Original Research Paper

Multi-Feature Recognition of Healthy Vegetable Seedlings Based on Machine Vision Technology

[1,2]**Kaikang Chen**, [1]**Yongkun Fu**, [1]**Yongjun Zheng**, [2]**Bo Zhao**, [2]**Yanwei Yuan**, [2]**Liming Zhou** and [3]**Xin Jin**

[1]*College of Engineering, China Agricultural University, China*
[2]*State Key Laboratory of Soil Plant Machine System Technology, Chinese Academy of Agricultural Mechanization Sciences, China*
[3]*College of Agricultural Equipment Engineering, Henan University of Science and Technology, China*

Abstract: The quality of potted seedlings has an important influence on the yield of vegetables during seedling raising and transplanting. The inconsistency of potted seedlings after transplanting is the main factor causing the decline in vegetable quality and yield. To eliminate or reduce this influence, the health test of potted vegetable seedlings before transplanting is particularly important to ensure crop yield. In this study, an image recognition technology based on machine vision is proposed. It is a multi-feature recognition method for the non-destructive detection of healthy vegetable seedlings. The color of the pot seedling image is enhanced by the industrial control computer system and the self-written image recognition algorithm (hereinafter referred to as the SIXA algorithm). The image segmentation and denoising are realized by the ultra-green threshold segmentation method and 3D Block Matched filtering (BM3D) algorithm. Information about the color and leaf area features of vegetable pot seedlings was collected. The criteria for healthy vegetable pot seedlings are confirmed and analyzed. Among them, the color feature thresholds of healthy vegetable pot seedlings in this study were set as $R \geq 60.7$; $G \geq 119.4$; $B \geq 1.9$, and the leaf area feature thresholds were set as $F \geq 0.15$. This is to reduce the limitation of identifying healthy vegetable potted seedlings based on single information and establish a multi-feature identification method for healthy vegetable potted seedlings, aiming to improve the accuracy of identifying healthy vegetable potted seedlings. The experimental verification shows that the overall recognition rate of the experimental platform is as high as 96.67%, which meets the experimental expectations.

Keywords: Machine Vision, Image Recognition, Pot Seedling, Leaf Area, Leaf Color, Multi-Feature Recognition

Introduction

As the world's largest vegetable producer, China has a long history of vegetable cultivation. The incomplete statistics revealed that the national vegetable planting area reached 20,862.74 Hawith an annual output of 721,025,600 tons of vegetables and a large number of vegetable seedlings in 2019 (National Bureau of Statistics, 2020). At present, about 2/3 of the vegetable varieties in China are planted by seedling transplanting (Zhang *et al.*,

2018). However, in the process of seedling raising and transplanting, the quality of pot seedlings seriously affects the yield of vegetables. In addition, the inconsistency after pot seedling transplanting is the main trigger for the decline in vegetable quality and yield. To eliminate or reduce this impact, it is particularly important to carry out health inspections on vegetable pot seedlings before transplanting, thus ensuring crop yield and quality. Therefore, it is of great significance to develop a rapid, accurate, non-destructive, and popular intelligent

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recognition method for healthy vegetable pot seedlings regarding vegetable transplants in China.

With the advanced technology, foreign countries occupy the leading position in the color appearance, quality detection, and other aspects of agricultural products (Kaur and Kaur, 2019; Tong *et al.*, 2013; Bickramdass *et al.*, 2021; Zhong *et al.*, 2020). They have established relatively complete crop quality detection systems. The agricultural production automation and agricultural modernization have developed well (Calixto *et al.*, 2019; Mustafa *et al.*, 2020). A field weeding control system based on machine vision technology was developed, which is combined with a 3D geometric detection algorithm, it could recognize tomato, lettuce crops, and weeds in the field and automatically control weeding operations (Raja *et al.*, 2020). The field experiment showed that the accuracy of crop detection was 97.8% and the number of weeds in the crop area could be reduced by 83%. A mobile, low-cost, high-resolution root phenotypic system based on machine vision technology has been developed. This is to establish a seamless end-to-end pipeline-from acquiring a large number of root samples to image-based feature processing and analysis (Falk *et al.*, 2020). The shape, length, quantity, and quality of soybean roots were studied to analyze different soybean germplasm. The quality and volume of cherry tomatoes were detected through machine vision technology. The depth of cherry tomatoes gas of BBB1 in different directions was obtained and verified by image processing technology (Nyalala *et al.*, 2019). This lossless, accurate, and consistent technology can also be used for the online classification and grading of tomatoes. Plant health and physiological conditions have a significant impact on chlorophyll content and photosynthetic capacity. On this basis, leaf reflectance information is analyzed by digitizing leaf images to provide a high-throughput, non-invasive and real-time estimation of chlorophyll content in plant leaves economically and efficiently (Agarwal and Gupta, 2018). Besides, the information provided by various image features was used to distinguish spinach seedlings with high and low chlorophyll content. The color, size, and other physical characteristics of pepper seeds were analyzed by image recognition software, to establish a standard model for judging high-quality seeds and to separate high-quality seeds from low-quality seeds (Tu *et al.*, 2018). For a higher germination rate of seeds,non-destructive machine vision technology is used to assess the quality of watermelons and to replace the time-consuming, laborious, and tedious conventional methods by providing a real-time, rapid and effective approach to the harvesting, sorting, and grading of watermelons. This practice focused on the feasibility of technology application and performance (Ali *et al.*, 2017).

Limited to farmland use in China, machine vision technology is mainly used in the quality inspection and classification of agricultural products in the agricultural engineering field (Wu *et al.*, 2013; Jin *et al.*, 2020). For example, it is used to recognize the size and shape of seeds, the appearance quality of rice, the maturity of agricultural products, and the recognition of weeds used in fine agriculture, etc (Dou and Chen, 2016). In Chinese plants, NDT has not been widely used. The late blight of potato leaves was detected based on machine vision technology. The characteristic parameters of the leaf surface were extracted and a mathematical model was established. According to the different characteristic parameters of the color, texture, and shape of the blight spots on potato leaves, to evaluate the degree of the disease. The tomato image is recognized by the support vector machine (Zhang, 2020). By extracting the color features, edge direction features, and mixed features of the sample image, the feature data is classified and the tomato image of disease is screened out to achieve the recognition effect. The best recognition accuracy is obtained by using different characteristic data through experiments. According to the characteristics of grape disease leaf images, the grape disease recognition methods were studied by computer image processing and pattern recognition technology, which can improve the accuracy and efficiency of grape disease recognition (Liu and Feng, 2017). A total of 28 features of color and texture of disfigured leaf spots on the leaves were extracted by collecting images of various disfigured leaves at different growth stages under natural light in the field. This aims to analyze the recognition standard with the highest accuracy for grape disease recognition. A visual measurement system of seedling parameters based on linear structured light was designed. It could measure the seedling leaf area, height, and other parameters online and capture the seedling information in the hole and disc in real-time (Feng *et al.*, 2013). A machine vision detection method based on ellipse fitting of leaf contour was proposed to recover the lost seedling information due to mutual shading of leaf surfaces and to extract the parameters of robot automatic grafting (He *et al.*, 2013). This method can overcome the mutual shading of leaves and the success rate of seedling recognition and location can reach 97.5%. According to the characteristics of the seedling, the hole tray seedling image was segmented and studied by using the super green method (2G-R-B), normalized super green method (g-r-b), and Color difference method (Cr). The grayscale seedling image was obtained by super green and gray color difference analysis methods. Then, the fixed threshold was used for segmentation. The normalized super green method was used to segment the seedling images. The white adaptive threshold was used for segmentation. Finally, the experimental results verified that the gray image of the hole plate seedling image obtained by the super green method was the best for segmentation of the fixed threshold.

With higher labor intensity and lower efficiency, the traditional recognition and screening of vegetable pot

seedlings rely on manual work (Schierup and Ålund, 2020). Based on the current situation of agricultural development at home and abroad, the existing research, as well as the actual demand for vegetable production, this study provides a theoretical basis regarding the technical difficulties of the industry, to improve the planting quality of vegetables. This study proposes a multi-feature recognition method for healthy vegetable pot seedlings. This method can realize the intelligent recognition of vegetable pot seedlings, ensure the overall quality and quality of vegetable transplanting, and lay a theoretical foundation for realizing the automation of agricultural production and promoting better development of agricultural modernization.

Materials and Methods

Design of the Image Recognition Platform Based on Machine Vision Technology

A typical visual system includes a light source, camera, image acquisition card, an image processing module, input and output module, etc. The quality of image acquisition directly determines the quality of the results of image processing and analysis. There are stricter requirements for the performance of image acquisition devices. Therefore, this study developed and designed an image recognition platform, while ensuring the experimental results. The hardware system mainly consists of an image acquisition device and industrial control computer. The image acquisition devices mainly include a camera, lightbox, light source, data line, computer, etc. An industrial control computer was connected to the image acquisition device in real-time through the data line, which could control the image acquisition device to retrieve the image information of vegetable pot seedlings in real-time and store the image of vegetable pot seedlings in a specific folder. The established experimental platform is shown in Fig. 1.

Phase Module

Compared with ordinary camera speed, image quality, stability, etc, the industrial camera in the image has great advantages and it mainly adopts CCD and CMOS sensors. The CCD, when compared to the CMOS sensor, has better photosensitive characteristics and can resist noise, which can be applied to lower contrast of target detection, with a widely used scene; in contrast, CMOS cameras have fast reading and writing speed, but higher imaging noise. According to the different image colors, CCD image sensors can be divided into black and white and color. In addition, this study needs to recognize the color characteristic information of vegetable pot seedling leaves and hole plates. Therefore, the SunWag microscopic industrial camera is selected in this study, and a color CCD image sensor is used, which is a Charge-Coupled Device

(CCD), a silicon wafer used to detect light, and the semiconductor potential is generated and controlled by a clock pulse voltage. Changes in wells enable solid-state electronic devices that store and transfer charge information. The main technical indicators of the sensor are pixels, target size, signal-to-noise ratio, focal length multiplier, etc., as shown in Table 1.

In this study, an AFT-0614 MP Effite photoelectric lens was used. The lens has a size of 1/2 inch and a focal length of 6 mm. The high-performance, high-resolution camera lens industry, adopts designs with low distortion, and low distortion rate, and has a variety of optical correction methods, where the maximum limit reduces the aberration and ensures that it's in the spatial frequency for the high-frequency band to maintain higher MTF values, high contrast resolution. Also, its suitability for machine vision and image processing on image quality requirements is very high, it can cooperate with a third "industrial camera use" and is widely used in high precision measurement, detection, recognition, and other industrial machine vision and image processing system. The parameters of the AFT-0614 MP lens are shown in Table 2.

Auxiliary Light Source

A stable lighting environment is also an important factor affecting the quality of image acquisition. While designing a special lighting box to avoid external light interference, a reasonable light source should be used to provide stable and good lighting conditions. Therefore, it is very important to select an appropriate auxiliary light source to ensure a good image acquisition effect. LED light source has the advantages of strong applicability, stable performance, and long life and provides large-area uniform lighting and low cost. At the same time, to ensure the light evenly covers the rectangular area in the whole plate, this study uses two strips of Kamei visual supplement lamps with a length of 400 mm, a power of 5.76W/m, and light color of a white light source. The light source position diagram is shown in Fig. 1.

Industrial Control Computer

The industrial control computer controls the image acquisition device to collect the image of the vegetable pot seedlings and store the data in a specific folder. In combination with the image recognition algorithm, it then controls the image recognition software to write (hereinafter referred to as the SIXA algorithm) a code to collect pot seedling image processing, thus ensuring the smoothness of the experimental process at a fast speed and satisfying the requirement of image recognition software for computer performance. The machine vision platform is equipped with the Senker touch industrial

control computer produced by Guangzhou Senker Electronics Co., Ltd. The parameter information is shown in Table 3.

An industrial control computer with a 27-inch LCD standard screen to improve the visibility of the operation, as well as the image processing process. The user, through the page, can visualize how the SIXA algorithm pot seedling image is processed by the number of plants and inferior in the cave dish, pixel threshold, area threshold, and green and red information such as the threshold value.

Image Acquisition

The vegetable pot seedling image acquisition device uses an acrylic plate lightbox to block the interference light of the external environment, so that the vegetable pot seedling image is in a relatively stable light environment during the acquisition process, to ensure the acquisition of the pot seedling image. The industrial camera is fixed in the cantilever frame, about 80 cm above the ground. The optical axis of the camera is perpendicular to the working face to avoid geometric errors caused by camera tilt and reduce the accuracy of image recognition. When the hole seedling disk is located in a specific area of image acquisition, the computer controls the camera to take the hole seedling image and stores the image in JPG format in a specific folder on the computer. The collection image of vegetable pot seedlings is shown in Fig. 2.

To facilitate the description of the position of holes in the vegetable pot seedlings based on the dish below, a schematic diagram of the coordinate position of holes as shown in Fig. 3 is established based on the dish and the information format of the coordinate position of holes is extracted (column, row). Example (6, 1) represents the holes in the first row of column 6.

Image Processing

Image Enhancement

Influenced by various uncontrollable factors in the external environment, the image of the vegetable whole dish was unsuitable for subsequent processing and feature parameter extraction in many aspects, such as clarity, brightness, and contrast. Therefore, the vegetable pot seedling needs prior image processing analysis for image contrast enhancement, to stretch the image vegetable pot seedling with a matrix and hole tray background contrast, to highlight the vegetable pot seedling and inhibit the image background matrix and hole tray characteristics, to improve the quality of the image to enhance hole tray characteristics for detection and simplify the data to a great extent, thus improving vegetable pot seedling, the reliability of feature extraction and image recognition and improving the

efficiency of image processing.

Gray-scale transformation is a method based on the point-to-point transformation of pixels in the spatial domain. The gray value corresponding to each pixel in the image is converted into a new gray value through a certain mathematical function relationship and the contrast of the stretched image is changed through the gray level, to make the image more visible and the target features more obvious. The commonly used gray transformation has linear gray transformation, piecewise linear transformation, and nonlinear transformation. Due to the obvious enhancement effect of a linear transformation, simple algorithm, and strong applicability, this method is used to process the image grayscale transformation. The grayscale transformation formula can be expressed as Eq. 1:

$$g(x, y) = T[f(x, y)] \tag{1}$$

where T is the gray transformation function and it represents the transformation relationship between input and output gray values.

To purposefully enhance the local characteristics of vegetable pot seedling image, emphasize the characteristics of pot seedling blade, enlarge images of the seedling dish of vegetable pot seedling and the characteristic, the differences between the characteristics of the inhibition were not analyzed, to improve image quality, abundant information, strengthen the effect of image interpretation and recognition, as well as image segmentation, feature extraction and so on, in preparation for the upper operation.

Image Segmentation

The RGB color space is the most basic. A cube of unit length is used to represent the color. The 8 common colors of black, blue, green, red, purple, yellow, and white are located at the 8 vertices of the cube, and black is usually placed in the three-dimensional rectangular coordinate system. The origin, red, green, and blue is respectively placed on the three coordinate axes. The value range of the parameters is R: 0~255; G: 0~255; B: 0~255. The parameter value is also called the three-color coefficient or primary color coefficient or color value. After dividing by 255, it is normalized to between 0 and 1. When the R, G, and B color channels are all equal to 0, it is displayed as black, and when R, G, When the B color channels are all equal to 1, the display is white. Since each gray level is set to 256, the red, green, and blue components can be combined to represent a total of $256^3 = 16777216$ different colors, which can be used to approximate the colors in nature. The RGB color space is shown in Fig. 4 below.

Set the color F to represent any point in the cube coordinate and then F can be mixed by adding R, G, and B of different coefficients, which is expressed as Eq. 2:

$$F = r(R) + g(G) + b(B) \qquad (2)$$

For the collected color images of vegetable pot seedlings, it is impossible to directly set the color values of R, G, and B representing the vegetable pot seedlings in the image to perform threshold segmentation in the RGB color space. However, the ultra-green feature threshold segmentation method (2G-R-B) is an effective method to distinguish green from other colors in the image. This method can improve the weight of the green channel in the image, retain the green component in the original image and remove the other colors. Moreover, this segmentation method can capture the "green" feature in the image with a small amount of computation and is often applied to the quality inspection of agricultural products.

To highlight the color of capsicum seedlings in the image of capsicum seedlings and weaken the color component of the background, the ultra-green feature threshold method is used in this study to segment the image of capsicum seedlings. Figure 5 is a super green feature threshold segmentation effect, which can be seen from the image after processing, super green characteristic threshold segmentation will effectively separate a clear image of green seedlings, background matrix, hole tray is well suppressed and seedling leaf intersection region segmentation effect is ideal, split after seedling leaves still touching together, can guarantee the follow-up image tag simply connected domain, a single hole pepper seedlings as a complete simply connected domain.

It can be concluded that the ultra-green feature threshold segmentation method has strong adaptability to the growing environment and crop conditions and the ultra-green feature threshold segmentation method has the best effect on the image processing of pepper holes and dish seedlings.
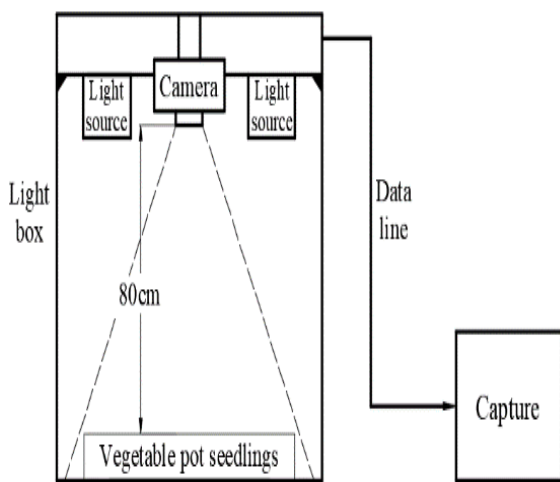

Fig. 2: Collection Image of Vegetable Pot Seedlings

Fig. 3: Schematic diagram of hole coordinate position

Fig. 4: RGB color space model

Fig. 1: Schematic diagram of image recognition platform based on machine vision
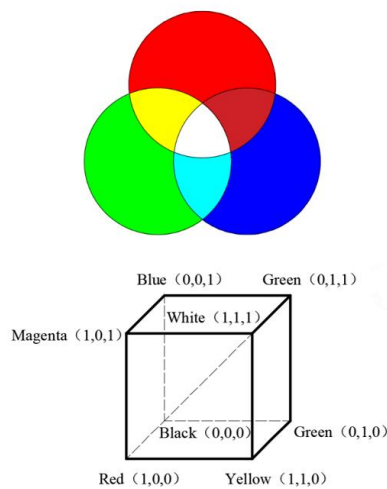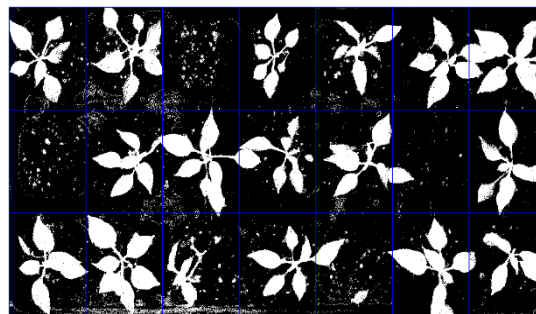

Fig. 5: Segmentation effect of ultra-green feature threshold

Image Denoising

In reality, most of the images of vegetable pot seedlings we obtained will be disturbed by noise. Hence, it is very important to de-noise the obtained images. The so-called image denoising, namely, the interference noise in the image is reduced or removed. The 3D Block Matched filtering (BM3D) algorithm is a denoising algorithm based on the 3D transform domain. It is also one of the best algorithms in video and image denoising at present. The reference blocks are successively extracted from the input noise images and processed as follows: In the first stage, basic estimation: 1. Block matching: Finding a fragment (block) that is similar to the reference block and calling it a similar block. They are arranged into a three-dimensional array according to the size of similarity, which is called a three-dimensional group.2. Collaborate with hard threshold filtering: 3D Transformation processing is carried out on 3D groups, image noise is reduced by the hard threshold filtering method and the estimated value of 2D similar blocks is obtained by the 3D inverse transformation method. 3. Aggregation: Each similar block may have multiple estimates and the weighted average of the multiple estimates can obtain the basic estimate of the image; in the second stage, the final estimation (using the basic estimation as input): 1. Block matching: finding the position of similar blocks by employing block matching in the basic estimation. By using the position of similar blocks, two 3D groups can be obtained, one from the noise image and the other from the basic estimation image. 2. Collaborative wiener filtering: in the above two 3D groups, 3D transform is applied to the basic estimation of 3D groups as energy spectrum of the real signal, using the energy spectrum of noise image synergy wiener filtering processing, the processed data to carry on the inverse transformation and return to the original position to get the final estimate of a similar block. 3. Aggregation: Weighted average processing is carried out on the pixels with multiple estimates to obtain the final estimate of the image. The process of the BM3D algorithm is shown in Fig. 6. After obtaining the extracted image of vegetable pot seedlings, all the connected regions in the image were obtained and the connected domains were sorted according to the size of the area, with the standard 3×7-hole dishes as an example. For leaves, since all the leaves of a seedling are not necessarily in a connected region, all the connected regions in the extracted leaf image are firstly obtained through the BWLABEL function. According to the pixel value, MP of the area with a small area, the connected domains whose pixel value is lower than MP

in all the connected regions are removed. Figure 7 shows before denoising and Fig. 8 shows after denoising.

Feature Extraction

This study aimed to establish a multi-feature recognition method for healthy vegetable pot seedlings through the correlation analysis between leaf color characteristics and leaf area characteristics and healthy vegetable pot seedlings, to reduce the limitation of relying on single information to identify healthy vegetable pot seedlings. The schematic diagram of feature extraction is shown in Fig. 9: 1. After the color enhancement, the first region segmentation extraction is performed to calculate the mean values of R, G, and B of pot seedling leaves; 2. Following image denoising, the second region segmentation extraction is performed to calculate the leaf area (the white area in the binary image) to get the leaf area threshold.

Color Characteristic Information

The color of the leaf of a vegetable pot seedling is an important indicator to reflect its growth state. The color is determined by the wavelength of the light reflected by the object itself. Because the object has different properties of light absorption and reflection, there are different colors. The color of the leaves can represent the characteristics of the plants. It is completely possible to extract the color characteristics of the leaves by analyzing the digital images containing the color information of the leaves through specific methods and analyzing and discovering the differences in color between healthy and non-healthy pot seedlings of vegetables.

In this study, leaf color parameters (color image RGB color channel) were selected as the reference. In a certain period, the color characteristics of seedling leaves are very similar. To judge whether the seedling is inferior, we can judge it according to the color characteristics of its leaves. In this study, the leaf color parameters were the mean values of R, G, and B of the leaves in each hole area.

Figure 10 is the original color image taken by a CCD industrial camera, as shown in Fig. 9. After the image enhancement processing of vegetable pot seedlings, the image of pot seedlings is segmented into 21 equal parts evenly according to the whole structure of the pot seedling plate. In addition, the leaf area in each hole is selected, as shown in Fig. 11.

Then, the RGB color parameter values of the leaves in each hole area were counted successively and the R, G, and B component values contained in the leaves of the pot seedlings in each hole were extracted (The blade area is composed of individual points. The SIXA algorithm written is used to calculate the R, G, and B

values of each point, and their R, G, B, and values are calculated separately and divided by the points in the blade area. The average value of R, G, and B in the leaf area can be obtained by the number of digits) and the average values were calculated and the average values were used as the color characteristic parameters of the pot seedlings in the hole. The mean values of the three-color characteristic quantities $\overline{R}$ $\overline{G}$ $\overline{B}$ are defined as follows:

$$\overline{R} = \frac{1}{n}\sum_{i=1}^{n} R_i$$
$$\overline{G} = \frac{1}{n}\sum_{i=1}^{n} G_i \qquad (3)$$
$$\overline{B} = \frac{1}{n}\sum_{i=1}^{n} B_i$$

The statistical color parameters are shown in Table 4. Through manual confirmation, the hole information of (1,2), (3,1), (5,3), and (6,2) are holes (marked blue in the table) and the vegetable pot seedlings with hole information of (3,3) are inferior (marked red in the table). It can be seen from the statistical data that the average value of R, G, and B is correlated with whether the vegetable pot seedlings are healthy or not and whether the holes are holes. For example, in Table 4, the holes in (1,2), (3,1), (5,3), and (6,2) are holes and their average value of B is higher than that in other areas. (3) Vegetable pot seedlings in regions were inferior and their average R was higher than that in other regions. Therefore, by extracting the color characteristics of the vegetable pot seedlings in the hole dish, the threshold values of R, G, and B can be set for the health judgment of the vegetable pot seedlings in the hole dish.

Leaf Area Characteristic Information

The binary image can be obtained after image processing for the image of vegetable pot seedlings, that is, the pixel point of the background color is $P(I, j) = 0$, and the pixel point of the leaf is $P(I, j) = 1$. According to the feature extraction diagram 7, region segmentation was performed on the binary image and the white area in each hole was extracted and counted, which was used as the leaf area of vegetable pot seedlings.

When calculating the number of pixel points of a binary image, each pixel point on the binary image is recognized and the number of pixel points with a threshold of 1 (Fig. 12) is calculated. The calculation process is as follows:

$$(m,n) = size(f) \qquad (4)$$

where F is the binary image that needs to be calculated.

Then the number of pixels whose threshold value is 1:

$$l = \sum_{i=0}^{m-1}\sum_{j=0}^{n-1} f(i, j) \qquad (5)$$

The area calculation method is as follows:

Through MATLAB region props function areas of the calculation of grayscale image BWS white graphics 'Area' is calculate the area of each segment of the white part of the pixels of the P, will be the result of the calculation is assigned to props and then according to the vegetable pot seedling image segmentation region and each Area of the soil hole increases with the number of the M, setting F P-value and the ratio of M value, namely the basis F is vegetable pot seedling size threshold.

Leaf area threshold F is defined as follows:

$$F = \frac{P}{M} \qquad (6)$$

where, in, F -- leaf area threshold of vegetable pot seedlings; M -- the number of pixels occupied by hole area (the number of pixels occupied by hole); P -- the number of pixels occupied by the white region (the number of pixels occupied by the leaf).

Experimental Analysis and Method for Determination Criteria of Healthy Vegetable Pot Seedlings

Experimental Materials

1. 3 × 7 standard hole plate; 2. The number of culture substrates of pepper seedlings; 3. Image recognition platform based on machine vision; 4. Taking 30-day-old pepper seedlings as the experimental object, a 30-day-old healthy pepper seedlings model was established (through artificial judgment): 120 dishes (2520 plants in total) of healthy pepper seedlings were randomly selected as the experimental object.

Experimental Methods

2520 strains of health pepper seedlings were randomly divided into 20 groups, each group of six holes seedling dish health pepper plants (126 cases), acrylic lightbox internal adjustment to the appropriate brightness as the fill light, the image recognition based on machine vision platform in turn 6 holes in 20 groups of the seedling dish to sample processing, internal carry SIXA algorithm by the industrial control computer, in turn, collected for the vegetable pot seedling image recognition analysis, extract each hole seedling dish in vegetable pot seedling leaf color features and leaf area characteristic parameters.
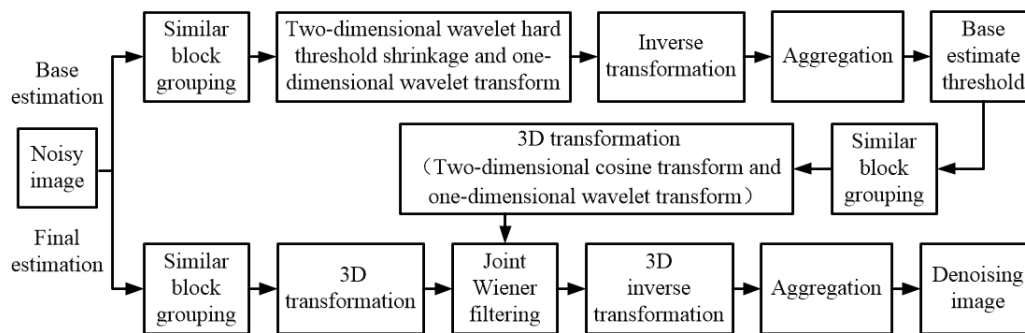
Fig. 6: BM3D algorithm flow chart

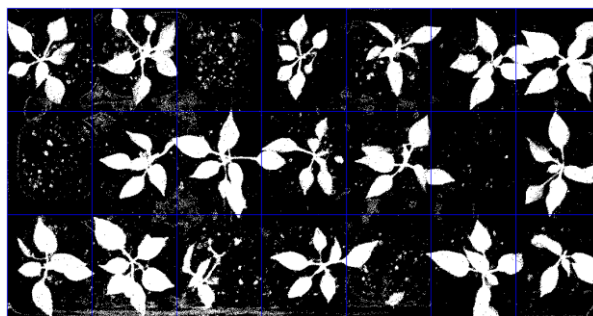**Fig. 7:** Undenoised processing diagram

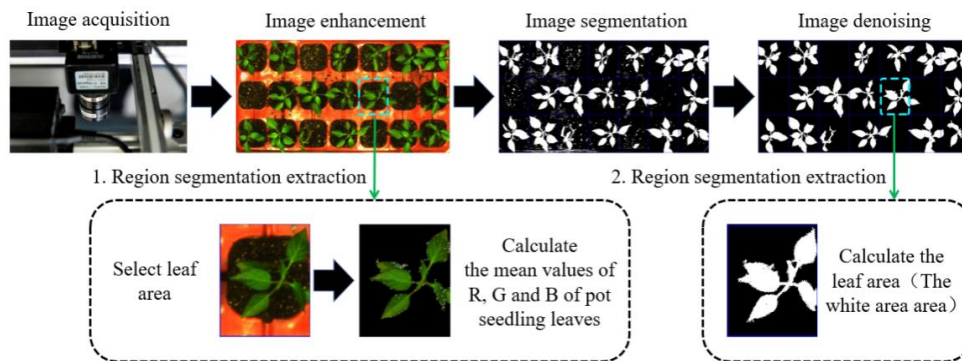
Fig. 8: Result of denoising

Fig. 9: Schematic diagram of feature extraction

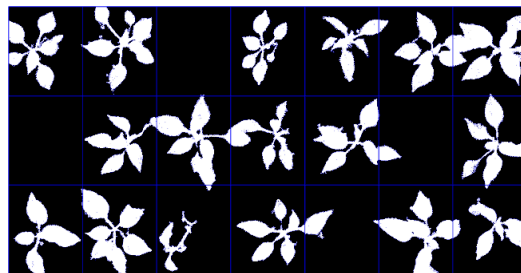**Fig. 10:** Raw image

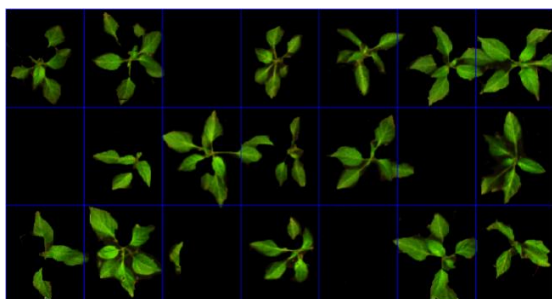**Fig. 12:** Image processing results

Fig. 11: Extraction image of leaf area

Fig. 13: Cavity area diagram of treatment results
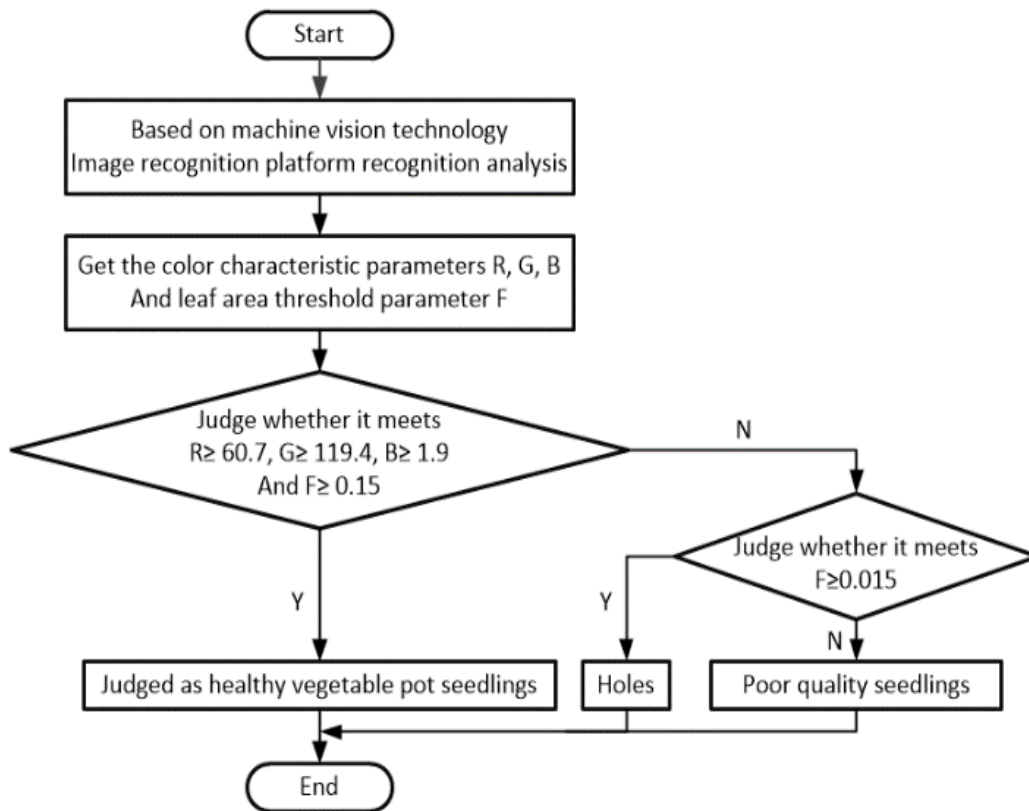

Fig. 14: Flow chart of an overall judgment of vegetable pot seedlings

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Results

Color Characteristic Parameters of Healthy Vegetable Pot Seedlings

The color characteristic parameters of 20 groups of healthy vegetable pepper seedlings were analyzed and the mean values of R, G, and B characteristics of leaf color of each group of healthy vegetable pepper seedlings were calculated as shown in Table 5.

Threshold Parameter of Leaf Area of Healthy Vegetable Pot Seedlings

The measured leaf area characteristic parameters of 20 groups of vegetable healthy pepper seedlings were analyzed and the maximum, average and minimum values of leaf area threshold F of each group of vegetable healthy pepper seedlings were calculated, as shown in Table 6.

The establishment of the judgment standard should be based on the regular analysis of the test parameter data. Therefore, it is particularly critical to find out specific information about the judgment standard of healthy vegetable pot seedlings in the test results.

Establishment of Judgment Standards for Color Characteristic Parameters of Healthy Vegetable Pot Seedlings

Analyze the statistical data of the average color parameters R, G, and B of the 20 groups of healthy pepper seedlings in Table 5 and obtain the average color parameters R, G, and B of the 30-day-old healthy pepper seedling model as shown in the Table 7 shows.

Therefore, the thresholds of R, G, and B can be set. Through the color extraction of vegetable pot seedlings in the hole dish, such kind of hole dish seedlings less than the threshold value can be removed. The color feature extraction method is simple. In this study, the color characteristic threshold was set as $R \geq 60.7$ $G \geq 119.4$, $B \geq 1.9$ and the color characteristics of healthy vegetable pot seedlings should meet this condition.

Table 1: CCD image sensor parameters

Imaging element	pixel	Signal to noise ratio	The focal length multiplier	Sensor Size		
				The length of the	*The width of the*	*area*
A third "Sony CCD	437664	>48db	7.2	4.8 mm	3.6 mm	17mm^2

Table 2: AFT-0614MP lens parameters

Model	Focal length	Viewing Angle	The F value	Interface to the Mount	Distortion	Focusing range	Overall dimensions
AFT -0614MP	6mm	42.30°	Allows to F32	C	< 1%	$\infty \sim 0.1m$	∅ 32 x 32.514 mm

Table 3: Industrial control computer parameters

Brand	Mr. G
Processor	Core i7-62001 - U
Memory	8GB
Hard disk	64GB
Touch screen	capacitance
Operating system	Windows10

Table 4: Statistical table of the average value of leaf color parameters R, G, and B in each hole area

Column number	The first line			The second line			The third line		
	$\bar{R}$	$\bar{G}$	$\bar{B}$	$\bar{R}$	$\bar{G}$	$\bar{B}$	$\bar{R}$	$\bar{G}$	$\bar{B}$
1	73	124	3	116	93	17	68	129	4
2	68	127	4	68	128	2	83	167	4
3	132	103	20	77	150	3	106	130	6
4	74	121	4	67	116	4	76	146	3
5	72	123	5	59	119	4	85	126	9
6	62	122	5	74	89	15	68	141	2
7	72	151	3	60	128	3	79	127	3

Table 5: Statistical table of the average value of leaf color parameters R, G, and B in the 20 groups of holes

| Set no. | The average | | | Set no. | The average | | |
	$\overline{R}$	$\overline{G}$	$\overline{B}$		$\overline{R}$	$\overline{G}$	$\overline{B}$
1	73.8	124.5	3.7	11	68.7	141.5	4.5
2	68.4	132.8	4.3	12	81.3	127.9	5.0
3	81.8	138.5	2.7	13	75.7	128.7	1.9
4	73.2	129.3	4.3	14	76.8	141.8	3.3
5	70.9	126.4	4.9	15	76.5	127.7	5.2
6	62.5	122.1	5.6	16	79.9	137.5	2.5
7	78.1	143.7	3.2	17	78.5	125.9	4.6
8	80.9	132.8	4.7	18	61.7	121.7	2.2
9	78.5	122.7	2.5	19	74.8	135.8	3.6
10	78.5	119.4	3.5	20	60.7	128.7	3.7

Table 6: Leaf area threshold F of 20 groups of healthy pepper seedlings

| The serial number | The threshold value F | | | The serial number | The threshold value F | | |
	The maximum	The average	The minimum value		The maximum	The average	The minimum value
1	0.20	0.19	0.16	11	0.21	0.2	0.18
2	0.25	0.24	0.23	12	0.24	0.19	0.17
3	0.24	0.21	0.20	13	0.27	0.21	0.18
4	0.19	0.17	0.16	14	0.22	0.21	0.20
5	0.20	0.18	0.16	15	0.21	0.19	0.17
6	0.25	0.23	0.21	16	0.25	0.22	0.19
7	0.23	0.23	0.20	17	0.20	0.19	0.18
8	0.25	0.18	0.16	18	0.24	0.22	0.15
9	0.26	0.23	0.22	19	0.23	0.20	0.17
10	0.25	0.21	0.18	20	0.23	0.22	0.20

Table 7: Data analysis of mean values of color parameters R, G, and B

Color characteristic parameter	$\overline{R}$	$\overline{G}$	$\overline{B}$
The maximum	81.80	143.70	5.600
The average	74.06	130.47	3.80s
The minimum value	60.70	119.40	1.900

Table 8: Data analysis of leaf area threshold F

Leaf area threshold	F
The maximum	0.260
The average	0.206
The minimum value	of
0.150	

Table 9: Comparison table for the systematic determination of the accuracy of vegetable healthy pot seedlings

Systemjudgment manual judgment	Healthy seedlings	Poor quality seedlings	Hole	Accuracy
100 healthy seedlings	96	4	0	96%
100 inferior seedlings	3	94	3	94%
100 holes	0	0	100	100%

Discussion

Establishment of Judgment Criteria for Leaf Area Threshold Parameters of Healthy Vegetables

The author analyzed the statistical data of threshold F among 20 groups of healthy pepper seedlings in Table 6. Then, the parameters of the threshold of the middle leaf area of the 30-day-old healthy pepper seedlings model were established, as shown in Table 8.

In the process of recognizing healthy vegetable seedlings, the threshold value F extracted by the image recognition platform based on machine vision was compared with the minimum value of 0.15 obtained in

the experiment, to judge whether it was a healthy vegetable pot seedling.

For the hole plate hole, in the theoretical operation recognition of the existing SIXA algorithm, its extraction threshold F size should be 0. However, the interference factors of the experiment could not be eliminated, so there was some error in the process of image processing and what was found in the actual inspection hole extracting leaf area threshold is generally not 0 F, but uncertainty values close to zero. By using the image recognition platform based on machine vision to extract the threshold F of the leaf area of 210 holes, the maximum value of the threshold F of the hole is 0.015. Therefore, the threshold value is taken as the standard threshold value of the leaf area to determine whether it is a hole.

Establishment of the Overall Judgment Process for Healthy Vegetable Bowl Seedlings

The judgment flow chart of healthy vegetable pot seedlings is shown in Fig. 14. The color feature parameter judgment standard and leaf area threshold parameter judgment standard obtained from the analysis are used to realize the multi-feature recognition of vegetable pot seedlings, aiming to improve the efficiency of agricultural operations. It is extremely important to promote the development of facility agriculture.

Experimental Verification

On the premise that the thresholds of leaf area characteristics and leaf color characteristics of healthy vegetable pot seedlings are determined, the vegetable pot seedlings are randomly sampled to verify the characteristic thresholds. Taking pepper seedlings as experimental samples, 100 healthy vegetable pot seedlings, 100 inferior vegetable pot seedlings, and 100 holes were selected by manual judgment, and then the vegetable pot seedlings were processed using an image recognition platform based on machine vision. The SIXA algorithm embedded in the platform identifies and determines the vegetable pot seedlings and the accuracy of the statistical system detection is shown in Table 9.

The statistical results are shown in Table 9. It can be seen from the table that the recognition accuracy of healthy seedlings is 96%, the recognition accuracy of inferior seedlings is 94% and the recognition accuracy of cavities is 100%. Overall, the system recognition rate is as high as 96.67%, which meets the experimental expectations.

In a similar study in the past, Zhang *et al.* (2020). used machine vision technology to conduct experimental research on plug seedling detection, but

it was only based on the pixel size of the leaf area (the size of the leaf area) and this single-factor experiment could not guarantee a higher The accuracy rate is high and the chance is high; Varghese *et al.* (2021) explored the use of machine vision technology for fruit identification and classification. The parameters based on it are only the appearance size of the fruit, but the appearance size cannot fully explain the quality of the fruit. A single factor does not have integrity, or the integrity is insufficient; Ramdan *et al.* (2018) used RGB and HSI features (leaf color) to detect cabbage leaves, but they did not detect the size of the leaves. When evaluating vegetable quality, its shape and size cannot be ignored.

Therefore, in the quality inspection of vegetable pot seedlings, the multi-factor selection of identification parameters is very necessary, which can well ensure the accuracy of the inspection results and can also verify the scientificity and rigor of the inspection experiment itself from many aspects.

Conclusion

This study uses machine vision technology and the self-written SIXA recognition algorithm to detect the health of vegetable pot seedlings according to the leaf color feature threshold and leaf area feature threshold as identification parameters, to achieve the purpose of identifying healthy vegetable pot seedlings by multiple factors, aiming to prove the MVT technology. The importance of the intelligent detection process of healthy vegetable pot seedlings provides some thoughts and suggestions for the health detection of vegetable pot seedlings, making it closer to the actual testing environment.

Although the experimental results show that the design expectations have been met, its use environment can only be limited to the simple identification of vegetable potted seedlings, which has good ease of use, but cannot be applied to relatively complex (such as detecting the specific disease of vegetable potted seedlings) intelligent detection, these are the limitations of the content of this study.

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Author's Contributions

Kaikang Chen: Designed and developed the method, performed the numerical experiments, analyzed the data, and wrote the paper.

Yongkun Fu: Analyzed the data and wrote the paper.

Yongjun Zheng: Revised the manuscript.

Bo Zhao: Performed the numerical experiments and revised the manuscript.

Yanwei Yuan: Performed numerical experiments.

Liming Zhou: Revised the manuscript.

Xin Jin: Performed the numerical experiments.

Ethics

The authors declare their responsibility for any ethical issues that may arise after the publication of this manuscript.

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