고안전도 차량을 위한 자율주행 시스템

Autonomous Driving System for Advanced Safety Vehicle

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요약

본 연구는 고안전도 차량의 자율주행을 위해 필수적인 장애물 차량 탐지를 위한 시스템 개발에 관한 것이다. 먼저 칼만필터를 이용해 차량에 부착된 CCD 카메라에 의해서 획득한 전방 영상으로부터 주행차선의 경계를 탐지한다. 그리고 탐지된 경계의 회귀분석을 통해 차선을 인식한다. 다음으로 주행 방향을 인식하기 위해 탐지된 차선내의 도로 굴곡 파라미터를 오류 역전파 알고리즘의 입력값으로 사용한다. 마지막으로 전방과 측방에 탐지영역을 설정함으로써 탐지영역으로 들어오는 장애물 차량을 탐지할 수 있다. 제안한 방법으로 실험한 결과 주행방향 인식과 장애물 차량의 인식 모두 90% 이상의 높은 정확도를 보였다.

■ 중심어 : | 차선인식 | 오류 역전파 알고리즘 | 장애물 차량 탐지 | 칼만필터 | 지도학습 |

Abstract

This paper is concerned with development of system to detect an obstructive vehicle which is an essential prerequisite for autonomous driving system of ASV(Advanced Safety Vehicle). First, the boundary of driving lanes is detected by a Kalman filter through the front image obtained by a CCD camera. Then, lanes are recognized by regression analysis of the detected boundary. Second, parameters of road curvature within the detected lane are used as input in error-BP algorithm to recognize the driving direction. Finally, an obstructive vehicle that enters into the detection region can be detected through setting detection fields of the front and lateral side. The experimental results showed that the proposed system has high accuracy more than 90% in the recognition rate of driving direction and the detection rate of an obstructive vehicle.

■ keyword : | Lane Recognition | Error-BP | Obstructive Vehicle Detection | Kalman Filter | Supervised Learning |

I. Introduction

The vehicle with a system which guarantees safe driving is called an intelligent vehicle. The main purpose of the present phase of intelligent vehicles is to actualize ASV(Advanced Safety Vehicle). One of the main functions of ASV is to recognize lanes and detect objects in front and lateral. Sensors and

* This work was supported by the Brain Korea 21 Project in 2006.

접수번호 : #070110-003
접수일자 : 2007년 01월 10일
심사완료일 : 2007년 02월 05일
교신저자 : 장동식, e-mail : jang@korea.ac.kr

detection methods are changed according to the condition of obstacles or lanes. A main obstacle while driving in the daytime and nighttime is vehicles. As this causes the majority of car accidents, many studies concerning a method which can prevent an accident are actively performing. Mathematical Morphology[1], Hough Transform[2], Snake[3] and using the connection information of Edge[4] are used for the study on lane recognition which is the most important to set up the detection region of vehicles. These methods can adapt well to a change in the weather, the circumstance of road and the brightness of light. But due to the complication and long process time of these methods, a high-priced hardware is needed to deal with them in real time. Furthermore it should be considered that the lanes can be hid by other cars. To complement these problems, the system for recognition of driving direction and vehicle detection is developed using a Kalman filter and error-BP. The overall diagram is shown in [Fig. 1].

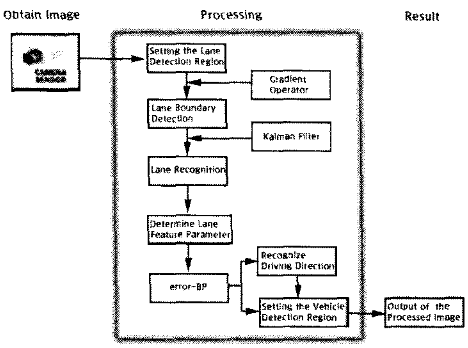

Fig. 1. The Overall Diagram

First, set up the CCD camera in the vehicle to observe the front and lateral side. A Kalman filter is used to detect lanes, after obtaining images from the CCD camera while driving. From the detected lanes, driving direction can be recognized by error-BP. According to the driving direction, the vehicle detection regions are set up for the front and lateral side and obstructive vehicles are detected.

II. Lane Detection

Recognition of the road lane while driving is a preceding phase to recognize driving direction and vehicles in front. After the lane detection regions are set up, the left and right lanes can be extracted by the identifier of lane detection. Lanes can be extracted accurately by a Kalman filter and middle distance lanes also can be extracted by statistic models and Hough conversion at the extension of the lane. Driving direction is determined by vanishing points which are existing in a long distance region of the driving lane.

1. Determination of Lane Detection Region

A CCD camera is set up in the vehicle to obtain an image of driving direction. From the obtained images, the lane markings are extracted. The lane markings can be of solid or intermittent lines. Thus, it should be considered that the solid line can exist on only one side of the lane and the intermittent line can exist on both sides of the lane. As a result, the lane detection region is selected first to detect lanes in every case. we use six lane marking points of the left and right lane on the coordinate of an image for the fast processing time and lane detection region. The location of six marking points is determined through the experiment. It is shown in [Fig. 2].

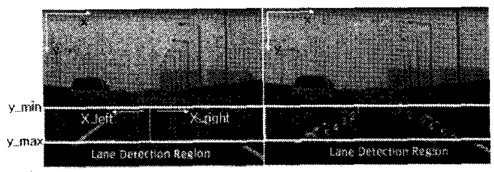

Fig. 2. Setting up the Lane Detection Region

2. An Operator for Lane Boundary Detection

For recognition of driving lane, the only vertical edge detection mask of Sobel operators is used. As a result, the processing time for edge detection is reduced. The gradient operator which has 3×3 size is shown in equation (1). $f(i,j)$ is defined as gray-level value of each pixel, i, j, coordinates of x-axis and y-axis in an image.

$$\triangle_x f(i,j) = [f(i-1,j-1)+2f(i-1,j)+f(i-1,j+1)] - [f(i+1,j-1)+2f(i+1,j)+f(i+1,j+1)] \quad (1)$$

$\triangle_x f(i,j)$ is the variation of pixel value in the direction of the x-axis. If this variation is greater than threshold value, the location is discriminated as a provisional lane. Using the static threshold value can cause the loss of information due to the change in light. Thus, the dynamic threshold value is applied to an input image. In case of intermittent lines, first the lane edge is roughly detected using the gradient operator. Then every left and right lane edge is detected. Second, the twenty-four sub-windows which have 1×3 [pixel] size are set up. Third, the sub-windows are located in each lane detection region, R Pixel and L Pixel. The procedure for the left lane edge is as follows:

Step1. Move the sub-window in the direction of left within the first detection region using the gradient operator.

Step2. If the sub-window in the detection region satisfy the next threshold value then recognize edge detection of the region, otherwise move the next step after temporarily determining the initial driving lane as much as the driving lane width.

Step3. Move the sub-window in the direction of y-axis within the second detection region, and go to Step1.

An other side of edge can be recognized by the similar method above.

3. Detection of Lane Edge using a Kalman filter

When lanes are detected using the gradient operator, an error can occur. Thus, the procedures for revision are needed. In this paper, a Kalman filter, recursive computational solution is used to detect a signal from noise so that a system can predict a change according to the time. It tracks the time-dependent state vector that has noisy and equation of motion in real time. So, the lane boundary location of an image can be predicted at $k+1$ from $k-1$, determined points and k, a present point. In other words, the location of k is predicted by information of the location at $k-1$ point. An one-dimensional Kalman filter is used to revise an error between the predicted value and the actual value[5]. In addition to these facts, the lane boundary location of an indefinite image at $k+1$ point can be also detected by approximating the information of lane boundary location at $k-1$ point.

3.1 Estimation

First, assume that x_k^- is a prediction at k point based on the actual measurement at $k-1$ point. x_k^-, State vector, is defined as follows:

$$\hat{x}_k^- = F\hat{x}_{k-1}^+ + w_{k-1} \quad (2)$$

F is a conversion factor. w_{k-1} is white noise which means Gaussian noise. Q_{k-1} is dispersion. (-) indicates that revision through measurement has not been done. Covariance of the state estimate error is defined as follows:

$$P_k^- = E[(x_{k-1} - \hat{x}_{k-1})^2] \quad (3)$$

$$P_k^- = P_{k-1}^+ + Q_{k-1} \quad (4)$$

3.2 Measurement

A measurement vector, y_k is shown in equation (5). v_{k-1} is a measurement error and assume that v_{k-1} is not correlated with w_{k-1} at the estimate stage. y_k is Gaussian noise whose average is zero and R_{k-1} is its dispersion. H is an observed value representing the relation between state vector and measured vector.

$$y_k^- = Hx_{k-1} + v_{k-1} \quad (5)$$

3.3 Revision

The state estimate errors are revised as equation (6)and(7) to revise state vector by adding observed deviation to the estimated value.

$$x_k^+ = x_k^- + G_k(y_k - Hx_k^-) \quad (6)$$

$$P_k^+ = P_k^- - G_k H P_k^- \quad (7)$$

$$G_k = P_k^- H[H^2 P_k^- + R_k]^{-1} \quad (8)$$

Equation (8) represents Kalman Gain, G_k which adjusts state vector by giving adequate weight between estimated value and measured value. State estimate of the next point in regard to revised state vector is as follows:

$$x_{k+1}^- = Fx_k^+ + w_k \quad (9)$$

A Kalman filter is made by x_0^-, initial information including error estimates, an initial value and covariance of a measurement error and P_0^-, initial covariance. Therefore, the measured value of G_k is revised by initial value, and the accuracy for the next state estimate is improved because G_k is adjusted for every repetition in regard to observed deviation.

4. Lane Detection

Once the lane boundary location is determined by a Kalman filter, the driving lane should be detected. The lane detection process is essential to discriminate whether the points obtained by lane boundary can detect lanes. In this paper, a least square method in simple linear regression methods is used to recognize lanes. Actual lanes have a linear form in detected regions. These points can be used as a scatter diagram in a statistic model and these are defined from the coordinates, x_i and y_i of each point, n as equation (10). In equation (10), $e_1, e_2, \ldots e_n$ are independent each other and an unknown error term and unmeasurable random variables. This term follows the normal distribution $N(0, \sigma^2)$. α, β in equation (14) can be estimated by the least square method. R in equation (15) is the square value of the error and $(y_i - \overline{\alpha} - \overline{\beta} x_i)$ is residual. If this residual become less and less, $\hat{y} = \hat{\alpha} + \overline{\beta} x$ in equation (15) would represents a linear equation, $y = \alpha + \beta x$. This indicates that there is close linear relation between x and y.

$$y_i = \alpha + \beta x_i + e_i \quad i = 1, 2, 3, \ldots., n \quad (10)$$

$$\overline{x} = \frac{1}{n}\sum x_i, \ \overline{y} = \frac{1}{n}\sum y_i \quad (11)$$

$$S_x^2 = \sum (x_i - \overline{x})^2, \ S_y^2 = \sum (y_i - \overline{y})^2 \quad (12)$$

$$S_{xy} = \sum (x_i - \overline{x})(y_i - \overline{y}) \quad (13)$$

$$\hat{\alpha} = \hat{y} - \hat{\beta}\hat{x}, \ \hat{\beta} = \frac{S_{xy}}{S_x^2}, \ \hat{y} = \hat{\alpha} + \hat{\beta} x \quad (14)$$

$$R = S_y^2 - \overline{\beta}^2 S_x^2 = (y_i - \overline{\alpha} - \overline{\beta} x_i)^2 \quad (15)$$

If the coordinates in each left and right direction concerning scatter diagram are given, two linear regressions that come under the left and right lane would be obtained. The large number of coordinates whose residual value is small indicates that there are many points which are close to a line. Thus we judged that if detected coordinates satisfy the threshold value more than 75%, a lane is detected. Unless the detected coordinates satisfy the condition, the present lane value would be maintained until satisfying the condition.

III. Recognition of Driving Direction

To detect the left and right vehicles, this study proposes a method that can recognize the rotation direction of driving lane and adjusts the detection region. When driving along the curved road, sight of the left and right detection region is restricted. Therefore, a variable detection window is needed according to each road. To actualize this function, at first, a typical image and detect feature parameters which are associated with rotation features of driving lane should be sampled. Then the correlation between feature parameters and actual lane patterns is statistically analyzed. For the experiment, error-BP algorithm which has input layers, feature parameters and output layers is used to estimate the pattern of lane curvature.

1. Definition of Lane Feature Parameters

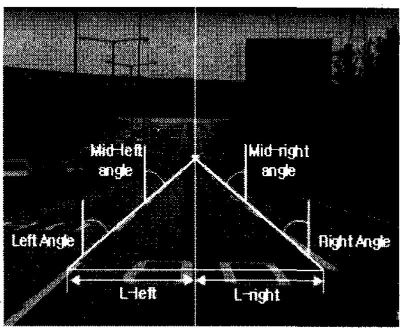

Fig. 3. Definition of Lane Feature Parameters

This is to recognize driving direction by inputting the lane feature which is at a short and middle distance into the error-BP algorithm. [Fig. 3] shows the feature parameters of the lane at a short and middle distance[6]. L-left, L-right are the location of the left and right lane at a short distance. Left angle, Right angle are the left and right slope, and Mid-left angle, Mid-right angle are the left and right slope at a middle distance. The slope of the left and right lane has correlation with the lane curvature as shown in the [Fig. 3]. For example, in case of a straight lane, the slope of the left and right lane is same. But in case of right turn or left turn, each left or right slope would be decreased. Besides, when a vehicle is not in the center of the lane, the left and right slope would be different. After all, information of the lane curvature can not be obtained correctly with the only slope, because the slope is influenced by not only the lane curvature but the location of vehicle. To correct a change in the slope according to the location of vehicle, L-left, L-right are used together. Detecting a change in the lane curvature with only Left angle and Right angle is also difficult. Thus, Mid-left angle and Mid-right angle are used together. The middle-distance information has a little amount of information compared to the short-distance information. While it is more sensitive to the change in the lane curvature.

2. Evaluating correlation between the feature parameter and the lane curvature

To detect the feature parameters which are input of the error-BP algorithm, images are divided into the straight, left turn and right turn images. The left and right location of lanes and the left and right slope of lanes at a middle distance are obtained from 878 frames of the straight road, 440 frames of the left turn road and 316 frames of the right turn road. The slope is normalized between the section, 0 and 1, and the left and right location of the lane is represented as pixel. The 30 representative parameters are sampled by each road. [Table 1] shows each correlation coefficient according to the classification.

Table 1. Correlation coefficient of lane parameters

Classification	Correlation Coefficient
left and right location of a lane at a short distance	-0.874
left and right slope of a lane at a short distance	-0.231
left and right slope of a lane at a middle distance	-0.941

The validity of parameters defined above can be verified through [Table 1] which indicates that the lane location at the short-distance and the lane slope at middle-distance have more correlation than the lane slope at the short-distance.

3. error-BP algorithm

Error-BP algorithm is shown in [Fig. 4]. error-BP which has the organization of second layer including an input layer can not be applied to the problem that can not be linearly separated. Thus, error-BP which has the organization of third layer is constituted to solve it. The number of nodes in the input layer is the six feature parameters, and the number of nodes in the output layer is three. left turn, straight and right turn. Learning information which is input information of error-BP uses the feature parameter. The learning information is extracted from the frames obtained by images of each road. error-BP algorithm is used for learning, and an error concerning the learning result was 0.0278. It took approximately 10 minutes for learning with a pentium IV 1.8 Ghz computer.

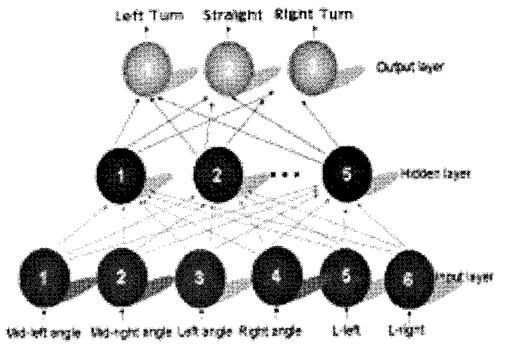

Fig. 4. error-BP algorithm using feature parameters

Ⅳ. Vehicle Detection Algorithm based on error-BP Algorithm

The variable detection region is selected by the error-BP algorithm and the recognition of driving road. Through the vehicle detection in the selected region, the obstructive vehicles can be detected which are the cause of the front and lateral accident.

1. Determination of detection region for the front and lateral vehicle according to road conditions

When driving along the straight road, the front vehicle can be detected by setting up the front detection region. But, in case of right turn, the lateral vehicle can be detected as the front vehicle. Therefore, the detection region is partially changed to prevent the error. Through the error-BP algorithm, the front detection region recognized as a curved road is reduced and the detection region at a middle distance is converted into the detection region at a short distance. As a result, when vehicles pass through the curved road, the detection error is decreased with reducing the range of detection. This method can equally apply to the left turn road.

2. Detection of the front and lateral vehicle

If the detection region is selected as described before, it will be determined whether a vehicle is in the detection region. The previous method for the front or rear detection used a Sobel mask operator to detect the boundary between the wheel and road. This method makes it possible to detect the edge region using the difference of brightness between the wheel and road. But, at the phase to verify the wheel, the method uses a special feature that the wheels symmetrically exist. Thus, this method is not appropriate for the curved road. Consequently, we propose a method that detects the vehicle region with considering the one side wheel and the shadow around the vehicle. A big difference according to whether the vehicle exists is the change in gray nuance. This value is less than 80. If the vehicle exists in the detection region, many values which are less than the threshold value would occur by the influence of the shadow or wheel. In addition, the vehicle's color is also an important factor. So, a method that can verify the nuance made by vehicles is needed[7]. In this paper, whether the vehicle exists is judged by considering the fact that the dark points of the wheel exist above and below. $f(i,j)$ is gray-level of pixel whose coordinates of x-axis and y-axis in an image are $f(i,j)$. If all the values of $f(i,j-3)$, $f(i,j)$, $f(i-3,j)$ and $f(i,j+3)$ are less than 80 and the brightness difference of $f(i-3,j)$ and $f(i,j-3)$ is less than 2, this region is selected as a nuance candidate region. If the points are selected as nuance candidate regions within the front, left and right detection region occurs. Consequently, we judge that a vehicle exists in the detection region. It is shown in [Fig. 5].

Fig. 5. Selection of nuance candidate regions

V. Experiment and Result

The images used in the experiment are obtained by the CCD camera located in the vehicle and the experiment is performed for half an hour from 5:00 pm at expressway between SuSeo & BunDang. All experiments were computed on a Pentium IV 1.8 Ghz computer with a CCD camera, a camcorder and an image processing board. A model VQ29B-B36 CCD camera and a model VM-A630 8mm camcorder are used. The focal distance of the CCD camera is 3.6mm. We received the NTSC signal from the camcorder using the image processing board, MyVision made by microrobot. The experiment is performed with the image whose size is 320X240 in Visual C++. The proposed system takes 30 to 35 ms to process each frame.. A CCD camera is connected with a camcorder to verify an input image, and the location of the CCD camera is adjusted while verifying the front road image. However, due to the feature of the mono image, an error can occur at a slant road. Thus, it is assumed that the road of the input image is horizontal. To recognize the curved road, first of all, after dealing with the lane detection algorithm in an input image, the feature parameters that are associated with the curved road should be extracted. Consequently, the curved road can be recognized by the learning of error-BP. An error that recognizes a lateral vehicle at the curved road as a front vehicle is reduced by changeably applying the vehicle detection region according to the curved road. [Fig 6] shows the windows experiment environment for image processing.

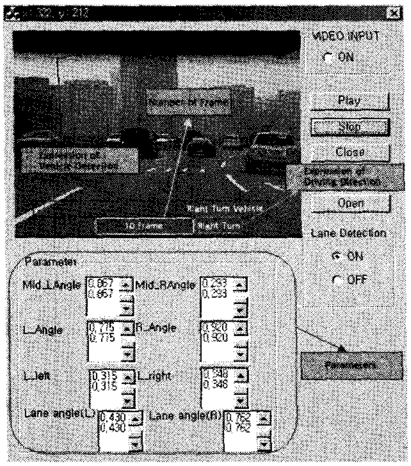

Fig. 6. A window experiment for image processing

1. Recognition results of the lane curvature

After feature parameters are extracted from the lane, the recognition rate is examined according to the lane curvature. [Table 2] shows the recognition rate for each curved road from total 4612 frames of the driving image.

Table 2. Recognition results for each road

Result / Road shape	Recognized as left turn		Recognized as straight		Recognized as right turn		Total frame
	Frame number	Rate	Frame number	Rate	Frame number	Rate	
Left turn road	800	96.9 %	26	3.1 %	0	0 %	826
Straight road	129	4.4 %	2786	94.7 %	26	0.9 %	2941
Right turn road	4	0.7 %	28	3.0 %	822	96.3 %	854

The recognition rate for each road using the error-BP and lane trend was greater than 95%. The remarkable fact is that a serious error has not occurred.

2. Detection results of Obstructive Vehicle

[Table 3] shows the detection results according to the road conditions using the proposed method which detects obstructive vehicles to the front, left and right side under the driving direction recognition. To detect dangerous vehicles, a changeable detection region is used. The vehicles that enter the dangerous region ahead of 10-15m were detected. We could deal with the vehicle which enters the straight, left and right region. The average time was 70 ms for each frame. Therefore, it is possible to deal with in real time.

Table 3. Detection results of Obstructive Vehicle (Vehicles entered at 3307 frames out of 4621 frames)

Classification	Detection (frame)	Error (frame)	Accuracy (%)
Left turn vehicle	1264	61	95.2
Straight vehicle	852	92	89.2
Right turn vehicle	987	51	94.8

The wrong recognition and noise from the point ahead of 10-15m were defined as an error. In Table 3, the detection rate of the straight vehicle was relatively low due to the indefinite selection of detection regions and the slope in the downhill and uphill road. Shake of an input image by vehicle's vibration also influenced on many parts of the error.

Ⅵ. Conclusion

This paper proposes an algorithm and a system using computer vision to prevent a car accident by front, rear and lateral collision. The contribution of this research is in developing the system that is faster and more accurate in detecting an obstructive vehicle than other system proposed previously[8]. The accuracy rate for the road recognition was greater than 90% and an error-BP algorithm was used to recognize the straight and curved road. Besides, the vehicle detection in real time was possible by applying a changeable detection window according to each road section. Previous systems using a laser sensor or supersonic are too expansive and sensitive to the surrounding environment. Therefore, an image sensor is more useful for vehicle detection in restricted regions. The system we developed shows high reliability in the daytime under the general road conditions. However, the system could not be applied to the three cases below.

1. At nighttime
2. Severely damaged lane
3. No lane on the road

The malfunction can also occur when the vehicle doesn't drive in the center of driving lane. Thus, we should consider the design character which is appropriate for road conditions in our country to recognize the accurate curvature direction. Hereafter, a further study on the front driving algorithm is needed for an unmanned car which can recognize driving direction and objects without lanes on the paved or unpaved road.

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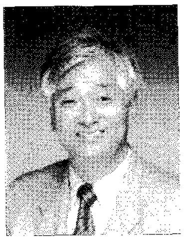

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