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Vision Based Lane Detection in Autonomous Vehicle

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***Abstract* - A novel method for finding and tracking road lanes for vision-guided autonomous vehicle navigation is present in this paper. First an inverse perspective mapping is applied in order to remove the perspective from the camera observed image. Then the edges of the road lanes are detected from the inverse perspective mapping images. A particle filtering algorithm is used which allows us to compute the likelihood between all the particles with the edge images, then the three parameters of the real state of lanes can be estimated. The new lane detection method described in this paper has been tested in real road images and the result is robust and reliable.**

Index Terms* - *Machine vision. Lane detection. Intelligent vehicle.

I. INTRODUCTION

Autonomous intelligent vehicles have found many applications in many industries areas [1,2,3], such as hospitals for transportation of patients, automated warehouses and other hazardous related areas. It enables a vehicle to drive within a given portion of the road. A control system for self-driven car could be built using the vision based lane detection system. And it can help the driver and improve his security.

An autonomous intelligent vehicle has to perform a number of functionalities. Lane detection and tracking are two main tasks for vision guided vehicle navigation, first the relative position of the vehicle with respect to the lane is computed, and then actuators are driven to keep the vehicle in a safe position. The lane marking (or road boundary) detection from the road images captured by camera mounted on the vehicles had received great interest, many different vision-based lane detection systems have been developed worldwide, each relying on various characteristics, such as different road models (two or three dimensional), acquisition devices (mono or stereo vision), computational techniques (template matching, neural networks, etc) [4,5,6,7].

A novel approach to vision based lane detection will present in this paper. First an inverse perspective mapping is applied in order to remove the perspective from the input image. Then the edges of the road are detected from the inverse perspective mapping images. A particle filtering algorithm is used which allows us to compute the likelihood between all the particles with the observed images, then the three parameters of the lanes can be estimated.

II. THE INVERSE PERSPECTIVE MAPPING

Because of the camera perspective effect, the parallel lane mark in real world will intersect into one point (Vanishing Point) in the image plane. The inverse perspective mapping (IPM) [8] allows us to transform an image from a perspective view (the images on the screen) to a view from the sky by remapping each pixel toward a different position. The result is a new 2-dimensional remapped image that represents a top view of the road region in front of the vehicle, as if it were observed from a significant height. Then the parallel lane mark in 3D world is still parallel in the image plane.
We define two Euclidean spaces:

$$\bullet\ w = \{(x,y,z)\} \in E^3$$

Representing the 3D real world space.

$$\bullet\ I = \{(u,v)\} \in E^2$$

Representing the 2D image space where the 3D scene is projected.
Fig.1 shows the relationship between the two spaces w and I.

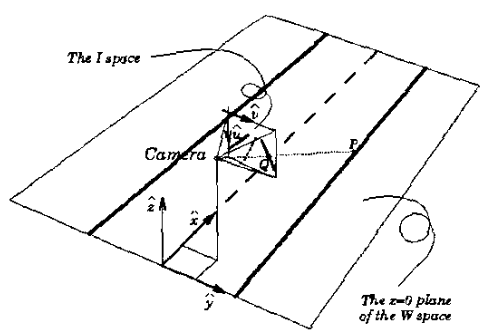

Fig 1. The relationship between the two coordinate systems

The image acquired by the camera belongs to I space, the remapping process projects the acquired image onto the z = 0 plane of the 3D world space W. Given the coordinates (u,v) of the a point in the I space, equation (1) returns the coordinates (x,y,0) of the corresponding point P in the W space.

$$\begin{cases} x(u,v) = \dfrac{h}{\tan[(\bar{\theta} - a) + u\dfrac{2a}{n-1}]} \times \cos[(\bar{\gamma} - a) + v\dfrac{2a}{n-1}] + l \\ y(u,v) = \dfrac{h}{\tan[(\bar{\theta} - a) + u\dfrac{2a}{n-1}]} \times \sin[(\bar{\gamma} - a) + v\dfrac{2a}{n-1}] + d \\ z = 0 \end{cases} \quad (1)$$

With u, v=0,1...n-1.
The camera parameters is the following:
• Viewpoint: the camera position is $C = (l,d,h) \in W$

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• Viewing direction: the optical axis is determined by the following angles:
$-\bar{\gamma}$: The angle between the projection of the optical axis on the plane z = 0 and the x-axis. $-\bar{\theta}$: The angle between the optical axis and the horizon.
• Aperture: the camera angular aperture is 2α ;
• Resolution: the camera resolution is n × n.

As an example, a synthetic computer generated texture image representing the road scene seen by a camera is shown in fig.2.a, and its remapped image is show in fig.2.b.

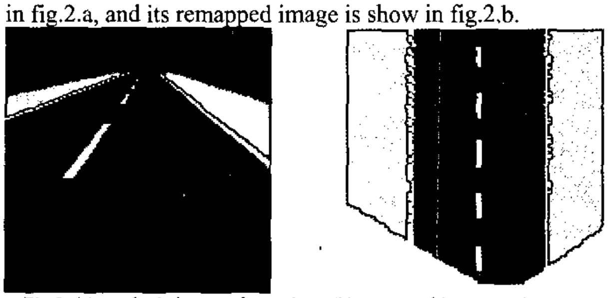


Fig.2. (a) synthetic image of a road (b) remapped image road

III. Edge Detection and Lane Detection

After the IPM transform, a road lane marking is in the z=0 plane of the w space, and it is represented by a quasi-vertical bright line of constant width surrounded by a dark road region. The following processing is in charge of the reconstruction of the road geometry.

From the remapping image of the road, the pixels belonging to a lane marking have a brightness value higher than their left and right neighbours. To detect the lanes, an edge detection algorithm with a sobel mask is used. And in order to remove the image noise effect, a smoothing process is applied before the edge detection. After the edge detection, we obtain a binary image of the lane mark boundary. This image represents coarsely the edges of the lane.

After the edge detection of the lane, we have to find how to describe mathematically a road with small parameters and few computation times. Because the road is either a portion of circle or line, we can use a three-dimensional vector to represent a road viewed from the sky. We model road via its edges, and we assume that the wide of the road is constant, so the state of road Xn can be represented by:

$$X_n = \begin{bmatrix} \frac{1}{R} \\ \theta \\ d \end{bmatrix} \qquad (2)$$

R is the curvature of the road, which can be infinite if the road is straight.
θ is the angle between the road and the direction the car goes.
d is the distance between the right side of the road and the position of the camera.
The proposed road lane state model is show in Fig.3.

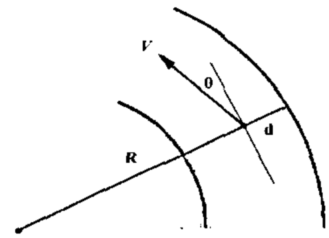


Fig.3 Road Lane State Model

With the three parameters described the road lane state, we can easily draw a binary image using the three parameters, and then the likelihood between the binary images of the detection lane edge and the binary image with the three road parameters can be calculated.

A particles filtering theory for the filtering of non-Gaussian non-linear state space models will be used to calculate the likelihood between two images. This algorithm has been presented in [9].

Given the observation y_n and the particle $p_n^{(j)}$, compute $a_n^{(j)}$, the likelihood of the particle $p_n^{(j)}$ based on the observation y_n, that is:

$$a_n^{(j)} = p(y_n \mid p_n^{(j)}) = r(G(y_n, p_n^{(j)}))\left|\frac{\partial G}{\partial y_n}\right| \qquad (3)$$

For j=1…m particles

To measure the likelihood between this two images, we can count how many pixels at 1 for these images is also at 1 for the image of observation. The more there are, the more likely the estimate happens. So we compute the following formula:

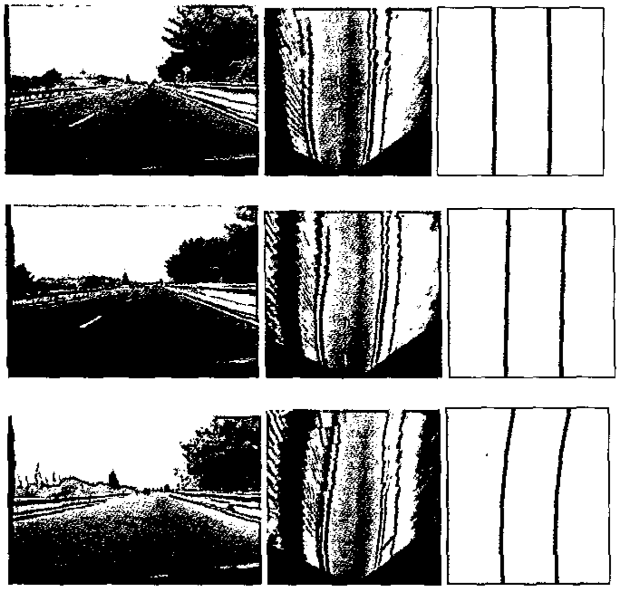
$$likelihood(Y) = \sum_{(i,j)/X_n(i,j)\neq 0} Y(i,j) \qquad (4)$$

Where Xn is the binary image of one forecast and Y is the observation. After having computing the likelihood between all the particles with the observation images, the three parameters of the observation lane detection images can be estimated.

IV. Real Image Experiment

The proposed algorithm has successfully applied to real road images with the road conditions: without obstacles, on straight and curved roads. Fig.4 presents a few results of lane detection using the proposed method and the three parameters of the road state can be calculated.

Fig.4 (a) and 4(b) show the observation original images and the images after the inverse perspective mapping, and the camera parameters using for inverse perspective mapping is: $\theta = 6°, \gamma = 7.2°, \alpha = 30°, height = 0.7m$. Fig.4(c) presents the final result of the lane detection. The lanes are detected and the parameters of the lanes are reasonably estimated using 100 particles to simulate the road states in this experiment.



(a) (b) (c)

Fig.4 some experiment results on land detection

(a) Original images

(b) The images after the inverse perspective mapping

(c) Result of the detection lane.

The result of the calculated lane parameters are shown in table I

TABLE I
RESULT OF THE CALCULATED ROAD PARAMETERS

	The width of road is 8m.		
	R (m)	θ (°)	D (m)
Road 1	341.8	4.61	1.6
Road 2	331.1	5.48	1.2
Road 3	90.9	5.29	0.19

V. CONCLUSION

A novel approach of lane detection for vision-based Autonomous Vehicle system has been presented in this paper. It works on flat roads with good painted road markings. After the inverse perspective mapping of the input images, the lane boundaries can be extracted using edge detection, and then the road parameters can be estimated using the particles filtering theory.

Unfortunately when the road region is in bad condition, we need to deal with many difficulties, such as Obstacle Detection, Vehicle Detection and Tracking, and Pedestrian Detection, a different method must be devised for the robust determination of the road lane.

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