Automatic Truck Loading System based on Machine Vision

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Abstract

In view of the current requirements of reducing labor cost and improving low loading efficiency of grain and oil products in grain and oil factories or farms, the global planning of freight truck loading process was carried out by using image recognition system combined with spatial coordinate allocation algorithm. In the process of traditional cargo loading, SSD target tracking detection algorithm is added to obtain the precise location coordinates of the truck bucket in real time from the truck entering the work area, and extract its center coordinates. Start from the midpoint and carry out the loading operation outward, providing the maximum loading plan within the height of the truck. The numerical simulation results show that the algorithm can save most manpower, improve the loading efficiency, and save the transportation cost and time of agricultural products.

Keywords

Image Identification, SSD Target Tracking Detection Algorithm, Loading Planning.

1. Introduction

With the increasing development of smart farms, while grain output has increased significantly, the environment for loading and transportation has also become increasingly complex. At present, many freight places still employ the method of hiring loaders to load goods manually. As early as the 1980s, machine vision technology began to carry out a number of studies in agricultural machinery, and the initial research mainly focused on quality inspection and product classification of fruits and vegetables. Image recognition systems are widely used in agricultural machinery, mainly involving three aspects: automatic inspection of agricultural machinery, agricultural harvesting, and field operations [1, 2]. In the continuous development of image recognition systems, agricultural machinery has also begun to introduce image recognition systems into the field of machine vision to achieve high efficiency in crop collection and processing [3-5]. For the identification of trucks loaded with grain and oil products, in recent years, Lin Jianbing et al. proposed to use fixed-distance double spheres as positioning markers, and designed and implemented an indoor automatic transport vehicle positioning system based on monocular vision to solve the low positioning accuracy of traditional indoor positioning methods. The question Wang Qian et al. [6-8] also proposed a fast side-measurement method of truck size based on binocular vision [9-11]. At present, in the process of loading grain and oil products, there are few related studies on the application of image recognition systems to identify loaded trucks and goods, optimize loading tasks and improve loading efficiency. In this paper, the SSD target tracking algorithm is used to detect vehicle targets and cargo targets, and on this basis, an image segmentation method based on HSV color space is used to extract the car body [12]. Compared with the traditional lidar method and infrared light curtain method, this method has the advantages of simple installation structure, less space occupation, low cost, and fast measurement speed [13-15].

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2. Truck Automatic Loading System Scheme

In order to improve the loading efficiency, this paper uses the image recognition system combined with the spatial coordinate allocation algorithm to make a global plan for the cargo loading of the truck. As shown in Figure 1, this paper proposes to add a machine vision algorithm to obtain the precise position coordinates of the truck body in real time from the time the truck enters the work area, and extract its center coordinates. Calculate the vehicle body space, start from the midpoint to carry out cargo loading operations outside, and provide the maximum loading plan within the allowable range of the truck height.

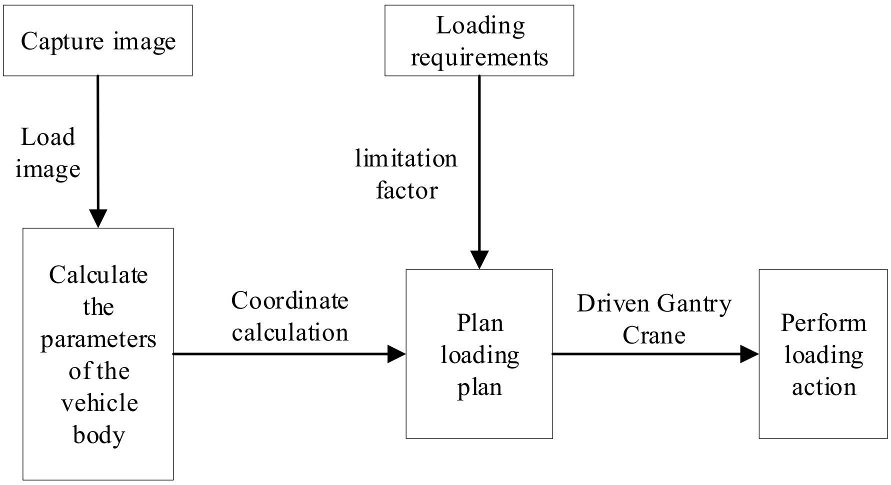

Figure 1. Loading planning process diagram

In order to solve the problem of accurately detecting the target vehicle, determining its location and identifying its body part within a certain loading range, it is necessary to establish a powerful visual recognition model to accurately identify the truck. Image processing is performed according to the acquired image information to obtain relevant data information of the truck body. According to the size of the cargo, it provides a reasonable and optimal loading plan for the truck and executes the loading action.

3. SSD-based Truck Tracking Detection Algorithm Model

In this paper, the SSD target tracking and detection algorithm model is used to capture and coordinate the target truck. The image processing module marks the target truck with a green rectangular prediction box and labels it and its target similarity. On this basis, the location information of the target truck is collected by extracting the coordinate information in the SSD target tracking detection algorithm model to achieve The conversion from relative coordinates to geodetic coordinates, and the output can intuitively reflect the relevant information of the target truck.

The SSD target tracking detection algorithm model is based on the VGG-16 network as a basic model, and a detection method that adds the feature pyramid of the RPN network. The SSD target tracking detection algorithm combines YOLO's regression idea and the Anchor boxes mechanism in Faster-RCNN. By comprehensively using the complementary features of each layer of the multi-scale feature layer, it solves the problem of using only a single-layer feature layer target detection algorithm to the detection network. Inadequate, SSD is simpler and more accurate. Compared with YOLO using a fully connected layer that can only accept a fixed size input, SSD uses a fully convolutional layer and abandons the fully connected layer, so that it can accept the input of any size picture and generate an output of the corresponding size. Finally, the detection effect is also better than the single-feature layer target detection algorithm. The network structure is as follows:

(1)The feedforward neural network uses VGG, which abandons the final fully connected layer;

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(2)After the feedforward neural network, multiple convolutional layers are connected to provide different feature maps;

(3)For each point on a specific feature map, generate a specific number and specific size of default boxes (hereinafter referred to as a priori boxes) by setting the corresponding parameters to detect different targets in the feature map;

(4)Set the convolution kernel, and generate the category score and prediction coordinates corresponding to each a priori box by convolving the feature map, then the length of the prediction vector generated for each point is (number of categories + number of coordinates) × The number of prior frames at this point;

(5)Finally, a suitable prediction box is selected through non-maximum suppression and labeled.

In order to improve the accuracy of the target tracking and detection of the system, the weight coefficients and adjustment parameters of the logistic regression equation of the SSD target tracking and detection algorithm model are modified. Formula 1 is as follows:

$$\begin{cases} z = w^T x + b \\ \hat{y} = a = \sigma(z) \\ Loss(a, y) = -(y\log(a) + (1-y)\log(1-a)) \end{cases} \tag{1}$$

Among them, z is the objective function (optimal solution), w is the input picture information, w is the weight coefficient, b is the adjustment parameter, $\hat{y}$ is the predicted value in the training set, a is the sigmoid activation function, and y is the label value (0, 1), $Loss(a, y)$ is the logistic regression loss function.

The correction method is to firstly collect a large number of different types of truck photos in different scenarios to establish a data set, and divide the data set into a training set and a test set. After Labelme labeling software is used to label the selected target in the training set and the label of the target, the output json file is converted into a csv data file that can be recognized by the neural network. Repeat training on a working machine with powerful GPU image processing capabilities. After multiple neural network model training, multiple weight coefficients and adjustment parameters are obtained, and then the test set is compared with the training set to finally select the weight coefficient and adjustment parameters that best match the target detection effect. As shown in Figure 2, the revised SSD target detection model has significantly improved the accuracy of truck detection.

(a) Recognition effect 1

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(b) Recognition effect 2

Figure 2. Data set correction detection model

The SSD target tracking detection model is revised, and finally a model that can accurately capture the target and continuously track the target is obtained. The prediction frame is obtained through the model, and the prediction frame includes the accuracy rate and its category label.

Therefore, the infrared camera is used for continuous shooting, and after multiple trainings, the weight coefficients and adjustment parameters of the neural network are adjusted, and the above regression equation is established. The target recognition module can convolve the feature map according to the feature values extracted from the training set. Generate the category score and prediction coordinates corresponding to each a priori box, generate the prediction vector length for each point, and finally filter out the appropriate prediction box through non-maximum suppression. The SSD target tracking detection algorithm model is trained to generate an executable file, which contains the image coordinate storage function boxes function. Then the image processor analyzes the obtained image information, and extracts the coordinates of the feature map under the prediction box according to the prediction box size information in the boxes function and performs analysis and calculation to obtain the required information.

$x_{\min}$, $y_{\min}$ are the coordinates of the lower left corner of the feature map, and $x_{\max}$, $y_{\max}$ are the coordinates of the upper right corner of the feature map, then the area can be obtained as formula 2:

$$s = (x_{\max} - x_{\min}) \times (y_{\max} - y_{\min}) \tag{2}$$

Center point coordinates as formula 3:

$$c_{ox} = \frac{(x_{\min} + x_{\max})}{2} \quad c_{oy} = \frac{(y_{\min} + y_{\max})}{2} \tag{3}$$

C_{ox} is the x-direction coordinate, and C_{oy} is the y-direction coordinate.

The coordinates obtained above are relative coordinates, which can be converted into geodetic coordinates by searching for reference points in practical applications. The coordinates described below in this article are all geodetic coordinates.

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4. Determination of Distribution Plan and Loading Plan

According to the recognized image information, the target truck body data is obtained, as well as the limited height of the truck's walking section and the target load capacity to calculate a reasonable plan. The flow chart is shown in Figure 3.

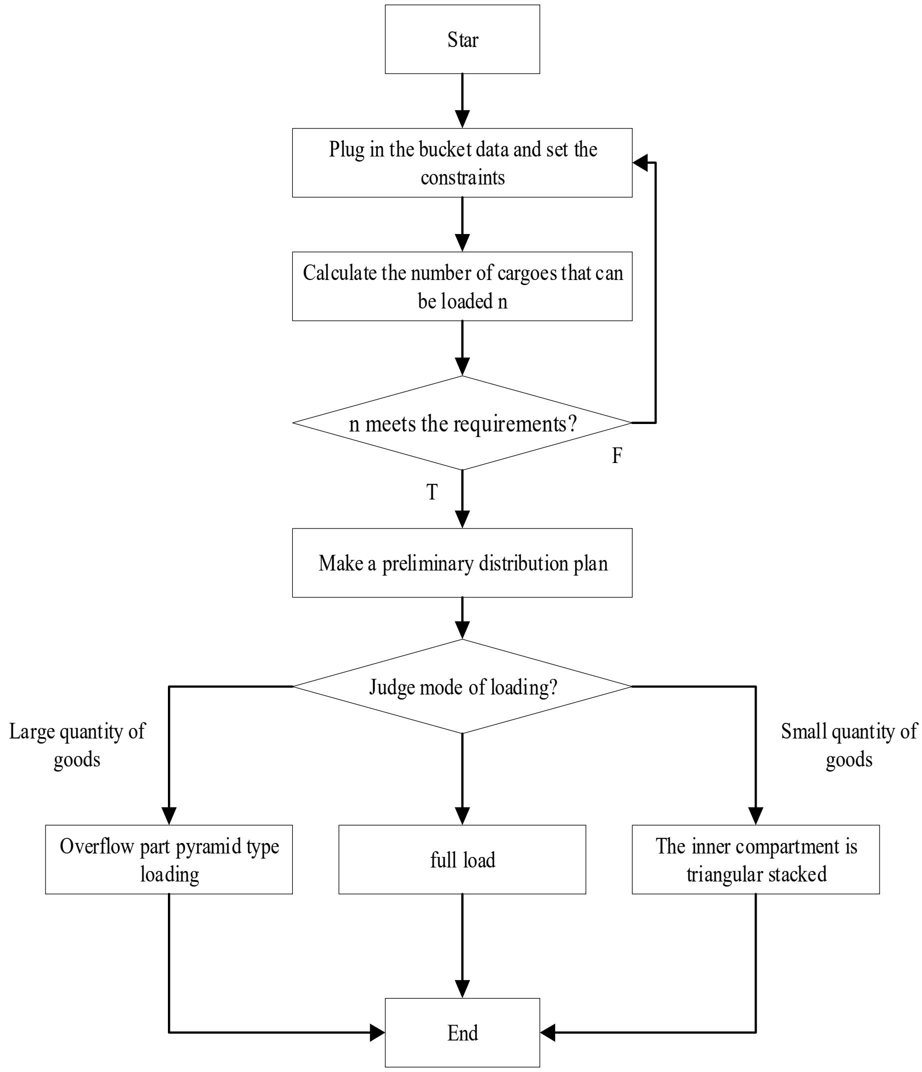

Figure 3. Loading planning process

According to the size data of the vehicle body and the size of the cargo, the maximum number of cargo n (the total number of the full-loaded part plus the largest pyramid-shaped part in the plan) can be calculated in the available car city, and then compared with the truck loading demand. If the requirements are not met, the parameters need to be reset, and if the loading requirements are met, then enter the program link. This link is mainly based on the full capacity of the vehicle body, which is the result of dividing the volume of the vehicle body by the volume of the cargo. If it exceeds the full capacity of the vehicle body, it should be stacked outside at this time, in a pyramid shape. The bottom of the largest pyramid should follow the principle of no more than 2/3 of the area of the bottom of the vehicle bucket plus the area of the bottom of the cargo; if it is exactly equal to the full-load quantity, it will be filled with full load one by one; if it is less than the full-load quantity, it should follow the priority to fill it inside. Then pile it out, forming a triangle. Figure. 4 below shows a schematic diagram of the loading method.

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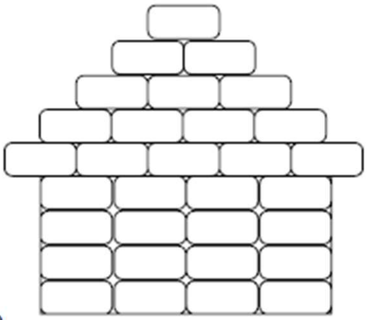
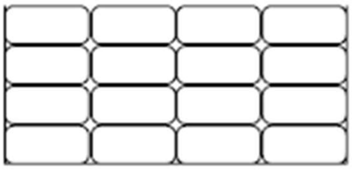


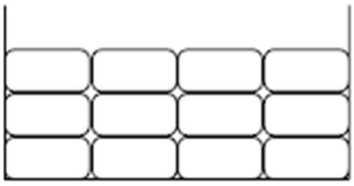
(a)

(a)Overflow part pyramid type loading



(b)

(b)full load



(c)

(c)The inner compartment is triangular stacked

Figure 4. Schematic diagram of loading method

After determining the plan, the system will process the coordinates, and calculate the stacking coordinate sequence of the goods according to the size of the vehicle body and the size of the goods. Output in the form of (x_1,y_1,z_1), (x_2,y_2,z_2),…, (x_n,y_n,z_n), and convert the coordinate position according to the servo motor manual used, and convert the coordinate information into the motor's Rotation angle signal. At the same time, the feedback position information of the motor is collected for data analysis. To improve the operation accuracy, the average filtering algorithm is added to the conversion program to reduce the vibration of the equipment caused by the high frequency action of the motor due to the excessively fast data transmission. This vibration sensation produces a serious error to the accuracy of the equipment action. Therefore, after adjusting the data collection frequency, perform operations such as angle calculation after the average filtering of the data. At the same time, because the resolution is limited by the lens parameters, for the target truck at the edge of the working area, there is a certain error in calculating the angle according to the equal resolution of the resolution. For this reason, when calculating the angle, the angle value and the lens resolution value should be scaled and calculated at the same time to improve the calculation accuracy of the target truck to be loaded on the edge. After performing multiple experiments, the collected data can be analyzed and the two precision-improving operations have better results, see Figure 5.

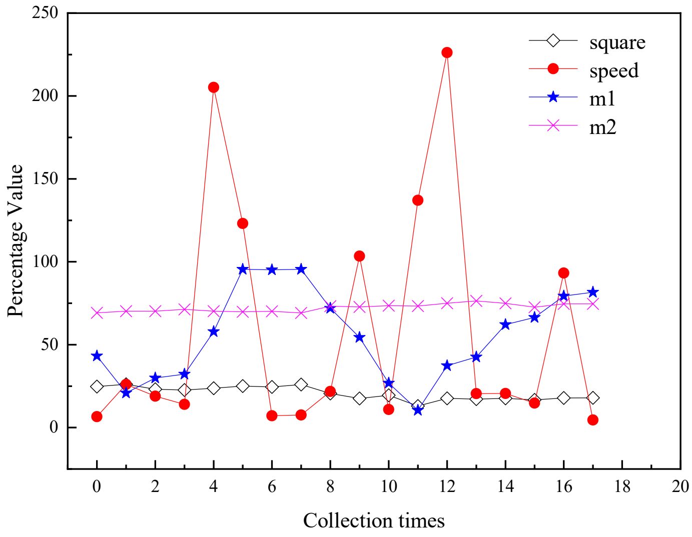


Figure 5. Real-time data detection and analysis

Using industrial cameras as the acquisition equipment, deploying a workbench of the SSD target detection model for data processing, and output driving a two-axis machine lathe equipped with a DC brushless motor to perform the loading action for the experiment. As shown in the experimental data in Figure 5, the abscissa represents the acquisition. The number of times, the acquisition frequency is 1Hz, and the ordinate is the score (for the convenience of observation, the indicators are processed by hundred differentiation). It can be observed in real time that the vehicle information speed is collected in real time to reflect the running speed of the vehicle. Collection times 1-4, 7-8 and 14-16 are the target vehicles waiting to be loaded. The area of the vehicle body when the vehicle is parked in the work area is square, and the angle operation information of the gantry crane's dual motors is recorded as m1 and m2. The data collection process is consistent with the actual operation, and the loading effect is significant.

5. Conclusion

Use the SSD target tracking detection algorithm to identify the target truck in the working area to obtain real-time location information, which solves the shortcomings of the single-layer feature-layer target detection algorithm for the detection network, which is simple and has higher accuracy. Practical application has a good detection effect.

Determine the loading plan algorithm according to the information and restriction conditions such as the information of the vehicle body space and the cargo information, and standardize the loading method, which can effectively save the loading space of the vehicle body, reduce the cargo gap, and improve the loading efficiency, thereby saving the transportation of finished products.

The coordinate sequence calculation of the stacking of the goods determined according to the loading plan is converted into the angle signal of the motor operation, thereby driving the gantry crane to automatically load the goods without manual handling and loading, which greatly saves labor and greatly improves work efficiency.

Acknowledgments

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