a lane via Moving Window

After detecting lanes, based on the information which has been acquired so far, Section Ⅲ will deal with how to move the position of a sub-block to improve the accuracy of lane detection at the next instance of time. The technique will be defined as "Moving Window" in this paper.

3.2. Central moment and Check point

The central moment for the edge of the lane area in Fig. 6 can be marked as Fig. 7.

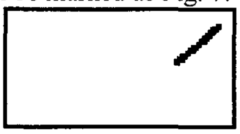


Fig. 6. Input image.

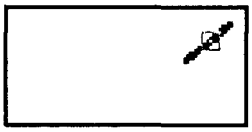


Fig. 7. Central moment.

The detected central moment can be moved to a certain position along the Y-axis as shown in Fig. 8 with the aid of the curve fitting method which will be explained in the next section. The moved central moment is renamed as "Check point" in this paper.

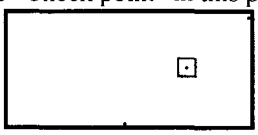


Fig. 8. Measurement value.

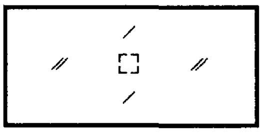


Fig. 9. Predicted value.

3. Lane detection via Moving Window

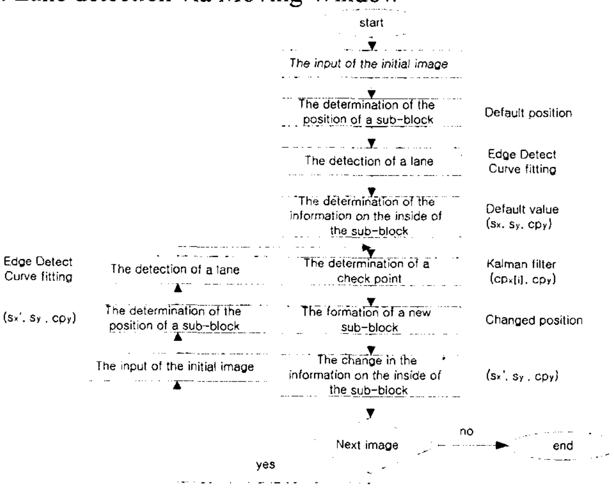


Fig. 10. Flowchart of the moving window technique.

The whole procedure, the lane constituents are detected through Prewitt Mask, a check point is determined through operations, moving windows are determined to detect lanes and obstacles, and based on these, the new position of a sub-block (that is a moving window) is determined using Kalman filter, can be shown in a flowchart as Fig. 10.

3.3. The estimate of the position of a moving window via Kalman filter

In order to designate the specified part of the image at the next instance of time (k+1) as a searching area, the moving window method is necessary to determine the position of searching area. The present position of a moving window (k) can be estimated, based upon the information on the check point of the previous one (k-1) that is obtained by the aforementioned preprocessing and curve fitting, and the error between the estimated and the measured will be compensated via Kalman filter[10-12].

First, in the estimation step, when the estimate of the state at the present instance (k) is defined as x_k^-, based upon the actual estimate at the previous point of time (k-1), x_k^- can be denoted as (14)[10]. A system matrix F, is defined as the following (15) where the kinetic equation of a vehicle. Δ_t means the measurement time of the check point.

$$x_k^- = F x_{k-1}^+ + \omega_{k-1} \tag{14}$$

$$F = \begin{pmatrix} 1 & \Delta_t \\ 0 & 1 \end{pmatrix} \tag{15}$$

Where ω_{k-1} means noise from the system model and it is assumed to be Gaussian noise. If its covariance matrix is denoted as Q_{k-1}, the covariance matrix for the estimated can be described as (16).

$$P_k^- = P_{k-1}^+ + Q_{k-1} \tag{16}$$

In the measurement step, the measurement vector y_k is denoted as (17) and v_{k-1} is the measurement error caused by the Gaussian noise with zero mean.

$$y_k^- = H x_{k-1} + v_{k-1} \tag{17}$$

v_{k-1} is uncorrelated with ω_{k-1} in the estimation step and its covariance matrix is R_{k-1} in the measurement step. Since the image itself does not show the change of distance per image frame, the measurement matrix can be represented as (18).

$$H = [1 \quad 0] \tag{18}$$

The recursive Kalman filter to compensate the state vector by adding measurement deviation to the estimated can be described as follow :

$$x_k^+ = x_k^- + G_k (y_k - H x_k^-) \tag{19}$$

4. Detection of obstacles via moving window

Up to now, the focus has been on the accurate and rapid detection of a lane by the moving window method. In this section, the detection of the obstacle ahead of a moving vehicle will be addressed.

4.1 Detection of a middle line and the area for obstacles

The middle line of a lane can be determined when a vehicle moves within the right line and the left line, and it has the information on the moving direction of a vehicle. When the position of a right line and a left line is denoted as $F_L(y)$, $F_R(y)$, the middle line can be calculated as (20).

$$F_M(y) = F_R(y) - F_L(y) \tag{20}$$

The intensity of a middle line is $f_M(x,y)$ within 0 to 256 representing gray level. An obstacle ahead of the vehicle (the obstacle here is actually another vehicle) has the characteristics of horizontal constituents such as a rear bumper and a trunk. So if an edge gradient is detected in the horizontal direction, the expected obstacle can be characterized. Using $f_{MB}(x,y)$ that is the binary horizontal edge, the estimated area of the obstacle, that is $f_{Ob}(x,y)$, can be extracted.

The estimated area of the obstacle starts from the bottom line of the obstacle(Ob1) in Fig. 11, and the right bottom(Right1) and the left bottom(Left1) are determined by taking 60 [%] of the lane width, which is the average of the vehicle width. In order to distinguish between a vehicle and a road mark, the right top(Right2) and the left top(Left2) are determined by taking 50 [%] of the bottom width. Therefore, the scope for the obstacle recognition can be limited to the inside of a driving lane and Fig. 12 shows the designation of the detection area, using the suggested method.

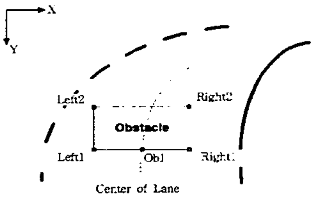


Fig. 11. Area for obstacle detection.

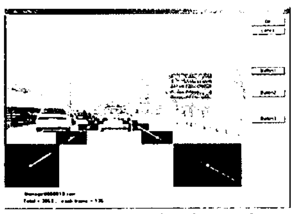


Fig. 12. Obstacle detection by the proposed method.

To distinguish the image inside the expected obstacle area (n×m), the gray level in the area is normalized as follows :

$$S_i = \sum_{j=1}^{m} f_B(x_i, y_j) \tag{21}$$

$$Histo_i = \frac{S_i}{\sup \| S_i \|} Res_d$$

Where Res_i represents the normalized gray level at (x_i, y_i), i=1 to n and Res_d is a predetermined value 50 for the normalized estimated area for obstacle detection using the proposed method can is represented in Fig. 13.

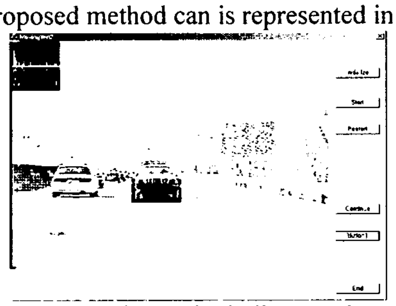


Fig. 13. Input image including an obstacle.

5. Experiment

In this section, the environment for the experiment will be described and the excellence of the moving window technique in the aspect of computation speed and accuracy will be demonstrated, compared with the other cases without this technique. Besides, it will be also shown that the real time process is possible if the proposed method is employed.

5.1. Experimental environment

To acquire an image from a real vehicle, a camcorder was fixed to the inside of a vehicle at the height of 1.1 [m] from the ground as shown in Fig. 14. The height is about the same as that of driver's eyes. After that, various conditions on the road was recorded to be used.

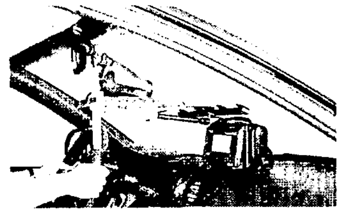


Fig. 14. The position of camera.

The driving speed was maintained at 100 [km/h], which is the standard speed of this experiment. And was continuously updated with new images.

5.2. Result

The following Fig. 15 shows the detection of a lane and the result of Kalman filtering by using the change in the X-axis's coordinate of the nearest moving window to the vehicle. The vehicle is moving from the rectilinear road to the curved road. Based upon the detected position of the lane, the proceeding direction of the vehicle is shown in Fig. 16.

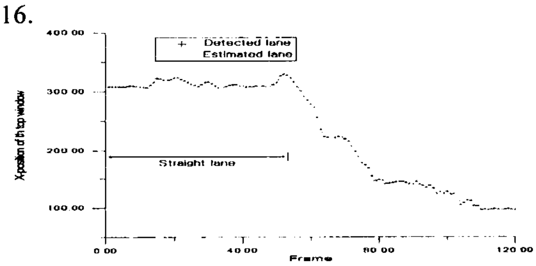


Fig. 15. The direction of the lane position by Moving Window and the result of Kalman filtering.

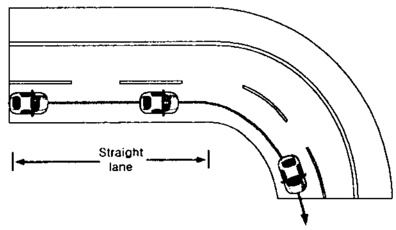


Fig. 16. The driving direction of the vehicle.

When the computation is performed on Pentium Ⅱ-450 with the total 120 frames like Fig. 15, the average processing time of each frame is approximately 95 [ms]. The processing time can be further reduced by using a batter PC.

When the size of a moving window is adjusted by

± 15 [%] in the same condition as Fig. 15, the detected position of a lane is shown in Fig. 17. The detected position in Fig. 17 does not show a big difference for the rectilinear road compared to the previous experiment, as long as the initial positions of the two moving windows are the same. However, when the vehicle enters the curved road, a big error occurs in the detected position of a lane. That is, in case of a smaller moving window, information is deficient due to the empty space between the lanes, and in case of a bigger moving window, the interference of the vehicles and the noise from the next lane decreases accuracy in detecting lanes. The proceeding direction of the vehicle based upon the position of the lane detected by the adjusted moving windows is shown in Fig. 18 and we can see that the vehicle deviates from the driving lane.

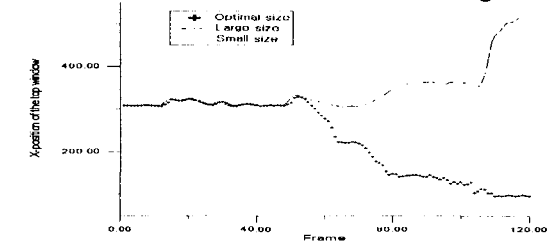


Fig. 17. The detection of the lane by different sizes of the moving window.

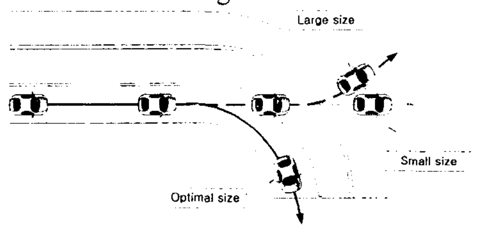


Fig. 18. The driving direction of the vehicle.

6. Conclusion

In this paper, the technique of selecting sub-blocks and optimizing the size was proposed. This new moving window technique showed excellence of detecting lanes and obstacle according to the road design conditions. The proposed size of a moving window was big enough to include some part of a lane at any time, considering the maximum admissible speed of a vehicle and the change of road conditions for maximum safety. Besides, the number of moving windows was minimized so that the area within maximum safety distance could be detected. The optimal size of a moving window at the present instance moved to the estimated position at the next instance through curve fitting and Kalman filtering. Moreover, when the proceeding direction was determined, fitting the detected information on lanes, the unexpected loss of information caused by external environment was resolved by extra-polating the information of the previous instance. Therefore, this method is valid, in case that input images disappear temporarily because of CCD's delayed response in the shadow below an overpass or inside a tunnel. By locating the middle line of the detected lane and searching obstacles, the front vehicles were considered as obstacles. This method is especially proper for the Korean freeways, the road shape of which changes frequently. It is also applicable to AGV(Autonomous Guided Vehicle), which moves slowly following land marks in various industrial fields.

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