Lane detection with roadside structure using on-board monocular camera

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***Abstract*—The lane detection function is an important aspect when constructing in-driving support systems. This function estimates the shape of the lane in which the vehicle is driving and the position of the vehicle within the lane. In this paper, we have proposed a lane detection algorithm that can not only operate on highways, but also on local roads by using information obtained from road-side structures. We have evaluated the performance of our algorithm under various conditions, such as day-light and night, sunny and rainy. The performance of the lane-detection system has been improved when compared with a conventional method that detects lane markers on both sides.**

I. INTRODUCTION

Recently, various driving support systems have been developed to improve vehicle safety and comfort, and some of these systems have been commercially released. In these systems, the driving environment is recognized using information obtained from sensors such as radar or cameras. The systems warn drivers of dangerous situations, and can take control of the vehicles to extricate them from danger. In a typical driving environment, information about the lane in which the vehicle is driving is of paramount importance. Lane detection systems that detect white lines on the highways as lane marks have already been used in practical applications. However, the lane detection systems also need to work robustly on local roads to expand the coverage of the driving support systems. On local roads, the systems need to deal with complex road shapes and a variety of lane boundaries.

Up to now, various methods have been developed to deal with complex road shapes. The road shape is expressed as a spline curve or as a series of circular arcs in [1] [2] [3]. Methods for estimating non-flat road structures have been proposed using range information [4] [5]. Methods for improving the robustness of the systems by fusing digital map information and the outputs from sensors have been introduced [2] [6] [7].

As a method for detecting lane position using information other than white lines, methods which use texture or color information have been proposed [8] [9] [10], [11]. Methods for detecting road-side structures using range information have also been proposed [12] [13].

In this paper, we introduce a method that uses a monocular camera and estimates the position of the camera robustly by considering the types of road-side structures that are treated as noise in the traditional methods. We also describe a method for switching the process to update parameters affecting the lane according to the information obtained from the camera images. Finally, experimental results covering lane detection under various conditions are shown.

II. OVERVIEW OF LANE DETECTION SYSTEM

The lane detection algorithm estimates parameters relevant to the shape of the lane and the posture of the vehicle with respect to the lane. The parameters that are required to define the shape of the lane are; lane-width, curvature, and curvature rate. The parameters concerning posture are; pitch angle, yaw angle, and lateral position (Fig.1). Fig.2 shows a flowchart of the lane detection algorithm. The parameter estimation section is constructed including a particle filter. This generates a hypothetical set of parameters and verifies them using various information obtained from the on-board monocular camera image. The parameter estimation section is divided to two parts. In the first part, the posture of the camera is estimated by using information obtained from the entire structure around the lane, including the neighboring buildings. In the second part, the shape of the lane and the posture of the vehicle with respect to the lane are estimated using the road-side tectonic line and the white line.

The details of the proposed algorithm are described in following sections.

III. LANE DETECTION ALGORITHM

A. lane model

The lane boundary positions are expressed by the following equation.

$$x_{t,k}(z) = \frac{1}{2}kW_t + e_t + \theta_t z + \frac{1}{2}c_{0,t}z^2 + \frac{1}{6}c_{1,t}z^3 \quad (1)$$

$x_{t,k}(z)$ is the lane boundary position at distance z at time t. k specifies the side of the lane; if $k = -1$ then it is the left-hand side, $k = 1$ then it is right-hand side. W_t is the lane width and e_t is the lateral offset between the center of the vehicle and the center of the lane. θ_t is the yaw angle between the the

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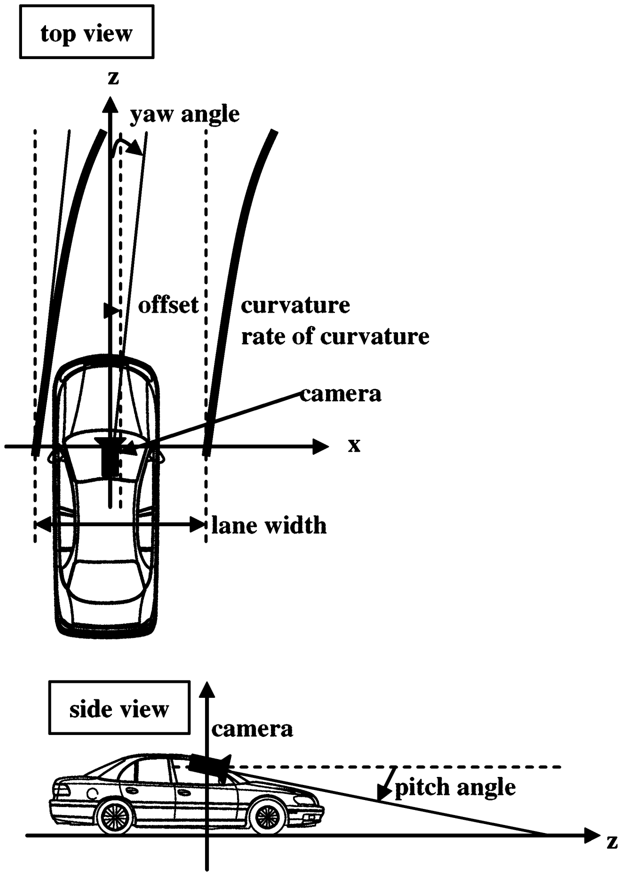

Fig. 1. parameters estimated by the lane detection algorithm

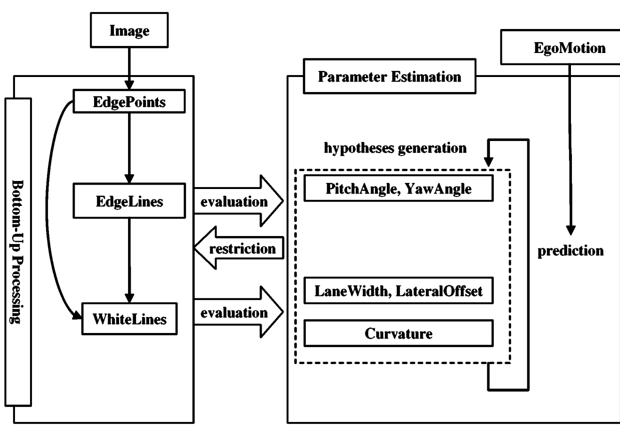

Fig. 2. flowchart for lane detection

direction of travel and the lane. $c_{0,t}$ is the curvature and $c_{1,t}$ is the rate of curvature. In addition, this algorithm estimates ϕ_t which is the pitch angle between the optical axis and the plane of the road plane. The estimated parameter is described as follows.

$$\mathbf{x}(t) = (W_t, e_t, \theta_t, c_{0,t}, c_{1,t}, \phi_t) \tag{2}$$

The update model of the parameters between time t and $t + \Delta t$ is shown in the following.

$$\mathbf{x}_{t+1} = \mathbf{A}_t \mathbf{x}_t + \mathbf{w}_t \tag{3}$$

$$\mathbf{A}_t = \begin{pmatrix} 1 & dz_t & \frac{1}{2}dz_t^2 & \frac{1}{6}dz_t^3 & 0 & 0 \\ 0 & 1 & dz_t & \frac{1}{2}dz_t^2 & 0 & 0 \\ 0 & 0 & 1 & dz_t & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix} \tag{4}$$

$\mathbf{w}_t$ is the Gaussian noise pertaining to each parameter. In this paper dz_t along the z axis was considered as the only motion of the vehicle. Improvements in the prediction accuracy can be expected by including the 'ego-motion' of the vehicle, such as the yaw angle rate.

The conditional probability distribution $p(\mathbf{x}_t|\mathbf{Z}_{1:t})$ of the lane parameter $\mathbf{x}(t)$ is expressed with a set of weighted samples $\mathbf{s}_t^1, ..., \mathbf{s}_t^N; \mathbf{S}_t^i = (\mathbf{x}_t^i, \pi_t^i)$ and is calculated using the observation value $\mathbf{Z}_{1:t}$ obtained from the image until time t using the framework of the particle filter.

The position of the vanishing-point in the image is determined by dividing the parameter obtained in the presumption section of the technique, and by considering the information obtained for the entire structure around the lane, including the buildings defined in the former steps, such that the posture of the camera can be deduced. In the latter section, the road-side tectonic line and the white line are detected in the divided road area, and the position of the car relative to the track shape and the track itself is predicted.

B. edge line detection

First, the gradient magnitudes $I_h(i,j)$,$I_v(i,j)$ in the horizontal direction and in the vertical direction are calculated for the input image $I(i,j)$ (Fig. 3-(a)), and the edge strength $E(i,j) = \sqrt{I_h(i,j)^2 + I_v(i,j)^2}$ and the direction $G(i,j) = tan^{-1}\frac{I_h(i,j)}{I_v(i,j)}$ of the edge of the normal are calculated. Secondly, any edge points for which the edge strength is more than the threshold and the maximum value of the direction of the normal are selected and a set of edge points P_{edge} is obtained(Fig. 3- (b)). Thirdly, the $(\rho - \theta)$ space is defined to detect straight lines in the input image. ρ is the distance from the origin point (i_0, j_0), and θ is the gradient of the line. A straight line of gradient θ_k that passes over each point $P(i,j)$ of P_{edge} is converted into the $(\rho - \theta)$ space by the following expression.

$$\rho_k = (i - i_0)cos\theta_k + (j - j_0)sin\theta_k \tag{5}$$

The straight line is detected by voting to the $(\rho - \theta)$ space with edge points and searching the local maxima for the voted value. The edge line group $L_{edge}$is consequently obtained(Fig. 3-(c)).

To use the detected edge line for the detection of the position of the vanishing point, the domain of ρ was limited by the setting of the range of θ to exclude nearly horizontal and

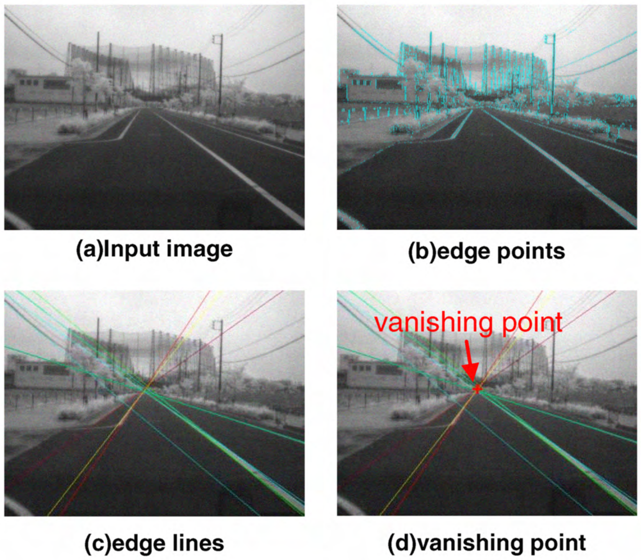

Fig. 3. flowchart for lane detection(1)

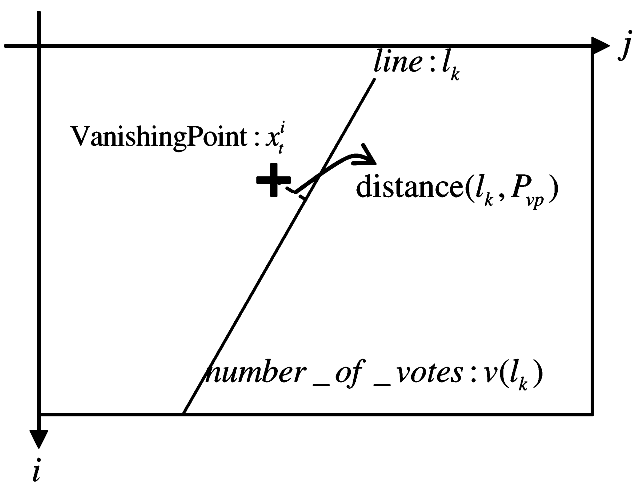

Fig. 4. likelihood calculation for vanishing point

nearly vertical straight lines. These lines are detected from the vehicles that are traveling in the forward direction. The point of origin (i_0, j_0) is set to the mean value of the vanishing point in order to limit the range of ρ.

C. parameter estimation (1)

The position of the vanishing point in the input image is estimated from the straight lines detected in the input image (Fig. 3 - (d)). After the sample set is diffused along the θ and ϕ axes, the likelihood is calculated from the vanishing point P_{vp}^i corresponding to each sample and the detected straight line $l_k \in L_{edge}$. The vanishing point P_{vp}^i is calculated by using $theta$ and ϕ. The weight of each sample is calculated using the $distance(P_{edge}, l_k)$ and the straight line vote number $v(l_k)$ (Fig. 4).

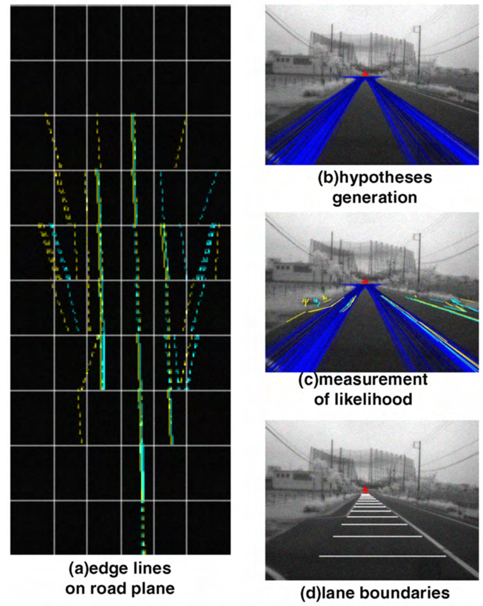

Fig. 5. flowchart of lane detection(2)

$$\sum_k f(distance(P_{vp}^i, l_k))v(l_k) \qquad (6)$$

$f(x)$ is assumed to be a function that becomes a non-negative, monotonous decrease for $x \geq 0$. After the weights of all the samples are calculated, the position of the vanishing point is estimated using the sample that has the maximum weight.

D. extraction of edge lines and lane markers extraction on road surface

The road plane is divided into sub regions along the direction of travel(Fig.5-(a)). The edge points detected in the input image are projected onto the road plane and the edge lines in each sub region are detected. At this time, the pitch angle corresponding to the vanishing point estimated in III-C is used. In addition, the pair for the edge line where the direction of the normal is different by almost 180 degrees is also detected as a white line candidate. The interval in the edge line is considered.

E. parameter estimation (2)

The parameters other than the pitch angle are estimated by using edge lines and white line candidates. The sample set for the lane parameter is diffused in the direction of each parameter (Fig. 5- (b)), and the likelihood is calculated by using the edge line and the white line detected in the preceding paragraph, and the weight of each sample is updated. (Fig. 5-(c)).

1) likelihood calculation with edge line: The likelihood for edge lines is calculated using the following equation.

$$\sum_k g(|\psi_k|) \qquad (7)$$

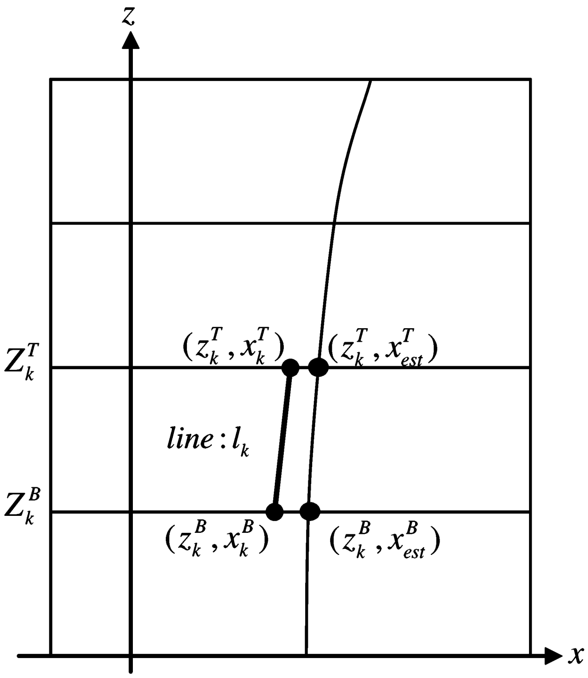

Fig. 6. calculation of likelihood of lane boundaries

ψ_k is the angle between the edge line l_k and the lane boundary line that corresponds to each samples(Fig. 6). $g(x)$ is assumed to be a function that becomes a non-negative, monotonous decrease for $x \geq 0$ here.

2) likelihood calculation with lane markers: The likelihood for edge lines is calculated using the following equation.

$$\sum_k (h(d_k^B)h(d_k^T)) \tag{8}$$

d_k^B is the distance between the white line and the lane boundary line that corresponds to each of the samples at the nearest point in each sub region. d_k^T is the distance between the white line and the lane boundary line that coresponds to each of the samples at furthest point in each sub region (Fig. 6). $h(x)$is assumed to be a function that becomes a nonnegative, monotonous decrease for $x \geq 0$ here. After the weights of all of the samples are calculated, and the lane boundary is estimated using the sample that has the maximum weight. (Fig. 5- (d)).

IV. Experimental results

Figs. 7-9 shows examples of the lane detection using movies filmed in different driving environments. The white horizontal lines indicates the estimated lane in which the vehicle is driving. The red cross indicates the position of the vanishing point. Fig. 7 is an example of a road with a white line down one side. (a) shows the result without pitch estimation and (b) shows the result with pitch estimation using the edge line of a roadside structure. The effect of the stabilization of the lane detection technique by using pitch angle estimation is confirmed. Stable lane detection is achieved in a scene where

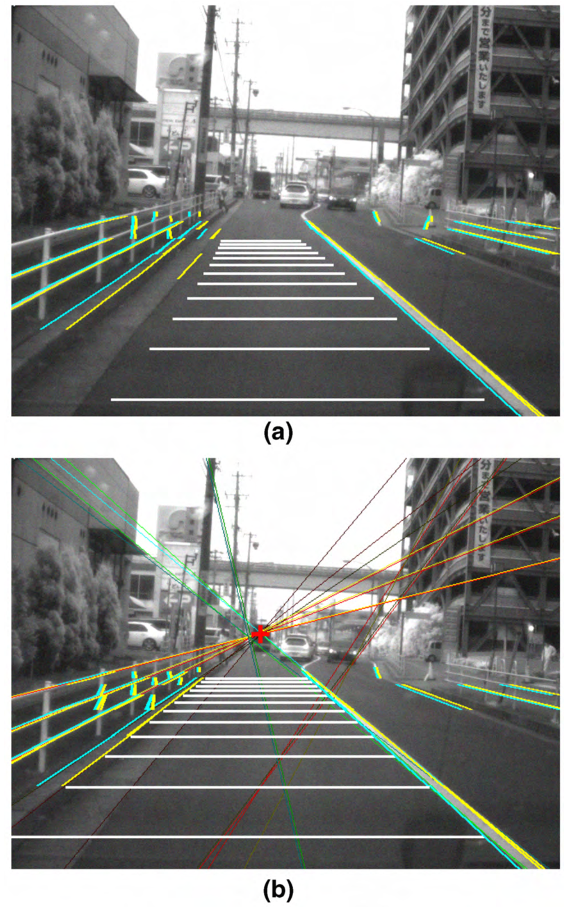

Fig. 7. results(1)-effect of estimating pitch angle initially-

the white lines are faded(Fig. 8-(a)) and where the white line exists only on one side (Fig 8-(b)).

Moreover, Fig. 9-(a) shows an example of a scene where the lane boundary is complex. Figs. 9 -(b) (c) show examples of scenes where it is difficult to detect any white lines due to poor illumination conditions(rain and darkness). The expansion of the situation to apply the lane detection algorithm is confirmed.

On the other hand, there are many situations where it is difficult to detect candidates for the lane boundary by using the differences in brightness in an image. In such situations, estimation of the lane parameters might become unstable. Therefore, it is important to manage the reliability of the lane detection technique, especially on a curved road.

For a quantitative evaluation, the rates of detection achieved by the proposed method and by a conventional method that detects lane markers on both sides of lane have been calculated. The detection rate is a number of frames in which the lane boundaries are detected are correctly within all of the frames.

The detection rate when there are lane boundaries on both sides is 98% by the proposed method. The rate achieved by the conventional method is 88%. The detection rate where there are not lane boundaries on both sides is 91% by the proposed

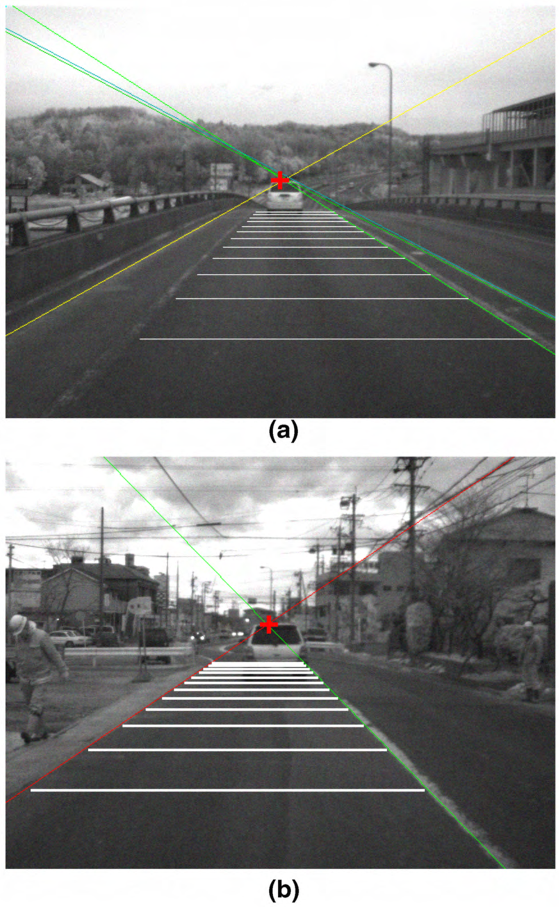

Fig. 8. results(2)

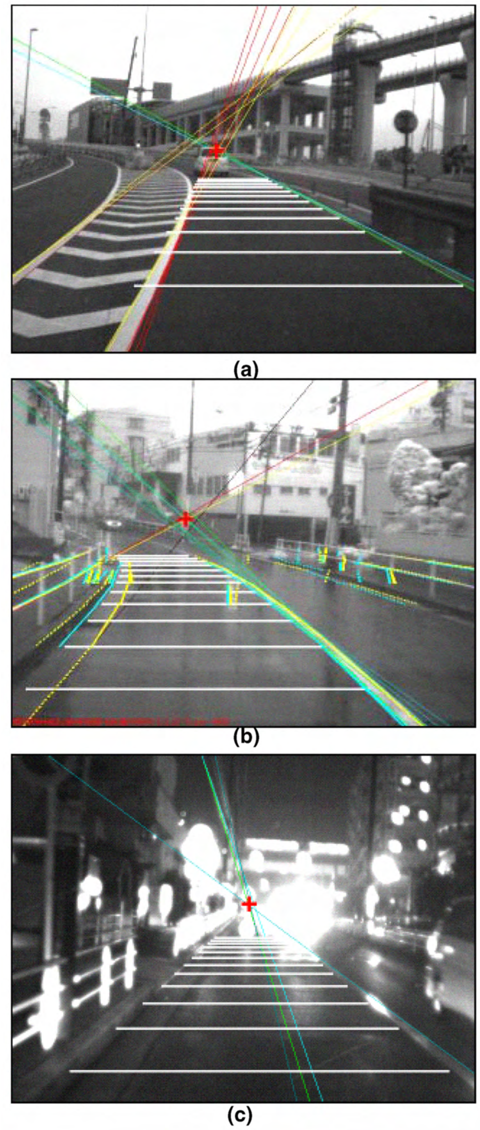

Fig. 9. results(3)

method, whereas the rate achieved by the conventional method is 69%.

V. CONCLUSION

Lane detection is an important function when constructing a driving support system based on an understanding of the driving environment. In this paper, to expand the applicable scope of lane detection techniques, we have proposed a lane detection method that uses information obtained from road-side structures. We have also evaluated the effectiveness of the new technique. To improve the performance of the new lane detection system further, we will fuse it with methods that use colors or other features of the surroundings in the next phase.

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