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A Fine Vehicle Model Measurement Method Based on Plane Ranging

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In this paper, a fine vehicle model measurement method based on plane distance measurement is proposed. This method involves several steps. First, the vehicle image is captured using a camera and then preprocessed. The key feature points of the vehicle are extracted using image processing and the faster regional convolutional neural network (R-CNN) algorithm model. Next, the feature points are accurately measured using a plane ranging algorithm, enabling the analysis of fine models of heavy vehicles, such as the number of axles, lanes, and speed information. The experimental results demonstrate that the proposed fine vehicle measurement method achieves excellent results in measuring vehicle size. Compared with conventional measurement methods, this method offers higher measurement precision and accuracy. Additionally, this method significantly reduces the measurement time and workload while improving measurement efficiency.

1. Introduction

Accurate measurements of vehicle size and shape play a crucial role in the automotive manufacturing and design process. Precise model measurements assist designers in optimizing vehicle appearance and performance, as well as ensuring compliance with regulations and standards. However, conventional measurement methods, such as manual measurement or the use of measuring instruments, are often time-consuming and lack the required precision to meet the high precision and efficient production demands of the modern automotive manufacturing industry.(1)

To address this issue, the fine vehicle measurement method based on plane ranging has emerged as a research focus in recent years. This method employs technologies such as optics, lasers, and computer vision to obtain accurate vehicle size and shape information by measuring

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point cloud data on the vehicle's exterior. Compared with conventional measurement methods, the fine measurement method based on plane distance measurement offers several advantages, including high precision, efficiency, and noncontact measurement.(2)

In this paper, we aim to review the research progress and application of fine vehicle measurement methods based on plane ranging. First, we will introduce measurement methods based on optical and laser technologies, including projected profiles and structured light scanning.(3) Second, we will explore measurement methods based on computer vision and image processing, such as those relying on feature point matching and contour extraction. We will then assess the accuracy and efficiency of these methods and compare them with those of conventional measurement approaches.(4) Finally, we will discuss the potential application of fine vehicle measurement methods based on plane ranging in the automotive design and manufacturing field, and propose directions for future research.(5)

By providing an overview of the research and application of fine vehicle measurement methods based on plane ranging, we aim to offer vehicle manufacturers, designers, and researchers an opportunity to gain a comprehensive understanding of and expertise in this emerging measurement technology.(6) Additionally, we expect to stimulate the development and implementation of fine vehicle measurement methods based on plane ranging, fostering innovation and progress in the automotive manufacturing industry.

2. Research Status of Fine Vehicle Measurement Methods Based on Plane Ranging at Home and Abroad

The fine vehicle measurement method based on plane ranging is a sensor-technology-based measurement method that can accurately obtain the size and shape information of a vehicle's appearance. This method is widely used in the fields of automobile design, manufacturing, and maintenance.(7)

In China, numerous research institutions and universities have conducted related research in this field. For instance, researchers at Huazhong University of Science and Technology have proposed a method for car shape reconstruction based on multisensor fusion. By combining the data obtained from cameras, laser scanners, and ultrasonic sensors, they achieved high-precision measurements of a vehicle's shape.(8)

Similarly, the China Automotive Engineering Research Institute has also conducted a similar study. They proposed a vehicle body size measurement method based on 3D point cloud data. Utilizing LiDAR scanners, they obtained point cloud data of the vehicle's surface, which is then analyzed and processed to achieve the rapid measurement of the vehicle's body size.(9)

Research institutions in the United States and Europe have also made significant progress in this area. For example, the Technical University of Munich in Germany has proposed a method of measuring body shape using cameras and laser scanners. By combining visual measurement with 3D scanning technology, they achieved accurate measurements of the body's curves and edges.(9)

In addition, General Motors in the United States has conducted related research as well. They developed a method of measuring vehicle dimensions based on optical sensors and LiDAR. This method allows the real-time acquisition of size and shape information, which can be utilized in the vehicle design and manufacturing process.(10) As sensor technology continues to develop, this method is expected to further improve measurement accuracy and efficiency, contributing greater value to the field of automobile manufacturing and maintenance.(1)

3. Fine Vehicle Measurement Method Based on Plane Ranging

To further identify the fine models of heavy vehicles, it is necessary to employ image ranging techniques. While 3D distance measurement requires extensive computational resources and binocular distance measurement relies on the cooperation of two cameras, in this study, we adopted a method based on plane distance measurement. Specifically, the selected plane is where the highway is located. To achieve object positioning and length measurement within this fixed plane, the camera undergoes a simple calibration process in order to obtain the necessary parameters for converting the world coordinate system to the image coordinate system.(11)

3.1 Establishment of a coordinate system

World coordinate system $o_w x_w y_w z_w$: We selected the plane where the measured object is located as plane $o_w x_w y_w$, with the z_w axis as the $o_w x_w y_w$ vertical plane. Camera coordinate system $o_s x_s y_s z_s$: we took the center point of the optical axis of the camera, o_s, as the origin of the coordinate system, the direction of the z_s axis is parallel to the camera optical axis, and we took the direction of the camera to the scene as the positive direction. The direction horizontal increase of image coordinates was taken in the x_s axis direction, and the vertical increase of image coordinates was taken in the y_s axis direction.(12)

3.2 Simplified camera calibration

The function of the internal parameter matrix of the camera can be understood as that the points in the camera coordinates pass through the camera lens and become pixels through pinhole imaging and electron conversion. The specific camera parameter model can be expressed as

$$z_s \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} k_x & 0 & u_0 \\ 0 & k_y & v_0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_s \\ y_s \\ z_s \end{bmatrix}. \tag{1}$$

In Eq. (1), k_x and k_y represent the amplification coordinates of the x and y axes, respectively. (u_0, v_0). The image coordinates representing the center point of the optical axis, (x_s, y_s, z_s), are the coordinates of the scene point in the camera coordinate system.

The external parameter model of the camera represents the description of the world coordinate system in the camera coordinates. Assuming that the coordinate of the object Q in the world coordinate system is (x_w, y_w, z_w), then the calculation method for the object in the camera coordinate system $o_s x_s y_s z_s$ is determined by the distortion parameter matrix for the camera, which can be expressed as

$$\begin{bmatrix} x_s \\ y_s \\ z_s \\ 1 \end{bmatrix} = \begin{bmatrix} n_x & o_x & a_x & p_x \\ n_y & o_y & a_y & p_y \\ n_z & o_z & a_z & p_z \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_w \\ y_w \\ z_w \\ 1 \end{bmatrix}. \tag{2}$$

In Eq. (2), $\boldsymbol{n} = [n_x\ n_y\ n_z]^T$, $\boldsymbol{o} = [o_x\ o_y\ o_z]^T$, and $\boldsymbol{a} = [a_x\ a_y\ a_z]^T$ respectively represent the direction vectors of the x_w, y_w, and z_w axes in the camera coordinate system, and $\boldsymbol{p} = [p_x\ p_y\ p_z]^T$ represents the position vector of the coordinate origin of the world coordinate system in the camera coordinate system.

We substitute Eq. (2) into Eq. (1); considering that the object is on the same plane, we set $z_w = 0$, and sorting can obtain

$$\begin{cases} z_c u = m_{11} x_w + m_{12} y_w + m_{14}, \\ z_c v = m_{21} x_w + m_{22} y_w + m_{24}, \\ \ \ z_c = m_{31} x_w + m_{32} y_w + m_{34}. \end{cases} \tag{3}$$

Because of $m_{34} = p_z \neq 0$, Eq. (3) cancels out z_c and divides it by m_{34} to obtain the equation:

$$\begin{bmatrix} x_w & y_w & 1 & 0 & 0 & 0 & -ux_w & -uy_w \\ 0 & 0 & 0 & x_w & y_w & 1 & -vx_w & -vy_w \end{bmatrix} \boldsymbol{m'} = \begin{bmatrix} u \\ v \end{bmatrix}. \tag{4}$$

In Eq. (4), $\boldsymbol{m'} = [m'_{11}\ m'_{12}\ m'_{14}\ m'_{21}\ m'_{22}\ m'_{24}\ m'_{31}\ m'_{32}]^T$. In this $m'_{11} = m_{11}/m_{34}$, $m'_{12} = m_{12}/m_{34}$, $m'_{14} = m_{14}/m_{34}$, $m'_{22} = m_{22}/m_{34}$, and $m'_{24} = m_{24}/m_{34}$.

According to Eq. (4), only $\boldsymbol{m'}$ is required to determine the transformation relationship between the world coordinate system and the image coordinate system. Since each point on the plane provides two equations, only four space points with known world coordinates are needed to solve $\boldsymbol{m'}$. For n points with known coordinates in the world coordinate system, each space point conforms to Eq. (4); then, the following can be obtained:

$$\boldsymbol{Am'} = \boldsymbol{B}, \boldsymbol{B} = \begin{bmatrix} u_1 \\ v_1 \\ \vdots \\ u_n \\ v_n \end{bmatrix}_{2n\times 1}, \boldsymbol{A} = \begin{bmatrix} x_{w1} & y_{w1} & 1 & 0 & 0 & 0 & -u_1 x_{w1} & -u_1 y_{w1} \\ 0 & 0 & 0 & x_{w1} & y_{w1} & 1 & -v_1 x_{w1} & -v_1 y_{w1} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{wn} & y_{wn} & 1 & 0 & 0 & 0 & -u_n x_{wn} & -u_n y_{wn} \\ 0 & 0 & 0 & x_{wn} & y_{wn} & 1 & -v_n x_{wn} & -v_n y_{wn} \end{bmatrix}_{2n\times 8}. \tag{5}$$

Here, (x_{wi}, y_{wi}, 0) represents the coordinates of the i-th scene point in the world coordinate system and (u_i, v_i) represents its image coordinates. We can use the least square method to solve and obtain the parameter matrix $\boldsymbol{m}'$:

$$\boldsymbol{m}' = (\boldsymbol{A}^T\boldsymbol{A})^{-1}\boldsymbol{A}^T\boldsymbol{B}. \tag{6}$$

After obtaining the parameter matrix $\boldsymbol{m}'$, we can obtain the following formula:

$$\begin{cases} (m'_{11} - um'_{31})x_w + (m'_{12} - um'_{32})y_w = u - m'_{14}, \\ (m'_{21} - vm'_{31})x_w + (m'_{22} - vm'_{32})y_w = v - m'_{24}. \end{cases} \tag{7}$$

According to Eqs. (4)–(7), the world coordinates of the target object can be solved on the basis of the image coordinates by the least square method.(13)

3.3 Fine model calculation

To use the above method to calculate the fine model of the vehicle, we need to place the calibration object within the shooting range of the camera, so that we can understand the specific scale information in the world coordinate system, and the calibration object must be placed on the plane where the highway is located. If the homemade marker is placed on the highway plane, it will affect the normal traffic, so it is necessary to complete the marker setting with minimal impact. After investigation, the monitoring road section used in this study is the surveillance video of the Hangjinqu Xinjie road section in Hangzhou, Zhejiang Province. The white dotted line in this road is set up in accordance with relevant regulations, that is, the white dotted line length of the second- and above-grade roads should be 6 m, and the length of the blank section is 9 m. The length of the white dotted line on other highways should be 2 m, and the length of the blank section should be 4 m.

In Fig. 1, since the road section taken is a four-lane road, the length of the white dotted line in the figure is 6 m, and the length of the blank section in the middle is 9 m. Thus, we chose four rectangles with corner points (A, B, C, and D) as the calibration object. In the world coordinate

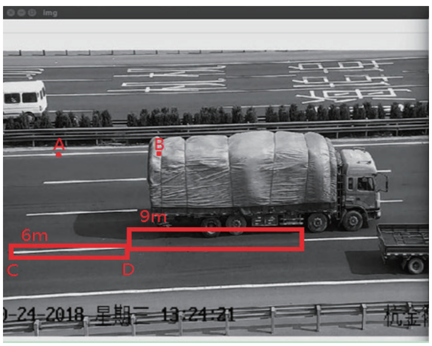


Fig. 1. (Color online) Object for camera calibration.

system, the four points A, B, C, and D should be a length rectangle; the CD side length is 6 m. Because the AC side length is used to calculate the lane information, we only need the proportion of the vehicle in the four lanes; thus, we can set the AC side length as 9 m (which can also be other lengths). Figure 1 shows the photo obtained after the world coordinate system is converted into image pixels. To obtain the relational transformation matrix, we need eight points as the base points.

For the world coordinate system, we chose point A as the origin, the AB direction is the positive direction of the x axis, the AC direction is the positive direction of the y axis, and we established the coordinate system. In the converted image, we set every 100 pixels to represent 1 m. Thus, in the converted image, the length of the AB line segment is equal to the length of the CD line segment, and the length is 600 pixels. Similarly, the length of the AC and BD segments is 900 pixels. That is, the coordinates of four points A′(0, 0), B′(600, 0), C′(0, 900), and D′(600, 900) are known. In Fig. 2, we can easily obtain the coordinate pixels of A, B, C, and D, so that we can obtain the coordinate information of eight points.

After obtaining the coordinate information of the eight points, by using the getPerspectiveTransform function in openCV, the transformation matrix can be calculated as

$$\boldsymbol{m}' = \begin{bmatrix} 1.17553500e+00 \\ 8.09768953e-01 \\ 1.85435999e+01 \\ 9.16861442e-02 \\ 2.59417855e+00 \\ -6.46662375e+02 \\ -3.33732893e-05 \\ 1.31704026e-03 \end{bmatrix}. \tag{8}$$

After obtaining the conversion matrix, we can convert the captured image into a plane image in the world coordinate system, and the result obtained after conversion is shown in Fig. 2.

Figure 2 is a schematic diagram in the world coordinate system transformed from Fig. 1. It can be seen that in the plane image of the world coordinate system, the quadrilateral (A, B, C,

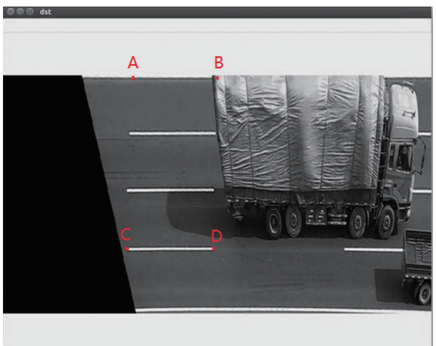


Fig. 2. (Color online) Converted plane image of the world coordinate system.

and D) has become a matrix with a length of 600 pixels and a height of 900 pixels. In the converted image, every 100 pixels in the horizontal direction represent a distance of 1 m. The wheelbase information of the wheel and the average speed of the vehicle can be calculated according to the pixel difference information of the wheel. In the vertical direction, the lane information can be calculated according to the distribution ratio of the wheel between the white lines. For the vertical direction, it is not necessary to calculate the distance scale information represented by each pixel.

3.4 Fine model test

To verify the feasibility of the above method, the monitoring images of real road sections are used to test the fine recognition system of heavy vehicles. The working flow of the fine-type recognition system of heavy vehicles is shown in Fig. 3.

Figure 3 shows the fine model recognition flow chart of heavy vehicles. First, the image to be detected is obtained, and the source of the image to be detected is generally a frame image in the surveillance video. Then, the detection image is preprocessed, for example, by grayscale

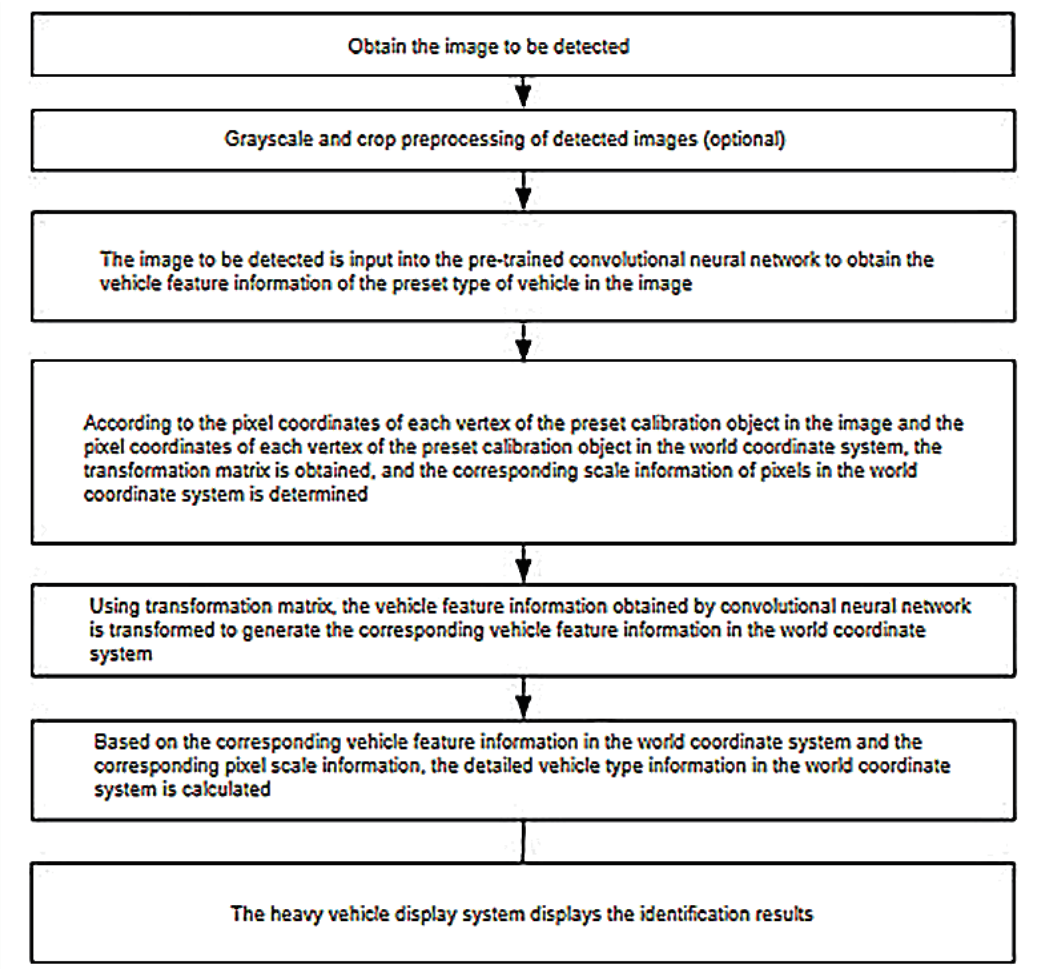


Fig. 3. Fine model recognition flow chart of heavy vehicle.

processing and clipping processing. The purpose of these two operations is to reduce the interference of useless information and improve the recognition speed of the algorithm as much as possible. This step can be omitted. Next, the image is sent to the convolutional neural network, that is, the faster regional convolutional neural network (Faster R-CNN) algorithm, to obtain the vehicle feature information in the image, as shown in Fig. 4.

Figure 4 shows the recognition effect diagram of the Faster R-CNN algorithm, and the specific recognition information is recorded in Table 1. The first column in Table 1 is the name of the image to be detected. In this experiment, 000008.jpg is selected as the test image. The second column is the category information identified by the algorithm, including a truck category and four-wheel information. The third column is the confidence of each identified class. The last two columns represent the pixel position of the identified target in the original image, which is given in the form of a rectangular box. The algorithm provides the pixel coordinate information of the upper left and lower right corners of the rectangular box.

After the characteristic information of the vehicle is obtained by the Faster R-CNN algorithm, we need to obtain the transformation matrix according to the pixel coordinates of each vertex of the preset calibration object in the image and in the world coordinate system, and determine the scale information corresponding to the pixel points in the world coordinate system. Then, we

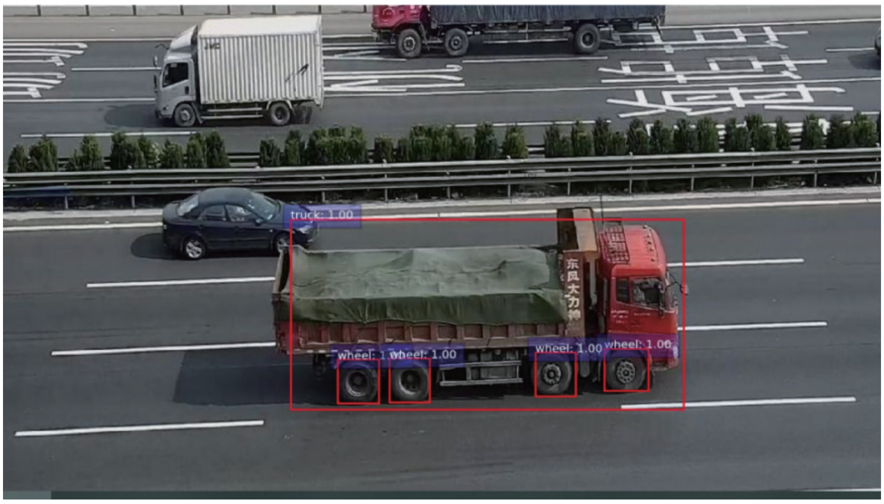


Fig. 4. (Color online) Recognition effect diagram of Faster R-CNN algorithm.

Table 1
Recognition results of Faster R-CNN algorithm.

Picture name	Identification information	Confidence degree	Pixel coordinates of upper left corner of resulting block diagram	Pixel coordinates of lower right corner of resulting block diagram
000008.jpg	truck	0.99940217	(295, 238)	(696, 450)
000008.jpg	wheel	0.9996260	(343, 394)	(385, 443)
000008.jpg	wheel	0.9995735	(615, 382)	(660, 429)
000008.jpg	wheel	0.99953043	(396, 393)	(437, 442)
000008.jpg	wheel	0.99925643	(545, 386)	(586, 435)

need to use the transformation matrix to transform the vehicle feature information obtained by the convolutional neural network to generate the corresponding vehicle feature information in the world coordinate system, that is, the vehicle feature information in the pixel image is converted to the feature information of the real highway plane, so as to facilitate the distance calculation operation. Then, on the basis of the corresponding vehicle feature information in the world coordinate system and the corresponding scale information of pixels, the detailed vehicle model information in the world coordinate system is calculated. Finally, the final identification results are shown through the heavy vehicle display system.

Figure 5 shows the detailed model recognition results obtained from the detailed model calculation of the vehicle feature information identified in Fig. 4. The box in the figure is labeled: 4zhoutruck zhouju: 1.48-4.75-1.92 chedao: 2 speed: 62.38, which respectively means that the vehicle is a four-axle truck, the wheelbases from left to right are 1.48, 4.75, and 1.92 m, the lane information shows 2 lanes from the bottom up, and the average speed is 62.38 km/h. To verify the accuracy of the method, the real information of the vehicle is compared with the identification information, as shown in Table 2.

As shown in Table 2, this method can correctly determine the number of axles of the vehicle and the information of the lane where the vehicle is located, the wheelbase, and the speed information. Although there are certain errors, they are relatively small, and the identification results have high accuracy.

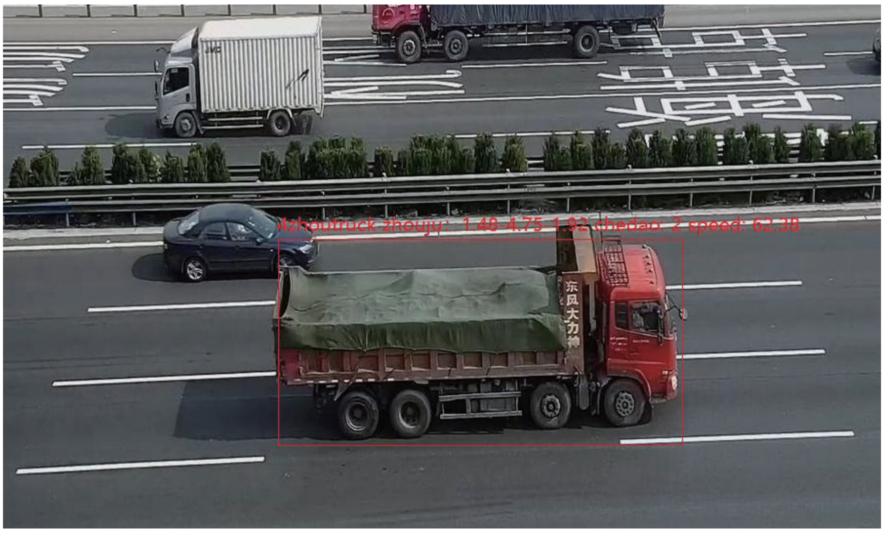


Fig. 5. (Color online) Results of fine identification of vehicle type.

Table 2
Identification accuracy comparison table.

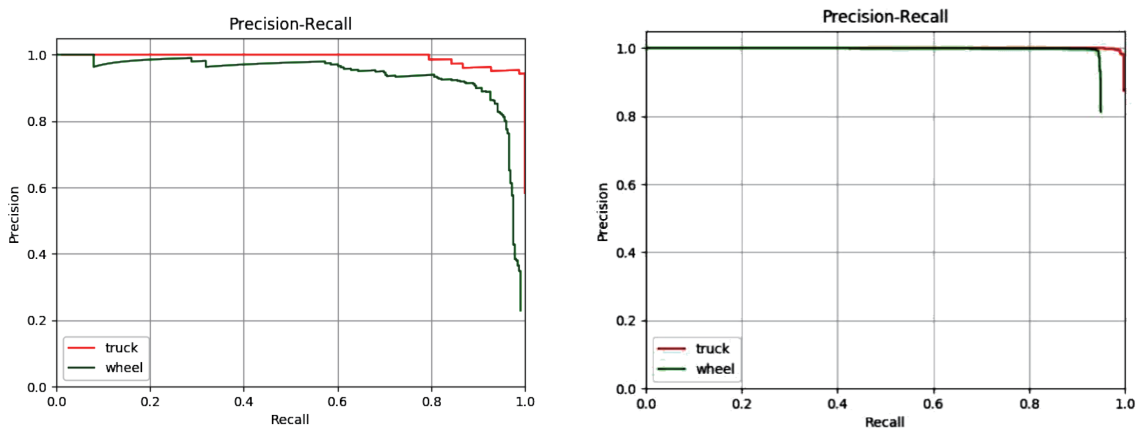
	Number of axes	Wheelbase (m)	Lane	Speed of vehicle (km/h)
Actual information	4	1.35–4.55–2.05	2	About 60
Identification information	4	1.48–4.75–1.92	2	62.38

4. Heavy Vehicle Display System

After the detailed vehicle information is calculated using the algorithm model, it will be shown through the heavy vehicle display system. In this section, we introduce the self-built heavy vehicle fine model detection system. This system interacts with users through the web, uses the Python Flask framework to process back-end business logic, adopts Caffe as the back-end image processing tool, and uses MySQL and other open-source toolkits to process the data layer.

Figure 6 shows the *P–R* curve of the Faster R-CNN algorithm model with the introduction of the plane ranging method during daytime and rainy weather. Figure 6 also shows the *P–R* curves of the Faster R-CNN algorithm during nighttime and early morning weather with the introduction of the planar ranging method. It can be seen from Fig. 6 that the model achieves high precision and recall, indicating that the proposed algorithm has strong classification ability for "Truck" and "Wheel". The analysis of the detection results under different weather conditions is shown in Fig. 7.

We take the (a) panel in Fig. 7 as an example. There are five red boxes in the panel, indicating that five objects have been detected. The "Truck" and "Wheel" labels above the red boxes indicate the truck body and wheel classes, respectively. The red boxes labeled "1.000", "0.998", "0.992", "0.996", and "0.997" represent the confidence that the detected object belongs to this category, (A) the graph represents the recognition result of the algorithm model under daytime weather conditions, (B) the graph represents the recognition result of the algorithm model under cloudy and rainy weather conditions, and (C) the graph represents the recognition result of the algorithm model under nighttime weather conditions, and (D) the small graph represents the recognition result of the algorithm model under early morning (evening) weather conditions. The careful analysis of Fig. 7 shows that (a), (b), and the target objects in the figure are all correctly detected, and the red box is accurate. In (D), there is the problem of inaccuracy of the label box. It can be seen that the recognition accuracy of the algorithm is relatively high under the daytime and rainy weather conditions, but decreases under the nighttime and early morning weather



(a) (b)

Fig. 6. (Color online) *P–R* curve of algorithm model during daytime and rainy weather.

(a) (b) (c) (d)

Fig. 7. (Color online) Effect diagram of algorithm model recognition under different weather conditions.

conditions. The main reason is that the illumination is insufficient under the nighttime and early morning weather conditions. This results in a poor resolution of the image captured by the camera. Taking the (c) diagram as an example, it can be seen that although the monitor has night vision function, owing to insufficient light, the picture taken by the camera is very blurred, resulting in false and missed detections.

4.1 Overall system structure

The system uploads the picture through the web page, and the operation is processed through the background. The user submits a picture from the web page for target detection and returns and presents the result on the web page, and the box selects the object in the picture and informs the model of the type, confidence information, location information, and detailed vehicle type information of the object returned.

The structure of the system as a whole is described below. Figure 8 shows the flow chart of the overall system.

In Fig. 8, the module described on the left, which handles the interaction between the system and the user, plays a vital role in facilitating the image input and presenting the final model detection results on the website. The middle part described in the context of an image processing system serves as a crucial bridge between the front-end and back-end models. It handles the preprocessing of input images and plays a vital role in coordinating the interaction between the user interface and the backend processing results. The three parts on the right are the Faster R-CNN algorithm model, the detailed model calculation method mentioned above, and the results of the algorithm recognition. Figure 8 briefly shows the trend of data flow in the system, and the specific contents of each item are explained in turn.

1. Users log in to the heavy vehicle display system through web interaction, as shown in Fig. 8.
2. The user selects and uploads an image of the target to be detected.
3. After the detection system receives the image uploaded by the user, the image is uploaded for preprocessing and converted into the format type of the model input, and the data is transmitted to the Faster R-CNN algorithm model for processing.
4. The Faster R-CNN algorithm model obtains the vehicle feature information in the image to be detected and transmits it to the fine model calculation module.
5. After a series of calculation and processing, the fine model calculation module obtains the fine information of the vehicle to be detected, including axle, wheelbase, lane, and speed information, and passes it to the next module.
6. The detection result module integrates the information of the fine model calculation module, marks the original image uploaded by the user, outputs the information, and returns it to the web interface.
7. The front-end Web page receives and displays the identification result, as shown in Fig. 9.

Figure 9 shows that after the user accesses the server through the browser, he/she selects the local image 000008.jpg to be detected and uploads it to the server. After receiving the image, the server returns the recognition result after processing by the detection system. As can be seen from the figure, the recognition result contains the annotation information in the original image after the Faster R-CNN algorithm detects the image. Detailed identification information is also

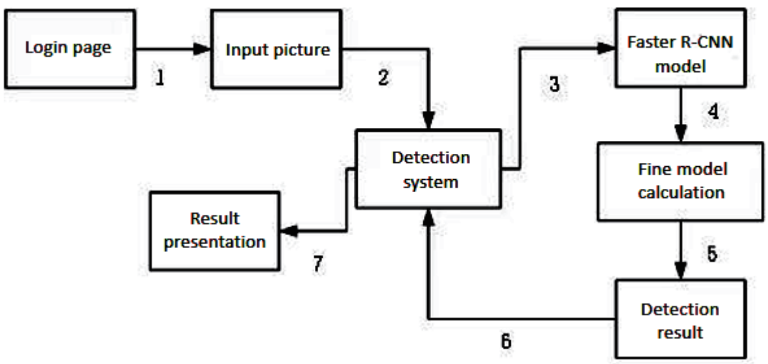


Fig. 8. Work flow chart of heavy vehicle display system.

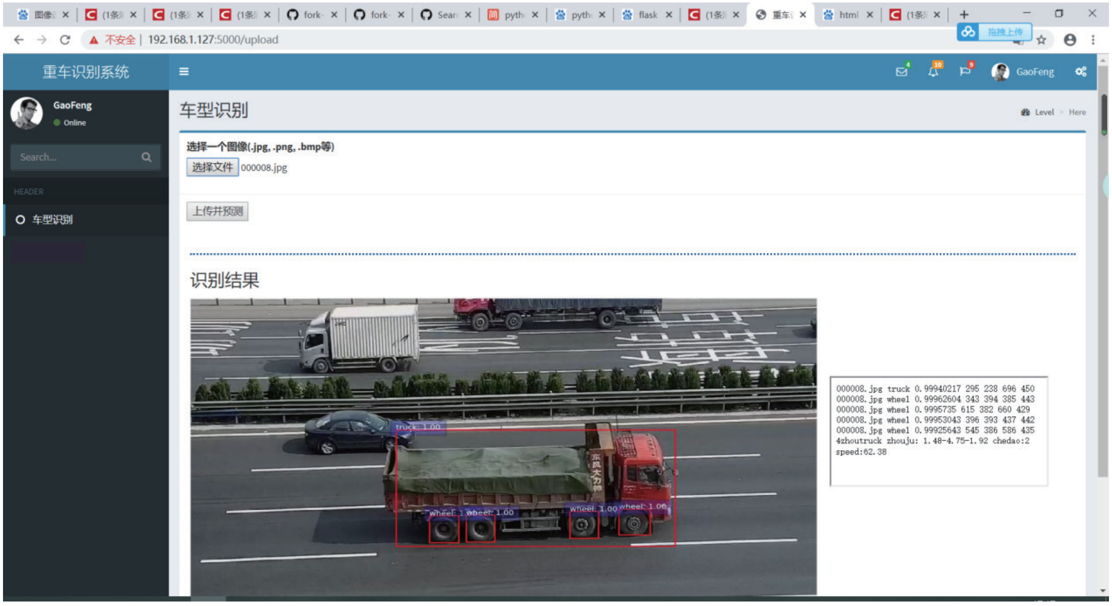


Fig. 9. (Color online) Display of recognition results of heavy vehicle identification system.

listed in the identification information display box on the right, and the last line of the identification information shows the results of the detailed model calculation of the system.

4.2 System implementation

We mainly introduce the implementation scheme of the system in this section. The system model is partially completed using the open-source deep learning framework Caffe, which is used in engineering, and Linux, MySQL, Python3, and Django are used in platform architecture engineering. Using open-source mature system tools to build all parts of a system indeed brings several benefits, including reducing the difficulty of system implementation, as well as improving the availability and stability of the system.

The whole system is divided into three parts namely, the presentation, processing, and data layers. In the following, we will introduce the technology and business logic used by each layer.

4.2.1 Presentation layer

The presentation layer is the user interface layer, which mainly deals with the business logic of users logging in to the system, uploading pictures to be detected, and displaying the results returned by the system target detection.

In this part, the MySQL database and the open-source Bootstrap front-end framework are used to assist with markup language HTML and CSS, and Ajax step refresh technology is used to package the request as JSON data and interact with the background, and the model detection results are displayed and compared in the front end. When a user logs in to the login page, there are two operations: registration and login. Figures 10 and 11 show the two operations. In the part

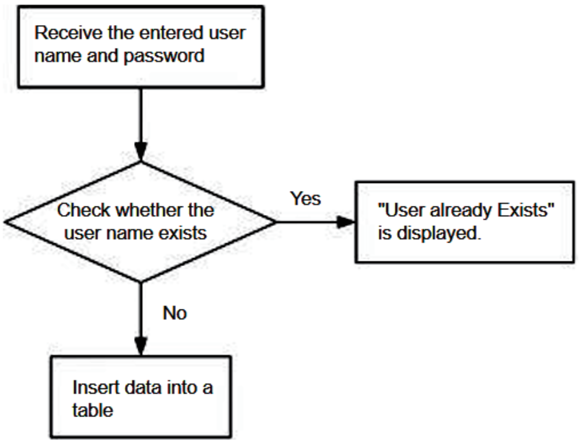


Fig. 10. User registration flow chart.

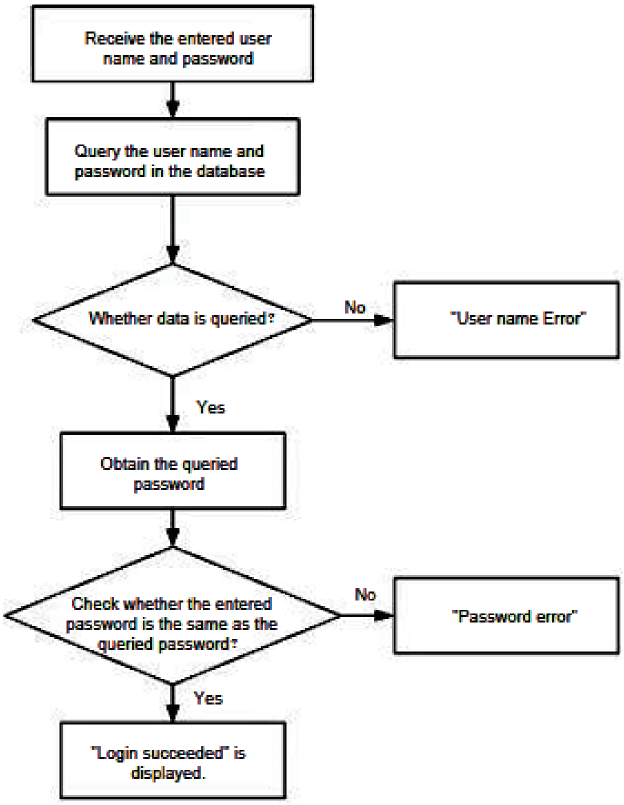


Fig. 11. User login flow chart.

of uploading pictures, after the user selects the pictures, the user uploads the pictures using the file upload tool of JQuery and transmits them to the server in the background through Ajax. Then, the server converts the pictures into the Numpy array format required for model input and processes them into the model.

After the model processing result is obtained, the target detection result is returned to the front end through JSON for display. The result includes the number of targets seen, the category of each detected target, and the corresponding position in the image.

4.2.2 Processing layer

The processing layer uses Python's Flask open source framework to handle HTMI requests sent from the front end. After a user uploads an image, the image is saved to the local server, then the Caffe model of the data layer is invoked for processing.

4.2.3 Data layer

In this module, we use the framework Caffe to build the model and core processing layer. Caffe is a clear and highly efficient deep learning framework, which allows us to build and train its own network structure model very rapidly. Caffe is a very useful scientific research and academic tool, especially in the field of image recognition. It is a pure C++/CUDA architecture that allows you to switch directly between CPU and GPU. Caffe is very popular in both academia and industry, especially because an online service has an irreplaceable position.

5. Conclusions

In this paper, a fine vehicle measurement method based on plane distance measurement is proposed, which uses digital image processing and computer vision technology to achieve accurate vehicle size measurement. Compared with the conventional measurement method, this method has higher measurement precision, accuracy, and working efficiency.

First, we obtained the vehicle image through the camera and preprocessed the image. Through the steps of denoising, image enhancement, and image segmentation, the accuracy and stability of the subsequent processing were improved.

Second, image processing and the Faster R-CNN algorithm model were used to extract the key feature points of the vehicle. These feature points accurately describe the shape and size of the vehicle, including key points for the wheels, body, and other important parts.

Then, the plane ranging algorithm was used to measure the feature points accurately. By using the parameters of the camera and the position of the feature points in the image, the actual dimensions of each part of the vehicle were calculated. Compared with standard measuring tools, the measurement precision and accuracy of this method were verified.

The experimental results showed that this method achieves good results in measuring vehicle dimensions. Compared with the conventional measurement method, it has higher measurement precision and accuracy. At the same time, this method can significantly reduce the measurement time and workload and improve the measurement efficiency.

In summary, the fine vehicle type measurement method based on plane ranging proposed in this paper can be widely used in vehicle manufacturing, traffic safety, and urban planning. In the future, we will further refine the method to adapt to the measurement needs of different types and sizes of vehicles, and promote the development of vehicle measurement technology. This method has important theoretical and application values for realizing accurate and efficient vehicle type measurement.

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