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RESEARCH ON PRECEDING VEHICLE DISTANCE MEASUREMENT WITH MONOCULAR VISION BASED ON LANE PLANE GEOMETRIC MODEL

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Abstract. *In order to solve the problem of the large error in vehicle longitudinal distance measurement based on gray processing with monocular vision, the longitudinal measurement model based on feature point in the back of preceding vehicle is deduced from the basic theory of imaging by a pinhole model camera and the boundary constraint of lane plane. Meanwhile, through counting a large number of characteristic parameters from motor coaches and trucks, and taking target source as the preceding vehicle simulation object, a dynamic compensation model of vehicle distance measurement error under multi-sample condition is established. Finally, the experiment of preceding vehicle longitudinal distance measurement under different known distances is performed with the reconstruction distance measurement model on the road. The result shows that the proposed approach has a high measurement precision and the relative error is less than 5%, and that it also can meet the practical application requirement of large vehicle longitudinal distance measurement based on monocular vision.*

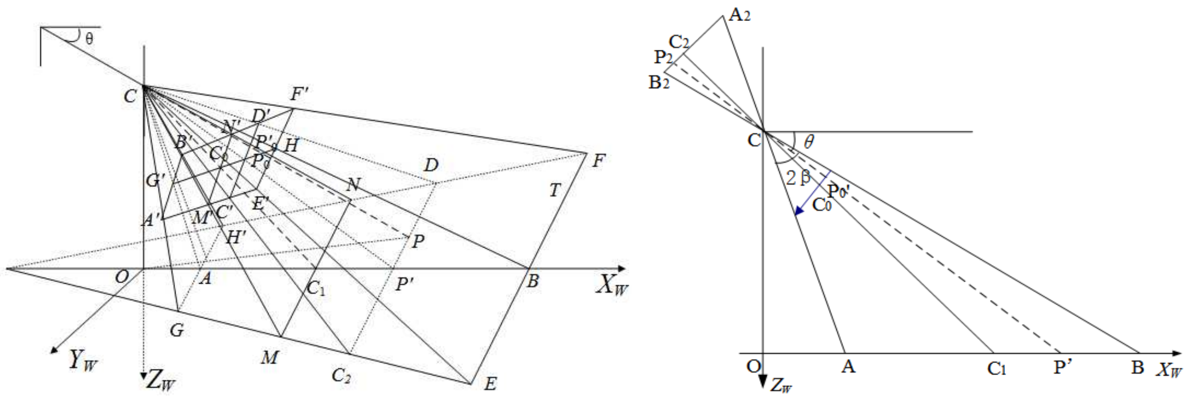
Keywords: Machine vision, Geometric model, Dynamic compensation, Preceding vehicle distance measurement

1. **Introduction.** Car-following is a basic and microscopic driving behavior on the road, and the risk vehicle faced during the period of car-following mainly comes from the longitudinal vehicle rear-end collision. Speeding and that the host vehicle does not keep a safe following distance are the main causes of vehicle rear-end accidents. Therefore, the preceding vehicle distance measurement is an important part of vehicle longitudinal safety driving assistance system; it has great significance for keeping the gap between vehicles, lane changing and vehicle collision warning system [1,2].

Machine vision-based distance measurement method has the advantage of simple hardware, low cost and flexible software algorithm. And it is very important to detect the preceding vehicle when measuring the vehicle distance based on monocular vision automatically, since detection accuracy directly affects the precision of preceding vehicle distance measurement. There are many methods for vehicle detection in the literature, such as vehicle shadow extraction [3], rear mathematical modeling [4] and vehicle outline detection [5]. As demonstrated in related literature, vehicle shadow-based method is greatly influenced by external light. Rear mathematical modeling method obtains the depth information of road image through calibrating corresponding points; however, subject to the equipment limitation and the objective reasons of calibration, it is unable to get higher accuracy transformation matrix, so its applicability is limited. Vehicle outline detection method is immune to interference from the outside environment with strong ability, which has been widely applied.

When detecting the preceding vehicle based on outline detection with monocular vision, it can only identify the rear outline, and the distance measurement feature point is usually selected from the lower edge of rear outline; due to the existence of rear overhang height above the ground, this method will certainly cause large measurement error. Therefore, an algorithm of preceding vehicle distance measurement based on the lane plane geometric model is proposed in this paper.

2. **Preceding Vehicle Distance Measurement Based on Feature Point.** As shown in Figure 1(a), distance measurement model under the lane geometric constraint is established according to the installation position of the CCD visual sensor. Several parameters are defined as follows: C is the optical center of the CCD visual sensor and is vertically projected to point O on the road surface. In the road coordinate system, O is defined as the origin, and the longitudinal motion direction of the vehicle is defined as the X-axis direction of the road coordinate system. Plane $A'B'F'E'$ is the CCD visual sensor imaging plane, while triangle CMN is the optical axis plane. The camera optical axis (CC_1) and the road plane (T) intersect at point C_1. θ is the pitching angle of the camera, P is the feature point of the preceding vehicle for measurement. As a result, the length of OP' in the road coordinate system represents the longitudinal distance between the front vehicle and the CCD visual sensor.



(a) Geometric relation of CCD sensor imaging (b) Lateral view model of measurement

FIGURE 1. Distance measurement based on lane plane constraint and feature point

According to the above distance measurement model under the lane plane constraint, the position of the preceding vehicle in the road coordinate system can be obtained. In other words, the task is to calculate the value of the feature point P in the road coordinate system.

As shown in Figure 1(b),

$$CC_0 = f, \ \angle OC_1C = \theta, \ OC = h \tag{1}$$

As for the triangle C_0CP_0',

$$\angle C_1CP' = \angle C_0CP_0' = \arctan\left(\frac{P_0'C_0}{CC_0}\right) = \arctan\left(\frac{P_0'C_0}{f}\right) \tag{2}$$

where, $P_0'C_0$ can be assigned with both positive and negative values; besides,

$$\angle OCP' = \angle OCC_1 + \angle C_1CP' = \frac{\pi}{2} - \theta + \arctan\left(\frac{P_0'C_0}{f}\right) \tag{3}$$

where, $P_0'C_0 = y(C_0) - y(P_0') = [v_0 - v(P_0')] \times dy = [v_0 - v(P_0)] \times dy$.

So the relation can be got as follows:

$$\begin{aligned} Y_W(P) = OP' = OC \times \tan \angle OCP' = h \times \tan\left[\frac{\pi}{2} - \theta + \arctan\left(\frac{P_0'C_0}{f}\right)\right] \\ = h \times \tan\left[\frac{\pi}{2} - \theta + \arctan\left(\frac{[v_0 - v(P_0)] \times dy}{f}\right)\right] \end{aligned} \tag{4}$$

where, v_0 is the longitudinal image coordinate of the optical center, $v(P_0)$ is the longitudinal image coordinate of the feature point, d_y is the longitudinal length of the unit cell of the image, and $Y_W(P)$ is longitudinal distance between host vehicle and preceding vehicle.

3. **Dynamic Compensation Model of Vehicle Distance Measurement Error under Multi-sample Condition.** The rear area of the preceding vehicle is divided into part A and part B by the lower edge of the rear outline, as shown in Figure 2. The vertical height of the area A is the preceding vehicle overhang height above the ground, D is the midpoint of the lower edge of the rear area, and is vertically projected to the point P on the road surface. Since the front vehicle identification algorithm can only detect the rear outline of the target vehicle in front, selecting point D as the feature point of longitudinal distance measurement will largen the longitudinal distance measurement value.

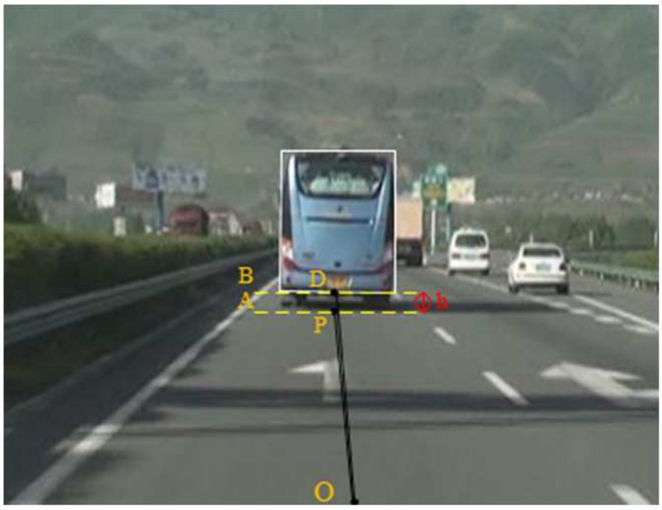


FIGURE 2. Error source analysis of longitudinal vehicle distance measurement

FIGURE 3. The longitudinal distance detection when the target is 0.2m above the ground

In order to reduce the measurement error caused by the rear overhang height for the longitudinal vehicle distance, and make the distance measurement value close to the real value as accurately as possible, a red target source is taken as the simulation object of the preceding vehicle. Through analyzing over 500 cases of motor coaches and trucks, the variation range of rear overhang height above the ground is determined as [0.2m, 1m], and the variation range of the target longitudinal position is [10m, 100m].

Part of the longitudinal distance test figures are displayed in Figure 3. By the Longitudinal Vehicle Distance Measurement Error Calibration System software developed with VC++6.0, related data about the distance measurement at different target clearance and different real distance can be got.

On the basis of the measurement error data of the target at different target clearance and different perception distance based on feature point, the reconstruction model of the longitudinal distance measurement can be expressed as:

$$\begin{cases} y = h \times \tan\left[\frac{\pi}{2} - \theta + \arctan\left(\frac{[v_0 - v(P_0)] \times dy}{f}\right)\right] \\ z = 118 - 1124x - 3.133y + 3522x^2 + 34.6xy - 0.0399y^2 - 4795x^3 - 86.22x^2y \\ \quad -0.1845xy^2 + 0.0017y^3 + 2676x^4 + 98.62x^3y + 0.1428x^2y^2 + 0.001313xy^3 \\ \quad -2.077e^{-5}y^4 + 8.835e^{-8}y^5 - 7.658e^{-6}xy^4 + 0.0004x^2y^3 - 0.1114x^3y^2 \\ \quad -38.23x^4y - 391.1x^5 \\ Y_W(P) = h \times \tan\left[\frac{\pi}{2} - \theta + \arctan\left(\frac{[v_0 - v(P_0)] \times dy}{f}\right)\right] - z \end{cases} \tag{5}$$

where, x is the target clearance, y is the perception distance based on feature point, and z represents the longitudinal measurement error.

4. **Experimental Result and Analysis.**

4.1. **Experimental design.**

The proposed algorithm was implemented on the iEi-TANK 820 hardware platform. As shown in Figure 4, a 1/3 inch CCD camera was connected to the hardware platform with a video cable and mounted behind the windshield of the vehicle. The experimental environment was set on proving ground in Chang'an University, and the variation range of the distance marker line ahead of the CCD sensor was [10m, 100m]. During the experiment, the rear of the truck was stopped at different distance marker lines, and the distance would be identified by the distance measurement system automatically.

FIGURE 4. CCD sensor installation and experimental process

4.2. **Experimental result analysis.** Camera Calibration Toolbox module of the MATLAB was used to calibrate intrinsic parameter [6] and method based on vanish point in the lane image was used to calibrate extrinsic parameter of the CCD sensor [7]. In order to test the proposed model established in this paper, experiment under real road environment was done. The preceding vehicle was stopped in every five meters from 10 $\sim$ 100m ahead of the CCD and the preceding vehicle images at different distance were collected by the CCD.

On the basis of the intrinsic and extrinsic parameters calibration, comparison and analysis were conducted between the detection distance and actual distance. As Table 1 shows, the relative error is less than 5% and the average absolute error is about 1.7m.

Table 2 shows a comparison of preceding vehicle distance measurement between the proposed model and the traditional model using the feature point from the rear outline. Through analyzing the data, the proposed approach has a higher measurement precision, and the average relative error is reduced by 16%.

Table 3 shows a comparison between the proposed approach and other distance measurement approaches, including approach based on projection transformation and approach based on data regression modeling. Compared with the other two approaches, the

Table 1. Comparison of preceding vehicle distance measurement result

Test No.	Actual distance (m)	Detection distance (m)	Absolute error (m)	Relative error (%)
1	10	10.46	0.46	4.6
2	15	15.59	0.59	3.9
3	20	20.65	0.65	3.2
4	25	25.78	0.78	3.1
5	30	30.92	0.92	3.1
6	35	36.16	1.16	3.3
7	40	41.37	1.37	4.6
8	45	46.58	1.58	3.5
9	50	51.88	1.88	3.7
10	55	57.13	2.13	3.9
11	60	62.22	2.22	3.7
12	65	67.58	2.58	3.9
13	70	72.67	2.67	3.8
14	75	77.78	2.78	3.7
15	80	82.83	2.83	3.5
16	85	88.16	3.16	3.7
17	90	93.18	3.18	3.5
18	95	98.36	3.36	3.5
19	100	103.55	3.55	3.6

Table 2. Comparison between the proposed model and the traditional model

Test No.	1	2	3	4	5	6	7	8	9	10
Actual distance (m)	10	20	30	40	50	60	70	80	90	100
Using proposed model (m)	10.46	20.65	30.92	41.37	51.88	62.3	72.67	82.83	93.18	103.5
Using traditional model (m)	12.44	24.64	36.43	47.86	58.73	70.57	82.26	95.78	108.6	122.8

TABLE 3. Comparison with other distance measurement approaches

Test No.	1	2	3	4	5	6	7	8	9	10
Actual distance (m)	10	20	30	40	50	60	70	80	90	100
Using proposed approach (m)	10.46	20.65	30.92	41.37	51.88	62.3	72.67	82.83	93.18	103.5
Data regression approach (m)	11.25	21.55	31.95	42.16	52.6	63.85	74.96	85.62	97.39	109.8
Projection transformation approach (m)	11.86	22.63	33.17	43.82	54.51	65.2	77.33	89.5	112.2	125.5

proposed approach has a better effectiveness, and the average relative error is reduced by 8%.

Also, in order to test the robustness of the proposed approach when car driving, the Third Circle Highway of Xi'an City was selected as the test road. The result shows that the proposed approach has a good identification accuracy (91%) and the average relative error is about 7%, which can meet the requirement of the actual application.

5. **Conclusions.** In order to improve the identification efficiency of the preceding vehicle longitudinal position, this paper presents an algorithm of preceding vehicle distance measurement based on the lane plane geometric model. Distance measurement model under the lane geometric constraint is built according to the installation position of the CCD visual sensor. Meanwhile, on basis of counting a large number of characteristic parameters from motor coaches and trucks, a dynamic compensation model of vehicle distance measurement error under multi-sample condition is established. At last, the experiment of preceding vehicle longitudinal distance measurement is performed with the reconstruction measurement model on the road. The result shows that the proposed algorithm has a higher measurement precision and the relative error is less than 5%, and that it also can meet the practical application requirement in accuracy for the large vehicle longitudinal distance measurement. For further studies, more environmental factors must be considered to optimize system performance and make the algorithm more robust.

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