Vision-Based Vehicles in Japan: Machine Vision Systems and Driving Control Systems

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***Abstract*—This paper surveys three intelligent vehicles developed in Japan, and in particular the configurations, the machine vision systems, and the driving control systems. The first one is the Intelligent Vehicle, developed since the mid 1970's, which has a machine vision system for obstacle detection and a dead reckoning system for autonomous navigation on a compact car. The machine vision system with stereo TV cameras is featured by real time processing using hard-wired logic. The dead reckoning function and a new lateral control algorithm enable the vehicle to drive from a starting point to a goal. It drove autonomously at about 10 km/h while avoiding an obstacle. The second one is the Personal Vehicle System (PVS), developed in the late 1980's, which is a comprehensive test system for a vision-based vehicle. The machine vision system captures lane markings at both road edges along which the vehicle is guided. The PVS has another machine vision system for obstacle detection with stereo cameras. The PVS drove at 10–30 km/h along lanes with turnings and crossings. The third one is the Automated Highway Vehicle System (AHVS) with a single TV camera for lane-keeping by PD control. The machine vision system uses an edge extraction algorithm to detect lane markings. The AHVS drove at 50 km/h along a lane with a large curvature.**

I. Introduction

It IS necessary for an autonomous intelligent vehicle to have functions of obstacle detection and navigation in order to drive safely from a starting point to a goal. Machine vision systems play an important role in both obstacle detection and navigation because of the flexibility and the two-dimensional field of view.

The first intelligent vehicle that employed the machine vision system for obstacle detection was the Intelligent Vehicle [1] that we developed in mid 1970's. It was followed by the Personal Vehicle System (PVS) [2]. However, little work on obstacle detection using machine vision has been done until now. The Intelligent Vehicle and the PVS are the typical, but only a few examples. The principle of the obstacle detection of the vehicles is parallax with the stereo vision.

On the other hand, machine vision for lateral control is employed in many intelligent vehicles. The PVS [2], ALV [3], Navlab [4], VaMoRs [5], and the Automated Highway Vehicle System (AHVS) [6], [7] employed machine vision to detect road edges or lane markings for lateral control. However, the algorithms of lane detection differ from each other.

This paper surveys the configurations, the machine vision systems, and the driving control systems of the vehicles in Japan: the Intelligent Vehicle, the PVS, and the AHVS.

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II. The Intelligent Vehicle

The Intelligent Vehicle of Mechanical Engineering Laboratory, developed since the mid 1970's, has a machine vision system for obstacle detection and a dead reckoning system for autonomous navigation system on a compact car.

A. Obstacle Detection System

The machine vision system includes a stereo TV camera assembly and a processing unit. It detects obstacles in real time within its field of view in a range from 5 m to 20 m ahead of the vehicle with a viewing angle of 40 degrees. The cameras are arranged vertically at the front part of the vehicle. The system locates obstacles in the trapezoidal field of view. The scanning of each camera is synchronized and the processing unit uses hard-wired logic in stead of a programmable device in order to realize high speed processing of video signals from the cameras.

The principle of the obstacle detection is parallax. When two images from both of the cameras are compared, the two images of an obstacle are identical except the positions in the frames. On the other hand each image of figures on the ground differs due to the positions of the cameras. Fig. 1 illustrates the principle of the obstacle detection. The video signals are differentiated regarding time and the signals are shaped to obtain pulses that correspond to edges in the images. Each time interval of the pulses from each cameras, (*signal* 1 and *signal* 2 in Fig. 1), discriminates an obstacle from a figure on a road. An obstacle generates same time intervals, but a figure on a road generates different time intervals. The cameras have to be, thus, synchronized with each other, and have to employ vertical and progressive scanning techniques. The position of a scanning line corresponds to the direction to the obstacle, and the point where the optical axes of the cameras are crossing indicates the distance to the obstacle.

Delaying of one of the signals from the TV cameras is equivalent to rotation of the optical axis of the camera. Thus, varying the delay time enables us to detect obstacles at other locations. For enlargement of the field of view and detection of obstacles in the two-dimensional field of view during one scanning period, parallel processing with 16 kinds of delay time is employed, which yields the field of view of 16 zones arranged longitudinally at intervals of 1 m. Time required to detect obstacles is 35.6 ms, which consists of 33.3 ms of scanning of one frame and 2.3 ms of processing to detect and locate obstacles. Fig. 2 shows an example of the obstacle detection. The guardrail is identified as a series of obstacles that are indicated by black elements in the figure at the bottom.

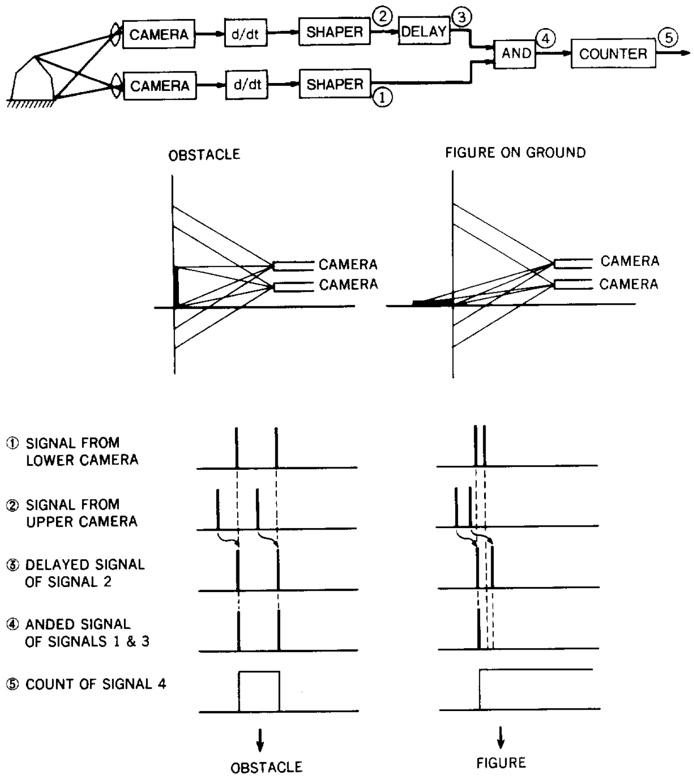

Fig. 1. The principle of the real time obstacle detection.

Since the system had no measures against brightness, shadows, and shades, the operating condition was restricted.

B. Lateral Control System

At the early stage the Intelligent Vehicle was steered based on locations of obstacles [8]. The control was retrieved from a table with a key word generated with locations of obstacles. It drove at the maximal speed of 30 km/h. After the vehicle was equipped with a dead reckoning function with differential odometers, it drove along a designated path with an autonomous navigation function.

The navigation system is featured by the steering control algorithm assuming the dead reckoning. The algorithm is named a target point following algorithm [9] after that the vehicle is steered so as to hit designated points representing the path sequentially to the goal. The designated points, called target points, are defined on a map that the vehicle has in the on-board computer.

1) Target Point Following Algorithm: In the derivation of the algorithm, the dynamics of a vehicle of an automobile type is described as follows:

$$\dot{x} = v\cos\theta, \tag{1}$$

$$\dot{y} = v\sin\theta, \tag{2}$$

$$\dot{\theta} = \frac{v}{l}\tan\alpha \tag{3}$$

Fig. 2. The obstacle detection: a road scene (top) and obstacles in the scene (bottom).

where (x, y) is the position of the vehicle, θ is the heading of the vehicle, v is the speed of the vehicle, α is the steering angle, and l is the wheelbase of the vehicle. The relations hold when the vehicle drives without slip. As shown in Fig. 3,

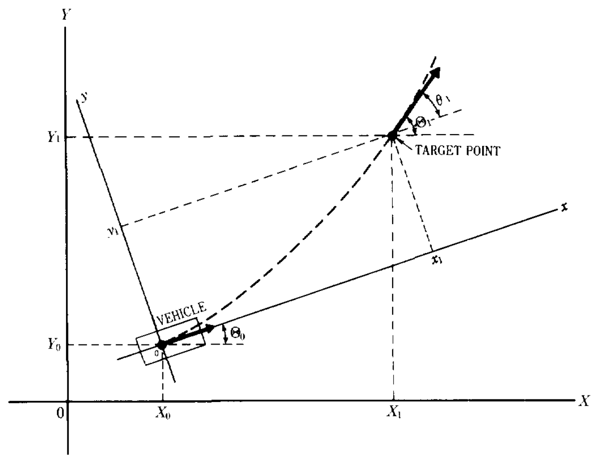

Fig. 3. Derivation of the lateral control algorithm.

let (X_0, Y_0) and Θ_0 be the current position and heading of the vehicle in the fixed reference frame (the $X - Y$ system), (X_1, Y_1) be the current target point, and Θ_1 be the expected heading of the vehicle at the point. In the new coordinate system (the $x - y$ system), where the position of the vehicle is at the origin and its heading is zero, let (x_1, y_1) be the present target point and θ_1 be the heading (assume that $\theta_1 \neq \pm\pi/2$). The headings at the origin and the target point are assumed to be tangential angles of a curve going through the origin and the target point at these points. Then, a cubic curve that goes through the two points is uniquely defined as follows:

$$y = ax^3 + bx^2 \tag{4}$$

where

$$a = \frac{x_1 \tan\theta_1 - 2y_1}{x_1^3}, \quad b = \frac{3y_1 - x_1 \tan\theta_1}{x_1^2}. \tag{5}$$

By use of the cubic curve, the steering control angle at the origin in the $x - y$ system that leads the vehicle to hit the point $T(x_1, y_1)$ with the heading θ_1 is given as follows:

$$\alpha = \arctan 2lb. \tag{6}$$

2) Procedure for Autonomous Navigation: When the vehicle autonomously drives from its starting point to its goal, the procedure for autonomous navigation is designed as follows:

begin
  A path is planned with an on-board map and the designated goal.
  A series of target points is placed along the path.
  Let the first target point be a current target point.
  repeat
    repeat
      The $x - y$ system is defined by translation and rotation of the $X - Y$ system to make the current position of the vehicle be the origin of the $x - y$ system and the current heading be the x axis.
      The steering control is found with (6).
      The vehicle drives with the steering control for one control period.
    until the vehicle approaches the vicinity of the current target point.
    The target point is updated.
  until the vehicle arrives at the goal.
end.

This algorithm is applicable to obstacle avoidance by putting a temporary target point beside an obstacle. The speed of the vehicle is independently controlled from the steering, which is one feature of the algorithm. However, the steering control has open-loop structure.

3) Experiments: The navigation system includes a 16-bit microcomputer system. Pulses generated by rotary encoders attached to both the rear wheels for dead reckoning are counted without asynchronous errors to measure precise speeds of the wheels. The computer integrates the speeds of the wheels to provide the position and the heading of the vehicle. Data regarding obstacles are also fed into the computer. Then, the navigation system finds optimal control of a steering angle and a speed of the vehicle. The control period of the system was 204.8 ms.

Driving experiments of the Intelligent Vehicle were conducted under some conditions. Fig. 4 shows results the trajectories of the vehicle when it drove along a designated path while avoiding a obstacle, and Table I shows the series of target points for the driving. When the vehicle approached within 3 m from a target point, the vehicle aimed at the next target point. On obstacle avoidance a temporary target point was put beside the obstacle when it came into the field of view. The speed of the vehicle was about 10 km/h.

III. The Personal Vehicle System

The Personal Vehicle System (PVS) was developed in the late 1980's by Fujitsu and Nissan under support of Mechanical Social Systems Foundation in Japan. It was a comprehensive test system for a vision-based vehicle. It comprises a TV camera for lane detection, a stereo TV camera assembly for obstacle detection, an image processor, and control computers. At the early stage of the research, three TV cameras were attached on the roof to detect lanes in the left, central, and right directions, but they were replaced by one TV camera on a swivel inside the windshield for experiments under a rainy condition and in the nighttime. The TV camera captures lane markings at both road edges in the field of view from 5 m to 25 m ahead of the vehicle for lateral control. It drove at the maximal speed of 60 km/h. Several algorithms of lane detection and lateral control were studied, but the latest ones will be described here.

A. Lane Detection System

The lateral control of the PVS is based on lane markings of white lines along both road edges. Lane markings are captured by a TV camera and the scene is processed by the image processor to detect white lines in every control period as follows:

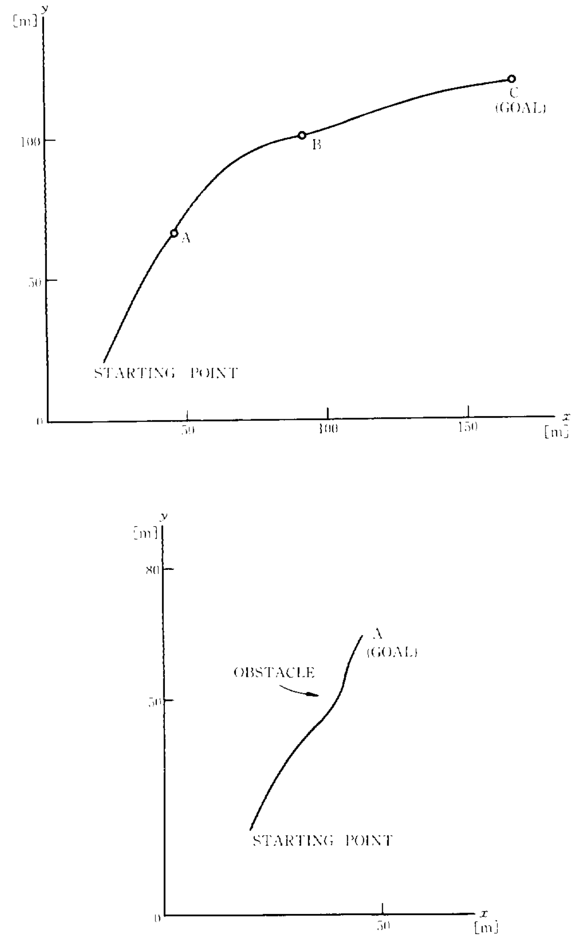

Fig. 4. Driving experiments: trajectories of the vehicle along a path (top) and obstacle avoidance (bottom).

TABLE I
THE SERIES OF TARGET POINTS FOR THE EXPERIMENT

		Positions		Heading
		x [m]	y [m]	θ [rad]
Start		20.0	20.0	1.0472
Target points	A	46.0	66.0	1.0472
	B	92.0	100.0	0.2443
	C	167.0	118.0	0.2443

1) The scene is spatially differentiated by two filters:

$$\begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix} \text{ and } \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}$$

to extract vertical edges and horizontal edges. Two image frames comprising edges are obtained.
2) White lines are searched from a point 5 m ahead of the vehicle in one of the two frames referring to the result of the last period. When they are found, directional vectors of edges are calculated.
3) White lines will generate a pair of edges, and each edge that makes pairs of the edges is searched in the direction of the normal vector of the directional vector. White lines are identified by referring the width of the paired edges.
4) One of edges generated from a white line is traced using the directional vector to compensate a part or parts where the white line is not obtained or missing due to shadows, shades, and something covering the line.

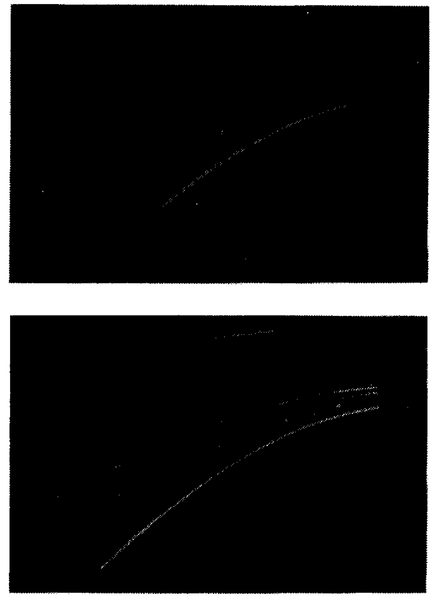

Fig. 5. The lane detection: a road scene (top) and a white line detected (bottom).

Fig. 5 shows the result of the lane detection where a shadow is covering the white line. The detection is performed at a video rate with the image processor.

B. Lateral Control System

The lateral control of the PVS is based on a driver behavior model which simulates driving by a human driver. The steering control is, therefore, determined with following three factors: a target point, weighting at each observed point, and weighting on left and right white lines to be followed. The target point is defined as a point that the vehicle is headed for, and the observed point is defined as a point where a human driver is mainly looking at while steering. The driving control system of the PVS consists of work stations, which the image processor is connected to.

After sensors including the vision system and a speedometer of the vehicle acquire locations of white lines or lane information and the vehicle speed, the information is delivered to calculation of steering control and camera swivel control. The lane information includes not only locations of white lines but also the tangential angles at every 1 m from 5 m to 25 m ahead of the vehicle.

The driving control system has originally had data for planning of navigation including the path, the heading, and the speed, and rules of driving. Thus, global driving commands and geographical data of the route generated in the driving control system are used to define observed points, a target point, and weighting at each observed point.

The steering control is calculated using an angle between the vehicle and the white line ahead of it, and the distance to the white line. Referring to Fig. 6, an element of steering control is defined as follows:

$$s_l[i] = \{f(L_i) \cdot (X_i - x_i) + g(L_i, t_i)) \cdot (T_i - t_i) + h(L_i, \phi)\} \cdot \varepsilon(v) \quad (7)$$

where

$s_l[i]$: an element of steering control based on the left white line,
L_i : the distance to the target point i,
$f(L_i)$: a quadratic function of L_i,
X_i : the target lateral distance,
x_i : the distance to the left white line,
t_i : the tangential angle,
$g(L_i, t_i)$: a quadratic function of L_i and t_i,
T_i : the target yaw angle,
$h(L_i, \phi)$: a cubic function of L_i and ϕ,
ϕ : the camera swivel angle,
v : the speed of the vehicle, and
$\varepsilon(v)$: a quadratic function.

Then, steering control S is defined as weighted sum of $s_l[i]$ and $s_r[i]$ as follows:

$$S = \frac{1}{2}\left(\frac{\sum_i w_l[i]s_l[i]}{\sum_i w_l[i]} + \frac{\sum_i w_r[i]s_r[i]}{\sum_i w_r[i]}\right) \quad (8)$$

where:

$s_r[i]$: an element of steering control based the right white line, and
$w_l[i], w_r[i]$: weightings for left and right observed points i.

The experiments of the PVS were conducted on a proving ground to confirm the lateral control algorithm in conjunction with the swivel control of the TV camera not only under fair weather in the daytime but also in the nighttime or under a rainy condition. Fig. 7 shows a result of an experiment under a fair condition. The control period was 200 ms. Eleven target points between 5 m and 15 m from the vehicle were defined, and the largest weight was on the point at 7 m from the vehicle. The rate of successful detection of white lane lines was 100% under the fair weather in the daytime, but it became 70% on average in the nighttime. However, the PVS drove stably in the nighttime as well as in the daytime, because missed observed points were interpolated by varying the weightings.

IV. The Automated Highway Vehicle System

Some automobile manufacturers in Japan have been conducting research on vision-based vehicles similar to the Intelligent Vehicle and the PVS, aiming at a possible solution to issues caused by automobile traffic. One example is a vision-based vehicle developed by Toyota, named the Automated Highway Vehicle System (AHVS). It has a function of lane-keeping with machine vision, and drove at a speed of 50 km/h.

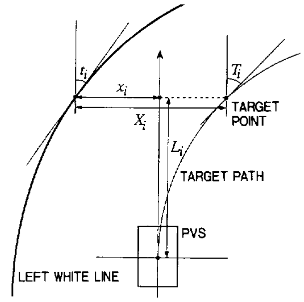

Fig. 6. The lateral control algorithm.

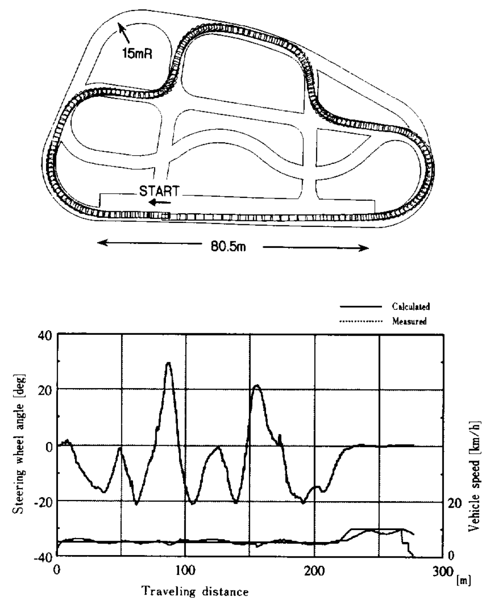

Fig. 7. A driving experiment: the trajectory on the test site (top) and the steering angle and the speed of the vehicle (bottom).

The AHVS is built on a medium-sized car. The driving control system includes a multiprocessor system, which consists of a host electronic control unit (ECU) as well as an image processor and an actuator controller, both of which are connected to the ECU. The image processor functions to process data from a CCD camera and to detect white lines on a road.

A. Lane Detection System

The AHVS employs machine vision to detect lane markings or white lines along both sides of a lane as well as the PVS. An algorithm for lane detection based on edge extraction [6] has been developed to have robustness against changes of brightness of such as road scenes, the position of the sun, shadows, and shades of guardrails, other vehicles, and constructions.

A road scene is input through a monochrome camera, and quantized to 256 × 256 pixels, each of which is represented by 8 bit data. A window of 256 × 30 pixels is set corresponding to the field of view from 10 m to 20 m ahead of the vehicle. Special hardware was made for real time processing.

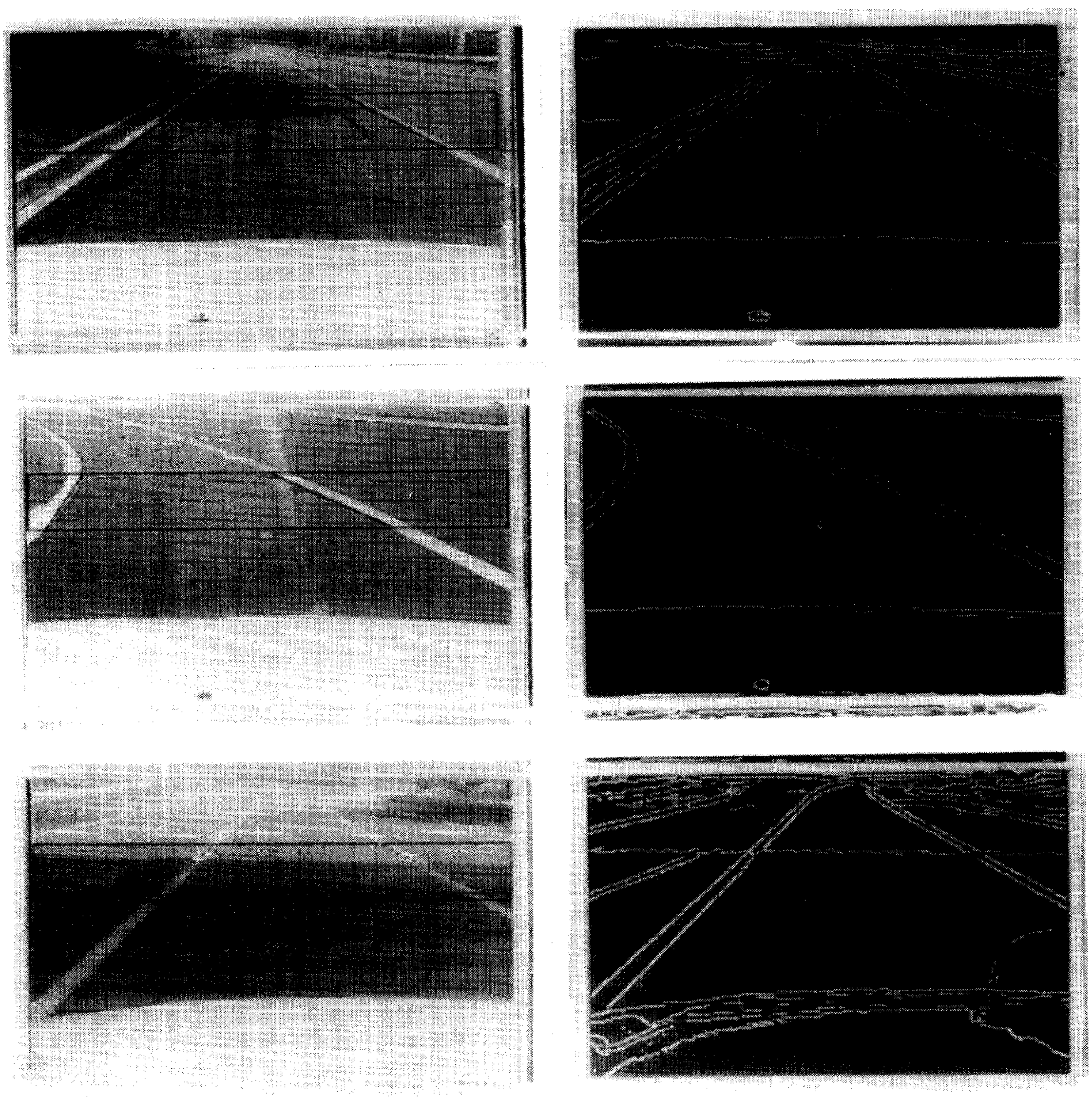

Fig. 8. Experiments of white line detection under various conditions by the edge extraction system: the field of view (left) and the segmented lines (right). The conditions are: a shadow (top), lens flare (middle), and a shade (bottom).

It operates with a period of 100 ms from input of a road scene to output of locations of white lines.

The processing for edge extraction comprises two steps of preprocessing and white line detecting. At the step of the preprocessing, the input scene is differentiated with a 3×3 Sobel operator to get values and directions of each edge, and then, the differentiated scene is thresholded, followed by peak extraction and line segmentation processing. The line segmentation processing generates a list of segmented lines based on continuity of the peaks. At the detecting step, white lines are detected among the list of segmented lines with following characteristics of white lines:

- White lines are continuous.
- The locations of the white lines vary continuously.
- White lines can be approximated with straight lines.
- Curvature of a route does not change rapidly.
- The edges are much longer than other noisy pieces of white lines.

Experiments were conducted with a 2/3 in CCD monochrome TV camera with a function of auto-iris. The focal length of the lens is 10 mm. Fig. 8 shows three experiments with the lane detection system under conditions: a) there is a shadow of a tree and marks of tires; b) there is lens flare; and c) there is a shade under a construction. White lines in each condition have been detected. An experimental result to measure a valid range on an electronic shutter speed of the camera for a fixed image shows that the speed was between 1/250–1/2000 s in the edge extraction system and it shows the robustness.

B. Lateral Control System

The vehicle is steered to follow a target lane by keeping the heading along the lane. Fig. 9 shows the lateral control

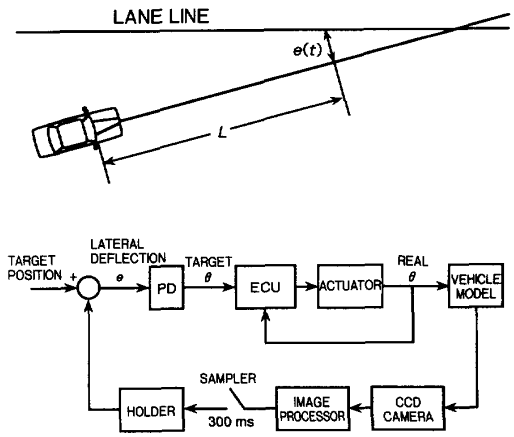

Fig. 9. The lateral control: definition of lateral deviation (top), the block diagram of the lateral control system (bottom).

system. The control period was 300 ms. The lateral control is based on PD control:

$$\theta(t) = k(L, v)e(t) + g(L, v)[e(t) - e(t-1)] \tag{9}$$

where
θ : the steering angle,
L : a distance to a point which is observed for control,
v : a speed of the vehicle,
$e(t)$: lateral deviation of time t at the distance L from the vehicle,
$k(L, v)$: a proportional gain, and
$g(L, v)$: a differential gain.

The distance L depends on shapes of the lanes. It was found that $L = 25$ m was optimal along a straight lane, and $L = 20$ m along a curved lane under limited experiments on a proving ground at 50 km/h. Thus, the distance is fixed to $L = 20$ m in the experiments, and the proportional and differential gains are varied with the speed of the vehicle.

Fig. 10 shows results of automatic driving with machine vision and manual driving by a human driver at the speed of 50 km/h. The edge extraction system was used to detect the lane. Compared to the result of the manual driving, the automatic driving yielded early steering at the entrance to the curvature and late steering along the curvature.

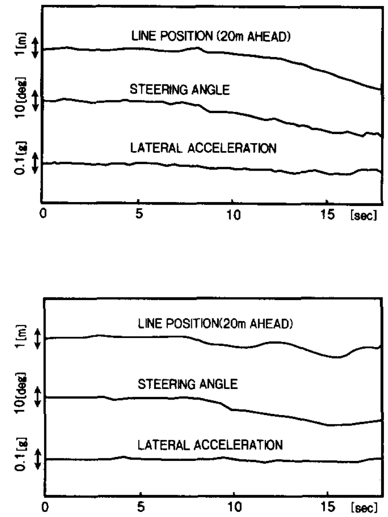

Fig. 10. Experimental results: automatic driving (top) and manual driving by human driver (bottom).

V. Discussion

Two points in the vision-based vehicles surveyed here are to be discussed. One point is the obstacle detection system in the Intelligent Vehicle. It can process video signals at a video rate. However, it does not have robustness due to the principle of the obstacle detection. It does not have measures to avoid an optical illusion and to protect against the influence of shadows, shades, and brightness. Active machine vision may be one of the measures.

The other point is delay caused by image processing. Even if the processing is achieved in real time, it takes some time from input of a road scene to output of control. The delay in the closed-loop control systems will cause instability, even if it is not large. Although the influence was not explicit in the experiments of the PVS and the AHVS, a simulation study [10] indicates existence of unstable motion of a vehicle in a visual navigation system. Compensation of the delay will be necessary in the visual navigation.

VI. Conclusion

Three vision-based vehicles developed in Japan have been introduced. The machine vision was used for obstacle detection and lateral control. The obstacle detection system in the Intelligent Vehicle operates in real time to locate obstacles in the field of view from 5 m to 20 m ahead of the vehicle. The lane detection systems in the PVS and the AHVS are robust enough to some extent to be influenced by optical noises.

The navigation system of the Intelligent Vehicle depends on the dead reckoning and, thus, is an open-loop control system. However, the algorithm has been extended to a closed-loop visual navigation algorithm [10]. The algorithm in the PVS shows a driving performance similar to that by a human driver, though it is complicated. On the other hand the simple PD lateral control algorithm in the AHVS shows a different performance from that of a human driver.

Research on intelligent vehicles or vision-based vehicles will be much more important, because in the future they will provide a possible solution to automobile traffic issues: accidents, congestion, and pollution.

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REFERENCES

[1] S. Tsugawa, T. Hirose, and T. Yatabe, "Studies on the intelligent vehicle," *Rep. Mechanical Eng. Lab.*, no. 156 Nov. 1991 (in Japanese).

[2] A. Hattori, A. Hosaka, and M. Taniguchi, "Driving control system for an autonomous vehicle using multiple observed point information," in *Proc. Intell. Vehicles* '92, June–July 1992, pp. 207–212.

[3] M. A. Turk, D. G. Morgenthaler, K. Gremban, and M. Marra, "VITS—A vision system for autonomous land vehicle navigation," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 10, no. 3, pp. 342–361, May 1988.

[4] C. Thorpe, Ed., *Vision and Navigation—The Carnegie Mellon Navlab.* Norwell, MA: Kluwer Academic, 1990.

[5] V. Graefe and K. Kuhnert, "A high speed image processing system utilized in autonomous vehicle guidance," in *Proc. IAPR Workshop Comput. Vision*, Tokyo, Japan, Oct. 1988, pp. 10–13.

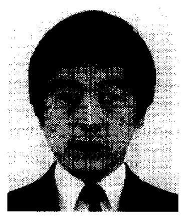
[6] T. Suzuki, K. Aoki, A. Tachibana, H. Moribe, and H. Inoue, "An automated highway vehicle system using computer vision—Recognition of white guidelines—," in *1992 JSAE Autumn Convention Proc. 924*, vol. 1, Oct. 1992, pp. 161–164 (in Japanese).

[7] A. Tachibana, K. Aoki, and T. Suzuki, "An automated highway vehicle system using computer vision—A vehicle control method using a lane line detection system—," in *1992 JSAE Autumn Convention Proc. 924*, vol. 1, Oct. 1992, pp. 157–160 (in Japanese).

[8] S. Tsugawa, T. Yatabe, T. Hirose, and S. Matsumoto, "An automobile with artificial intelligence," in *Proc. 6th Int. Joint Conf. Artif. Intell.*, Tokyo, Japan, Aug. 1979, pp. 893–895.

[9] S. Tsugawa and S. Murata, "Steering control algorithm for autonomous vehicle," in *Proc. 1990 Japan-U.S.A. Symp. Flexible Automat.*, Kyoto, Japan, July 1990, pp. 143–146.

[10] K. Tomita, S. Murata, and S. Tsugawa, "Preview lateral control with machine vision for intelligent vehicle," in *IEEE Proc. Intell. Vehicles '93 Symp.*, Tokyo, Japan, July 1993, pp. 467–472.



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In 1973 he joined the Mechanical Engineering Laboratory of Japan's Ministry of International Trade and Industry. Now, he is the director of the Machine Intelligence Division of the Applied Physics and Information Science Department. His interests are in informatics for vehicles that includes the Intelligent Vehicle with machine vision, vehicle-to-vehicle communication systems, and visual navigation of intelligent vehicles.

Dr. Tsugawa is a member of the Society of Instrument and Control Engineers (SICE), the Japan Society of Mechanical Engineers (JSME), and the Institute of Electrical Engineers of Japan (IEEJ). He received the best paper award from SICE in 1992.