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Design and Implementation of a Miniature Intelligent Vehicle Test Platform

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Abstract

The test platform plays an important role for the development of intelligent vehicles. In this work, we propose to design and build a miniature test model before building a real scene. The whole test system consists of the simulated traffic environment, the micro-intelligent vehicle and the visual information processing. Firstly, a micro-intelligent vehicle test platform applied to visual information perception is proposed. Secondly, some algorithms about traffic environmental element detection such as lane detection, traffic light and traffic signal recognition and obstacle detection are presented. The experiment validated the proposed approach. On the one hand, the main visual technologies of intelligent vehicles such as line detection, obstacle detection, and traffic signal recognition can be tested in this system; on the other hand, the test result can be used to evaluate and improve the design of the real test platform.

Keywords: *intelligent vehicle; miniature test platform; visual information perception*

1. Introduction

The test platform is of great importance to the development of intelligent vehicles. For example, DARPA held three challenges, which are Grand Challenge in 2004 and 2005, Urban Challenge in 2007 [1].There was no vehicle finishing the route in the first competition of the DARPA Grand Challenge; however five vehicles successfully completed the race in the second competition. In a sense, the test and evaluation system can help the teamwork optimize the performance of technology and improve the reliability of the intelligent vehicle further. Based on the reasons, the design of the test environment is crucial.

During the past four competitions of China Intelligent Vehicle Future Challenge [2,3], we have participated in the design of the test environment for three times. In summary of the previous design experiences [4], in this paper, we propose to design and build a miniature test model according to the design drawing before building an actual scene, which is different from the test bed described in [5], since the competition mainly focus on visual information.

The traffic environment consists of basic structure of road (such as the lane line and stop line), traffic lights, traffic signals (such as stop sign) and obstacles in front of the vehicle. The main visual technologies of intelligent vehicles include lane detection, obstacle detection, stop line detection and traffic lights and traffic signal recognition.

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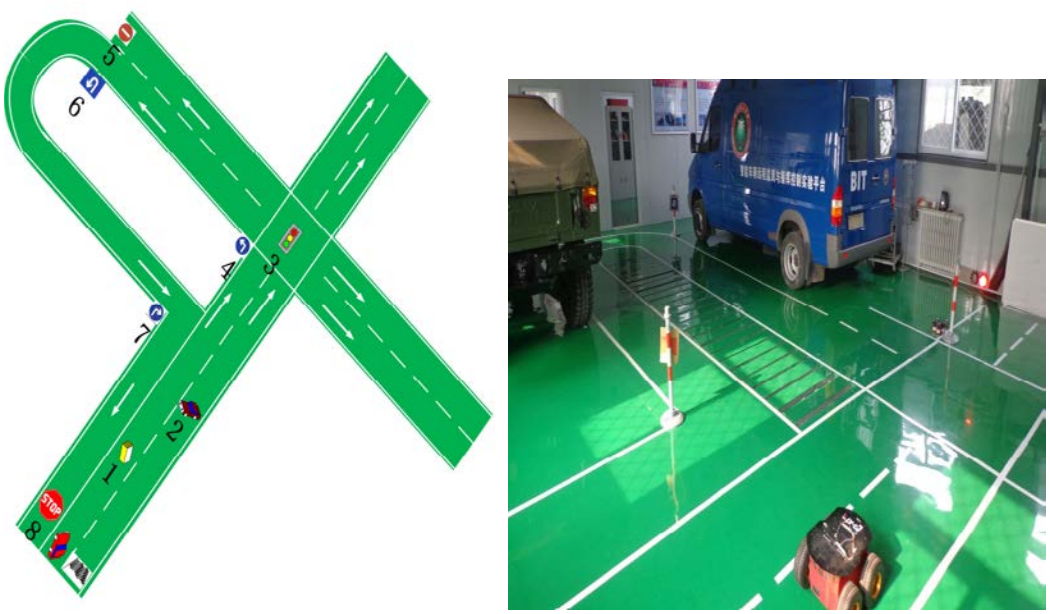
The visual information for the intelligent vehicle in the driving environment can be collected and processed in the miniature traffic environment. Through the processing of visual information including information extraction, processing and feedback, the micro-vehicle can identify the basic traffic environment, and then move intelligently.

2. Architecture of Miniature Test Platform

The whole system consists of the simulated traffic test platform, the micro-intelligent vehicle and the visual information processing software.

Wherein, the simulated traffic test platform is focused on the visual information gained from driving environment. It provides a lot of traffic elements, such as the lane line, stop line, traffic light, traffic signals and obstacle. The overview of the test platform environment is shown in Figure 1.



(a) The overall design scheme **(b)The actual effect of the design**

Figure1 Simulated Traffic Environment

In Figure 1 (a), there are three test points labeling 1 to 3 used for testing the performance of the intelligent vehicle including static obstacle detection, dynamic obstacle detection and traffic light recognition. In addition, there are five guiding points labeling 4 to 8 set at the intersection, which consists of turning left, no entry, U-turn, turning right and stop sign. These guiding points are used for giving the intelligent vehicle driving directions.

According to the attributes of the guiding points, the testing work can be divided into three levels: low level, middle level and high level as follows.

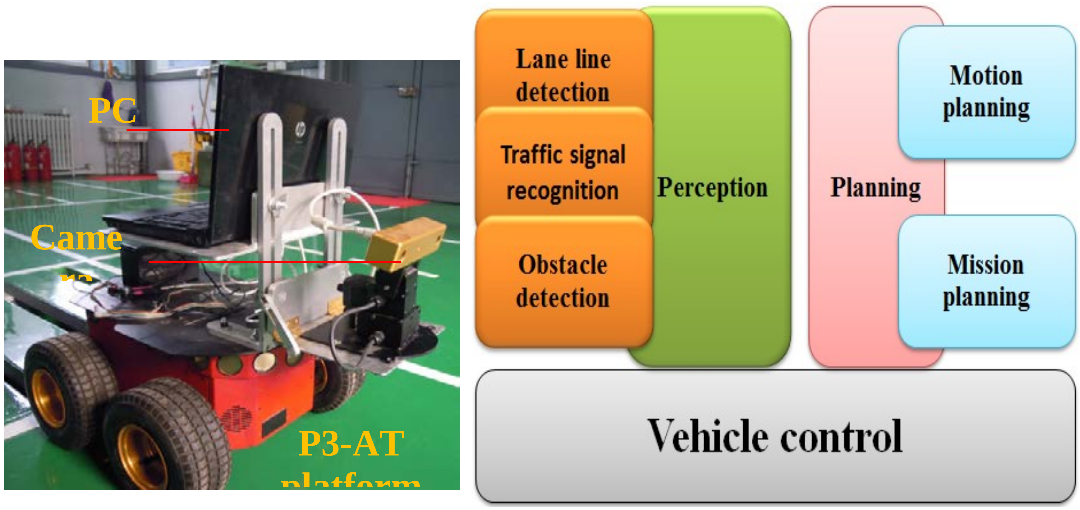
(1) Low level: The information of guiding points including position and type are given in advance. The intelligent vehicle can pass the intersection only with traffic signal recognition.

(2) Middle level: Similarly, the position of guiding points is given. But the type of guiding points is unknown. So both traffic signal detection and recognition are essential while the

intelligent vehicle approaches the intersection in order to determine which action to take such as U-turn or turning left.

(3) High level: None information of guiding points are provided. The intelligent vehicle has to detect and recognize traffic signals all the way whether it approaches the intersection.

The P3-AT wheeled robot is used as the micro-intelligent vehicle platform, which is shown in Figure 2 (a).The control system of the micro-intelligent vehicle is shown in Figure 2 (b).



(a) Micro-intelligent vehicle platform **(b) Control system**

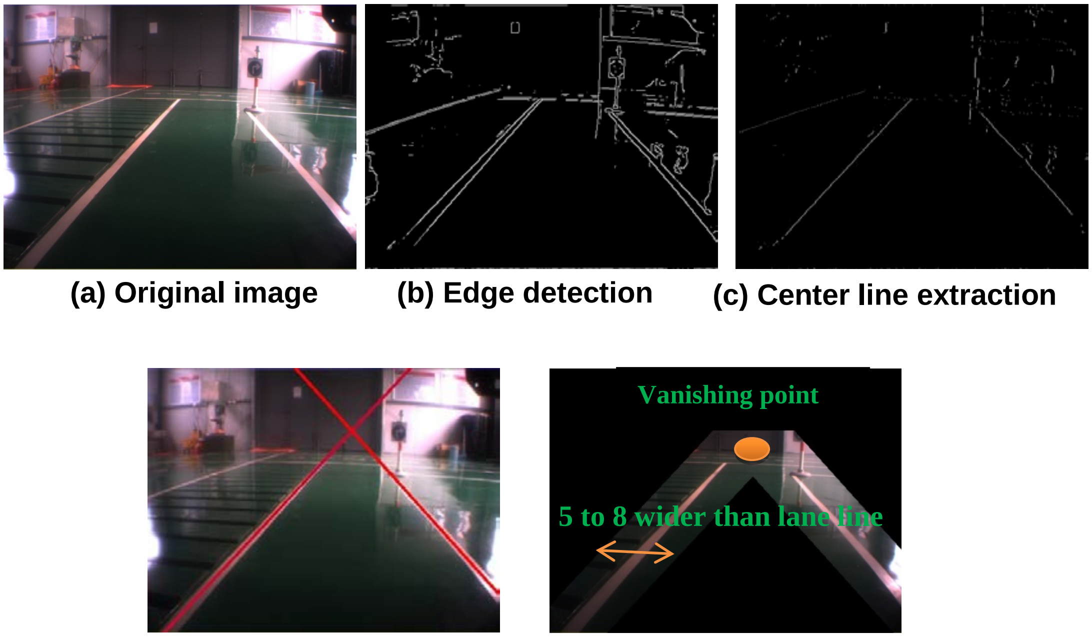
Figure 2. Platform of the Micro-intelligent Vehicle

3. Lane Detection and Tracing

3.1. Lane Detection

The lane information received by the camera is shown in Figure 3(a).For the lane line detection, the edge of source image is detected firstly using Canny edge detection [6], as shown in Figure3 (b).In order to filter the edge image, we need do a lot of assumptions, such as the lane line is white, the width of the lane line is known according to the height of camera and the extending direction of the lane line can be known, too. Using above information, we can extract the lane line. After the filtering, the center line of the lane line is shown in Figure 3 (c). After that, this paper uses the algorithm of Hough transforms [7] to detect the lane line.

To reduce the interference of the non-lane line in the image, such as the vertical line in Figure 3 (c), the angle of the left line is between 20^{o} and 70^{o}, according to camera calibration information. Similarly, the angle of the right line is between 270^{o} and 335^{o}. To some extent, the processing can reduce the effect of the noise information and improve the rate of the calculation. The detected result of the lane line is shown in Figure 3 (d).



(a) Original image (b) Edge detection (c) Center line extraction

(d) Detection result (e) Extraction of ROI

Figure 3. Lane Detection and Tracking

3.2. Lane Tracking

In this paper, the lane tracking is also tested using the trapezoidal lane region extraction [8]. It makes full use of the figure that the lane line is trapezoidal distribution in a plan view. It can reduce the detection range as we can see from Figure 3(e).

995 images collected from 5 different road sections are tested. The results are shown in Table 1.

Table 1. Contrast of Lane Tracking Effect

Group	Amount	Without lane tracking		With lane tracking	
		Positive detection rate	Average detection time /s	Positive detection rate	Average detection time /s
1	163	89.57%	0.094	100.00%	0.020
2	100	96.00%	0.062	100.00%	0.019
3	102	96.12%	0.060	100.00%	0.020
4	400	100.00%	0.160	100.00%	0.020
5	230	83.04%	0.084	92.17%	0.020
Total	995	93.57%	/	98.19%	/

It can be seen from Table 1, the detection time is shortened remarkably owing to adding the lane tracking algorithm. And the accuracy of lane detection is obviously improved.

4. Traffic Light Recognition

In terms of traffic light recognition, the usual method is divided into two parts: extraction of interesting color and recognition based on characters.

The former part is usually extracted in the HSV color space according to the correlation of color. After that, we can use the template matching algorithm or machine learning algorithm to recognize the traffic light. In this paper, we just use the algorithm described in [9] to complete the recognition and the result is shown in Figure 4.

(a)Red traffic light **(b)Green traffic light**

Figure 4. Traffic Light Recognition

5. Traffic Signal Recognition

The processing of traffic signal information is mainly dependent on color information and shape distribution of the visual information [10]. In this paper, we make good use of the color characters in different color space and combine these color information. Then we extract the region of interest from the image using the color information. And we can get the shape of the traffic signal by filtering the image through masks, in which the main shapes is included, such as circle, octagon and square. Next, we classify the signals by the shape and use the machine learning algorithm of multi-layer perception to recognize the traffic signal.

5.1. Procession in HSV and RGB Color Space

According to the general color information of the traffic light, we extract the region of interest in HSV and RGB color space.

The color distribution of traffic signs in the RGB color space can be obtained by linear function as shown in the following formula 1:

$$f(x) = w * I_x + b, x = (v_1, v_2, v_3, 1)' \quad (1)$$

wherein, I_x stands for the color channel of the RGB color space, v_1, v_2, v_3 is the element of I_x, they stand for three color channels of R, G, B. 1 represents a constant, w represents a variable factor, which is the coefficient of the matrix I_x, b indicates a constant factor. The parameter (w, b) is calculated by the ridge regression method.

Thus, we can get the correlation between traffic signs and color. If the value of $f(x)$ is positive, it means that there is a positive relationship between the color and the traffic signs. On the contrary, there is a negative relationship.

5.2. Edge Detection

In this section, we use Sobel operator to do edge detection for the region of interest in order to get the center position of the region.

In the specific process, we introduce the positive and negative correlation of the edge detection. The purpose is to detect the lateral distribution and vertical distribution of the region of interest so that we can get the center position of the sign. Since the outer ring of the signs region has good symmetry, we can use edge detection to reduce the amount of information. Then the center position and radius of the region can be roughly gained.

5.3. Shape Classification

According to the complexity of the shape of signs, we can divide them into three categories:

(1) The special shape signs, such as no entry sign, stop sign and U-turn;

(2) Other red circle signs;

(3) Other blue circle signs.

The shape of the first category is easily recognized compared with the other two, so they can be recognized by template matching. The template is shown in Figure 5. Because of similarity, the other two categories can be recognized by machine learning. In this paper, we use the multi-layer perception algorithm as the learning method. Before recognition, we use the algorithm of OTSU [11] to strengthen the characteristics of ROI.

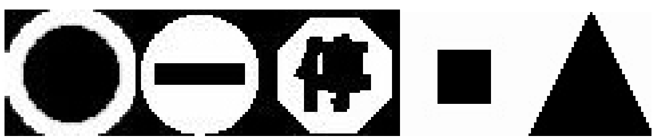


Figure 5. Pattern Matching Template

5.4. Signs Recognition through Multi-layer Perception

Next, we use the multi-layer perception machine learning method [12]. By using the training result of the sample set, the signs can be recognized. The recognition results are shown in Figure 6.

The traffic signal recognition is mainly used for taking action such as turning or stopping at guiding points. And different modes are corresponding to different levels of difficulty mentioned in Section 2.

(a) U-Turn **(b) Turning right** **(c) Stop sign**

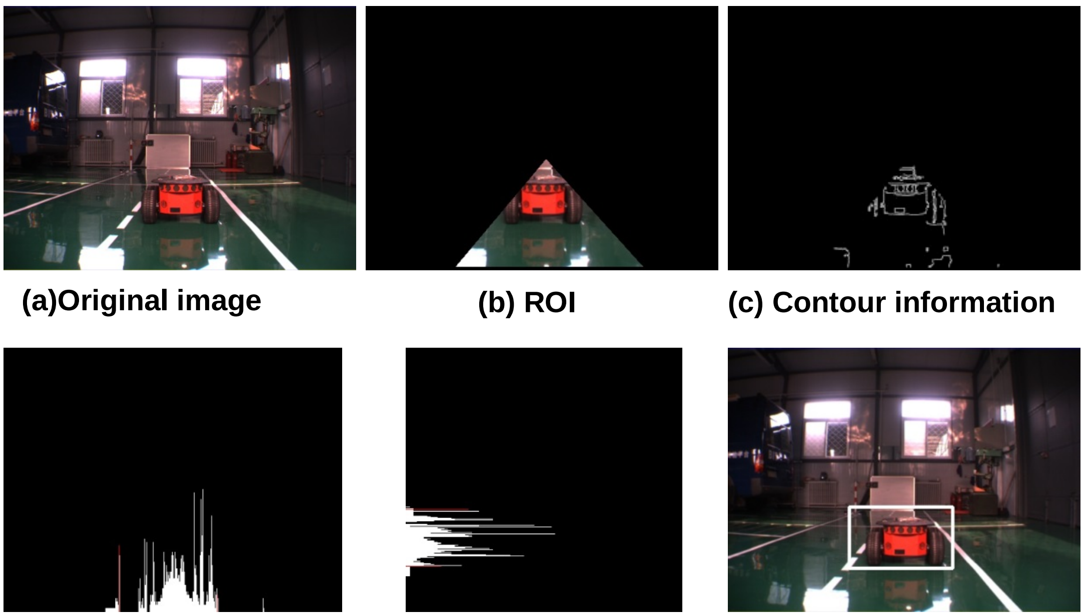
Figure 6. Traffic Sign Recognition

6. Obstacle Detection

In this section, we test the obstacle detection using monocular and binocular vision respectively. And we make a comparison for the two methods.

6.1. Obstacle Detection under Monocular Vision

According to the obtained lane line detection, the region of interest where the obstacle is can be identified. Form Figure 7 (b), we can see that the ROI is usually a triangular area.



(a)Original image (b) ROI (c) Contour information

(d)Histogram of vertical contour (e)Histogram of horizontal contour (f)Detection result

Figure 7. Obstacle Detection under Monocular Vision

Then the method of Canny edge detection is used again to gain the contour information of ROI just shown in Figure 7(c).

Next, the histogram statistics is applied to do with horizontal and vertical edge information as shown in formula 2:

$$\begin{cases} Count_{Longitudinal} = \sum_{i=0}^{Width_{img}} \sum_{j=0}^{Height_{img}} ((Pixel(i,j) > thres)?1:0) \\ Count_{Transverse} = \sum_{j=0}^{Height_{img}} \sum_{i=0}^{Width_{img}} ((Pixel(i,j) > thres)?1:0) \end{cases} \quad (2)$$

Wherein, $Pixel(i,j)$ corresponds to the effective edge point. $Count_{Longitudinal}$ is the vertical statistical unit while $Count_{Transverse}$ is the horizontal statistical unit. $Thres$ is a threshold whose value is set 0 here. The schematic view is shown in Figure 7(d) and (e).

A threshold defining the size of the obstacle is added in order to reduce the influence of lane line edge and other tiny noise. From experimental verification, the size of the obstacle which is larger than 15 x 15 (in pixels) is satisfied. In addition, the length of vertical and horizontal edge of the obstacle should meet the following requirements as shown in formula 3:

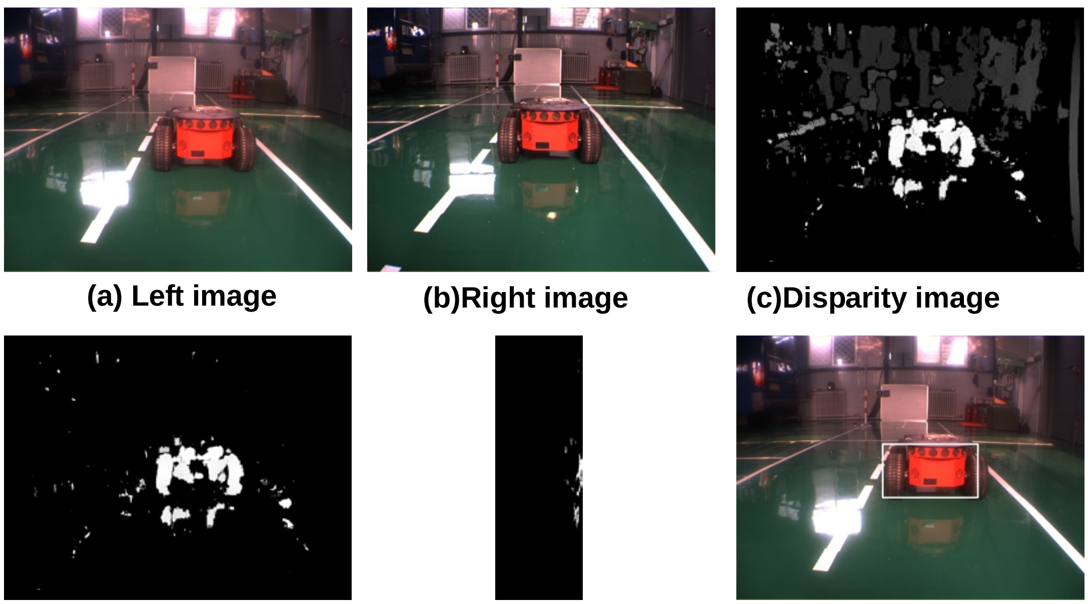
$$\begin{cases} Count_{Longitudinal}[i] > Thres_1 \ \&\&Count_{Longitudinal}[i \pm 1] > Thres_2 \\ Count_{Transverse}[j] > Thres_1 \ \&\&Count_{Transverse}[j \pm 1] > Thres_2 \end{cases} \quad (3)$$

Wherein, $i, i \pm 1 \in [0, \mathrm{Width}_{\mathrm{img}}\text{-}1]$, $j, j \pm 1 \in [0, \mathrm{Height}_{\mathrm{img}}\text{-}1]$, the value of $Thres_1$ and $Thres_2$ are set 9,5respectively.

By the above vertical and horizontal histogram statistics, the location of the obstacle can be determined. The result is shown in Figure 7 (f).

6.2. Obstacle Detection under Binocular Vision

In this paper, a stereo vision detection algorithm called V-disparity [13, 14] is used. The disparity image is shown is Figure 8 (c).



(a) Left image (b)Right image (c)Disparity image

(d)De-noise (e) V-disparity image (f) Result image

Figure 8. Obstacle Detection under Binocular Vision

Since the error of stereo matching exists, the real distance of the obstacle is not sure as a result of the noise information. But based on the distance of the disparity, the interference of farther object can be filtered out just shown in Figure 8 (d). Then we use the clustering algorithm to do depth statistics for the same obstacle. This method can separate the noise information, so we can get an explicit V-disparity map about the obstacle, as shown in Figure 8 (e). Next, we use the same method to gain the statistics in the horizontal direction and get a U-disparity map. After the detecting, we can make sure the position of the obstacle in front of the micro-vehicle. The detection result is shown in Figure 8 (f).

6.3. Contrast of Monocular Vision and Binocular Vision in Obstacle Detection

The method of obstacle detection based on monocular vision is simpler and has a lower time complexity. However, some assumptions such as a flat and smooth road plane and obvious texture of obstacles must be guaranteed for the monocular vision detection. Otherwise, the detection will be affected significantly. The influence for binocular vision detection is less, so the latter method has a strong detecting capability for unknown traffic scene.

7. Conclusions

In this paper, we built a miniature test environment before building an actual scene. The whole system consists of simulated traffic test environment, micro-intelligent vehicle and visual information processing software. In the test content, there are some test points for testing the performance of the intelligent vehicle including static obstacle detection, dynamic obstacle detection and traffic light recognition. In addition, some guiding points are added to change the degree of the difficulty. According to the attributes of the guiding points, the testing work can be divided into different levels. Furthermore, some visual algorithms such as lane detection, traffic light and traffic signal recognition and obstacle detection are presented to verify the feasibility of this test platform. In the lane detection test experiments, the comparison was made with/without lane tracking. Also, in the obstacle detection test experiments, different methods were introduced to detect the same obstacle. In the future work we will focus on the complexity of the micro-traffic environment as well as the diversity of sensors, to make the proposed miniature test platform provide more contributions for the design of the real test platform.

Acknowledgements

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