Detection of Lane Curve Direction by using Image Processing Based on Neural Network and Feature Extraction

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Lane detection plays a vital role in the research of CWS (Collision Warning System), which is based on the radar system that detects positions and velocities of vehicles over the detectable range. In CWS, the first target of warning is the vehicle in the same lane as the vehicle with CWS. Lane detection is required to distinguish this vehicle among whole vehicles detected by radar. It is especially necessary in the curved lane, because the radar beam crosses over the other lanes. For this purpose, the machine vision technique is considered a powerful method. In this article, the image-processing algorithm for recognizing the lane curve direction, before locating the lane, is proposed. By using near and middle field lane image, it can recognize the lane curve direction in the far field which contains imperfections. In this algorithm, lane features like positions and angles of lane marks in the image frame are extracted first. Then, using the neural network of inputs from lane features, the lane curve direction is determined. Test results for 2,000 frames of real road images showed a success recognition rate of over 90%.

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Introduction

For safe and efficient driving operations, research in driver-supporting systems has received more and more attention worldwide in recent years. Especially, significant developments have been made in improving vehicle intelligence with research in CWS (Collision Warning System), CAS (Collision Avoidance System), and CCS (Cruise Control System). Vision-based lane detection plays a vital role in these systems. For example, CWS is based on the measurement of range and velocity of a vehicle running directly in front of my own vehicle, using radar to predict the possibility of collision. However, radar may detect vehicles in the other lanes due to the diffraction of radar beam. In most mm-wave radar's developed for automobiles, the detectable range covers three lanes at long distances of up to 100 m.[1–3] Sometimes, it may detect the road indicators or guide-rail as another target for warning, and this leads the system to miss warnings or make fault warning. In curved lanes, this situation can be serious. Therefore, CWS must be able to detect lanes, even curved lanes, in order to distinguish the most important target vehicle, the one running in the same lane as my own vehicle, from multi targets detected by radar.

Generally, lane detection systems make errors when the images contained changes in illumination due to shadows, glare or darkness, and obstructions by other vehicles, rain, snow, salt or other foreign objects. Especially, the detection performance of these systems is known to deteriorate at night and in harsh weather. In response to this problem, the evaluation of lane marking detection under poor visibility has been reported.[4] This research specified candidate technologies for lane markings, image sensors and headlamps of the next generation lane marking system, and performed experiments on systems that utilize those technologies.

The most common method of lane detection systems are all edge-based. These systems rely on tracking specific features, such as lane markings, from one image to the next and thresholding the image intensity to detect potential lane edges.[5–7] Others depend on detecting regions of the image representing the road based on features such as color or texture.[8,9] The LANELOK system[10] developed at General Motors relies on strong road models. It estimates the location of lane boundaries with a curve fitting method, using a quadratic equation model. Carnegie-Mellon University developed ALVINN[11] based on neural networks and RALPH[12] based on image pro-

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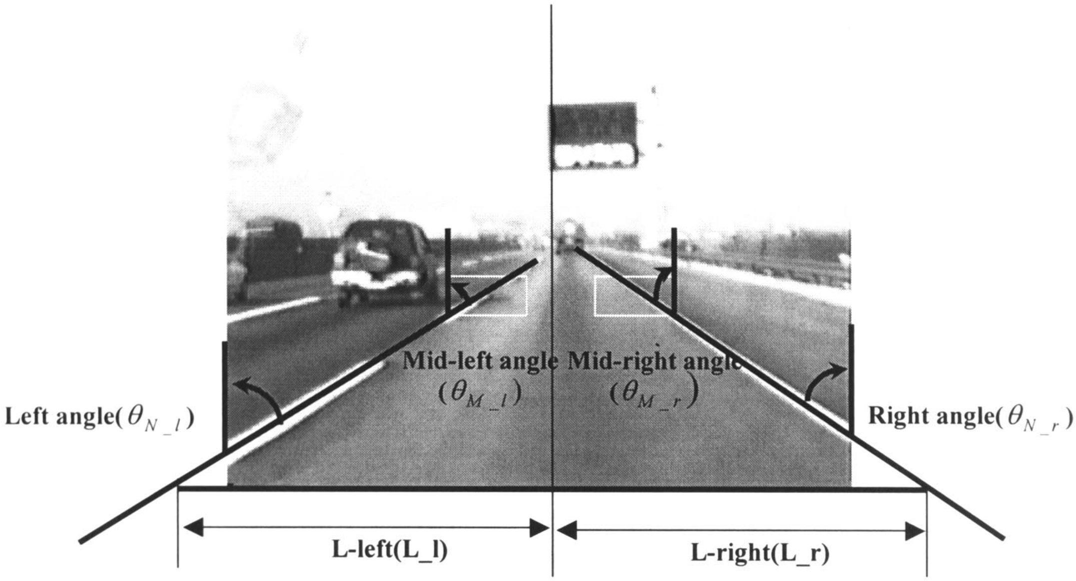


Figure 1. Lane feature parameters in the near field and the middle field lane

cessing. ALVINN employs an artificial neural network that learns the characteristic features of particular roads under specific conditions. The crux of RALPH is a matching technique that adaptively adjusts and aligns a template to the averaged scanline intensity profile in order to determine the lane's curvature and lateral offsets. ARCADE[13] uses global road shape constraints derived from an explicit model of how the features defining a road appear in the image plane. Among these systems, edge-based lane detection systems are insufficient, when used in images containing extraneous edges or at night and in harsh weather. Therefore, the latest systems work directly with the image intensity array and use a global model of lane shape. Because of the dependency of the model, however, when the accuracy of the model deteriorates, these systems have performance degradation. In addition, many of these systems have been subjected to several hours of testing, which involved the processing of extremely large and varied data sets. To detect lane curve, this previous research has placed major interest on the use of total lane shape, but not so much on the contribution of partial lane section.

In this article, an image processing algorithm that recognizes the lane curve direction containing imperfections in the far field is considered by using the near and middle field lane image. The detection algorithm of lane curve direction is considered the first step for the development of a total system including curvature detection or lane location in the real road coordinates. For the applicability to real road, our algorithm was designed to satisfy the following requirements: first, the curved lane should be recognized as well as the straight lane and second, the processing time should be enough short. Finally, it must work even in cases with unfavorable environmental conditions like partial loss of lane marks, lack of illumination or occlusion by the forward vehicle, etc.

In the proposed algorithm, the image frame is divided into three sections along the distance from the camera: the near, middle and far fields. The near field corresponds to the range between 10 m and 30 m ahead, where 10 m is the nearest distance viewed by the camera in our case. The middle field covers between 30 m and 50 m, and the far field shows images further than 50 m. The far field image will not be used, however, because the lane mark images in this field have bad contrasts. Moreover, this field has insufficient illumination in the evening or at night. Besides, it is easily occluded by front vehicles. The lane mark considered in this study is a dashed line, and the measures of both the lengths of the mark and the gap are 10 m. Thus 20 m intervals for the near and middle fields assures us of catching enough of the lane mark.

As for the feature parameter to determine the lane curve direction, slopes of lane marks on the left and right sides in each image field are estimated. However, the processing method was differentiated in each field in order to save the time. That is, the cumulative distribution function method of the gradient vector proposed in the previous work[18] was applied to near field processing, while the Hough transform was used in middle field processing. The Hough transform is known as a nice line detector;[14,16] it is strong against background noise, but time consuming for large-size data. The lane mark image in the near field occupies many more pixels than the middle field due to the perspective effect, making it more reliable statistically. Thus, the near field does not need such a fine, but time consuming, algorithm.

On the other hand, the slope of the lane mark depends not only on the lane curvature, but also on the lateral bias of the vehicle (strictly saying, camera) in a lane. This means that the curve direction can not be determined uniquely from the slope of the lane mark. Another information about lateral bias of vehicle is needed. Therefore, the position coordinates of lane marks in the near field was defined as another feature parameter. In spite of that, the determination of lane curve direction is yet difficult, because the feature parameters are complexly related to the lane curve and vehicle bias. In order to solve this problem, we intended to use the neural network technique.[15] The requirements declared above were satisfied.

The performance of the proposed algorithm is demonstrated for the real road image.

Left angle < Right angle   Left angle = Right angle   Left angle > right angle

(a) When the vehicle is located in the center of the lane

(b) When the vehicle is located on the right side of the lane

(c) When the vehicle is located on the left side of the lane

Figure 2. Relationship between lane curve direction and angles of lane mark

Lane Feature Parameters

Definition of Lane Feature Parameters

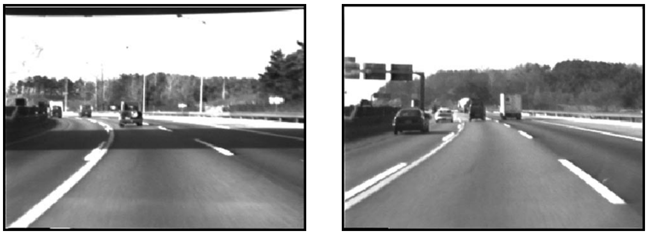
The image frame is divided into three sections: the near, middle and far fields. Lane feature parameters were defined in only the near and middle fields of these three sections. The near field is the range between 10 m and 30 m from the camera, and the middle field is between 30 m and 50 m. The far field is the image section further than 50 m.

The target processing time in this research is 0.2 sec/frame. Therefore, if we consider the vehicle speed of up to 100 km/hr (27.8 m/s), the movement per frame is less than 5.56 m/frame, and the 20 m interval of each field has enough continuity in image. The minimum lane curvature is 460 m, so the lane mark in each field covering 20 m of real road can be approximated to a straight line. We also used the information of camera calibration data to establish the position of near and middle fields in the images.

Lane feature parameters considered in this research are defined on the image frame as shown in Fig. 1.

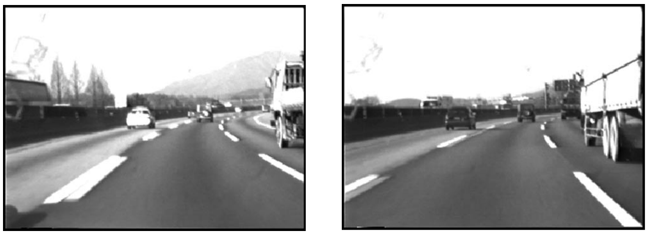
That is, L_l, L_r are positions of the left and right lanes in the near field. θ_{N_l} and θ_{N_r} are left and right lane slopes in the near field. θ_{M_l} and θ_{M_r} are left and right lane slopes in the middle field. In Fig. 1, the angles of the lane slopes are defined clockwise for left lane marks, and counterclockwise for right lane marks.

It can be easily expected that the angles of the left and right lanes will be related to the lane curve. For example, the straight lane has the same angle as the left and right lane mark. Whereas, the left-turn lane has a smaller angle in the left side lane mark and the right-turn lane has a smaller angle in the right side lane mark, as shown in Fig. 2.



(a)

(b)



(b)

Figure 3. Sample of road image

These relationships are always valid only when the vehicle is located in the center of the lane. Because the camera was located at the center of the vehicle, the vehicle position is the same as the camera position. If my vehicle is bias to the right side, the angle of the right side lane mark will be smaller even in the straight lane. If my vehicle is bias to the left side, the opposite phenomenon occurs. This means that the angles of the left and right lane marks are related to the vehicle position in a lane as well as lane curvature. Therefore, the lane curve direction can not be determined with the angle of lane mark alone. For this reason, the lane mark position defined in Fig. 1 was included in the lane feature parameters to compensate for the angle varied by vehicle bias in a lane.

On the other hand, because the near field occupies more than half of the road image, and the lane mark in this field is usually clear, detection of the lane feature parameters in this field is fairly reliable. However, the angle of lane mark in the near field is not as sensitive to the change of lane curve as the angle of lane mark in the middle field. This is the reason for using the middle field. That is, the near field gives the information of the lateral bias of the vehicle and the initial angle of lane mark, while the middle field gives the information of lane curve.

The Evaluation of Correlation between Lane Parameter and Lane Curve

In this section, how the feature parameters are correlated to the lane curve direction is shown. For this purpose, real road images were captured by CCD camera installed in the vehicle, whose details will be described later. The number of total sample images used in the correlation analysis is 60 frames. Figure 3 shows the representative sample images of left, right turn, and straight lanes acquired in this research.

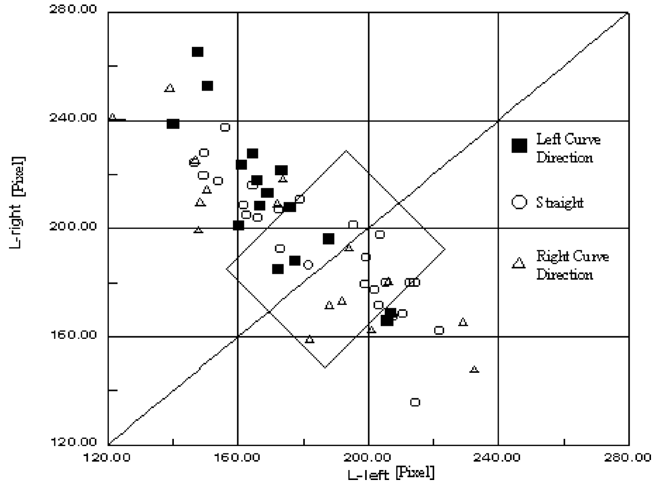


Figure 4. Relationship between lane position and lane curve direction

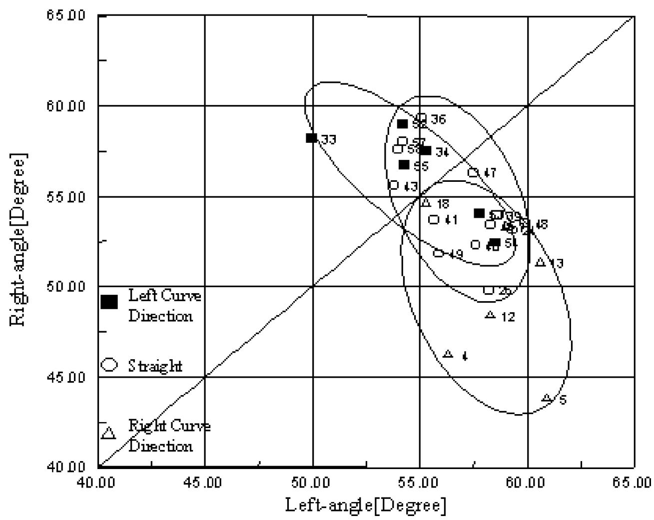


Figure 5. Relationship between the angles of lane mark in the near field and the lane curve direction

Figure 4 shows the correlation between the lane position and the lane curve direction. The centered diagonal line indicates L_left = L_right, which means the vehicle runs the center in a lane. The upper-left area of the diagonal line indicates vehicle bias to the left side, and the lower-right area indicates vehicle bias to the right side. We can see that the vehicle tends to bias toward the left on left turns and toward the right on right turns, which are very common driving habits.

However, in order to confirm the pure relationship between the lane curve and the angle of lane mark, we selected frames in the centered rectangle. Figure 5 shows the correlation between the angles of lane mark in the near field and the lane curve direction. Figure 6 shows the correlation between the angles of lane mark in the middle field and the lane curve direction. We can see that the angles of lane mark in the middle field have stronger correlation to the lane curve direction than those in the near field.

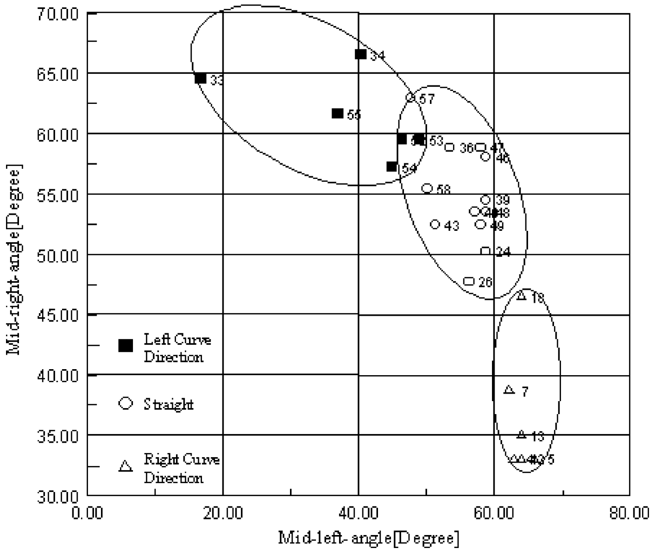


Figure 6. Relationship between the angles of lane mark in the middle field and the lane curve direction

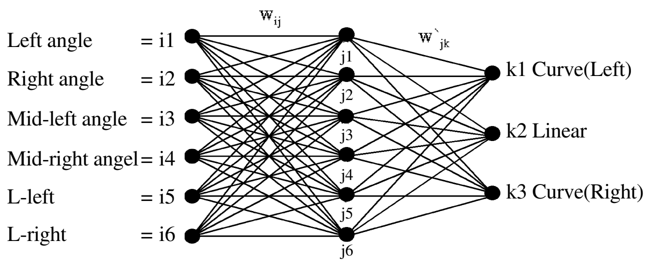


Figure 7. Construction of neural network

Extraction of Lane Feature Parameters

As mentioned above, the lane mark can be regarded as straight linear in each field; therefore, our problem is reduced to determine the line from the image of each field. The Hough transform is a well-known line detector, and it is usable in this study. However, the size of the near field data is too large for applying that method within the required processing time. Fortunately, the lane mark image in the near field usually has good contrast and is statistically reliable. So, the simpler and more time-saving algorithm using the Cumulative Distribution Function, proposed in the previous work, was adopted.[18] The lines in the middle field were obtained by using the Hough Transform.[14,16]

Neural Network

Now, our goal is to determine the lane curve direction from lane parameters. Then, as was described in the previous section, the lane feature parameters are complexly related not only to the lane curve but also to vehicle bias. The lane curve direction can not be determined simply from the angles of lane marks in the two fields. In order to solve this problem, we intended to use the neural network technique.

Structure of Neural Network

Figure 7 shows the construction of the neural network used in this study. It has three layers: the input, hidden and output layers. The input layer is constituted of the lane parameters, and the output layer is constituted of three nodes to classify the lane curve to one of left turn, right turn, or straight lane.

Training Neural Network

The neural network was trained by using the general back-propagation-method (BPM).[15] For the training, 60 frames of real road image for typical road pattern were used. They involve the same number of frames for each of the left-turn, right-turn, and straight lanes. That is, 20 frames were used to train one of lane patterns. Neural network is trained as the output node corresponding to a given lane pattern has 1.0, while the other nodes have 0.0. The resulting error of training was evaluated by Eq. 1.

$$E = \sum_{p=1}^{NP} \sqrt{\sum_{k=1}^{NK} (t_{p,k} - O_{p,k})^2} \tag{1}$$

where,
$t_{p,k}$: real value of output layer node (0 or 1)
$O_{p,k}$: estimated value of output layer node ($0 \le O_{p,k} \le 1$)
NK: number of output layer node (= 3)
NP : number of image frame for learning (= 60)

It was sufficiently small, 0.0278, in our case.

Experimental Equipment and Method

Experimental Equipment

With the CCD Camera equipped to a test vehicle, the superhighway scene was recorded on videotape. After that, by replaying the videotape, the road image was captured with a frame grabber equipped to a Pentium II 300 MHz PC. The obtained image was processed in Visual C++.

Experimental Method

In the superhighway section including all kinds of curve pattern, left turn, straight, and right turn, 2000 frames were captured and 60 frames were used to train the neural network and the rest was tested. The test frames are composed of curve and straight sections at almost an even rate, and the curve section is composed of left and right turn with roughly the same rates.

The test is performed in three different ways. The first (Test-1) uses only the near field information, and the second (Test-2) uses both the near field and the middle field information. Comparing these two results, we can confirm the effect of using the middle field information. The last test (Test-3) considers the recursive effect under the assumption that the lane curve direction is not changed suddenly. By this, we can reduce the intermittent errors that may occur in the case of the vehicle's severe leaning to a lateral side in a lane, or vague images resulting from damages in the lane or another vehicle's interruption.

Equation 2 shows the used recursive filter.

$$\mathbf{P}_n = \frac{1}{N} \sum_{k=0}^{N-1} (N-k)\mathbf{Q}_{n-k} \tag{2}$$

where
$\mathbf{P}_n$: new numerical curve direction after filtering
$\mathbf{Q}_{n-k}$: old numerical curve direction before filtering
N: size of filter (in this research, 10)

TABLE I. Results of Lane Curve Recognition by Using the Near Field Information

Experimental Result	Left-turn		Straight		Right-turn		Total Frame Number
Real Curve Direction	Frame	Percentage	Frame	Percentage	Frame	Percentage	
Left-turn	333	70.1%	109	22.9%	33	6.9%	475
Straight	41	4.2%	677	69.3%	259	26.5%	977
Right-turn	21	4.4%	29	6.1%	428	89.5%	478

TABLE II. Results of Lane Curve Recognition by Using Both the Near Field and the Middle Field Information

Experimental Result	Left-turn		Straight		Right-turn		Total Frame Number
Real Curve Direction	Frame	Percentage	Frame	Percentage	Frame	Percentage	
Left-turn	366	77.1%	108	22.7%	1	0.2%	475
Straight	41	4.2%	828	84.7%	108	11.1%	977
Right-turn	3	0.6%	32	6.7%	443	92.7%	478

TABLE III. Results of Lane Curve Recognition by Considering Recursive Effect

Experimental Result	Left-turn		Straight		Right-turn		Total Frame Number
Real Curve Direction	Frame	Percentage	Frame	Percentage	Frame	Percentage	
Left-turn	402	84.6%	73	15.4%	0	0.0%	475
Straight	38	3.9%	886	90.7%	53	5.4%	977
Right-turn	0	0.0%	4	0.8%	474	99.2%	478

Results and Discussion

Table I shows the results of Test-1. It shows the given frame numbers for each curve pattern and the recognized result in frame number and percentage. For example, in the right turn section, 4.4% was recognized as left turns, 6.1% as straight, and 89.5% as right turns. Thus 89.5% was correct. Similarly, the correct recognition percentage was 70.1% for left turn and 69.3% for straight.

Table II shows the results of Test-2. Compared to the previous case, we can see that the correct recognition rates in all the cases of left turn, right turn, and straight lane are improved. Specifically, the severe mistake of recognizing a left turn as a right turn, or a right turn as a left turn was largely reduced. From this, we can confirm the effectiveness of using the middle field information.

Table III shows the results of Test-3 as a result of remembering the lane tendency of the past 10 frames. Its correct recognition rate averages more than 90%. It is especially very remarkable that there are no severe errors.

However, in a transition section from curve to straight or from straight to curve, it may be vague to classify the road pattern to one of curve or straight. Success percentages shown in Tables I, II and III were obtained by classifying the transient road pattern with referring the mid-point of transition. If we neglect the transition section, the correct recognition percentages in Table III increased to more than 93%.

Conclusion and Future Work

In this article, we have proposed an image processing technique that can recognize lane curve direction by using just the near and middle field road images. The following are the results.

The lane feature parameters were defined, under the assumption that it is related to the lane curve direction. The relationship was evaluated by the classification graph, and we demonstrated that the relationship was valid. We then constructed the neural network, which was constituted of the lane feature parameters for the input layer and the lane curve direction for the output layer. The test was performed under three different ways concerning the real road image. We can confirm the effect of using both the near field and the middle field information. To reduce the intermittent errors, the recursive effect was considered, and the recognition result was improved. If we neglect the transition section, the correct recognition percentages are over 93%. There were errors due to noise in the middle field and the linear assumption in the severe curve lane, therefore, we must also consider the variance of the camera view angle.

Future work will involve further statistical analysis of the lane feature parameters and improvement of robustness against noise.

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