Vision-Based Distance Estimation for Multiple Vehicles Using Single Optical Camera Feature

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***Abstract*—This paper presents a novel algorithm which can be applied in the telematic systems to detect the multiple vehicles' distances. The characteristic of the proposed algorithm is that it only makes use of a single optical camera to capture images of vehicles and without using other auxiliary equipment. The working principle of the proposed algorithm is to use width of the license plate as the known information, and then calculate the pixel size of the license plate appeared in the CCD image. The extraction of the license plate region is performed by the image processing software. This paper derives a distance-pixel relation equation from the evaluation CCD images with known vehicles' distances. After a simple mathematical operation, one can immediately obtain the distance information of multiple vehicles within the CCD image using the distance-pixel relation equation. This distance measure method can display the individual distance of multiple vehicles located at difference positions. Moreover, in comparison with other traditional methods, the overall structure of the proposed algorithm is quite simple. It just requires only a camera with a data processor and is very applicable in telematic systems.**

Keywords- vision-based distance measurement, CCD, telematic system

I. INTRODUCTION

Vehicle detection and distance estimation is an important issue in the field of intelligent transport systems (ITS). One of the main applications of vehicle detection and distance estimation is the vehicle collision avoidance system and automatic vehicle driving system [1]. A lot of methods for the detection of vehicles in the automotive environment have been proposed [2]. Some of these well-developed systems, e.g., pre-crash detector and adaptive cruise control (ACC) [3], have currently come with many vehicles on the roads today. With the developments of electronic equipment as well as measuring method, the accuracy of vehicle distance measurement has been improved greatly. These proposed vehicle detection and distance estimation methods can be categorized into two classes: (a) active vehicle detection system and (b) passive vehicle detection system [4].

Active vehicle detection system usually utilizes a transmitter and receiver, e.g., radar (radio detection and ranging), lidar (light detection and ranging), sonar (sound navigation and ranging)[4, 8]. Due to the reliability and accuracy, the active vehicle detection system has been implemented commercially in vehicles this present day. Active vehicle detection system provides many benefits over passive type. For example, this system could perform well under the changing ambient light conditions. However, one major limitation is that the active vehicle detection system is prone to interference from other similar systems. Hence it can not detect several vehicles at the same time. Also, the hardware used is generally more expensive [4, 8].

In comparison with the active vehicle detection system, the passive vehicle detection system has fewer interference issues. Most of the proposed passive vehicle detection systems are based on the vision-based analysis technology. They usually use either charge-coupled device (CCD) or complementary metal-oxide semiconductor (CMOS) to get a digital image of the surroundings of a vehicle. The captured video can be processed in real-time so as to calculate speed, direction, distance, or size of objects appearing in image frame [8]. Therefore, the passive optical sensor usually has higher spatial resolution and faster scanning speed than active one. In addition, due to the passive vehicle detection system needs not to emit radar or laser signal, they are more power efficient then passive type. Recently, vision-based passive vehicle detection system is becoming more popular because of lower cost and multiple applications [4, 8].

There are two methods to implement the vision-based vehicle detection systems, i.e., stereovision and monocular camera. The stereovision system, namely, uses two cameras (tightly coupled) [5, 8]. However, the stereovision system is costly due to an additional camera, higher processing power requirements, and calibration problems [6-8]. On the other hand, a monocular system only makes use of one camera and could reduce its implementation cost. However, this system lacks depth information cues and will influence the accuracy of distance estimation. Recently, lots of monocular vision methods have been proposed for distance-measurement with a quite high accuracy [6-8]. Shibata et al. apply only optical flow to measure distance and direction of an object using single camera. Dagan et al. develop a method for calculating the distance and relative velocity to the vehicle in front. Wu et al. compare the gray intensity with the highway surface and use image coordinate model for distance measurements. Goto and Fujimoto use perspective model in order to find distance by means of square measure of the object in image plane.

These proposed vision-based vehicle detection systems use various cues that can be used for vehicle distance estimation. These cues include size and position of the objects, lane width, and point of contact of a vehicle and the road [6-8]. Because the size of the license plate used in

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Taiwan is fixed [10], this paper proposed a novel algorithm to detect the multiple vehicles' distances based on a single optical camera. This paper derives a distance-pixel relation equation from the evaluation CCD images with known vehicles' distances. After a simple mathematical operation, one can immediately obtain the distance information of multiple vehicles within the CCD image using the distance-pixel relation equation. Experimental results show that the average error rate of the proposed vehicle distance estimation algorithm is less than 2% and prove it is very applicable in telematic systems.

The rest of this paper is organized as follows: Section II will review the principle of vision-based vehicle distance estimation system. Sections III and IV describe the proposed algorithm and its experimental results. Finally Section V concludes this paper.

II. The Principle of Vision-based Vehicle Distance Estimation System

A vision-based vehicle distance estimation system uses cameras installed on a vehicle. The image captured by a camera is affected by many parameters which include angle of view, focal length, camera height, total number of pixels, motion blur, exposure time, and etc [8].

When CCD or CMOS camera takes a picture, the area of scene covered by the picture is determined by the field of view (FOV) which defines the angle of view (α) of a camera lens. A wide-angle lens can see wider and larger area but has lower resolution. On the contrary, a narrow-angle just can see narrower and smaller area but has higher resolution. A wider angle of view and higher optical power are usually associated with a shorter focal length. Please refer to Figure 1 that the focal length, namely F, is the distance from a lens to its focal point (point of convergence of light). An image produced by a camera lies in the image plane which is perpendicular to the axis of the lens. The total number of pixels of an image in horizontal direction is called as image width. The height from the ground at which a camera is installed is called as camera height. In automotive applications, it is useful to identify the point of contact which is a point where two things meet, e.g. bottom of the wheel where vehicle and the road meet [8, 9].

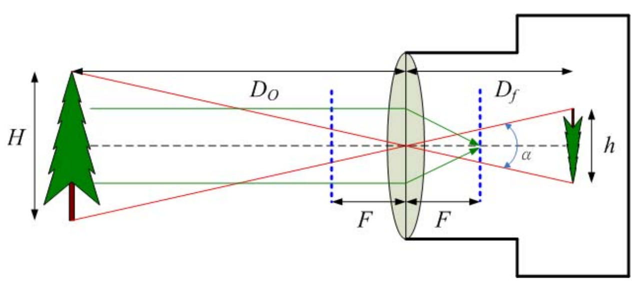


Figure 1. The camera lens parameter.

If the distances from the object to the lens and from the lens to the image are D_o and D_f , respectively, for a lens of negligible thickness with focal length F, these three distances are related by the thin lens formula [9]. That is

$$\frac{1}{D_O}+\frac{1}{D_f}=\frac{1}{F}. \tag{1}$$

If one can determine D_f and F, the distances from the object to the lens, D_o, can be described as

$$D_O=\frac{F\cdot D_f}{D_f-F}. \tag{2}$$

Using basic trigonometry formula, one can find that

$$\tan(\frac{\alpha}{2})=\frac{h}{2D_f}, \tag{3}$$

and could drive the following equation:

$$D_O=\frac{F\cdot(h/2\tan(\alpha/2))}{(h/2\tan(\alpha/2))-F}. \tag{4}$$

Generally, the parameters of the angle of view α and the focal length F are known. Therefore, the distances from the object to the lens D_o can be calculated by the use of image size shown in the frame.

III. The Proposed Vehicle Distance Estimation Algorithme

In Taiwan, the vehicle license plate is administered by the Ministry of Transportation and Communications (MOTC) and the size of vehicle license plate is fixed and regular. Table I and Figure 2 show the size of vehicle license plate used in Taiwan [10].

TABLE I. The Size of Vehicle License Plate Used in Taiwan

Vehicle type	Color specification	Size (mm)
Tour bus	Red background with white words	320×150
Taxi	White background with red words	
Commercial coach	Green background with white words	
Commercial truck		
Commercial van		
Commercial container truck		
Commercial trailer		
Private truck	White background with green words	
Private coach		
Private trailer		
Private car	White background with black words	
Rental car		
Transportation vehicles	Yellow background with black words	

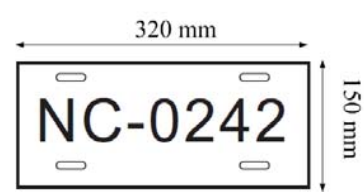


Figure 2. The dimension of the license plate used in Taiwan.

It follows from Table I that all of the vehicles in Taiwan have the same license plate dimension. Therefore, this paper makes use of this property and the equation (4) to develop a new vision-based vehicle distance estimation algorithm. Figure 3 is the flowchart of the proposed algorithm. This algorithm consists of training phase and estimating phase.

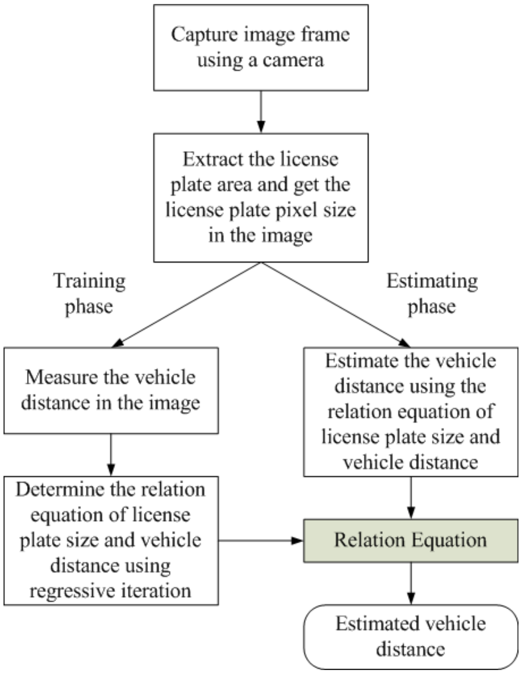


Figure 3. The flowchart of the proposed vision-based vehicle distance estimation algorithm.

The training phase will generate a relation equation using various known license plate pixel sizes and vehicle distances. Then in the estimation phase, the proposed algorithm can use this relation equation with the captured license plate pixel size to estimate the vehicle distance.

IV. Experimental Results

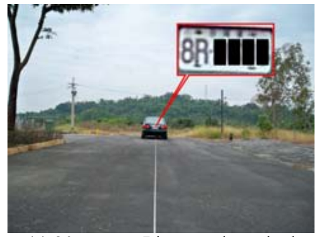
This paper prepares two types of relation equations, namely sparse type and dense type, for estimating the vehicle distance. The maximum vehicle distance of these two types of relation equations is 50 meters.

A. Sparse type of relation equation

In the sparse type of relation equation, the training vehicle is arranged at every 10 meters from 20 meters to 50 meters. In the other words, this type just has 4 sets of training distances, i.e., 20, 30, 40, and 50 meters. Figure 4 shows the training license plate pixel size as well as the corresponding vehicle located at different distances. Using the width of license plate pixel size and vehicle distance as the training data, one can obtain the sparse type of relation equation:

$$y = 1054.6x^{-0.956} \tag{5}$$

where x and y are the width of license plate pixel size and the estimated vehicle distance, respectively.



(a) 20 meters. License plate pixel size: 60×28

(b) 30 meters. License plate pixel size: 41×20

(c) 40 meters. License plate pixel size: 31×15

(d) 50 meters. License plate pixel size: 25×11

Figure 4. The training license plate pixel size as well as the corresponding vehicle located at different distances for the sparse type of relation equation.

B. Dense type of relation equation

In the dense type of relation equation, the training vehicle is arranged at every 3 meters from 5 meters to 50 meters. Therefore, there are 16 sets of training distances, i.e., 5, 8, 11, 14, 17, 20, 23, 26, 29, 32, 35, 38, 41, 44, 47, and 50 meters. Figure 5 shows the partial training license plate pixel size as well as the corresponding vehicle located at different distances. Using the width of license plate pixel size and vehicle distance as the training data, this paper generates the dense type of relation equation:

$$y = 1486.5x^{-1.045} \tag{6}$$

where x and y are the width of license plate pixel size and the estimated vehicle distance, respectively.

(a) 5 meters: license plate pixel size: 233.5×107.5

(b) 14 meters: license plate pixel size: 85.5×41.5

(c) 26 meters: license plate pixel size: 49×21

(d) 38 meters: license plate pixel size: 34×14

Figure 5. The training license plate pixel size as well as the corresponding vehicle located at different distances for the dense type of relation equation.

Figure 6 demonstrates two of the testing images used in this paper. There are two vehicles appeared in Figure 6. The proposed algorithm has to extract the license plate area of these two vehicles individually. Then it can estimate the vehicle distance via the sparse type (5) or dense type (6) of relation equations. Table II summarizes the simulation results. The average error rate of the sparse type and the dense type of relation equations are 2.81% and 1.22%, respectively. It goes without saying that the dense type of relation equation has better accuracy rate.

(a) License plate pixel size, Left: 88×40.5, Right: 54×23.5

(b) License plate pixel size, Left:53×23, Right: 39×16.5

Figure 6. The testing license plate pixel size as well as the corresponding vehicle located at different distances.

TABLE II. THE SIMULATION RESULTS OF THE PROPOSED ALGORITHM USING THE SPARSE TYPE AND DENSE TYPE OF RELATION EQUATIONS.

No.	Real distance (Meter)	Sparse type		Dense type	
		Estimated distance	Error rate (%)	Estimated distance	Error rate (%)
1	22.7	23.28	2.54	23.00	1.34
2	13.8	14.59	5.75	13.81	0.07
3	29.9	30.29	1.30	30.68	2.60
4	20.6	21.39	3.82	20.97	1.80
5	32.2	31.77	-1.33	32.32	0.38
6	23.2	23.70	2.14	23.46	1.11
Ave. error rate:		2.81%		1.22%	

Finally, this paper evaluates the performance of the proposed algorithm under the multiple vehicles condition. Figure 7 shows some of the testing images used in this paper. Each image contains at least four vehicles. Table III lists the testing results using the dense type of relation equation. Its average error rate is 1.91%.

TABLE III. THE SIMULATION RESULTS FOR THE MULTIPLE VEHICLES CONDITION USING THE DENSE TYPE OF RELATION EQUATION.

No.	Real distance (Meter)	Width of license plate (Pixel)	Estimated distance (Meter)	Error rate (%)
1	19.5	64	19.26	-1.22
2	13.3	92	13.18	-0.88
3	28.5	45	27.83	-2.34
4	18.8	68	18.08	-3.83
5	24.3	50	24.93	2.60
6	18.6	65	18.95	1.90
7	33.8	37	34.15	1.04
8	24.1	52	23.93	-0.71
9	22.9	53	23.46	2.44
10	16.7	72	17.03	1.98
11	31.4	40	31.48	0.25
12	21.4	60	20.61	-3.71
				Average error rate: 1.91%

(a) The image of the testing multiple vehicles. ZP: 19.5M, QS: 13.3M, MD: 28.5M, DU: 18.8M

(b) The image of the testing multiple vehicles. ZP: 24.3M, QS: 18.6M, MD: 33.8M, DU: 24.1M

Figure 7. Two testing images that contain multiple vehicles located at different distances.

V. CONCLUSIONS

This paper proposed a novel vision-based distance estimation algorithm for multiple vehicles using single optical camera feature. Because the size of license plate in Taiwan is fixed and regular, the working principle of the proposed algorithm is to use the width of the license plate as the known information, and then derives a distance-pixel relation equation. This distance measure method can display the individual distance of multiple vehicles and has the average error rate within 2%. In comparison with other traditional methods, the overall structure of the proposed algorithm is quite simple. It just requires only a camera with a data processor and is very applicable in telematic systems.

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