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RESEARCH ARTICLE

Online Recognition of Small Vegetable Seed Sowing Based on Machine Vision

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ABSTRACT The lightweight, small diameter, and irregular shape of small vegetable seeds create difficulties for online monitoring of sowing quality. We propose a machine vision-based online monitoring method with a sowing test bench designed to address the challenges. Vision devices and image processing systems are employed to detect the quality of seed sowing. Firstly, the seed segmentation image is obtained by completing the steps of median filtering, graying and image segmentation. We then implement the Circumscribed circle method to detect the position of the seed. Afterward, the coordinate system is converted using calibrated results to eliminate non-seed impurities. Finally, we count the number of identified seeds to evaluate the recognition accuracy. The trial compared three algorithms: the image segmentation algorithm OTSU, the critical point localization algorithm SIFT, and the algorithm designed in the experiment. The algorithm we designed outperformed the others regarding recognition accuracy and processing time. The experimental method employed in the study encompasses various functionalities, including seeding counting, understanding detection, replaying, and monitoring deviations from seed bands during sowing. Cabbage seeds (1.50 mm–2.00 mm), tomato seeds (1.00 mm–1.50 mm), and radish seeds (0.50 mm–1.00 mm) were selected as the experimental subjects due to the uniform particle size distribution. The results demonstrate that the relative error between the online image recognition algorithm and the system's seeding rate monitoring is below 3.0%. Moreover, the accuracy of missed seeding monitoring is 92.5%, while the accuracy of deviation monitoring during seeding is 92.0%. We observed that the image recognition algorithm employed in the system achieved a processing time of 0.29 seconds, with a seed band recognition rate of 96.8%, fulfilling the monitoring requirements for small seed sowing experiments. The processed images and collected data are presented in real-time on the upper computer terminal. This study significantly contributes to the advancement of small-grain vegetable seed sowing monitoring technology.

INDEX TERMS Small vegetable seeds, image recognition, monitoring of sowing quality, algorithm comparison.

I. INTRODUCTION

China is the world's largest producer and consumer of vegetables [1]. Currently, vegetable production has become the second-largest agricultural industry in China, second only to grain production. The two primary methods of vegetable farming are seedling transplanting and direct seeding, with the latter remaining the predominant mode in actual vegetable farming processes [2].However, traditional manual screening requires improvement in efficiency and accuracy, leading to challenges of high labor intensity and increased costs [3]. Therefore, developing a quality monitoring system holds promise in enhancing vegetable seed sowing production. Vegetable seeds exhibit distinctive characteristics, characterized

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by small particle size, irregular shape, and identification difficulties, necessitating advanced recognition technology. Employing image recognition technology to evaluate the quality of small vegetable seeds can alleviate issues such as poor seed emergence rates and uneven sowing while simultaneously elevating the system's intelligence level. This technology serves as a pivotal component within the seeding operation supervision system [4].

In recent years, various sowing quality detection systems have been developed for vegetable planting both domestically and internationally [5], [6], and researchers have validated their performance in practical applications, including laser sensing [7], photoelectric sensing [8], and image recognition [9], etc. The air suction seeder has been widely applied in large-scale high-speed precision vegetable sowing [10]. However, the sowing process faces challenges, including issues with air suction pressure, fluctuations in seed quantity, and blockage of seed suction holes [11], resulting in compromised sowing quality and accuracy. Real-time detection of sowing accuracy is required to ensure and uphold the sowing quality [12]. Jin et al. [13] employed fiber optic sensors to identify missing seeds and calculate the seeding rate of the electric vegetable seeder, thus validating its system monitoring capabilities through rigorous experimentation. The rapid development of machine vision technology has found widespread applications in various domains, such as transportation, agriculture, medicine, and industry [14]. It has emerged as an effective method for feature recognition and achieved significant breakthroughs in target detection [15]. In agricultural engineering technology, image recognition processing has proven valuable in improving recognition speed [16], [17] and ensuring evaluation process repeatability, particularly in seed quality assessment [18]. For instance, it is utilized for evaluating seed quality, identifying seeds, and counting grains. Cui et al. [19] used hyperspectral image (HSI) technology to conduct feature correlation analysis and germination performance prediction of sweet corn seeds, realizing non-destructive and accurate identification of seed vitality and completing seed quality evaluation. Li et al. [20] established a visual detection system for vegetable seed vitality and used image feature extraction to calculate seed vitality index (SVI). Qiu et al. [21] Used Fourier transform near infrared (FT-NIR) spectroscopy combined with discriminant analysis technology to realize rapid and non-destructive sweet corn seed variety recognition and classification. Tan et al. [22] proposed a contact rice grain separation and counting algorithm composed of watershed algorithm, improved corner detection algorithm and neural network classification algorithm. The application of deep learning algorithms in the field of agricultural seed monitoring has garnered considerable attention [23], [24]. Recent research on tiny particle-size seeds [25] demonstrates that image processing accurately measures the distance between sources [26]. Uzal et al. [27] applied deep learning to estimate individual seed pods in plant breeding, while Chaugule and Mali [28] explored a novel method for extracting rice seed features, enhancing the discriminative power of the feature set through the removal of redundant elements, which significantly benefits seed discrimination. De Medeiros et al. [29] employed Convolutional Neural Networks (CNN) to grade the quality of sea anemone seeds based on X-ray images. Zhang et al. [30] used the advanced YOLO-V5s method to build target detection models for rape seedlings during three key growth stages, laying a solid foundation for survival rate detection in crucial plant growth phases. Furthermore, Zhang et al. [31] utilized Hough linear detection and feature extraction to identify unclosed glutinous rice seeds, leading to enhanced accuracy in online identification and elimination of unclosed glutinous rice seeds.

The specific objectives of this study are as follows: (1) Investigate the seeding quality level of small diameter vegetable seeds by using the developed air suction seeding experimental platform and system, along with machine vision and image processing methods. (2) Apply image segmentation technology on small seed images for real-time online monitoring. (3) Develop a real-time performance measurement system for the air suction seeder tailored to small vegetable seeds. (4) Evaluate the accuracy and adaptability of the air suction seeder in sowing small vegetable seeds onto a conveyor belt by comparing the results obtained using the designed algorithm.

II. HARDWARE SYSTEM DESIGN OF TEST BENCH

A. OVERALL STRUCTURE

As shown in FIGURE 1. The test bench consists of a seed metering device, an air pump, an image acquisition device, an LED(Light Emitting Diode) light source, an industrial control system, a conveyor belt rack, a servo motor, and an adjustable rack. The conveyor belt simulates real-field conditions, enabling the controlled descent of seeds onto its surface ranging from 0 to 10 m/s. A speed-measuring photoelectric sensor(manufactured by OMRON Company in Japan) is installed adjacent to the motor, with a response time of less than 10 ms. An air pump (Taizhou Otus Industry and Trade Co., Ltd., S1100W-8L) is installed at the negative pressure hole of the device, with a power of 2200kW and an Engine displacement of 200L/min, functioning as a negative pressure device generates the required suction for precise seed metering. The motor is controlled by the Inviton PLC(Programmable Logic Controller) (Shenzhen Inviton Electric Co., Ltd., IVC1-1006MAR/MAT), while the image acquisition device employed is the HIK high-definition industrial array camera (Hangzhou Haikang Robot Technology Co., Ltd.).

In this study, we used a pneumatic seeder in our test bench. This type of seeder can carry out seeding operations according to different shapes, sizes and seed types. By replacing the seed tray, the seeding requirements for seeding operations in practical applications can be met as much as possible.

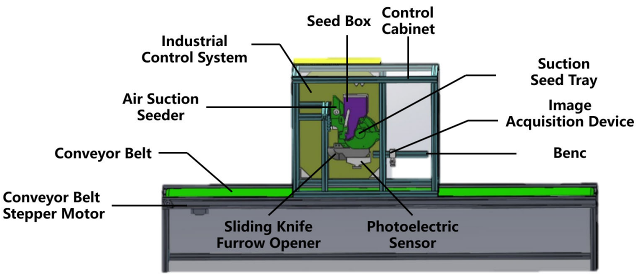

FIGURE 1. Schematic diagram of the structure of the vegetable seed suction sowing monitoring test bench.

B. WORKING PRINCIPLE

As shown in FIGURE 2. The monitoring system uses a high-speed CMOS camera to continuously capture seed images as they fall onto the conveyor belt and then transmit the image data to the industrial control system on the upper computer in real time via a communication network. Employing computer digital image processing technology, the upper computer software swiftly processes and identifies the seed images, determining their distance based on sowing time and speed. Consequently, the system can calculate missed seeding, replanting, and seed deviation from the seed belt. Moreover, the monitoring system displays and records the processed images in real time, with the capability to save screenshots, enabling real-time monitoring for small vegetable seed sowing operations.

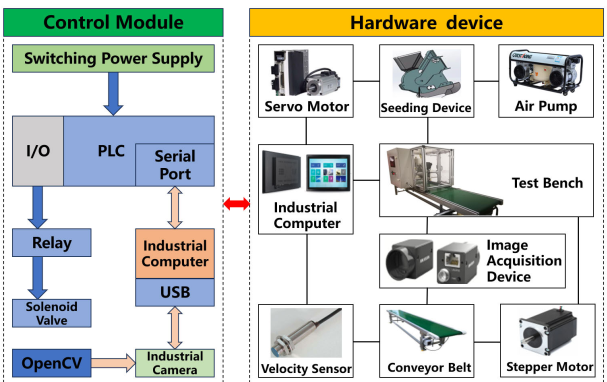

FIGURE 2. Structure diagram of the vegetable seed air suction sowing control system.

C. IMAGE RECOGNITION INSTITUTIONS

As shown in FIGURE 3. The image acquisition device features a built-in CMOS(Complementary Metal Oxide Semiconductor) sensor with 20 million pixels, utilizing Sony's IMX183 chip. It operates within a voltage range of 5∼15 VDC and supports the POE(Power Over Ethernet) power supply, enabling real-time transmission of uncompressed images through a gigabit Ethernet interface at a maximum frame rate of 5.9 fps. The 6-pin Hirose connector provides power supply and I/O: 1 optocoupler isolated input (Line0), 1 optocoupler isolated output (Line1), and 1 bidirectional configurable non-isolated I/O (Line2). These allow the device to be used with a light source, facilitating image capture without motion blur in dynamic environments and offering support for automatic or manual adjustment of gain, exposure time, LUT(Look Up Table), gamma correction, etc. The image acquisition device is connected to the industrial computer interface through USB communication and is securely installed and fixed vertically above the conveyor belt using profiles. Its primary functions encompass image preprocessing, image recognition, and image detection. By manipulating the button controls on the industrial control screen and selecting "Start Camera," "Turn on Light Source," and "Calibrate," the generated image processing results will be displayed in the configuration interface. An LED light is installed at the sensor's lower end, serving as the light source to enhance seed capture.

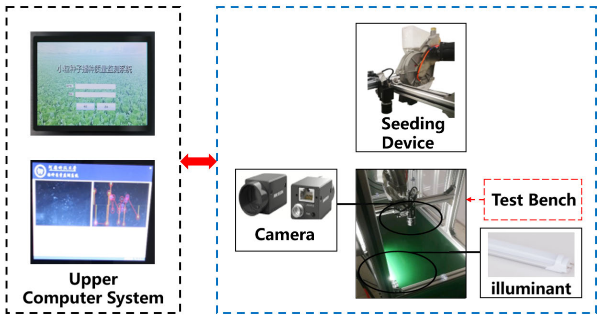

FIGURE 3. Construction of upper computer image recognition system.

III. SOFTWARE SYSTEM DESIGN

The main workflow diagram of the system is shown in FIGURE 4. After powering on, the system undergoes initialization, and program operation instructions are input to initiate the execution. The test bench is then activated, along with the industrial computer system, air pump, seed metering device, image camera, and lighting device. Moreover, users can adjust parameters in real time via the industrial control screen.

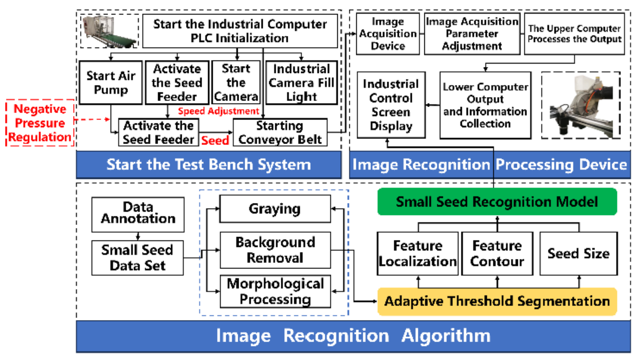

FIGURE 4. Software system main program flowchart.

In the design section of the main program, the upper computer rapidly analyzes continuous seed images captured by the camera on each conveyor belt. The sowing quality of seeder operation was evaluated by images, and the quantity and quality of seeds on the conveyor belt were determined and calculated.The system also computes the recognition rate of small and medium-sized seeds during the sowing operation, including sowing quantity, replanting, missed sowing, and deviation from the seed belt. The monitoring criteria, based on GB/T 6973-2005Test method for single grain (precision) seeder, are as follows: $0.5d \leq v\Delta T \leq 1.5d$ (normal), $v\Delta t > 1.5d$ (missed broadcast) and $v\Delta T < 0.5d$ (replay). d is the theoretical plant spacing. ΔT is the time interval between two adjacent seeds falling.The seeder test method is based on the specific judgment basis obtained from the ''Single precision seeder test method'', which comes from the national standard specially for the monitoring of seeding quality. Where d is the theoretical plant distance, and the unit is m; ΔT represents the time interval of two adjacent seeds falling, in s; v is the forward speed of the planter, expressed in m/s, which can be obtained from the planter speed sensor. Through the formula, a more accurate judgment can be made on the normal, missing and reseeding state of the seeder during the sowing operation.

In cases of missed broadcasts, replays, and deviations from the seed belt, the computer automatically captures and records the corresponding data locations. Moreover, the computer uses color coding to facilitate easy identification, representing missed broadcasts in red, replays in yellow, and deviations from the seed belt in purple. Subsequently, the computer performs image analysis and calculations.

IV. DATA COLLECTION AND PREPROCESSING

A. TEST MATERIALS AND EQUIPMENT

A seeding quality identification and detection test were conducted to verify the performance of the device and algorithm. We selected vegetable seeds, specifically cabbage (Jingyan 2, 0.50-1.00mm), tomato (Deli 5, 1.00-1.50mm), and radish (Shouguang Lesenyuan Seed Industry, 1.50-2.00mm) as experimental materials. Corresponding seed holes were replaced to accommodate the different seed sizes, as the air pressure value of the test bench was adjusted accordingly. Vegetable seeds with relatively uniform sample parameters were used as test samples.

TABLE 1. Physical property data of small grain size seeds.

Seed Type	Cabbage	Tomato	Radish
1000 GrainWeight[g]	3.60~4.10	2.20~2.50	1.20~1.50
Seed Size[mm]	1.50-2.00	1.00~1.50	0.50~1.00

B. IMAGE PROCESSING

1) IMAGE ACQUISITION AND PROCESSING

Firstly, perform grayscale processing using the average grayscale method for the image. Image denoising is achieved through median filtering, with the filtering kernel size adjusted. A kernel size of 5*5 is found to remove noise effectively. The grayscale histogram method is chosen for image binarization due to the high contrast between sample particles and the background. The step above successfully separates the particles in the binary image from the environment, allowing for the extraction of particle feature parameters. Subsequently, conduct RGB channel histogram analysis on all frame images. Extract the R, G, and B component images, emphasizing the R-G channel to highlight seed features. Finally, transform the image into an 8-bit grayscale image using equation (1), completing the preprocessing of the video frame image.

$$Gray(x, y) = 0.11R(x, y) + 0.59G(x, y) + 0.3B(x, y) \quad (1)$$

Among them, x is the horizontal pixel position of the image; y is the vertical pixel position of the image.

2) IMAGE CALIBRATION

To ensure the accuracy and recognition effectiveness of image acquisition, we calibrated the distance represented by a single pixel before capturing the images. Since the height direction of the collected image is parallel to the seed belt during acquisition, we converted and calculated the actual distance represented by the height using a conveyor belt speed sensor, as shown in equation (2), which enables us to determine the capture interval of the images and the distance between seeds, facilitating the identification of missed, replayed, and deviated seed bands.

$$n = \frac{100ah}{3.14d} \quad (2)$$

Among them, a is the actual distance represented by a single pixel; h is the height of the image; d represents the diameter of the seed tray; n is the number of pulses of the speed sensor. 3.14 in the formula stands for π, or PI. Both a and h are calculated and measured by hand in meters; But d uses the disc diameter in centimeters, so here the molecule is multiplied by 100 to achieve unit unity.

C. TEST METHODS

1) SIFT KEY POINT EXTRACTION ALGORITHM

Based on the characteristics of image acquisition and analysis of the practicality of existing methods, we observed that existing deep learning object detection models perform poorly when dealing with small seed pixels in images, leading to inadequate detection results for such small targets. Therefore, this article thoroughly examines the image characteristics and seed states during camera shooting at different speeds, selecting SIFT (Scale Invariant Feature Transform) and image processing-based feature point extraction algorithms for experiments.

As shown in FIGURE 5, SIFT is a local feature description operator that can adapt to the effects of scale, brightness, noise, etc. It has excellent stability and invariance, enabling precise information matching and localization. The algorithm implementation is as shown in the figure. Firstly, the size space extreme value detection searches image positions across all scales, identifies the regional extreme value points using the Difference of Gaussian pyramid, and obtains extreme value points in Discrete space. Subsequently, key points are located in the region of interest for interpolation fitting while removing low-contrast key points and unstable edge response points to enhance matching stability and determine the position and scale of key points. Calculate the gradient direction histogram to determine the direction information based on the local gradient direction of the seed in the image. Finally, describe the regional location, scale, and direction of the neighborhood around the key points.

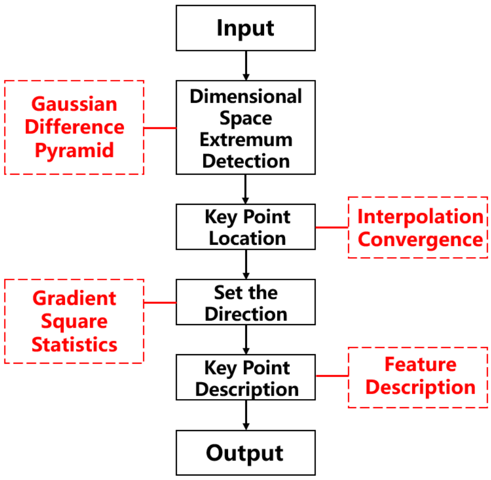

FIGURE 5. SIFT image processing process.

2) THRESHOLD SEGMENTATION ALGORITHM

The image segmentation method is applied to the real-time online monitoring of seed images, and the gray histogram of image is divided into several classes by the threshold value. It is considered that the pixels in the same class of gray value belong to the same object, which can directly use the gray characteristics of image to achieve effective segmentation of different targets and backgrounds, and has the advantages of simple calculation, high efficiency and fast speed.

An experiment-specific seed feature extraction algorithm is devised based on image features. The specific methods are as follows:

Step 1: Image filtering is applied to improve image quality and enhance recognition results. The experiment employs the median filtering method for noise reduction, using a filtering kernel size of 3*3. Median filtering involves sorting pixel values from the current pixel point and its surrounding neighbors in ascending order, then selecting the middle value as the new pixel value for the current pixel point.

Step 2: Grayscale processing is performed by calculating the average grayscale value of the image. The processing formula is as follows:

$$\mu(n) = \sum_{t=1}^{n} tpt \tag{3}$$

Among them, t is the grayscale value of the pixel, n is the grayscale level of the pixel value, and p is the probability of the grayscale value.

Step 3: Adaptive threshold segmentation, the maximum inter-class variance method, was proposed by Japanese scholar Otsu in 1979, abbreviated as OTSU. It divides the image into background and target based on its grayscale characteristics. The interclass variance represents the difference between the background and target regions, with higher variance indicating a more significant distinction. When a part of the target is misclassified as the background or a part of the background is misclassified as the target, the difference between the two parts becomes smaller. Therefore, minimizing the probability of misclassification is achieved by maximizing the interclass variance.

For image $I(x, y)$, the segmentation threshold between the foreground (i.e. target) and background is denoted as T, and the proportion of pixels belonging to the foreground to the entire image is denoted as ω_0, its average grayscale μ_0 The proportion of background pixel count to the entire image is ω_1. Its average grayscale is μ_1. The total average grayscale of the image is denoted as μ, The inter class variance is denoted as g. Assuming the background of the image is dark and the size of the image is $M \times N$. The number of pixels in the image whose grayscale value is less than the threshold T is denoted as N_0, and the number of pixels whose grayscale value is greater than the threshold T is denoted as N_1, then:

$$\omega_0 = N_0/M \times N \tag{4}$$

$$\omega_1 = N_1/M \times N \tag{5}$$

$$N_0 + N_1 = M \times N \tag{6}$$

$$\omega_0 + \omega_1 = 1 \tag{7}$$

$$\mu = \omega_0{}^{*}\mu_0 + \omega_1{}^{*}\mu_1 \tag{8}$$

$$g = (\omega_0\mu_0 - \mu_X)^2 + (\omega_1\mu_1 - \mu)^2 \tag{9}$$

The maximum variance threshold segmentation method employs a uniform threshold for each pixel in the image during the segmentation process. However, practical scenarios often involve uneven lighting, color variations, sudden noise, or significant changes in the background grayscale, rendering a single threshold unsuitable for the entire image segmentation. Employing a single threshold for processing each pixel may lead to incorrect division between the target and background regions. Therefore, adaptive threshold segmentation is introduced to address this limitation, where each pixel in the image is assigned a distinct threshold. The threshold is determined by calculating the weighted average of neighboring domains around each pixel, and the current pixel is processed using this modified threshold. This approach is more suitable for images with substantial variations in brightness and darkness.

Step 4: Morphological operations. The fundamental concept of morphology is to use structural elements with specific shapes to quantify and extract corresponding shapes in the image, facilitating image analysis and recognition. In this article, operations are conducted to extract seed feature images. First, a corrosion operation is performed, followed by an expansion to restore the seed pixels after the corrosion operation.

Let $f(x, y)$ be the input image, and $B(x, y)$ be the structural element.

Use B to perform expansion operations on $f(x, y)$:

$$f \oplus B(\mathrm{s}, \mathrm{t}) = \max\{f(\mathrm{s}-\mathrm{x}, \mathrm{t}-\mathrm{y}) + B(\mathrm{x}, \mathrm{y})\} \tag{10}$$

Perform corrosion calculation on $f(x, y)$ using B:

$$f \odot B(\mathrm{s}, \mathrm{t}) = \min\{f(\mathrm{s}-\mathrm{x}, \mathrm{t}-\mathrm{y}) + B(\mathrm{x}, \mathrm{y})\} \tag{11}$$

In the formula, the displacement parameter $(s-x)(t-y)$ is included in the domain of a function of image f.

Step 5: The open operation processing in the original seed image is used to locate the position of the seed in the image. The Circumscribed circle method is then employed to locate the seed area and obtain its diameter length in the image coordinate system, which is subsequently converted into the diameter length in the world coordinate system. Seeds with a diameter length less than 0.8mm are removed based on their respective vegetable seed types. Finally, the total number of seeds located and identified in the image is counted.

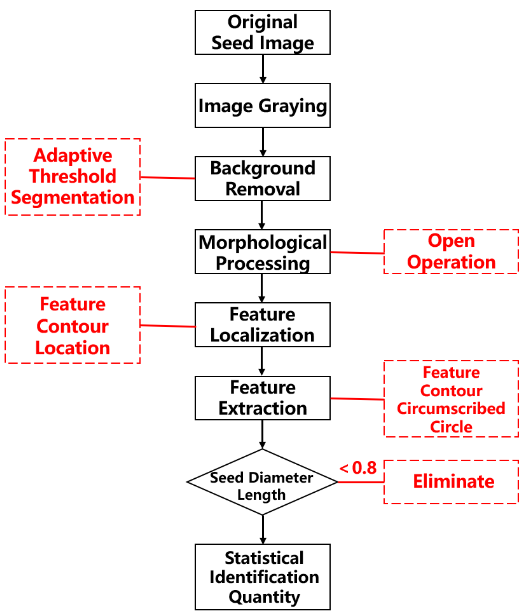

FIGURE 6. Threshold segmentation algorithm flow chart.

As shown in FIGURE 7. Based on the performance characteristics of seeds in the image, median filtering is applied to remove noise from the original image, and weighted average values are used for graying. The threshold value is then set, and experiments determine the best segmentation threshold value as 35. A morphological open operation is performed to remove impurities from the image. Finally, the processing results are used to locate the seed feature areas in the original image, marked with Circumscribed circles. After calibration, the marking principle involves converting the image's obtained Circumscribed circle diameter length from the image coordinate system pixel size to the actual length. Areas with a diameter length less than 0.8cm are eliminated and the total number of recognized seeds in a single image is counted.

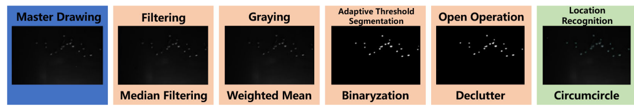

FIGURE 7. Seed location identification flow.

V. EXPERIMENTAL VERIFICATION

A. RESULT ANALYSIS

Select a total of 200 seeds of cabbage (60 seeds), tomato (60 seeds), and radish (80 seeds), define their two-dimensional structural elements as circles, and select a conveyor belt speed of 4km/h. During testing, manually block and add more seeds to prevent them from successfully falling or multiple seeds from falling normally. Simulate missed and replayed seeds, observing their distribution on the conveyor belt manually to determine the situation of missed and replayed seeds. At the same time, activate the image recognition monitoring system of the test bench to record and display the results. Compare the two to obtain the detection test results, as shown in TABLE 2.

TABLE 2. Image detection test results.

Seed Type	Detection Parameters	Image Recognition	Actual Labor	Accuracy
Cabbage	Missed Seeding	189	200	94.5%
	To Replay	185	200	92.5%
Tomato	Missed Seeding	185	200	92.5%
	To Replay	184	200	92.0%
Radish	Missed Seeding	185	200	92.5%
	To Replay	184	200	92.0%

The results in TABLE 2 demonstrate relatively high image recognition accuracy for the experimental seeds, with a minimum accuracy rate of 92.5% for identifying missed broadcasts and 92% for recognizing replays. However, the experiment revealed relatively lower accuracy in replay recognition. This discrepancy can be attributed to a visual dead angle in the camera setup, precisely when multiple seeds overlap in the camera's field of view. The camera can only capture the overall seed image, leading the system to recognize multiple seeds as a single entity.

B. DIFFERENT SPEED MONITORING TESTS

During the experiment, the system was powered on and initialized. The motor speed regulator adjusted the synchronous belt to move at speeds ranging from 2 to 6 km/h. The air pump and suction seeder speed motor were activated once the synchronous belt ran smoothly at the desired speed. A total of 100 cabbage (30 seeds), tomato (30 seeds), and radish

TABLE 3. Recognition accuracy of small vegetable seeds.

Speed km/h	Number of Manual Counting	Number of System Identification	Accuracy/%
2	100	100	100.00%
3	100	100	100.00%
4	100	99	99.00%
5	100	97	97.00%
6	100	97	97.00%

TABLE 4. Comparative analysis of algorithms.

Seed Metering Speed	Seed Type	Test Method	Row Recognition Rate	Average Processing Time
3km/h	Cabbage	The Algorithm of This Study	96.80	4.3
		SIFT Algorithm	95.33	18.9
		OTSU Algorithm	92.15	5.4
	Tomato	The Algorithm of This Study	97.15	4.4
		SIFT Algorithm	93.28	18.6
		OTSU Algorithm	91.52	5.2
	Radish	The Algorithm of This Study	96.68	4.1
		SIFT Algorithm	95.23	17.9
		OTSU Algorithm	92.35	5.9
6km/h	Cabbage	The Algorithm of This Study	94.58	4.3
		SIFT Algorithm	94.21	19.0
		OTSU Algorithm	91.73	5.5
	Tomato	The Algorithm of This Study	95.11	4.1
		SIFT Algorithm	92.22	17.0
		OTSU Algorithm	91.30	4.6
	Radish	The Algorithm of This Study	93.67	3.8
		SIFT Algorithm	92.56	16.8
		OTSU Algorithm	91.24	5.0

(40 seeds) seeds were selected, and 100 sets of data were collected at each speed.

The recognition accuracy of vegetable seeds with different particle sizes at various speeds is shown in TABLE 3. The experimental results demonstrate that the model proposed in this paper achieves a high recognition rate for small seeds, with an accuracy of no less than 97.00%. However, as the speed increases to 5 km/h, motion blur occurs, affecting the feature extraction of small seeds and reducing the recognition accuracy.

C. COMPARATIVE ANALYSIS OF ALGORITHM PERFORMANCE

In order to further verify the recognition effect of the model, under the same experimental conditions, the SIFT algorithm and algorithm were compared using Python as an analysis tool.

TABLE 4 shows that the algorithm in this study has a faster recognition speed at speeds of 3km/h and 4km/h. It achieves a recognition rate of at least 93.67% for rows of small seeds, surpassing the SIFT and OTSU algorithms, where errors occurred during detection. The reason for the mistake of the judgment lies in the sowing of small seeds where the seed belt is marked on the conveyor belt. During the image recognition process, the material of non-small seeds is mistakenly identified as a seed due to the small particle size of the small seeds, leading to judgment deviations from the seed belt and resulting in errors.

VI. CONCLUSION

This study developed a testing platform to detect the quality of small grain vegetable seed sowing using an air suction seeder. The online real-time monitoring of small grain vegetable seeds was achieved through the algorithm's monitoring capabilities.

1) In the hardware system, a specialized air suction seeding test bench for small vegetable seeds was meticulously designed. The single-unit power was sourced from an air pump and a driving motor. At the same time, the conveyor belt effectively simulated the field conditions for seed landing. Image recognition devices and supplementary light sources were strategically deployed to achieve real-time monitoring of the seeds and address the challenges of detecting missed and replayed small vegetable seeds during the seeding process.

2) In the software system, the PLC controller serves as the system control core, skillfully managing the servo motor speed and air pump pressure value of the seed metering device. The calibration, segmentation, and threshold setting of the seeds can be accomplished on the industrial computer to preprocess the images, such as graying, binarization, and denoising. The seamless real-time communication between software and hardware modules ensures online real-time detection of sowing quality.

3) This study adopts an innovative approach to address the issue of target information loss in small seeds using traditional binary methods. It utilizes the combination of median filtering and morphological image processing methods for seed feature extraction.The experimental results show that the missing recognition rate and replay recognition rate of the proposed method reach 92.00% and 92.50% respectively, and the line recognition accuracy reaches no less than 93.67%. Compared with other algorithms, this method has the advantages of higher recognition rate, relatively simple structure and short training time.

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