

Development of a Lane mark Recognition System for a Lane Keeping Assist System

Ken'ichi MINETA* Kiyozumi UNOURA* Tetsuo IKEDA*

ABSTRACT

A lane mark recognition system that processes images taken by a camera for a Lane Keeping Assist System (LKAS) has been developed. This system is a main component of the Honda Intelligent Driver Support System. This system uses a new algorithm that is a combination of Hough transformation and the process of extracting positive and negative edges which are features of lane marks. By employing this algorithm, we can remove noise and execute high speed image processing with a special chip. As a result, we can process images in real time even in such complex situation as a parting road or double broken line conditions.

In experiments on real images, we were able to verify a high rate of recognition and accuracy of output data sufficient for steering control.

1. Introduction

Recent advances in electronics technology have spurred considerable R&D on intelligent system for automobiles, and some technologies have already been commercialized. One advanced experimental system being developed, for instance, uses laser radar installed on the vehicle front to detect forward cars and automatically adjust distance to the forward car⁽¹⁾. The authors have developed a more evolved system: the Honda Intelligent Driver Support System. This system includes the Lane Keeping Assist System (LKAS), which recognizes lane marks from images taken by a camera and controls Electronic Power Steering (EPS) torque based on those results in order to assist the driver in staying in the current lane. The issues in developing this LKAS system were (1.) the inability of conventional line mark recognition systems to provide sufficient positional accuracy for lane keeping control and (2.) their inability to handle lane marks in complex situations such as turnoffs and double broken lane marks. To overcome these issues, we developed a new lane mark recognition system that supports LKAS. This paper gives an overview of this lane mark recognition system and describes the results from experimentation using actual road images.

2. Overview of the System

2.1. Overview of the Honda Intelligent Driver Support System

The Honda Intelligent Driver Support System is comprised of two main systems (Fig.1): the Adaptive Cruise Control (ACC) system, which uses laser radar to determine the distance to the forward car, then operates the accelerator

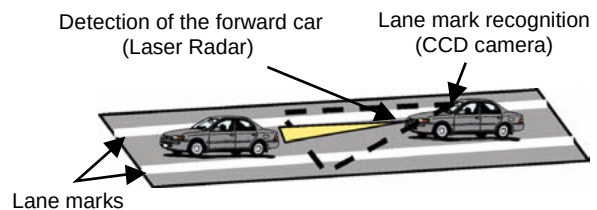


Fig.1 Main functions of Honda Intelligent Driver Support System

and brake to maintain proper distance to the forward car, and LKAS, which assists the driver in staying in the lane by using a CCD camera to take images of the road in front of the car, then controlling EPS torque according to the lane marks determined by processing those images. As the lane mark recognition system discussed in this paper was developed for LKAS, an overview of LKAS follows.

2.2 The Flow of Processing in LKAS

Fig.2 is a flowchart of LKAS processing, which controls EPS torque to help the driver to steer in order to keep the vehicle in the current lane. The data processing designed to achieve this goal begins by taking images of the road surface ahead of the car with a CCD camera mounted near the rearview mirror. Next, these images are processed by the image processing hardware and the CPU to extract the lane position and road curvature. This lane information is then used to calculate the EPS torque that is needed to assist the driver in staying in the lane. Lastly, this assist torque is sent

* Tochigi R&D Center

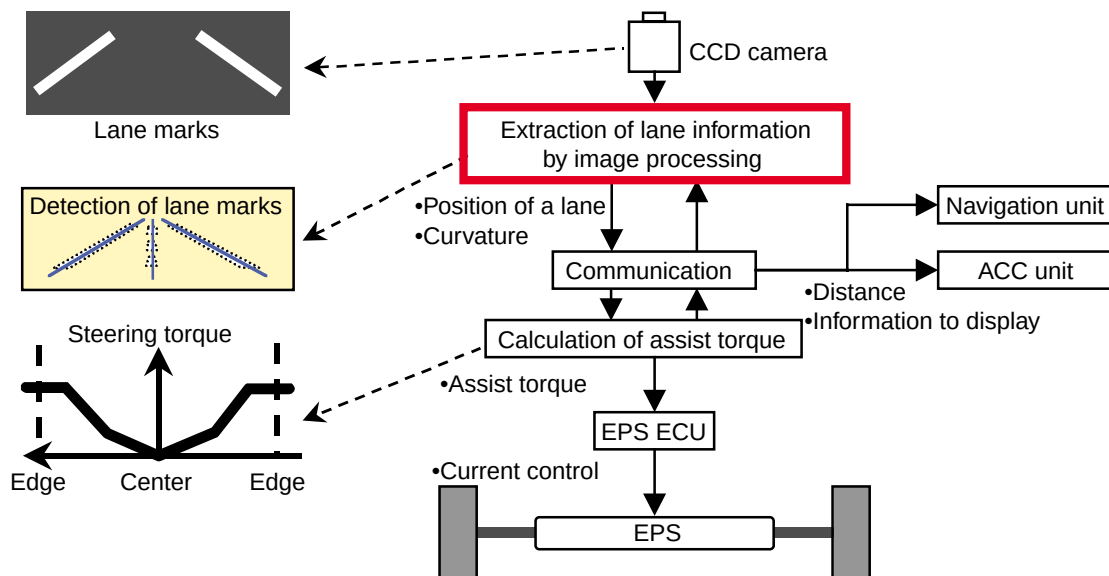


Fig.2 Flowchart of the LKAS process

to the ECU of the EPS for use in control of the EPS.

The flowchart in Fig.3 illustrates the image-processing portion of the process. As is indicated, the lane mark recognition process consists of two steps. In step 1, several sequences of points, each representing candidate lane marks, are identified. In this step, the goal is to extract as many sequences of points (i.e., lane mark candidates) as possible. Although these will include guard rails and other objects that are not lane marks, as well as lane marks that are unrelated to the car's current lane (as in the case of a turnoff), these extraneous sequences of points can be eliminated in the next step; the primary goal here is to avoiding missing the actual lane mark. In step 2, the candidate that is most suitable as the lane mark is selected, and lane information such as lane position and road curvature are calculated. Past

data is stored so that lane mark positions can be determined with greater accuracy in this step. Thus, lane mark position is estimated by selecting the most likely lane mark candidate based on consistency with past data, and then statistically processing the past data together with the selected lane-mark sequence of points. Steps 1 and 2 are discussed in detail later in this paper. First, section 3 describes the process of extracting sequences of points representing lane-mark candidates; section 4, the data evaluation process.

3. Method for Extracting Sequences of Points Representing Lane-Mark Candidates

3.1. Images Used

Fig.4 is an example of the type of images that must be processed in LKAS. In this system, the first stage of image processing is edge extraction to eliminate the effect of changes in density due to differences in brightness. Fig.4 is an edge-extracted image. Because the Honda Intelligent Driver Support System assumes use on expressways, the lane mark recognition system also targets lane marks not on ordinary roads but on expressways. Expressway characteristics include merges and turnoffs (b) at interchanges and service areas, along with double broken lines at relatively sharp curves (f). Here, "double broken line" refers to a broken line that is painted on the inside of an ordinary lane mark, and which is thicker and broken at shorter intervals, visually increasing the driver's sensation of speed so as to encourage him to decelerate. Other elements that must be addressed include road repair marks (d), guardrails, and the shadows of guardrails (e). An example of a complex image is one resulting from the shadows of a railway bridge (c).

3.2. The Basic Principles of Lane Mark Recognition

Let us consider the basic principles of how lane marks are recognized through image processing. In this system, lane marks are represented using pairs of positive and negative edges. A positive edge is an edge where density

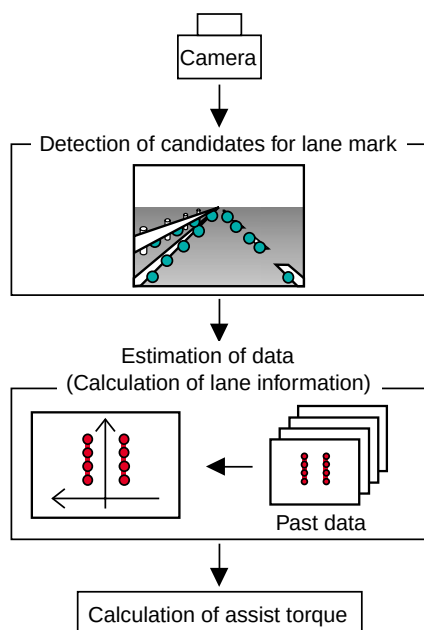


Fig.3 Flowchart of the lane mark recognition

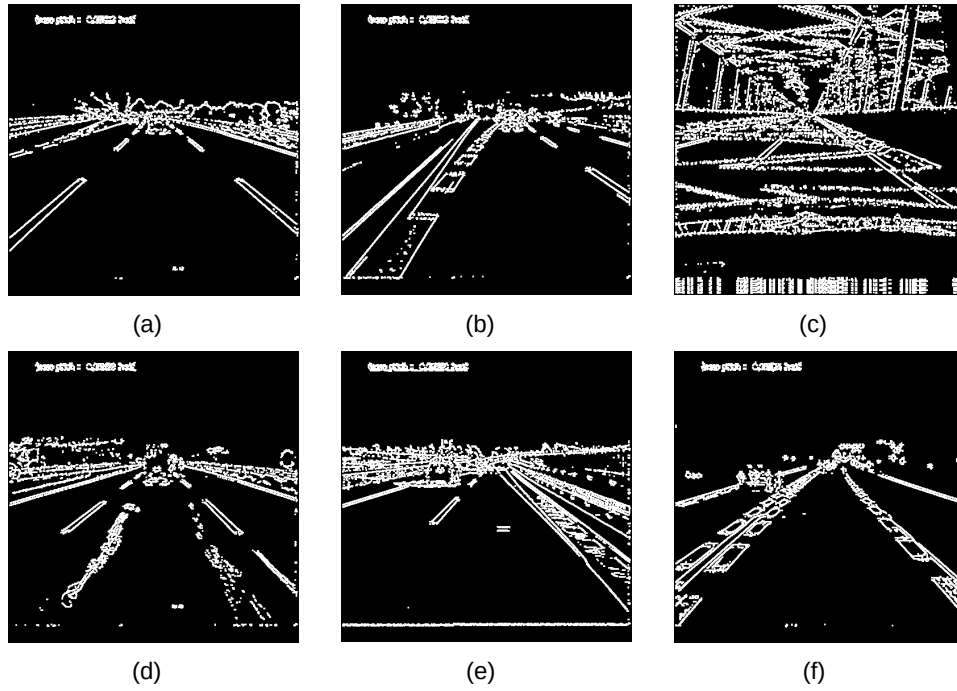


Fig.4 Sample of road images (after edge extracting process)

increases when the image is scanned from left to right. Similarly, a negative edge is where density decreases from left to right (Fig.5). A point is deemed a candidate lane mark when a positive and a negative edge are arranged in such a way that:

- (1) they are within a predetermined distance of each other and
- (2) they appear in the sequence positive $\rightarrow$ negative when

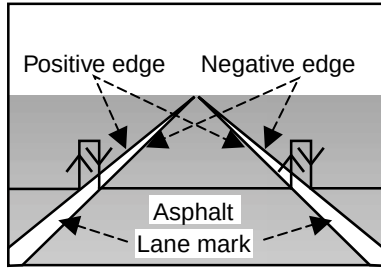


Fig.5 Definition of the positive/negative edge

the image is scanned from left to right.

Also employed in the recognition of a lane mark is the linear arrangement of a broken edge. On an expressway, the portion of a lane mark that is relatively close to the vehicle is, on the screen, nearly linear, even in places where the road curves. This portion is valid as it occupies the majority of the screen. Hough transformation⁽²⁾⁽³⁾ is widely used as an image processing technique for extracting sequences of points that are arranged linearly on screen, and research on the use of Hough transformation in lane mark recognition has, in fact, been carried out⁽⁴⁾⁽⁵⁾. As this system also utilizes this technique, explained next is the principle behind Hough transformation and how it is actualized on a computer. First, let us assume that a point (x, y) exists on plane X-Y, like that

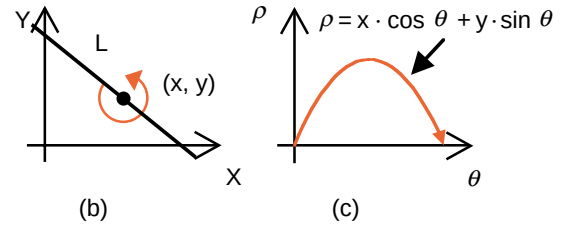
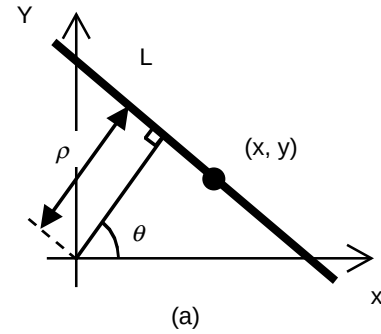


Fig.6 Definition of Hough transformation (1)

in Fig.6-a. As shown in the figure, ρ and θ are calculated for straight line L , which passes through this point, where ρ is the length of a perpendicular from the origin to L , and θ is the angle between this perpendicular and the X axis. The relationship between x , y , ρ , and θ is such that the following holds true.

$$\rho = x \cdot \cos \theta + y \cdot \sin \theta \quad (1)$$

When straight line L is rotated around point (x, y) (see Fig.6-b), ρ and θ change. This change, when drawn on plane ρ - θ , appears as in Fig.6-c. Next, Fig.7 shows this operation performed for multiple points (x_i, y_i) ($i = 1, 2, \dots$) arranged

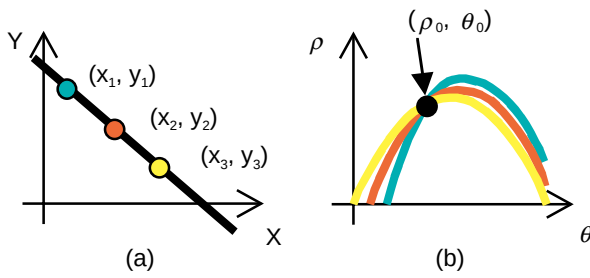


Fig.7 Definition of Hough transformation (2)

linearly on plane X-Y. Here, the intersection of the curves drawn on plane ρ - θ correspond to a common line passing through the points on plane X-Y. Thus, the straight line passing through the sequence of points is obtained by calculating the intersection of the curves on plane ρ - θ .

Defining the intersection on plane ρ - θ as (ρ_0, θ_0) , then the straight line can be represented thus:

$$x \cdot \cos \theta_0 + y \cdot \sin \theta_0 = \rho_0$$

Next, the steps for implementing Hough transformation on a computer are given.

(Step 1)

A two-dimensional array corresponding to plane ρ - θ is

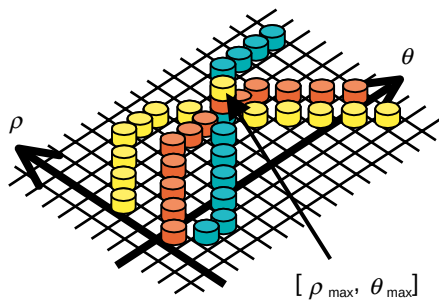


Fig.8 Implementation of Hough transformation

prepared (Fig.8). Each element functions as a counter.

(Step 2)

For each point on the image (x, y) , ρ is calculated for a value of θ from 0 [degrees] to 180 [degrees] so that the counter value of the array element referenced by $[\rho, \theta]$ is increased by 1 (i.e., voting).

(Step 3)

The above process (Step 2) is carried out for all edge points.

(Step 4)

The two-dimensional array with the maximum count value is selected. Defining the index of this array as $[\rho_{\max}, \theta_{\max}]$, then in the plane X-Y, this straight line is such that

$$\rho_{\max} = x \cdot \cos \theta_{\max} + y \cdot \sin \theta_{\max}$$

For instance, if an interval of 1 [degree] is used for θ , then equation (1) must be solved 180 times for each point in the image. This process, because it involves the repetition of simple calculations, is well suited to computerization.

The important requirements for Hough transformation can be summarized thus:

- (1) A linear sequence of points on image plane x-y correspond to a local peak in Hough space ρ - θ (Fig.9).
- (2) The height of a local peak in a Hough space corresponds to the number of points in the corresponding linear sequence of points (Fig.9).

Another characteristic advantage of Hough transformation is its ability to extract a straight line indicating an edge's general direction, without dealing excessively with the edge's intricate jaggedness. Conversely, its disadvantage is that when edge points are locally concentrated, as with a double broken line, numerous extraneous lines other than the one desired are also extracted.

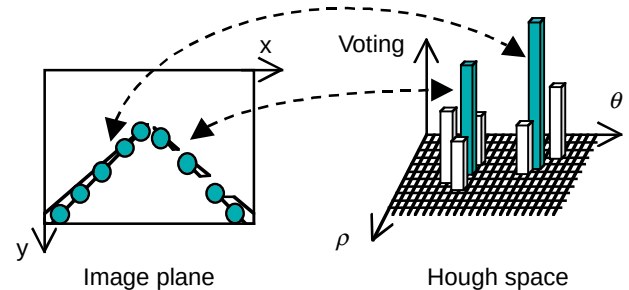


Fig.9 Hough transformation

3.3. Characteristics of the Lane Mark Recognition Technique of the Honda Intelligent Driver Support System

This system, by combining the basic principles explained in section 3.2, has achieved a lane mark recognition technique that can handle double broken lines and similarly complex images and which is resistant to the effects of noise. This section describes the characteristics of that technique.

The first technique is:

- (1) The ability to handle double broken lines and similarly complex images

As Fig.10 shows, edge extraction from a double broken line image results in a highly dense concentration of points

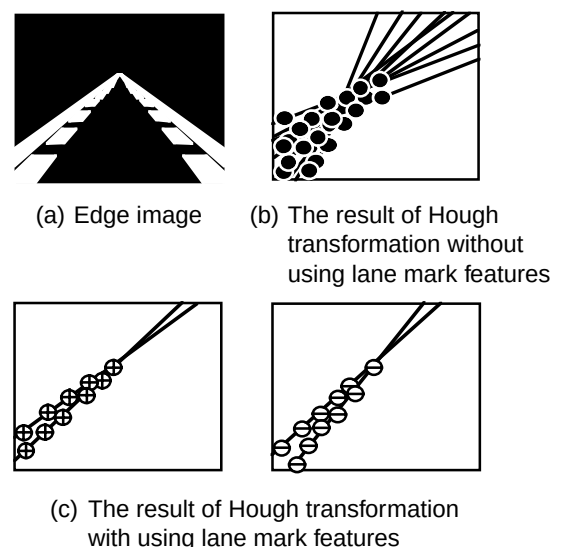


Fig.10 Features of the a lane mark recognition algorithm (1)

being extracted. In such cases, Hough transformation would normally result in line segments in many directions being extracted, obscuring the desired lane mark (Fig.10-b). Therefore, line segments in these extraneous directions are excluded during Hough transformation by utilizing the lane mark characteristics described in Fig.5 in section 3.2 (Fig.10-c). This makes it possible to recognize even a lane mark as complex as a double broken line with good probability.

The second characteristic of this technique is:

- (2) The ability to yield sequences of points, not linear parameters, as the results of recognition

Hough transformation normally yields linear parameters, which, when used as the results of recognition without modification in the processing of a gently curving lane mark like that shown in Fig.11-a, result in a considerable mismatch between the resultant line and the actual lane mark position, preventing sufficient accuracy in lane mark position (Fig.11-b). One way of avoiding this is to raise the angular resolution of Hough transformation. This approach, although permitting accurate representation of lane mark position by making it possible to represent curves with multiple line segments, is not practical because of the huge volume of Hough transformation calculations required. For this system, it was therefore decided to output not the Hough peak itself that is extracted as the candidate lane mark, but rather the sequences of points that comprise the Hough peak (Fig.11-c). In the next step, which is data assessment, these results are statistically processed along with past data, yielding a

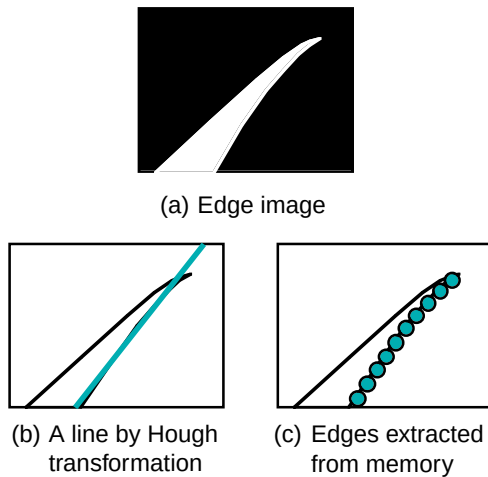


Fig.11 Features of the a lane mark recognition algorithm (2)

more-accurate lane mark position.

The third characteristic of this technique is:

- (3) Ease of hardware customization

Hough transformation, which in this technique accounts for the largest portion of the calculations, involves the repeated calculation of equation (1) in section 3.2 and so is conducive to hardware customization. In actuality, this system uses customized hardware for these calculations to achieve speeds nearly 100 times faster than software

processing with system CPUs. This makes it possible to process an entire image with limited hardware resources, and to detect the desired lane mark among multiple candidate sequences of lines, even in cases of turnouts and similarly confusing lane marks.

4. Data Assessment

The process up to section 3 yields segmented sequences of points as the candidate lane marks. These results are then used to:

- (1) identify the true lane mark and supplement lane marks that had not been extracted; and
- (2) estimate the true position of the lane mark

An overview of this process is given in Fig.12. First, the sequences of points for each lane mark segment are projectively transformed from the image coordinate system to a real world coordinate system. This projective transformation uses parameters identified in a stationary state, and so at this point noise caused by road gradient and vehicle pitch and roll changes, etc., enter. Next, the geometric interrelationship between the segments on the real world coordinate system is determined and represented with a graph and matched with a road shape model similarly expressed as a graph. This yields a candidate set for the current road shape while in motion. At this stage, the misextracted lines and omitted lines in the matched models are identified to calculate assessment values that indicate agreement between the models, as well as relative distance between the vehicle and the lane marks, among others. In the next stage, a map is drafted after collecting these candidates for a certain short period of time assuming that the lane marks flow smoothly, with no change in road structure while the vehicle is in motion during this short period. Next, candidate lists of current road shape and maps are generated by categorizing and arranging under the assumption that the lane marks and the vehicle's position in the lane continue smoothly. Lastly, each candidate list is compared with expressway design standards to determine the appropriateness of the road width and curvature change rate, etc. Once the optimum list is selected, least squares approximation is used to identify the true position of the lane mark.

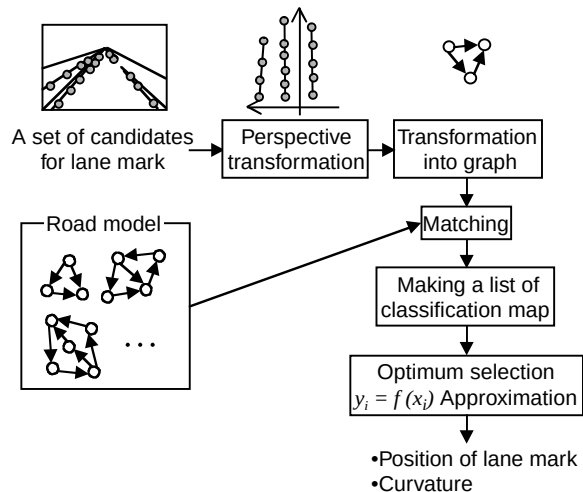


Fig.12 Flowchart of estimating data

4.1. Geometric Representation of Road Shape

The set of candidate lane marks is matched with the road shape model in order to select the true lane mark. Normally, the graph is represented thus, using node V and arc E , which represents the properties between nodes:

$$G = (V, E)$$

V has attributes and attribute value P , which in this system is defined thus:

$$P = (p, \text{value}), p \in \{\text{solid line, broken line, unclear}\}$$

“value” is the value of similitude to p

$$E = (e, \text{value}), e \in \{\text{parallel, serial, unrelated}\}$$

“value” is the value of similitude to e

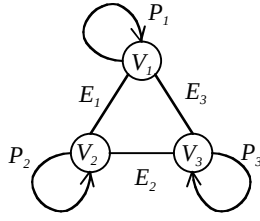


Fig.13 Example of graph

If interrelationship E is such that $E_{ij} = E_{ji}$, then graph G is a non-oriented graph. If $E_{ij} \neq E_{ji}$, then it is an oriented graph. In graph matching problems, ordinarily there is no significant difference between oriented and non-oriented graphs, which can be used according to the type of problem in question. This system symbolizes and defines E so that an absence of any relationship (“unrelated”) is represented with a non-oriented graph, a “parallel” relationship with an oriented graph whose orientation depends on the vehicle’s direction of travel, i.e., with the two in a mirror-image relationship, preventing a match with geometrically similar structures and making it possible to interpret solutions uniformly.

An example road shape model is given in Fig.14. This model’s definition is designed to be comprised of link information from map data of the current area provided by the navigation system.

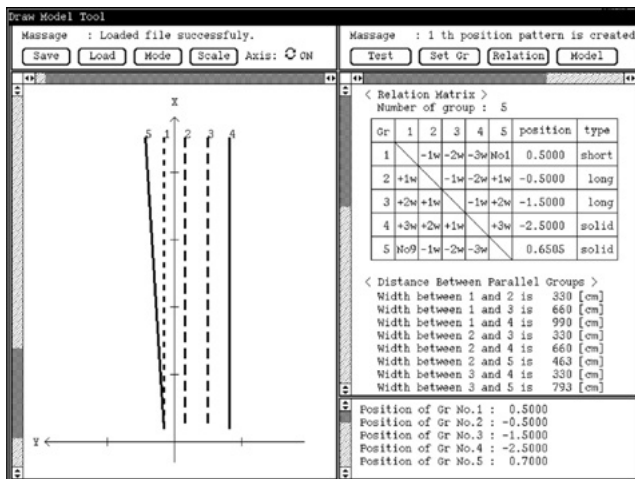


Fig.14 Sample of definition of road model

4.2. Matching Principle and Algorithm

Matching of candidate lane mark set graph G_1 and model graph G_2 can be treated as a problem of finding the portions of the two graphs that both have the same shape. Thus, one has only to create a combined graph from the combinations of nodes of G_1 and G_2 and then use it to solve the problem of extracting clique N . Here, no detailed description is given of the combined graph creation procedure, the N clique extraction algorithm⁽³⁾, or the method for calculating the assessment values. However, during creation of the combined graph, the matching process is sped up by omitting V_1 , V_2 and other combinations that lie outside of the lane on the assumption that the vehicle is located on the inside of the road division.

4.3. Estimating Lane Mark Position and Curvature

N number of lane marks on the real world coordinate system are expressed with the quadratic function $f = ax_i^2 + bx_i + c_i$ ($i=1 \sim N$), and coefficients a , b , c_i are calculated with the method of least squares. In other words, given that e_i is the error between each function and the original sequence of points (x_{ij}, y_{ij}) , then a , b , c_j are solved to minimize $e = \sum e_i$. This is done by solving simultaneous linear equation with $N+2$ variables.

$$\begin{pmatrix} \sum_{i=1}^N \sum_{j=1}^{n_i} x_{ij}^4 & \sum_{i=1}^N \sum_{j=1}^{n_i} x_{ij}^3 & \sum_{i=1}^N \sum_{j=1}^{n_i} x_{ij}^2 & \sum_{i=1}^N \sum_{j=1}^{n_i} x_{ij}^2 & \dots & \sum_{i=1}^N \sum_{j=1}^{n_i} x_{ij}^2 \\ \sum_{i=1}^N \sum_{j=1}^{n_i} x_{ij}^3 & \sum_{i=1}^N \sum_{j=1}^{n_i} x_{ij}^2 & \sum_{i=1}^N \sum_{j=1}^{n_i} x_{ij} & \sum_{i=1}^N \sum_{j=1}^{n_i} x_{ij} & \dots & \sum_{i=1}^N \sum_{j=1}^{n_i} x_{ij} \\ \sum_{i=1}^N \sum_{j=1}^{n_i} x_{ij}^2 & \sum_{i=1}^N \sum_{j=1}^{n_i} x_{ij} & \sum_{i=1}^N \sum_{j=1}^{n_i} 1 & 0 & \dots & 0 \\ \sum_{i=1}^N \sum_{j=1}^{n_i} x_{ij}^2 & \sum_{i=1}^N \sum_{j=1}^{n_i} x_{ij} & \sum_{i=1}^N \sum_{j=1}^{n_i} 1 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \sum_{i=1}^N \sum_{j=1}^{n_i} x_{ij}^2 & \sum_{i=1}^N \sum_{j=1}^{n_i} x_{ij} & \sum_{i=1}^N \sum_{j=1}^{n_i} 1 & 0 & \dots & \sum_{i=1}^N \sum_{j=1}^{n_i} 1 \end{pmatrix} \begin{pmatrix} a \\ b \\ c_1 \\ c_2 \\ \vdots \\ c_N \end{pmatrix} = \begin{pmatrix} \sum_{i=1}^N \sum_{j=1}^{n_i} x_{ij}^2 y_{ij} \\ \sum_{i=1}^N \sum_{j=1}^{n_i} x_{ij} y_{ij} \\ \sum_{i=1}^N \sum_{j=1}^{n_i} y_{ij} \\ \sum_{i=1}^N \sum_{j=1}^{n_i} y_{2j} \\ \vdots \\ \sum_{i=1}^N \sum_{j=1}^{n_i} y_{Nj} \end{pmatrix}$$

Here, each sequence of points (x_{ij}, y_{ij}) must be transformed to a simultaneous coordinate system using information about the vehicle’s path of motion (x, y, θ) . To reduce the amount of memory required and the cost of coordinate transformation calculations, this system compresses the point sequence coordinates into the shape of the coefficient matrix of normal matrix $A_i X=B_i$ for each lane mark, then performs time correction for each of these coefficient matrices. Fig.15, which shows the sequences of points on the map list and the estimated approximation curves (the coordinate origin in the illustration is the vehicle), demonstrates how this method of estimation has accurately approximated the lane marks, although lane marks far from the vehicle are subject to the effects of vehicle movement and other noise components.

5. Hardware Configuration

Fig.16 shows the LKAS ECU configuration. This ECU comprises three major parts: the image preprocessing unit, image processing CPU, and control CPU. Customized hardware in the image preprocessing unit performs positive and negative edge extraction and Hough transformation of the road images taken by the camera. This is the processing described in section 3.2. In the image processing CPU, using

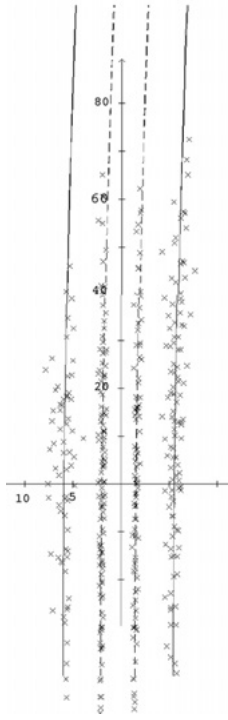


Fig.15 Points in map list and approximation functions

the results of processing by the image preprocessing unit, software narrows down the candidate lane marks, reconstructs the lane mark point sequences, and assesses the data as described in section 4. Lastly, the image processing CPU calculates the road position information and road curvature and sends them to the control CPU.

6. Results of Experimentation

6.1. Land Mark Recognition Rate

This system was used with actual road images to determine its lane mark recognition rate. Using a set of road images taken in various conditions on expressways, the experimenters judged the results of calculations as successful if they met the following criteria:

[Criteria] Edges of the target lane mark were detected over a distance of at least 50 m ahead of the vehicle, with a quantity and distribution that are sufficient for control purposes.

This set did not contain images in which lane mark recognition was completely impossible, e.g., due to road construction or backlight. The results are given in Table 1. The results for some of the images in the set are shown in Fig.17.

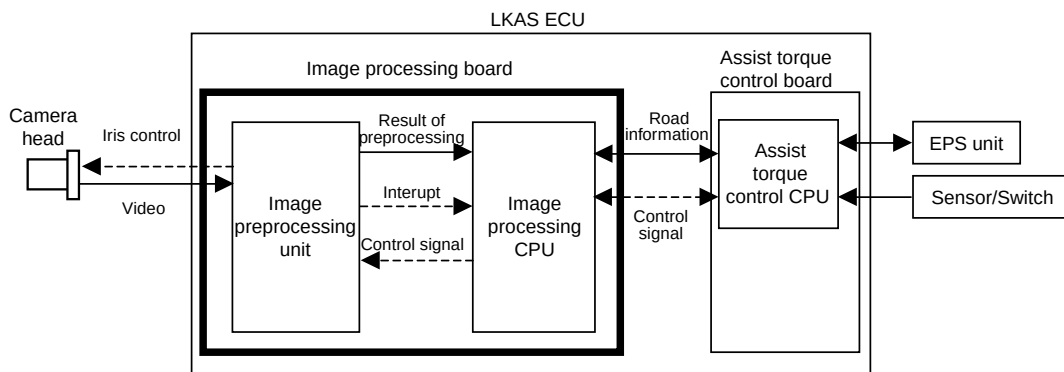


Fig.16 Architecture of LKAS ECU

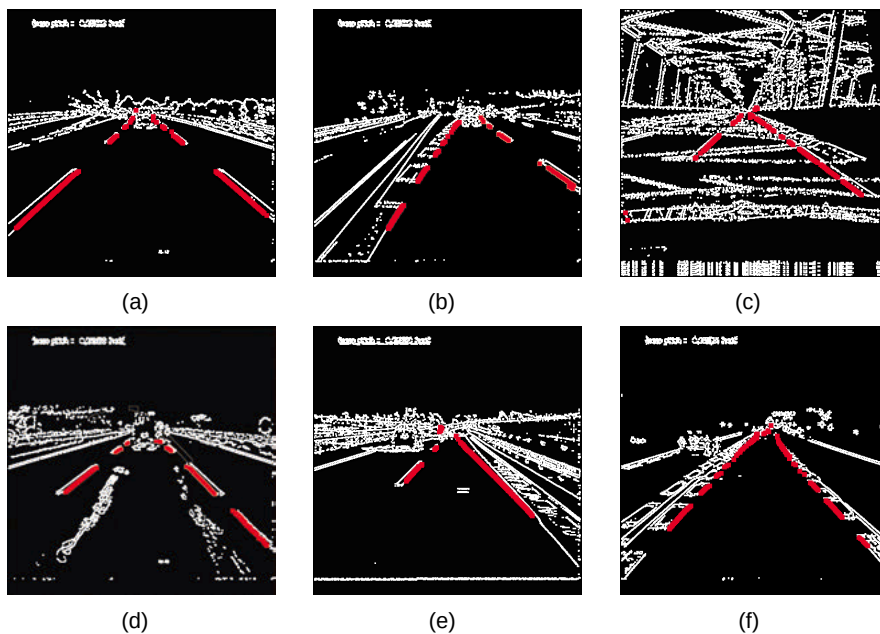


Fig.17 The result of lane mark recognition

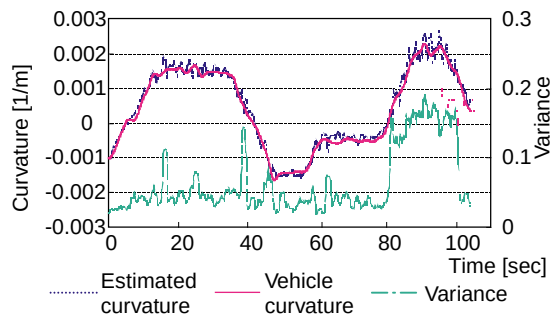
Table 1 Result of lane mark recognition

Number of image samples	Number of success	Recognition rate
293	274	94%

LKAS, which assumes steering by the driver, requires decision-making by the driver in all circumstances and gives priority to operations by the driver, and so is capable of assuring proper performance in this image processing.

6.2. Lane Mark Position Accuracy

Road images videotaped on an actual expressway along with vehicle motion data were computer-processed using this system; the results are in Fig.18. The data are the road curvatures and their distribution as determined by image processing, along with road curvatures calculated offline from vehicle path information. The section traveled was a winding section of the Tohoku Expressway, between the Shirakawa and Nasu Kogen rest areas. In the illustration, a double broken line section starting at the 80-second mark has resulted in an abrupt worsening of distribution, but experimentation that recreated these conditions on a test course verified assist control to be possible at this level without causing the driver to experience any incongruity.



(Tohoku expressway • Nasukougen PA to Shirakawa PA)

Fig.18 Estimated curvature and variance

7. Conclusions

The following conclusions were reached concerning the development of a new lane mark recognition algorithm that combines Hough transformation with extraction of positive and negative edges, which are used as characteristic of lane marks:

- (1) Eliminating extraneous linear components (noise) and using customized computer chips to repeat simple calculations speeds up processing and made possible the development of a lane mark recognition system that can recognize, in real time, double broken line lane marks and lane marks in turnouts and other complex situations on actual expressways.
- (2) Testing of the system on images of an actual expressway yielded a high rate of recognition and showed position accuracy to also be of a level sufficient for steering control.

References

- (1) Yasuhiko Fujita, Hayato Kikuchi, Shigenori Ogino, Seiji Ohsaki: Development of Intelligent Highway Cruise Control, Proc. of JSAE No.114-99, p.13-16(1999) (Written in Japanese)
- (2) Duda, R., et.al: Use of the Hough transformation to detect lines and curves in pictures, Communication of ACM, Vol.15, p.11-15(1972)
- (3) Ballard, D., Brown, C.: Computer Vision, *Nihon Computer Kyoukai*, Tokyo, p.147-160 (Written in Japanese)
- (4) Suzuki, A., et.al.: Lane Recognition System for Guiding of Autonomous Vehicle, IEEE Intelligent Vehicle '92, p.196-201(1992)
- (5) Hashimoto, K., et.al.: An Image Processing Architecture and a Motion Control Method for an Autonomous Vehicle, IEEE Intelligent Vehicle '92, p.213-218(1992)

■ author ■



Ken'ichi MINETA



Kiyozumi UNOURA



Tetsuo IKEDA