THE DESIGN OF GROUND AIR DUAL PURPOSE AGRICULTURAL INFORMATION ACQUISITION ROBOT
/
地空两用农业信息采集机器人的设计

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ABSTRACT
The key to the design of the ground air dual-purpose agricultural information acquisition robot is the application of machine vision technology to realize the collection of crop growth state information. This research mainly designs the machine vision system of the ground air dual-purpose agricultural information acquisition robot, including hardware, software and image processing algorithm. The machine vision system designed in this paper can effectively complete the collection of crop status information. In order to verify the effectiveness of machine vision system, blueberry was used as the experimental object. The control group was set up indoor and outdoor, the fruit condition and quality information were detected, and the blueberry yield was estimated according to the test results. The experimental results show that the image segmentation algorithm in the vision system can identify blueberry fruit well, and the system has strong information analysis ability, and can accurately predict the quality and yield of blueberry fruit according to the image. It can be seen that the machine vision system has a good ability of information acquisition and recognition, which has a high reference significance for the design and research of the ground air dual-purpose agricultural information acquisition robot.

摘要
地空两用农业信息采集机器人设计的关键是机器视觉技术的应用，实现作物生长状态信息的采集。本研究主要设计了地空两用农业信息采集机器人的机器视觉系统，包括硬件、软件和图像处理算法两部分。本文设计的机器视觉系统能有效地完成作物状态信息的采集。为了验证机器视觉系统的有效性，本研究以蓝莓为实验对象。设室内外对照组，检测果实状况和品质信息，根据检测结果估算蓝莓产量。实验结果表明，视觉系统中的图像分割算法能够很好地识别蓝莓果实，系统的信息分析能力强，能够根据图像准确预测蓝莓果实的品质和产量。可见，该机器视觉系统具有良好的信息采集和识别能力，对地空两用农业信息采集机器人的设计与研究具有较高的参考意义。

INTRODUCTION
As a basic industry in China, the production efficiency of agriculture and forestry is very important for the development of China. At present, there are mainly two modes of agricultural production: manual and machine. Labour not only has low efficiency, but is also limited by the fatigue of labour personnel, which hinders the improvement of agricultural production efficiency *(Vasconez et al, 2019).* Machine production can not only get rid of the problem of manual operation, but also facilitate agricultural production mode and effectively improve the efficiency of agricultural operation *(Bodunde et al, 2019).* As an emerging technology, machine vision technology is widely used in the fields of crop growth information collection, crop fruit recognition and real-time monitoring of crop status due to its advantages of large data processing capacity, fast data processing speed and high data analysis accuracy *(Choi et al., 2015).* The emergence of machine vision technology solves the high cost and low efficiency of manual work, which has a high practical significance for agricultural production automation and modernization.

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Human receiving external information is mainly realized through vision, so the robot has the function of human machine vision, which can greatly improve the machine's ability to receive external information *(Blanes et al., 2015).* Machine vision technology refers to the ability of machine vision judgment and visual analysis through image processing algorithm and image acquisition terminal, so as to promote the machine to complete complex tasks *(Zavala, 2017).* Based on the machine vision technology, this paper designs the machine vision system of the ground air dual-purpose agricultural information acquisition robot, and studies the overall design scheme of the system from two aspects of its hardware and software design and image processing algorithm, in order to contribute to improving the efficiency of agricultural information collection.

This research mainly includes four parts. The second part is to explore and analyse the current application status of agricultural robot, and summarize its optimization and improvement; the third part studies the design of vision system of agricultural information acquisition robot, and points out that the design of machine vision system should be carried out from the perspectives of system software and hardware and image processing. In the fourth part, through the experimental method, the fifth part summarizes the full text and points out the significance and shortcomings of this research.

Chebrolu's team proposed a large-scale agricultural robot data set for plant classification, positioning and mapping, which is of great significance for precision agriculture research *(Chebrolu et al., 2017)*. The *Adamides* research group has proposed a design plan to transform the universal mobile robot platform into a semi-autonomous agricultural robot sprayer. The design scheme details the hardware and software modules that the system must install, and focuses on the user interface of remote operation. The usability of the user interface is evaluated through relevant experiments. The results show that the user interface of the system has good interactivity and can create a good experience for users *(Adamides et al., 2017)*. *Raja et al* and his colleagues have developed an autonomous agricultural mobile navigation robot, which mainly detects the field environment of crops. The function is realized by using sensor technology and GPRS technology. The sensor technology obtains the field environment data, and GPRS technology transmits the data *(Raja et al., 2015).* An adaptive fuzzy sliding mode control model based on fuzzy logic theory to improve the control accuracy and stability of the agricultural tracked robot control system was proposed. Subsequently, by comparing with the traditional sliding mode control model, the high applicability and strong robustness of the model are proved (*Jiao et al., 2015*). *Kauser's* research team has designed a compound functional agricultural robot, which can independently complete agricultural production work, such as farming, fertilizing and sowing. The robot uses solar energy as the basic energy and has high environmental protection *(Kauser N., Banu S. and Yuvaraja T., 2018).*

The *Vijay*'s team has designed a robot that uses image processing and machine learning technology to detect leaf diseases. *(Vijay et al., 2018).* Colleagues from *Peña's* machine introduced the development technology of a remote robot platform for urban crop monitoring and management. The platform can remotely control the robot and make the robot perform seeding, irrigation, fumigation and pruning activities on small and scalable structured crops *(Peña et al., 2018). Noguchi* introduced a robot vehicle agricultural application technology, which is based on GPRS, combined with machine vision, image processing and sensor technology, which has great reference significance for the development of precision agriculture *(Noguchi, 2018). Bogue* summarizes the important research and development activities of agricultural robots in recent years, and points out that agricultural robots are mainly used in precise weed control, fertilization and crop harvest, and the main technologies used are machine vision and image processing *(Jin M. et al., 2020).* At the same time, the market demand trend of agricultural robots in the next ten years is predicted, and it is predicted that there will be greater market demand and great development potential for agricultural robots in the future *(Bogue R., 2016)*. *Zhang C et al*. developed a multi robot tractor system for agricultural field operation. The efficiency of the system depends on the number of robots, spatial pattern and field length. In order to determine the practicability of the system, three simulations were carried out, and the simulation results show that the system is more efficient in large field *(Zhang C., Noguchi N., 2017)*.

Through the summary of the above, it can be found that there are many related researches on the ground operation agricultural robot, and its application field is more extensive, and it is generally used in basic agricultural field work.*(Yu N. et al., 2020)* However, there is less research on the ground air dual-purpose agricultural robot, which is the important reason why the design and research of the ground air dual-purpose agricultural information acquisition robot is important for the technical innovation of agricultural robot.

MATERIALS AND METHODS

Vision system design

The vision system design of agricultural information collection robot can be divided into software design and hardware design. The software part mainly includes human-computer interaction interface design, image processing algorithm design and hardware driver installation; the hardware part mainly includes infrared emission module design, information processing system design and image acquisition design. The overall framework design is shown in Figure 1.

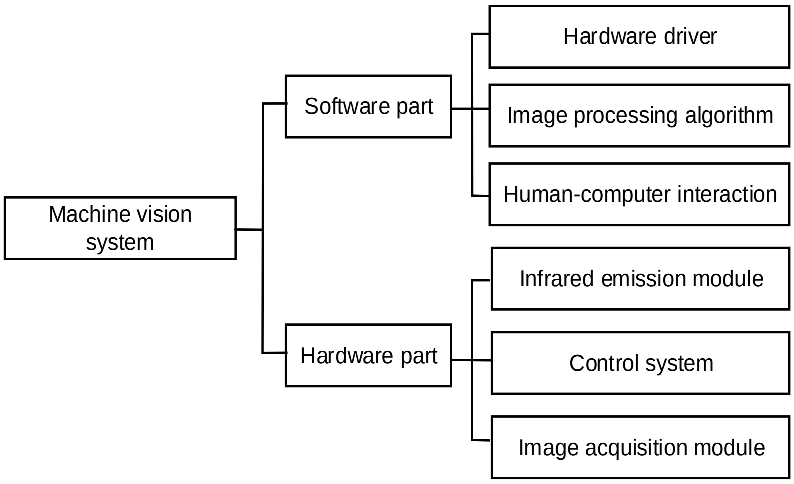

Fig. 1 - Frame diagram of machine vision system

The working process of agricultural information acquisition robot mainly includes two steps: firstly, the image signal of the object to be measured is collected, and the technology used in the acquisition includes infrared emission technology and image acquisition technology; secondly, the collected image signal needs to be converted into digital image, and the digital image is transmitted to the information processing system through the transmission path, and the image signal is processed in the processing system. Finally, it completes the identification of the object to be measured, information collection, yield prediction and other work, and the collected data is displayed in front of the user through the human-computer interface. The agricultural information collection robot needs to be able to collect clear and complete high-quality images. At present, the most widely used image acquisition chip is CCD chip and CMOS chip. Compared with CMOS, the application cost of CCD is lower and the quality of captured image is poor. CMOS is superior to CDD in image processing and noise reduction. Especially the latest CMOS chip, not only has ultra-high-definition camera processing technology, but the price is also low, so the comprehensive performance of CMOS is obviously better than CCD. With its high image SNR and image resolution, CMOS has gradually replaced other similar products and become the leading sensor chip for image acquisition. Therefore, the image acquisition tool in this study uses CMOS chip, and the corresponding system hardware framework is shown in Figure 2.

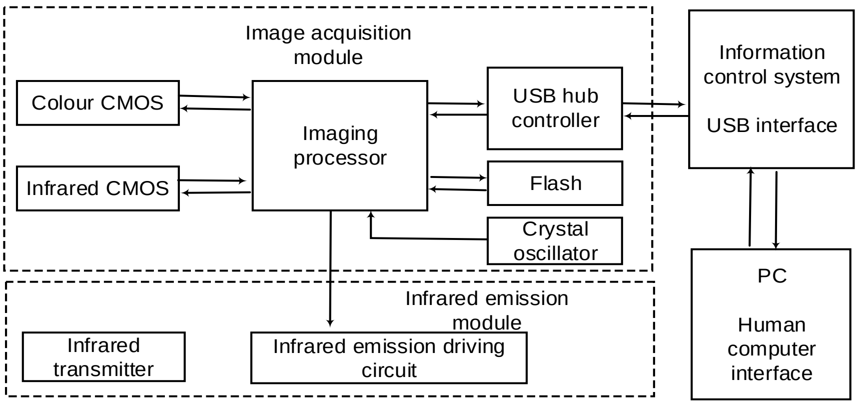

Fig. 2 - Hardware architecture of machine vision system

The hardware of vision system of agricultural information acquisition robot includes infrared emission module, image processing module and information control module. The signal acquisition tools of image processing module are colour CMOS and infrared CMOS. The main function of colour CMOS is to collect colour image, and the main function of infrared CMOS is to collect depth image signal. After completing the image signal acquisition, the imaging processor converts the two kinds of signals into digital images that can be recognized by the computer. The information control system needs to process the digital image, and the image processing mode of the information control system is wireless and wired. The information control system transmits the image processing results to the computer terminal, and then uses the human-computer interaction interface to output. In the process of image acquisition and processing, the specific devices supported include infrared CMOS camera, colour CMOS camera, infrared emitter and agricultural information acquisition robot. The image resolution of the colour CMOS camera is 1280 (H) x 960 (V), the shooting angle is 57°(H) x 43°(V), and the frame rate is 15fps. The depth of the camera is 320(H) x 240(V); the resolution of the camera is 0.8…4 m. Image processing requires the computer to have high speed and small volume, which is convenient for assembly on the information acquisition robot. The main function of the vision system is to identify the object to be tested and collect the relevant information. The operating environment of the software part is *LINUX* system, and the programming function is *OpenCV, OpenGL*. The corresponding software framework is shown in Figure 3.

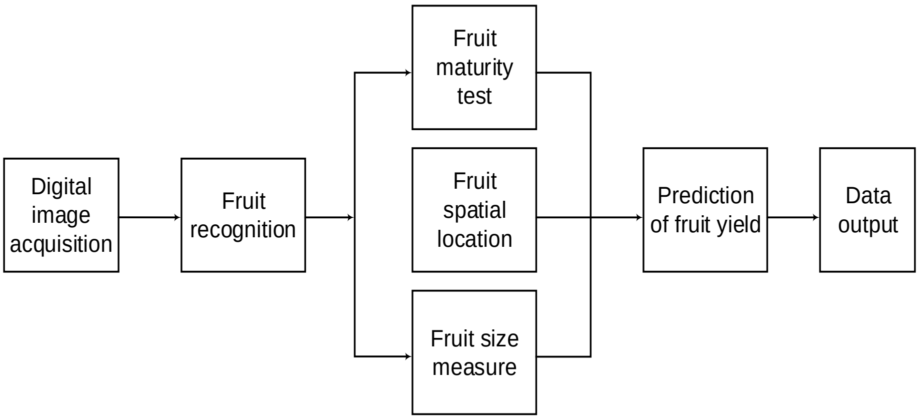

Fig. 3 - Software architecture of machine vision system

The data process between human-computer interaction interface and calculation mainly includes seven steps: the start-up of system and interface, the determination of data communication mode, the display of image, the conversion of C-D image, the state detection of the object to be collected, data printing and program closing. After opening the visual system and interactive interface, select the data connection mode as wired or wireless, and set the corresponding IP address; then output the corresponding image information in the computer terminal, and convert the colour image into depth image. After the image conversion is completed, we need to obtain the acquisition data of the vision system. After the acquisition is completed, the relevant data will be transmitted back to the computer to facilitate the user to view, and the data results will be printed to lay the data analysis results. After the above operations are completed, the program is closed.

Design of blueberry yield prediction module

Because the working atmosphere of agricultural information collection robot is usually strong light environment, the collected data are often affected by the outside world, resulting in large error of actual results. In addition, the branches and leaves of agricultural information collection are covered by each other, which will have a great impact on the results of collection and yield estimation. In order to solve such problems, first of all, it is necessary to process the collected images, and then identify the state characteristics of the objects to be collected, such as the fruit diameter, fruit maturity rate and fruit size of crops, so as to provide convenience for subsequent crop yield prediction and evaluation. The workflow of blueberry yield estimation module is shown in Figure 4.

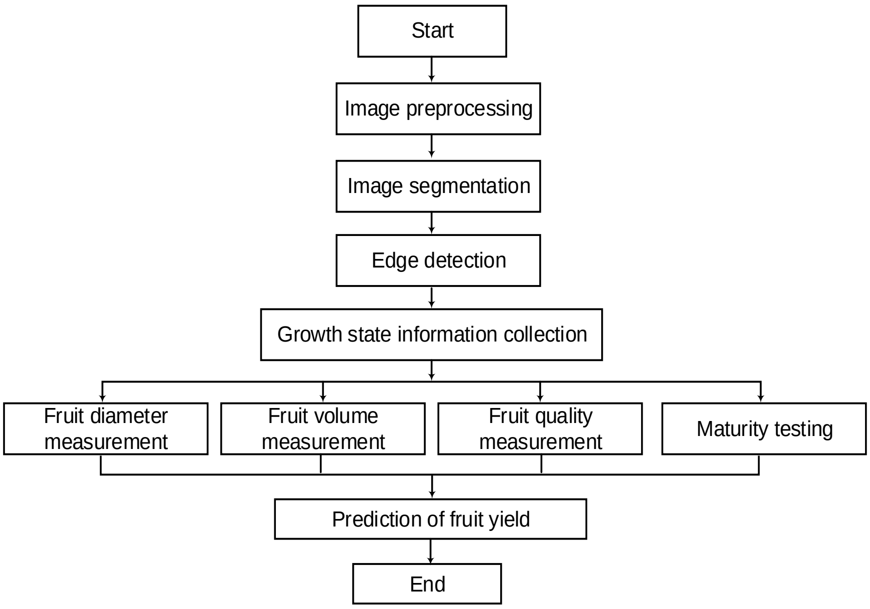

Fig. 4 - Flow chart of image processing algorithm

From the above figure, the core of blueberry yield prediction module includes image processing algorithm and blueberry production information processing. Image processing algorithm includes four steps: image preprocessing, image segmentation, image edge detection, image growth state information processing. Image preprocessing includes image denoising and image enhancement. The main function of the former is to eliminate noise interference and improve the detectability of the image, while the latter is to enhance the visibility and processability of the image and improve the efficiency of image processing. The effect of image denoising is related to the reliability of subsequent image processing, so this image preprocessing mainly introduces image denoising. At present, the most popular noise reduction algorithms are bilateral filtering, median filtering and nonlinear filtering. Experiments show that the adaptive median filter and vector median filter have good image denoising effect and can minimize the noise impact of the image. Therefore, the comprehensive median filter is mainly used to denoise the image. The comprehensive median filter includes adaptive median filter and vector median filter, and the comprehensive median filter mainly includes five processing processes.

They are vector median filtering, HSV colour space conversion, adaptive median filtering, image fusion and image conversion. In the process of vector median filtering, it is necessary to assume the relevant parameters in advance, assuming that the filter centre pixel value is $V(x_i,y_i)$, and the filter window length and width are *2m-1, 2n-1* respectively.

The correlation calculation model of window vector is shown in the following formula.

$$VMF=\{V(x_{(i-m)},y_{(j-n)}),V(x_{(i-m+1)},y_{(j-n)})...V(x_{(i+m)},y_{(j+n)})\} \tag{1}$$

Vector $VMFx\in VMF$, vector median filter calculation formula is as follows.

$$\sum_{i=1}^{N}\|VMFx-V_i\|\leq\sum_{j=1}^{N}\|V_j-V_i\|, j=1,2,3...,N \tag{2}$$

The minimum distance and vector of filtering window can be obtained by the above formula, and the output result of filtering is expressed by this value. Vector median filter has good image denoising effect, but due to the wide colour space of digital image, the denoising effect obtained by using median filter is quite different. In addition, due to the small correlation of each channel in HSV colour space, the image space conversion is realized by gray noise reduction in HSV colour space. Although the effect of adaptive median filter on noise suppression is good, the action space of the algorithm is only single channel gray image. Therefore, it is necessary to carry out h, s, V three channel median filtering processing for the above-mentioned colour space images. In the process of image fusion and image conversion, it is necessary to transform the image into RGB colour space. The evaluation indexes of filtering noise reduction effect are peak signal-to-noise ratio and minimum mean square deviation. The calculation model of peak signal-to-noise ratio is shown in the following formula.

$$PSNR = 10 \times \log_{10}(\frac{255^2}{MSE}) \tag{3}$$

There is a positive correlation between the denoising effects of PSNR images, that is, the higher the PSNR, the better the denoising effect. The formula for calculating the minimum mean square error is as follows.

$$MSE = \frac{1}{mn}\sum_{m=1}^{m}\sum_{n=1}^{n}\left\| I(i,j) - K(i,j) \right\|^2 \tag{4}$$

m, n in formula (4) respectively represents the maximum value of the horizontal and vertical coordinates of the image, and the corresponding unit is pixs; the noiseless gray value of the original image is represented by $I(i,j)$; the gray value of the image after noise reduction is expressed by $K(i,j)$. The important basis of blueberry fruit recognition is image segmentation, and the classic image segmentation algorithm is watershed segmentation algorithm. The essence of watershed algorithm is to segment the image effectively according to the external contour of the image, and the corresponding contour can be obtained after segmentation. If the image is segmented directly by watershed algorithm, over segmentation will occur, that is, the same region is divided into more small regions, which is not conducive to the overall grasp of the image. In order to solve the above problems, the target region labelling method emerges as the times require. The essence of the target region labelling method lies in the presupposition of the seed region and eliminates the irrelevant segmentation region according to the seed region. However, there are some defects in the seed region segmentation method, which is that the seed region may damage the external contour. Therefore, Canny edge detection algorithm is used to improve the watershed segmentation algorithm, and the corresponding processing flow is shown in Fig. 5.

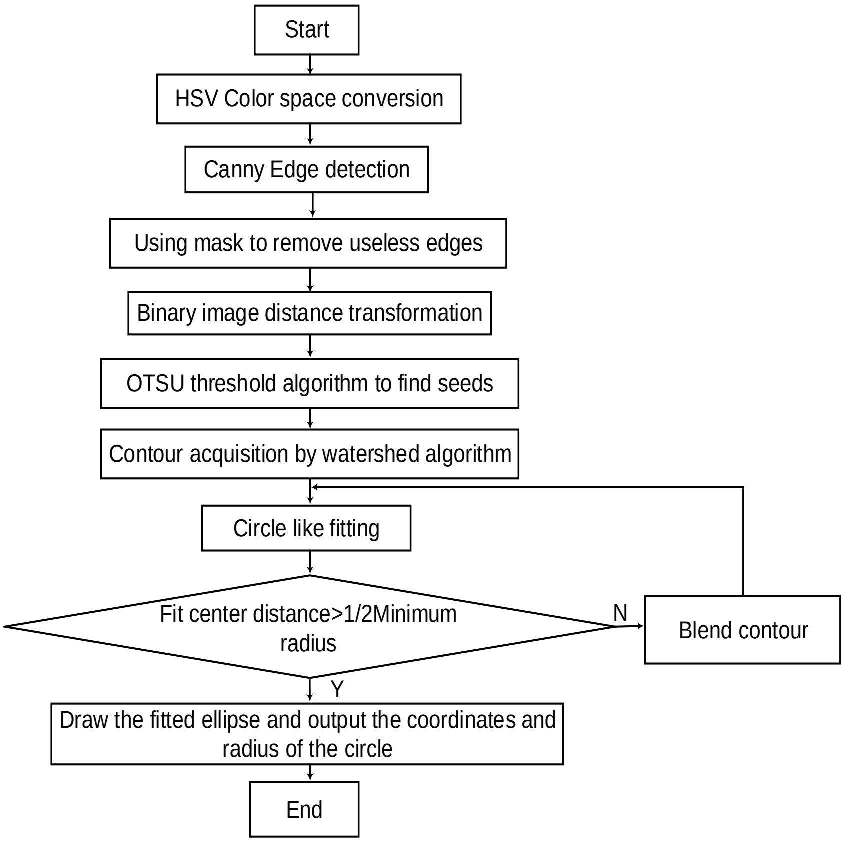

Fig. 5 - Watershed algorithm flow based on Canny edge detection

After image edge detection, data processing algorithm is needed to collect fruit growth information. The collected information mainly includes blueberry fruit diameter measurement, blueberry fruit volume detection, blueberry fruit density measurement, blueberry fruit quality detection, blueberry fruit maturity measurement and blueberry fruit yield prediction. The size of blueberry fruit was measured by machine vision. It was found that the size of mature blueberry fruit in the long diameter was basically the same.

Therefore, using vernier calliper to measure its short diameter size can realize the prediction of fruit volume. Electronic scale was used to measure the quality of blueberry fruit. According to the maturity, blueberry fruit can be divided into six stages: green, green with slight red, red with light green, red with blue and blue. Because the volume, hardness and colour of blueberry fruit are different under the mature state, the maturity degree of blueberry was judged by the skin colour of the fruit using machine vision technology. By calculating the mean pixel value of blueberry fruit image in channel A and channel B in lab space, the maturity of blueberry fruit can be obtained, and the ripeness greater than 0.8 is regarded as the symbol of blueberry maturity.

$$M = a\sum_{i=1}^{N} m_i \tag{5}$$

Formula (5) is the calculation formula of blueberry yield *M*. *N* is the number of ripe blueberry fruits under machine vision. m_i represents the individual mass of the *i*-th ripe blueberry; a is the weighted coefficient of blueberry yield estimation. Take an image of a blueberry in the East, West, North, South and top five directions, compare the blueberry yield shown in the image with the actual yield, and then get the specific value of a.

RESULTS

In order to verify the performance of the vision system of agricultural information collection robot, this experiment set up indoor and outdoor blueberry information acquisition control group to test the effectiveness of the system. As the platform of this system, the ground air dual-purpose robot is responsible for image acquisition of blueberry fruit. The robot consists of four parts: ground walking device, sky flying device, machine control system and visual processing system. The vision system can walk freely through the ground air dual-purpose robot, which is convenient for collecting blueberry fruit information. The field operation effect of the ground air dual-purpose robot is shown in Fig. 6.

Fig. 6 - Field operation of ground air dual purpose robot

The collected fruit information is output by human-computer interaction interface, and the output data information can be visualized after relevant processing. In the experiment, 100 blueberry fruit images were selected as the sample data, and the original image was segmented and the feature pixels were processed. At the same time, the weight coefficient of the characteristic data was determined by pixel labelling method. Finally, the blueberry fruit images of the two control groups were identified by the segmentation algorithm. The effectiveness evaluation indexes of the algorithm are true positive, false positive and similarity of the segmented image. The test results shown in Table 1 are obtained after relevant operations.

According to the above Table 1, the processed image has a high true positive, which shows that the segmentation algorithm can better identify blueberry fruit, meet the needs of actual operation, and can lay the foundation for subsequent fruit contour extraction. In addition, in order to verify the accuracy of the design algorithm to obtain crop fruit information, it is necessary to measure the fruit quality and diameter through the visual system.

Table 1

Blueberry fruit recognition test results

\	True positive	False positive	Similarity
Blueberry fruit image 1	97.835	1.998	95.917
Blueberry fruit image2	95.756	1.262	94.563
Blueberry fruit image3	98.938	1.393	96.127
Blueberry fruit image4	96.913	2.027	95.982
Blueberry fruit image5	98.714	1.532	94.127
Blueberry fruit image6	97.194	2.919	97.028
Blueberry fruit image7	97.914	1.415	98.917
Blueberry fruit image8	95.244	1.822	95.189
Blueberry fruit image9	94.922	2.567	94.614
Blueberry fruit image10	96.892	1.817	98.032
Comprehensive	96.932	1.875	96.049

The diameter measurement tool is vernier calliper, the quality measurement tool is electronic scale, 100 measurement samples are selected, 10 groups are randomly selected for result analysis, and the measurement results are shown in Table 2. It can be seen from table 2 that the vision system has high measurement accuracy for blueberry fruit, which basically conforms to the actual measurement value of blueberry fruit.

Table 2

Statistical table of blueberry fruit measurement parameters

Blueberry fruit number	Actual diameter (mm)	Measuring diameter (mm)	Relative error (%)	Actual quality (%)	Measurement quality (%)	Relative error (%)
Blueberry 1	17.61	17.43	1.034	2.38	2.42	1.661
Blueberry 2	17.84	17.45	2.237	2.42	2.44	0.824
Blueberry 3	18.95	19.08	0.786	2.84	2.81	1.072
Blueberry 4	14.96	15.34	2.479	1.52	1.54	1.308
Blueberry 5	13.81	14.02	1.499	1.34	1.35	0.752
Blueberry 6	15.37	15.42	0.325	1.62	1.64	1.228
Blueberry 7	13.08	12.87	1.633	1.34	1.28	4.725
Blueberry 8	13.88	12.92	7.437	1.42	1.41	0.710
Blueberry 9	18.21	18.72	2.726	2.62	2.52	3.985
Blueberry 10	17.61	18.03	2.331	2.22	2.32	4.330

After the quality inspection of blueberry fruit, it is necessary to estimate the yield. Two control groups were designed for yield prediction, namely, indoor yield prediction and outdoor yield prediction. Each group of prediction samples were set as 100 groups, and 10 groups were randomly selected for result analysis. Indoor blueberry prediction needs to put the blueberry fruit on the electronic scale to get its actual value, and then use the visual system to predict the yield of blueberry fruit. The predicted results are compared with the actual results, and the comparative analysis results are shown in Table 3. It can be seen from table 3 that the predicted yield of blueberry is generally consistent with the actual situation, and the error range of yield estimation is only 0.034% - 1.078%.

Table 3

Prediction results of blueberry fruit yield

Blueberry image	Actual blueberry fruit number	Estimated number of blueberry fruit	Quality measurement of blueberry fruit	Prediction of blueberry fruit quality	Relative error of production forecast
Blueberry fruit group 1	55	55	94.39	94.34	0.054
Blueberry fruit group 2	50	50	84.03	84.83	0.944
Blueberry fruit group 3	52	52	88.93	88.96	0.034
Blueberry fruit group 4	48	48	82.41	82.55	0.17
Blueberry fruit group 5	47	47	81.19	81.14	0.062
Blueberry fruit group 6	44	43	75.38	75.22	0.213

Table 3
Prediction results of blueberry fruit yield (continuation)

Blueberry image	Actual blueberry fruit number	Estimated number of blueberry fruit	Quality measurement of blueberry fruit	Prediction of blueberry fruit quality	Relative error of production forecast
Blueberry fruit group 7	40	39	68.68	68.56	0.176
Blueberry fruit group 8	37	36	63.27	63.96	1.079
Blueberry fruit group 9	33	33	55.74	55.93	0.340
Blueberry fruit group 10	28	28	46.52	46.91	0.832

After the prediction of blueberry fruit yield in the laboratory, it is necessary to carry out field blueberry fruit prediction experiment, and the setting and grouping of control group are the same as indoor. In the field prediction experiment, we need to collect the single cluster fruit image of wild blueberry, and then use the visual system to predict the single cluster fruit yield of wild blueberry. Finally, the electronic scale was used to measure the actual single cluster fruit yield of wild blueberry. After the completion of the two groups of tests, the yield values of the two were compared. The detailed comparative analysis results are shown in Table 4.

Table 4
Prediction results of blueberry fruit yield

Blueberry image	Quality measurement of blueberry fruit(g)	Estimation of blueberry fruit quality(g)	Relative error of yield estimation (%)
Blueberry cluster 1	81.65	79.53	2.667
Blueberry cluster 2	76.79	71.94	6.743
Blueberry cluster 3	70.75	75.19	5.906
Blueberry cluster 4	67.3	75.12	10.412
Blueberry cluster 5	80.62	86.55	6.853
Blueberry cluster 6	80.66	74.59	8.139
Blueberry cluster 7	66.64	61.66	8.078
Blueberry cluster 8	99.33	90.37	9.916
Blueberry cluster 9	75.44	69.53	8.502
Blueberry cluster 10	128.64	114.41	12.439

It can be seen from table 4 that the estimated blueberry fruit yield is generally consistent with the actual blueberry fruit yield. Generally speaking, there is a small estimation error, the error range is [2.667%, 12.439], and the maximum error is less than 13%. Therefore, the vision system can accurately collect blueberry fruit information, and can predict the fruit yield according to the collected information, and the prediction error is small. It has high practicability.

CONCLUSIONS

In the design and research of the ground air dual-purpose agricultural information collection robot, the most core is the design of machine vision system. This research designs a vision system based on the ground air dual-purpose agricultural information acquisition robot. The system design is mainly carried out from two aspects of software and hardware, image processing. The system is based on the ground air dual-purpose agricultural information acquisition robot, which can complete the crop information collection work in complex environment, so as to accurately judge the spatial position of crops and fruit maturity. In order to prove the effectiveness of the system, indoor and outdoor blueberry fruit information collection control groups were set up to verify the collection effect of the system. The fruit recognition detection results show that the fruit image processed by the vision system has high true positive, which indicates that the segmentation algorithm of the system can identify blueberry fruit better; the fruit quality detection results show that the vision system has high measurement accuracy for blueberry fruit, which basically conforms to the actual measurement value of blueberry fruit; the fruit yield prediction results show that the indoor and outdoor environment is good. The error between the predicted value and the actual value was 2.667% to 12.439%, and the maximum error was less than 13%. In conclusion, the vision system can not only effectively complete the information collection of blueberry fruit, but also has good information analysis ability.

Although this design has a certain reference significance for the research of agricultural information collection robot, there are still some problems in the experiment, such as less sample data and low experimental accuracy.

REFERENCES

[1] Adamides G., Katsanos C., Constantinou I., (2017), Design and development of a semi-autonomous agricultural vineyard sprayer: Human-robot interaction aspects. *Journal of Field Robotics*, Vol.34, Issue 8, pp.1407-1426, USA;

[2] Blanes C., Ortiz C., Mellado M., (2015), Assessment of eggplant firmness with accelerometers on a pneumatic robot gripper. *Computers & Electronics in Agriculture*, Issue 113, pp.44-50, England;

[3] Bodunde O.P., Adie U.C., Ikumapayi O.M., (2019), Architectural design and performance evaluation of a ZigBee technology based adaptive sprinkler irrigation robot. *Computers and Electronics in Agriculture*, Issue 160, pp.168-178, England;

[4] Bogue R., (2016), Robots poised to revolutionize agriculture. *Industrial Robot an International Journal*, Vol.43, Issue 5, pp.450-456, England;

[5] Chebrolu N., Lottes P., Schaefer A., (2017), Agricultural robot dataset for plant classification, localization and mapping on sugar beet fields. *International Journal of Robotics Research*, Vol.36, Issue 10, pp.1045-1052, England;

[6] Choi K.H., Han S.K., Han S.H., (2015), Morphology-based guidance line extraction for an autonomous weeding robot in paddy fields. *Computers and Electronics in Agriculture*, Issue 113, pp.266-274, England;

[7] Jiao J., Kong W., Wang Q., (2015), Self-adaptive sliding mode control based on input fuzzy for agricultural tracked robot. *Nongye Jixie Xuebao/Transactions of the Chinese Society of Agricultural Machinery*, Vol.46, Issue 6, pp.14-19 and 13, China;

[8] Jin M., Wang C.G, Wang P.P., (2020), CFD Numerical Simulation of Temperature and Airflow Distribution in Pigsty Based on Grid Independence Verification. *INMATEH Agricultural Engineering*, Vol.61, Issue 2, pp.241-250, Romania;

[9] Kauser N., Banu S., Yuvaraja T., (2018), IOT Based Agricultural Application Using Robot—Agrobot. *Journal of Computational and Theoretical Nanoscience*, Vol. 15, Issue 6, pp.2137-2139, China;

[10] Noguchi N., (2018), Agricultural Vehicle Robot. *Journal of Robotics and Mechatronic*s, Vol.30, Issue 2, pp.165-172, Japan;

[11] Peña César, Riaño Cristhian, Moreno G., (2018), RobotGreen. A Teleoperated Agricultural Robot for Structured Environments. *Journal of Engineering Science & Technology Review*, Vol.11, Issue 6, pp.145-155, Greece;

[12] Raja S.K.S., Balaji V, Vivekanandan M., (2015), Autonomous mobile navigation robot for agricultural purpose. *International Journal of Applied Engineering Research*, Vol.10, Issue 10, pp.27333-27341, Algeria;

[13] Vasconez J.P., Kantor G A, Cheein F.A.A., (2019), Human–robot interaction in agriculture: A survey and current challenges. *Biosystems Engineering*, pp.179-35-48, USA;

[14] Vijay K.V., Vani K.S., (2018), Agricultural Robot: Leaf Disease Detection and Monitoring the Field Condition Using Machine Learning and Image Processing. *International journal of computational intelligence research*, Vol. 14, Issue 7, pp.551-561, France;

[15] Yu N., Wang Q., Cao S.C., (2020), Road Recognition Technology of Agricultural Navigation Robot Based on Road Edge Movement Obstacle Detection Algorithm. *INMATEH Agricultural Engineering*, Vol.61, Issue 2, pp.281-292, Romania;

[16] Zavala Y.R., (2017), Ramírez-Mendoza, Ricardo A, García-Lara, Silverio. A 3-SPS-1S parallel robot-based laser sensing for applications in precision agriculture. *Soft Computing*, Vol.21, Issue 3, pp.641-650, USA;

[17] Zhang C., Noguchi N., (2017), Development of a multi-robot tractor system for agriculture field work. *Computers and Electronics in Agriculture*, Issue 142, pp.79-90, England.