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THE DESIGN AND TESTING OF INTELLIGENT ORCHARD PICKING SYSTEM FOR AGRICULTURAL MACHINERY BASED ON IMAGE PROCESSING TECHNOLOGY

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Abstract. This paper proposes an intelligent orchard-picking system for agricultural machinery based on image processing technology. The system uses binocular vision technology to obtain high-precision 3D point cloud data of fruit trees and uses the Mask RCNN algorithm to detect and segment fruit. The system design includes two parts: hardware selection and software algorithm implementation. The hardware part mainly includes a binocular camera, robot arm and end actuator, while the software part integrates image preprocessing, target recognition and positioning, path planning, and grasp control. In the system simulation stage, the whole process is optimized several times to ensure its stability and reliability in practical application. Finally, the effectiveness and practicability of the system are verified by testing in a natural orchard environment. The experimental results show that the system can accurately identify and locate fruits under complex backgrounds, realize efficient and automatic picking operations, and significantly improve orchards' production efficiency and economic benefits. The research results of this paper are of great significance for promoting the intelligent development of agricultural machinery.

Key words: Image processing technology; Intelligent orchard picking system; Binocular vision; Mask RCNN algorithm; System simulation

1. Introduction. Image processing technology is vital in intelligent agricultural machinery as an essential branch of computer vision. The fruit can be recognized and positioned efficiently and accurately through image acquisition, preprocessing, feature extraction and classification recognition.

In the design of intelligent orchard-picking systems, binocular vision technology has been widely concerned because of its ability to provide three-dimensional spatial information. Through binocular vision technology, the system can obtain the depth information of the fruit, to achieve an accurate grasp of the fruit. At the same time, combined with advanced deep learning algorithms such as Mask RCNN, the system can further improve the fruit's recognition rate and positioning accuracy. Literature [1] proposes a fruit-picking robot system based on image processing and machine vision. The system realizes the recognition and positioning of fruits through image processing technology and uses machine vision technology to guide robots to carry out picking operations. In reference [2], a fruit recognition method based on deep learning is proposed to solve the problem of fruit recognition under a complex background. This method uses a convolutional neural network to extract and classify fruit images, effectively improving fruit recognition rate. In addition, literature [3] also studied the 3D localization technology of fruit based on binocular vision. The three-dimensional coordinate information of fruit was obtained by binocular vision technology, which provided accurate location information for subsequent picking operations.

However, although predecessors have made substantial progress in this field, some problems still need to be solved. For example, in the complex and changing orchard environment, achieving fast and accurate identification and positioning of fruits remains a challenge. At the same time, how to improve the robustness and adaptability of the system so that it can adapt to different varieties, sizes and colors of fruit is also the hot and challenging point of current research.

An intelligent orchard-picking system for agricultural machinery based on image processing technology is proposed in this paper. The system integrates binocular vision technology and Mask RCNN algorithm to realize fast and accurate recognition and localization of fruit [4]. First, the fruit's depth information and three-dimensional coordinate information were obtained by binocular vision technology. Then, the Mask RCNN algorithm segmented and identified the fruit finely. Finally, according to the recognition results, the robot

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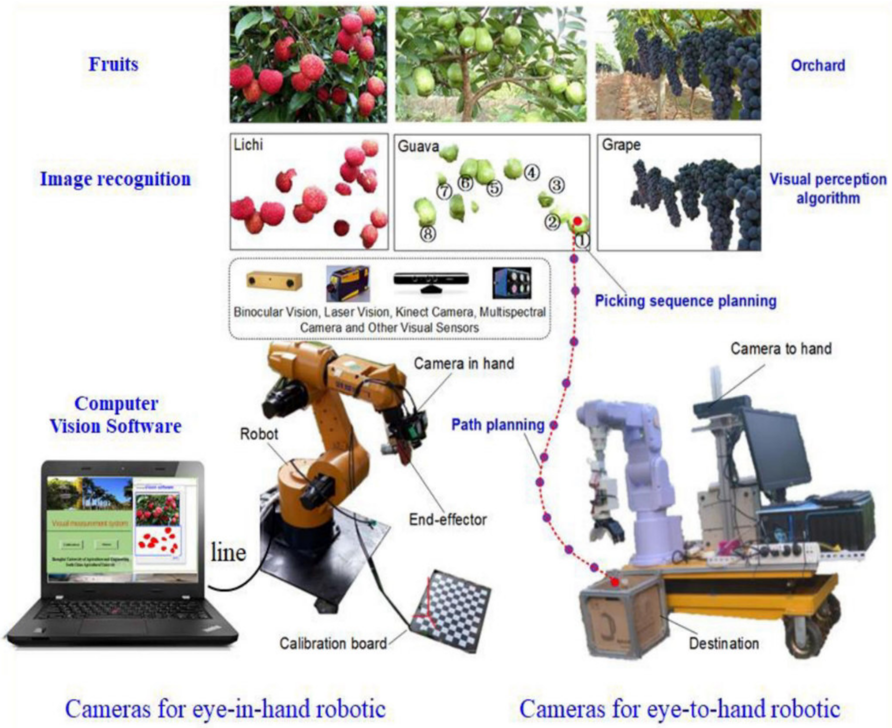

Fig. 2.1: Architecture of agricultural intelligent orchard picking system.

arm is controlled to carry out the automatic picking operation. The research in this paper not only helps to promote the development of intelligent agricultural machinery and improve the efficiency and quality of orchard production but also provides a valuable reference for researchers and engineers in related fields.

2. Design of agricultural intelligent orchard picking system based on image processing.

2.1. System Architecture.. The intelligent orchard-picking system designed in this study adopts the modular design concept, and the overall architecture is divided into four main parts: image acquisition, data processing, decision control and executive mechanism. The image acquisition module is responsible for the real-time capture of orchard scene images, using high-resolution cameras and binocular vision technology to obtain two-dimensional images and three-dimensional spatial information of fruits [5]. After receiving the image information, the data processing module uses image processing technology and deep learning algorithms, such as Mask RCNN, for image preprocessing, feature extraction, fruit recognition and location. The decision control module generates corresponding control instructions according to the processing results, coordinates the actions of the robotic arm and the end effector, and realizes the precise picking of the fruit. The actuator module comprises a robotic arm and an end actuator responsible for specific picking operations [6]. The whole system realizes the data transmission and cooperative work between modules through wireless communication technology to ensure the system's efficient operation. Figure 2.1 shows the architecture of the agricultural intelligent orchard Picking system (the picture is quoted in Recognition and Localization Methods for Vision-Based Fruit Picking Robots: A Review).

2.2. Hardware Design. The system mainly includes image acquisition equipment, a robot arm system, an end effector, and a central control unit. The image acquisition device consists of a high-resolution RGB camera and an infrared camera to obtain the color and depth information of the fruit [7]. The RGB camera captures the appearance characteristics of the fruit, and the infrared camera provides the depth information of the fruit by measuring the difference in thermal radiation on the surface of the fruit. Combining the two can

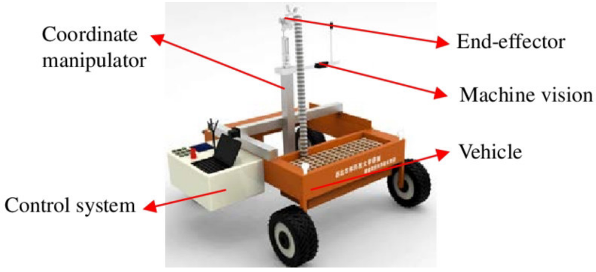

Fig. 2.2: Hardware structure diagram of fruit picking robot.

achieve an accurate three-dimensional reconstruction of the fruit [8]. The industrial robot arm with multiple degrees of freedom is selected for the robot arm system, which has flexible movement ability and high positioning accuracy and can adapt to the complex and changeable orchard environment. The end-effector is designed with an adjustable claw structure that ADAPTS the shape and size of the fruit to ensure stability and reliability during the picking process [9]. The central control unit adopts a high-performance embedded processor, which is responsible for the overall control and data processing of the system and ensures the coordinated operation of each module. Figure 2.2 shows the hardware structure diagram of the fruit-picking robot.

2.3. Control system and software design. The design of the control system and software is the key to realizing the function of an intelligent orchard-picking system. The control system adopts a hierarchical design, including the bottom controller and the upper computer control software [10]. The bottom controller receives instructions from the central control unit and drives the robot arm and the end actuator to perform the corresponding actions. The upper computer control software runs on the high-performance computer, displays the system's working state and parameter Settings through the graphical user interface (GUI), and provides the user interaction interface. Regarding software design, the system adopts the modular programming idea. The image processing, decision control and motion planning function modules are developed independently, which makes it easy to maintain and upgrade the system [11]. The image processing module uses the deep learning framework TensorFlow and PyTorch to realize the training and deployment of the Mask RCNN algorithm and improve fruit recognition rate and positioning accuracy. According to the image processing results and path planning algorithm, the decision control module generates the optimal picking path and action sequence to ensure that the robot arm can complete the picking task efficiently and safely [12]. The structure diagram of the Robot control System is shown in Figure 2.3 (the picture is quoted in the Four-wheeled Mobile Robot with Autonomous Navigation System in ROS). In software implementation, special attention is paid to the real-time and robustness of the system. Through multi-thread technology and a real-time operating system, real-time image processing response and decision control are ensured. At the same time, the exception handling mechanism and fault tolerance control strategy are introduced to improve the stability and reliability of the system in complex environments. In addition, the system also has self-learning and adaptive capabilities, which can continuously optimize algorithm parameters and control strategies through the analysis and learning of historical data and improve the intelligence level of the system.

3. How MASK RCNN works. Mask RCNN is a convolutional neural network developed based on Faster RCNN. In this way, the crack object in the image can be automatically detected and located, and the crack object can be segmented by the template [13]. The network consists of three modules: backbone, regional generation, and functional.

Residual and feature cone networks are used in backbone networks, and ResNet is used as a convolutional neural network to extract high-level visual features [14]. FPN is combined with the ResNet network, and the method of down sampling and up sampling is used to achieve the effective fusion of low-resolution, robust semantic features and high-resolution weak features.

3.1. Supervised Mask RCNN. In the case of guidance, Mask RCNN needs to preprocess a training picture. Each picture is annotated with a picture label system, and the crack location is marked. Then, a

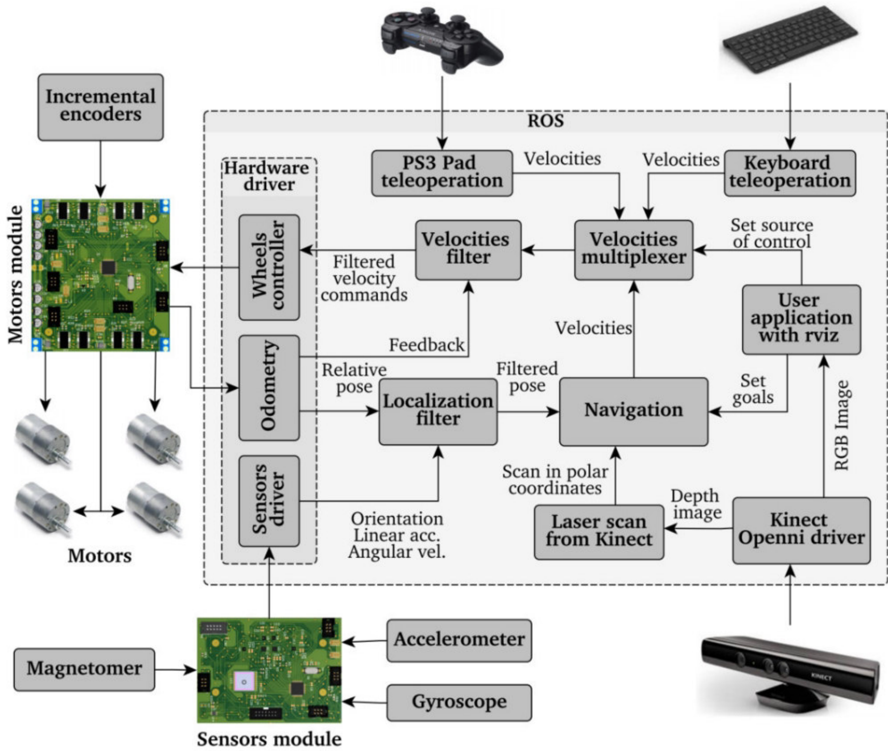

Fig. 2.3: Structure diagram of robot control system.

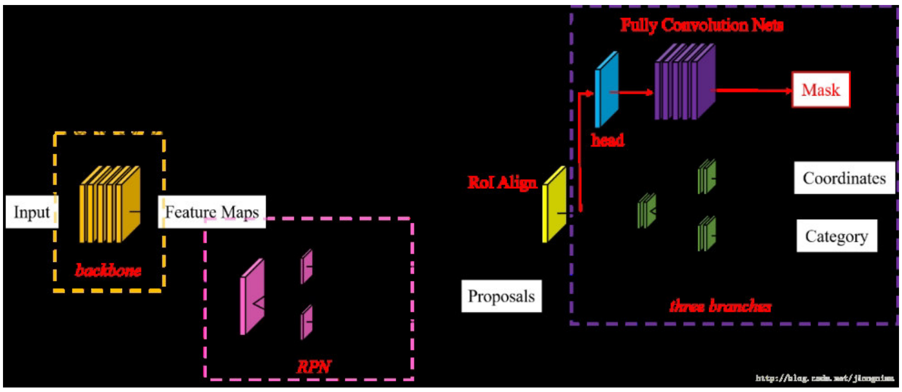

Fig. 3.1: Mask RCNN structure.

rotation method based on gray level, saturation, contrast, and other parameters is proposed to enhance the learning performance of the learning model and avoid overfitting [15]. The crack identification model was established by adjusting the learning rate, weight decay and iteration times. The high-resolution UAV image is input into the crack identification model for accurate location.

3.2. Loss function of Mask RCNN. This paper presents a learning method based on the BP neural network. Then, the loss of the network is minimized by learning the neural network's learning. Loss is the penalty for inaccurate prediction during neural network training [16]. The loss function is used to estimate the

Table 4.1: Analysis table of experimental results.

Speed (cm/s)	Picking target	Experimental picking times	scene images /n	target identification pictures /n	completed picks/n	Identify the extraction rate /%
	Mandarin orange	10	326	320	10	99.09
1	Strawberries	10	318	313	10	99.39
	Mandarin orange	10	260	249	10	97.07
2	Strawberries	10	251	242	10	97.78
	Mandarin orange	10	204	190	9	94.04
3	Strawberries	10	200	187	10	94.34

learning cost of the network.

$$H = H_z + H_1 + H_n \tag{3.1}$$

H is the total loss of the network. $\overline{U}$ is classification loss, which measures the accuracy of the network classification. H_1 is a function of the estimated error, which measures the accuracy of the boundary. H_n is mask loss, which is used to measure the positioning accuracy of the mask [17]. For each class of v, find H_z with the logarithm of the loss function of SoftMax

$$H_z(q, v) = -\log_2(q_v) \tag{3.2}$$

Find H_1 by the loss function smooth H_1

$$H_1(i^v, \gamma) = \sum_{i=\{x,y,w,h\}} \text{smooth}_{H_1}(i_i^v - \gamma_i) \tag{3.3}$$

$q = (q_0, \cdots, q_j)$ is a value calculated for the function SoftMax. $\gamma = (\gamma_x, \gamma_y, \gamma_w, \gamma_h)$ are the coordinates of the actual edge box of the measured object. $i^v = \left(i_x^v, i_y^v, i_w^v, i_h^v\right)$ is the coordinate correction for the border frame of class v. The loss function of smooth$_H$, looks like this

$$\text{smooth}_{H_1}(x) = \begin{cases} 0.5x^2 & |x| < 1 \\ |x| < 0.5 & |x| \geq 1 \end{cases} \tag{3.4}$$

H_n is very similar to H_{z1}. It is calculated using the mutual entropy loss function of the two means.

4. Experimental results and comparative analysis.

4.1. Experimental results. Combined with multi-layer RCNN network architecture, the collected results are tested and analyzed. The faster the arm of the acquisition robot moves, the lower the accuracy of feature extraction [18]. The recognition rates of citrus and strawberry are 99.09% and 99.39%, respectively, when the robot arm moves at a low speed of 1 cm/s. The results showed that the practical components of citrus and strawberry were 97.07% and 97.78%, respectively, at 2 cm per second. At 3 cm per second, the effective recognition of citrus and strawberries reached 94.04% and 94.34%, respectively. The analysis of specific experimental results is shown in Table 4.1.

4.2. Comparative experimental analysis. The Mask RCNN model based on Mask RCNN and Faster RCNN were compared to test the performance of the MASKRCNN model on the harvesting robot arm. In this project, two different neural network architectures are used to establish the corresponding learning models for strawberry harvesting, and the corresponding learning models are applied to the harvesting robot arm for the experiment. By collecting image information, the image information of Mask RCNN and Faster RCNN in various harvest stages is studied [19]. The training effect of Mask RCNN is better than Faster RCNNs when

Table 4.2: Comparison of experimental results.

Neural network framework	Speed (cm/s)	Picking target	Experimental picking times	scene images /n	target identification pictures /n	completed picks /n	Identify the extraction rate /%
	1		10	318	313	10	99.39
Mask RCNN	2	Strawberries	10	251	242	10	97.78
	3		10	200	187	10	94.34
	1		10	318	287	10	91.11
Faster RCNN	2	Strawberries	10	251	224	10	90.40
	3		10	200	178	9	89.80

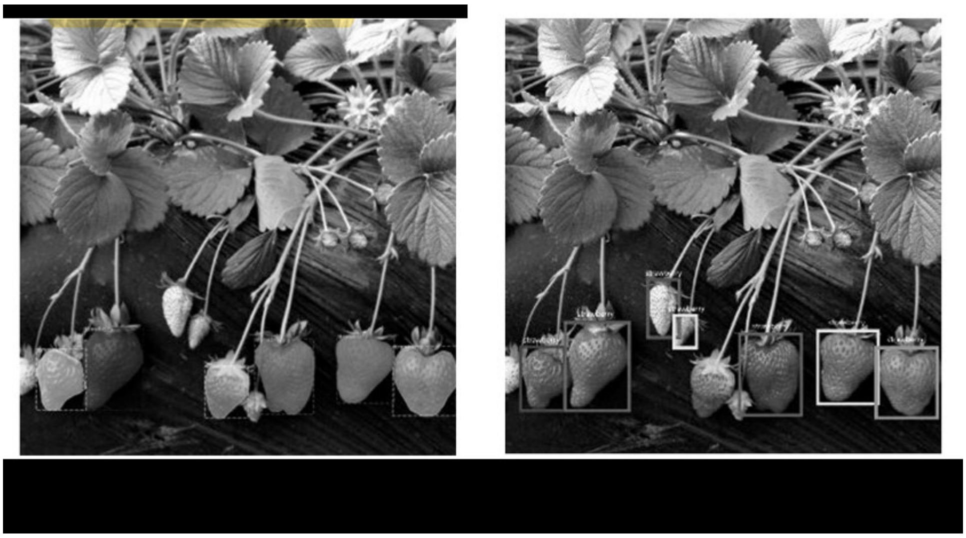

Fig. 4.1: Comparison of recognition of Mask RCNN and Faster RCNN.

the training rate is increased. Faster RCNN can't tell when a strawberry is ripe, as Mask RCNN can. The results of the comparative tests are shown in Table 4.2.

It can divide the categories of pixel level to improve the recognition ability of objects. Because the multi-layer neural network dramatically influences the object identification process, the multi-layer neural network can quickly classify the object in the collection process. Figure 4.1 is a diagram of Mask RCNN compared to Fast RCNN.

5. Conclusion. This research successfully designed and tested an intelligent orchard-picking system for agricultural machinery based on image-processing technology. The system integrates binocular vision technology and the Mask RCNN algorithm, effectively solving the complex problem of fruit accurate recognition and positioning. Through image processing technology, the system can efficiently analyze the orchard environment image and realize real-time detection and recognition of fruit. The binocular vision technology provides depth information for the system and dramatically improves the accuracy of fruit positioning. The Mask RCNN algorithm ensures the high accuracy of fruit recognition in complex backgrounds. This research focuses on the collaborative optimization of hardware selection and software algorithms to ensure the system's stable operation in the actual orchard environment. The simulation results show that the system can accurately identify and locate the fruit in the simulated environment, which verifies the effectiveness of the system design. This research promotes the application of image-processing technology in intelligent agricultural machinery and provides strong support for developing intelligent orchards in the future. Future work will focus on further optimizing the algorithm and expanding the system's capabilities to deal with more diverse orchard environments and more complex picking tasks.

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