Hough based robust lane boundary detection for outdoor environments

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***Abstract*-- The detection of a robust lane boundary is one of key in the technological development of autonomous vehicles. Practical problems in lane detection often occur in outdoor events due to sunshine and/or shadow effects. To solve these problems, we apply omni-directional camera with the Hough based active contour model to extract the lanes from captured images. The validity of the proposed method was verified by IGVC [1] in 2004.**

I. INTRODUCTION

The robust lane detection by using vision sensor is still challengeable key technologies for AGV (Autonomous Ground Vehicle) under outdoor environment, since the vision technology is applicable for any environment without any special infrastructures such as the magnetic markers. The Watanabe laboratory at Hosei University has been involved in the design of an outdoor AGV to compete at the IGVC (Intelligent Ground Vehicle Competition) conducted by the AUVSI(Association for Unmanned Vehicle Systems International). In the competition, an AGV must navigate around obstacle course under the prescribed speed limit of 8km/hr, avoiding the obstacles on the track using vision and/or other sensing devices. Outdoor environments pose optical problems for vision systems, making it especially difficult not only to detect lanes but also to distinguish between various obstacles. Steep lane curve recognition is also problem in the IGVC.

Fig.1 IGVC

In order to overcome the problems above, we propose new robust lane detection algorithm for AGV. The proposed method consists of the vision sensor as an omni-directional camera and lane recognition algorithm as a Hough based ACM model with alpha-beta filter. The advantages of proposed robust lane detection system can be summarized as following;

An omni-directional sensor can obtain a 360-digree field of view via a single lens camera without utilizing a dead angle of view. This feature can be useful for AGV especially in regard to lane detection.[2] The light intensity reaching the omni-directional camera is averaged by the 360-degree surrounding light intensity. Thus, changes in light intensity from the outdoor environment are filtered and their effects are minimized.[3]

The disadvantage of the omni-directional camera is inherently affected by direct sun-light, since the direction of the camera is turned toward the sky. The captured images from the camera frequently include the false with line caused by the effect of direct sunlight.

Fig.2 The effect of direct sunlight

In order to eliminate the direct sunlight effect in the images, the straight line based the Hough transform can be useful, since the straight lanes can be projected as distorted line in the projected images. Thus, we can easily distinguish between false straight line due to sunlight and straight lanes in projected images.

By using above technique, we can distinguish between direct sunlight and straight lanes in the captured omni-directional images. The problem of proposed method is steep lane curve recognition since the Hough transform is not suitable to detect curvy lines.

To achieve robust lane detection, regardless of steep curve lanes and/or straight lanes, we propose ACM with alpha-beta filter.

II. ROBUST LANE DETECTION ALGORITHM

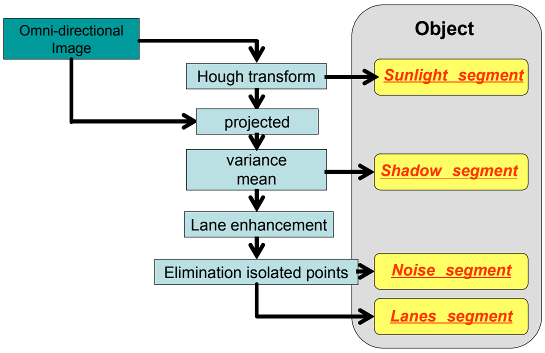


Fig.3 Detections processing flow

In order to detect lanes robustly, we have to recognize each objects in a sequence of omni-directional images. Considerable objects in outdoor situation for AGV are sunlight effect, shadow on the ground, lanes, and scattering noise due to camera noise. Figure.3 shows schematic diagram. Details are described as follows;

A. Sunlight detection

The omni-directional camera is inherently affected by direct sun-light, since the direction of the camera is turned toward the sky. The captured images from the camera frequently include the false with line caused by the effect of direct sunlight. Figure 4 shows typical example of captured image with affected by direct sunlight.

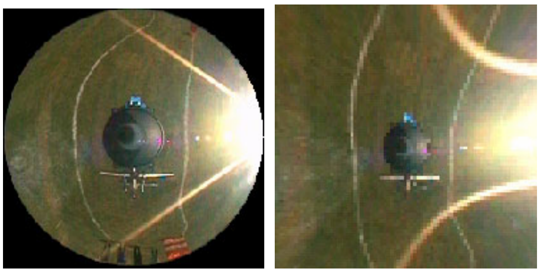


Fig.4 The example of captured image with affected by direct sunlight

In order to eliminate the direct sunlight effect in the images, the straight line based the Hough transform can be use since the straight lanes can be projected as distorted line in the projected images. Thus, we can easily distinguish between false straight line due to sunlight and straight lanes in projected images. Fig. 5 shows sample results of detection of sunlight effect by using the straight line based Hough transform.

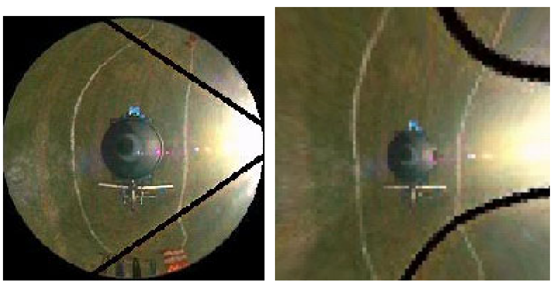


Fig.5 The sample results of detection of sunlight effect

B. Elimination of shadow effect

It is not difficult for human eyes to distinguish shadows from objects. However, identifying shadows by computer vision is challenging research problems. Shadows occur when objects totally or partially occlude direct sunlight. There are many outdoor situation shadows with lanes or partially shadows in lanes. The typical shadow characteristics in images are statistical difference in luminance of variances and mean intensity value. In order to detect shadows in images, we calculate 4x4 areas of images in luminance of variances and mean intensity. Table.1 shows calculated value in 4x4 areas in Figure 6.

Fig.6 The sample results of detection of sunlight effect

Table1 Calculated luminance of variance and mean intensity in each 4x4 areas in Fig. 6

variance mean	35 155	40 83	45 137	36 142
	17 169	44 85	48 90	26 52
	20 180	60 130	39 54	7 43
	13 198	46 180	30 63	34 71

By using between luminance of variances and mean intensity values, we can easily detect shadows in images.

C. Elimination isolated points

After eliminating shadow effect, we apply high pass filter and binarization in images. In order to eliminate scattering noise in binarized image, we define isolated points range. Fig. 7 shows a image of the isolated points range and elimination of isolated scattering noise in images.

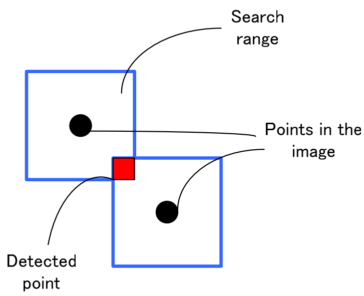
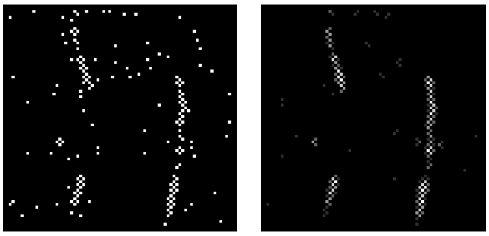


Fig.7 Elimination isolated points process

Figure 8 (a), (b) shows typical sample results of the elimination isolated points. This method can be useful to eliminated scattering noise in images.



(a) Before (b) After

Fig.8 Elimination isolated points

D. *Lane detection by using The Hough transform*

After the lane extraction, the lanes in the image can be approximated as two parallel straight-line segments. The straight-line segments in the images are easy to detect using the Hough transform. A convenient equation for describing a set of lines using parametric or normal notation is:

$$r = x\cos\theta + y\sin\theta$$

The coefficient is the length of a normal from the origin to this line and theta is the orientation of r with respect to the X-axis. For any point (x, y) on this line, r and theta are constant. Using the Hough transform, the two extracted straight parallel lines can be projected into two points in polar coordinates (r,θ) in Hough transform space. Since, by the rules of IGVC, the width of lanes is defined as constant L_w, the relationship between the projected two points in Hough transform space can be derived by

Lw : Lane width

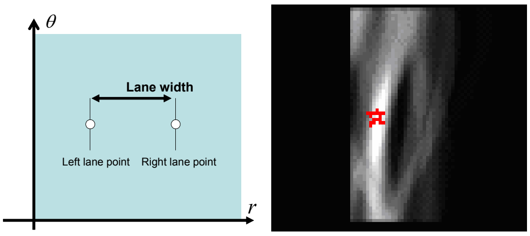
(rleft, 0) : Left lane point

(rlright 0) : Right lane point

$$L_w = r_{left} + r_{right}$$

$$\theta_{right} \cong \theta_{left} \cong 0 \tag{1}$$

Using the data obtained in eq. (1), apply OR logic to detect line segments in the Hough transform to one of the corresponding line points.



(a) (b)

Fig.9 Hough transform space and corresponding lines

(a) Parametric description of two lane points and the know ledge of the lanes width. (b) Hough-transformed image by applying OR logic to detect line segments.

Fig.10 Straight lanes detection

E. *Alpha-beta tracker for the detected lanes*

Because of characteristics of camera images on the AGV, noisy but continuous images should be available, in order to achieve smooth and robust detection of the lanes, we apply alpha-beta filter to estimate the future direction of the lanes in images. Assuming that AGV moves with a constant velocity in a certain time interval, the motion of the vehicle on the r-θ coordinate can by described by the following discrete state equations.

$$x_{k+1} = F_k + w_k$$

$$F_k = \begin{bmatrix} 1 & 0 & dt_k & 0 \\ 0 & 1 & 0 & dt_k \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$x_k = \begin{bmatrix} r_k & \theta_k & \dot{r}_k & \dot{\theta}_k \end{bmatrix}^T$$

Where r_k and θ_k at the sampling time k; F_k is the state transition matrix; and w_k is the system noise.

The measurement y_k with noise v_k is given as follows:

$$y_k = Hx_k + v_k$$

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

Here we applied Kalman filter to the state variable equation and measurement equation above. Among the variety of options in Kalman filtering, we selected the alpha-beta filter, which is an option designed specifically for moving objects with constant velocity as above.

$$y_k = Hx_k + v_k$$

$$\hat{x}_{k|k} = F_k\hat{x}_{k|k-1} + K_k\left\lfloor y_k - F_k H\hat{x}_{k|k-1}\right\rfloor$$

$$\hat{x}_k = F_k\hat{x}_{k|k}$$

$$k_k = \begin{bmatrix} \alpha & 0 \\ 0 & \alpha \\ \beta/dt_k & 0 \\ 0 & \beta/dt_k \end{bmatrix}$$

Where $x_{k|k}$ is the estimate of x_k at the k sampling.

Parameters α and β are included in the filter, and parameter β is automatically assigned when parameter α is specified.

$$\beta = 2(2-\alpha) - 4\sqrt{1-\alpha}$$

Parameter α ranges from 0 to 1. The value is selected as inversely proportional to the variable of noise in the range above.

F. *Estimated lane correction by using ACM*

By applying alpha-beta tracker, we can estimate direction of the lanes smooth and robustly, when lanes in captured images are straight. However, in practically, lanes are not always straight. In order to detect straight lanes as well as curvy lanes, we apply ACM based correction algorithm to detect especially for steep, curvy lanes. The proposed ACM has been successfully implemented for the edge detection, the corner detection.

Figure 11 shows the proposed ACM, in the algorithm. In

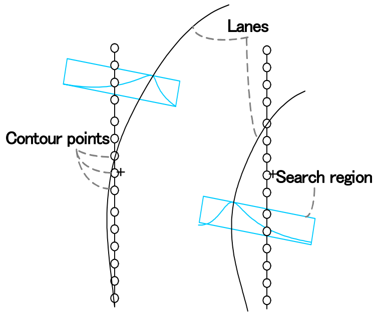


Fig.11 Active contour model

steep curve situation, projected left and right side of lanes are not symmetric, since we use two independent ACMs.

Variables of standard ACM are generally consist of internal energy and image energy and constraint energy. In the proposed ACM, we only use internal energy and image energy. In order to detect steep, curvy lanes such as IGVC field, we neglect constraint energy for the proposed ACM.

[Variables]

l_i : Image luminance level

α_1 : Weighting coefficients for estimated lane fitting

C_{model} :RGB image color model

C_i :RGB intensity for the detected lane color

α_2 : Weighting coefficients for estimated color intensity fitting

E_{int} : Internal energy

E_{images} : Image energy

E_{snake} : Snake energy

In the active contour model, the total energy of an ACM is given by the summation of two different energies of each pixel as distributed by eq. (2).

$$E_{snake} = \int \left(E_{\text{int}}(s) + E_{image}(s)\right) ds \qquad (2)$$

Internal energy can be defined as estimated lane direction from alpha-beta tracker. Since the internal energy is derived by spatial as well as time historical feature of the lanes information and is given by eq(3)

$$E_{\text{int}} = \sum_{i}^{N} \alpha_1 l_i \qquad (3)$$

The image energy is given by the features of images

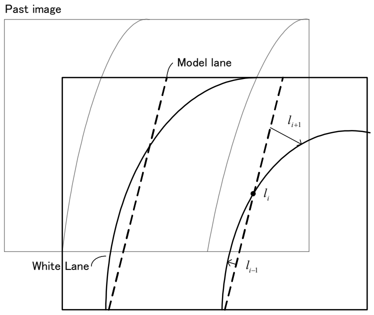


Fig.12 (a) Internal energy

detected color and luminance edge information as follows;

$$E_{images} = \sum_{i}^{N} \alpha_2 \left(C_{model} - C_i\right)$$

According to eq(2), we estimate the best fit of lanes as shown in Fig.12.

Fig.13 (a) shows an actual image of the Hough transformed

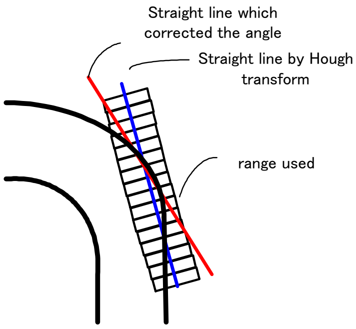


Fig.12 Estimated lane correction by using ACM

result. Fig.13 (b) shows estimated lane correction by using alpha-beta tracker and ACM lane correction algorithm.

Fig.13 Straight lane detection by using Hough transform

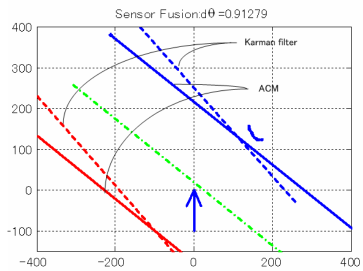


Fig.13 (b) Estimated lane correction

III. EXPERIMENTS

In order to confirm the validity of proposed method, we implements the electric wheelchair based vehicle which entried in 12th IGVC (2004). Because of the limitation of processing time, we use 80x80 pixel images. Actual signal processing time was 0.25 sec.

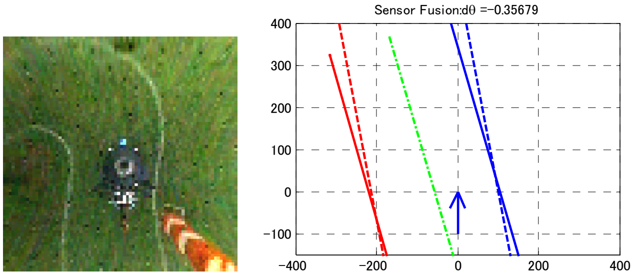


Fig.14 Result of proposed method

IV. CONCLUSION

According to result of the 12th IGVC, the validity of proposed lane detection algorithm is successfully demonstrated. Averaged ACM iteration time is almost 2 epochs and can satisfy real-time processing. The proposed method can be detecting lanes robustly regardless of sunshine and/or shadow effects.

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