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Research on High-Efficiency Rice Germination Recognition Algorithm Based on Image Processing

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Abstract: *Seed germination rate is a crucial factor affecting crop yield. To improve the efficiency and reduce the cost of seed germination detection, this study focuses on rice seeds and proposes an image processing-based method for rice seed germination recognition. The method separates seeds from sprouts and radicles through image segmentation and determines germination status based on the positional and area relationships before and after germination. The results show that the proposed method achieves an average germination recognition accuracy of over 98.5% for rice seeds within 0–7 days, meeting practical application requirements.*

Keywords: *Image Segmentation, Morphological Operation, Rice Seed Germination, Germination Recognition*

1. Introduction

China is a major rice producer and its rice planting area ranks first in the world [1]. Seed germination rate is one of the important indicators for measuring seed quality [2]. The traditional seed germination detection relies on manual observation and statistics, which has problems such as low efficiency, long time consumption and vulnerability to subjective factors, and is difficult to meet the demand of the modern seed industry for rapid and non-destructive detection [3]. Machine vision technology, as an efficient and non-destructive detection technology, has achieved remarkable results in agricultural phenotypic research, providing the possibility for the automated detection of seed germination.

In recent years, with the development of machine vision and artificial intelligence technologies, related technologies have gradually been applied in agricultural research. Seed germination detection techniques can be broadly categorized into image processing-based and deep learning-based approaches. Wu et al. developed a wheat seed germination point detection method based on morphological techniques, achieving rapid identification of wheat seed germination [4]. Zhao et al. used wheat seeds as the research subject, employing machine learning algorithms for seed segmentation and subsequently calculating radicle and plumule lengths through image processing to enable continuous monitoring of wheat seed germination [5]. Since 2023, Bai et al. designed an improved YOLOv5-based detection method for wheat seed germination, with experimental results showing a precision of 98.5% [6]. Zhang et al. proposed an automated method utilizing image processing and geometric feature analysis, demonstrating an average absolute error of 2.7% in germination rate measurement [7], though limitations remain in complex overlapping scenarios. Yao et al. studied wild rice seeds and introduced SGR-YOLO, integrating ECA attention, BiFPN feature pyramid, and GIOU loss, significantly improving the accuracy and efficiency of wild rice seed germination detection [8]. Liu et al. proposed a stripe–band + boundary + color image-based method for early-stage maize seed germination detection, achieving an average precision of 73.5%[9].

At present, most of the seed germination detection methods based on image processing are relatively simple when there is no occlusion between each other in the early stage of germination. However, although the deep learning-based methods have achieved good results, this method requires cultivating and labeling a large number of seed germination images, which is rather time-consuming and laborious. To this end, this paper proposes a rice seed germination recognition method based on image processing, and conducts germination discrimination by means of the positional relationship and area relationship before and after seed germination.

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2. Methods

The design of the image processing-based rice seed germination recognition method mainly includes the following steps: first, perform saturation enhancement and image segmentation on the collected rice seed images to obtain images containing only the seed body and images containing both the seeds and root sprouts, respectively; second, extract the positional and area features of the seeds in the two images using a feature extraction algorithm; finally, accurately determine the germination state of the seeds by analyzing the variations in these feature parameters, with the specific design method flowchart shown in Figure 1.

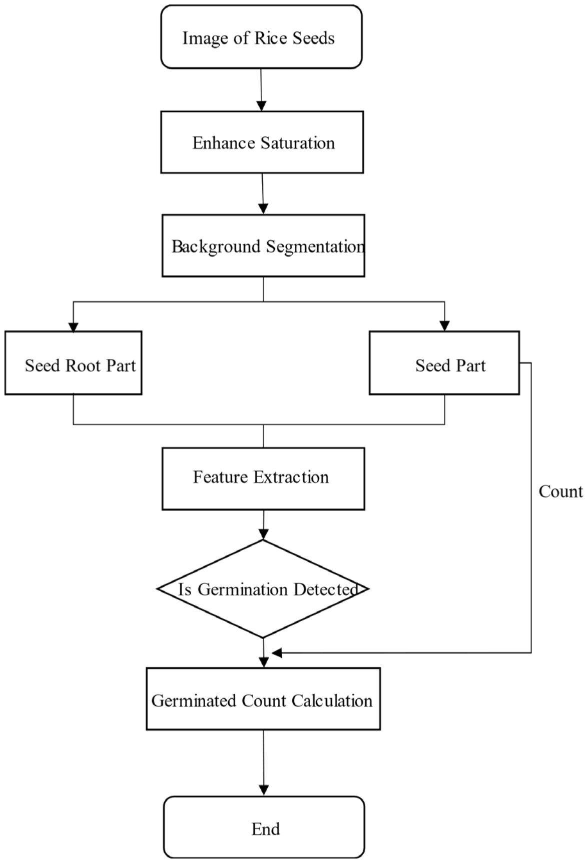

Figure 1 Flowchart of the methodology.

2.1 Saturation Enhancement

To make the color features of the image more prominent, a saturation enhancement operation needs to be performed on the image. First, the RGB image is converted to the HSL color space. Then, based on the relationship between the R, G, B values of each pixel and their average value, the saturation component S is adjusted. Finally, the image is converted back to the RGB color space, as shown in Figure 2(b).

2.2 Background Segmentation

To eliminate interference from image background noise on seed germination detection, this study employs a threshold-based segmentation method to remove image background disturbances, as illustrated in Figure 2(c). The background segmentation is performed using the B-channel from the RGB color space. Since the background color is blue, this study employs threshold segmentation based on the B-channel of the RGB image, which represents the blue component. By analyzing the histogram distribution of the B-channel's grayscale values, the background region exhibits significantly higher grayscale values than the foreground, resulting in a bimodal distribution. The optimal segmentation threshold can be determined by identifying the valley between these two peaks.

In the experiment, if the pixel grayscale value $g(x, y)$ at image position (x, y) is greater than or equal to the segmentation threshold T, the pixel value is set to 0. When the pixel grayscale value is less

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than threshold T, it is set to 255. This process converts the image into a binary format where all regions except the seeds, roots and sprouts are treated as background. Next, connected components in the binary image are identified and their pixel counts are calculated. Since noise areas typically contain far fewer pixels than seed regions, the mean pixel count of all connected components is computed as a decision threshold. Connected components with pixel counts below this mean value are considered noise and removed. Finally, the binary image undergoes bitwise AND operations with all three channels of the RGB image, followed by masking operations, resulting in background-removed rice seed images. The background segmentation process can be represented as

$$g'(x,y) = \begin{cases} 0, g(x,y) \geq T \\ 255, g(x,y) < T \end{cases} \tag{1}$$

Here, $g'(x,y)$ represents the pixel grayscale value at position (x,y) after threshold segmentation, $g(x,y)$ denotes the pixel grayscale value at position (x,y) before threshold segmentation, and T, indicates the segmentation threshold.

Original Image(a).

Saturation-Enhanced Image(b).

Background-Segmented Image(c).

Seed-Only Image(d).

Figure 2 Visualization Results.

2.3 Seed Region Segmentation

To distinguish rice seeds from their sprouts and roots, it is necessary to separate the rice seeds from their sprouts and roots. First, a 3×3 low-pass filter is applied to the image to remove high-frequency noise. Then, the image is converted from RGB color space to YUV color space. Through binary processing by setting threshold ranges for the U and V channels, experimental results show that when the U channel range is set to [0,130] and the V channel range is set to [145,255], the seed portions in the image can be identified as foreground while other areas are treated as background, resulting in a binary image. Finally, a bitwise AND operation is performed between the binary image and the original image to mask the original image, obtaining an image containing only the rice seed portions, as shown in Figure 2(d).

2.4 Feature Extraction

2.4.1 Rice Seed Counting

Select the images of rice seeds taken on the first day without adhesion, perform grayscale conversion, threshold segmentation and opening and closing operations on the images, then find their connected regions and count the area (number of pixels) of each connected region. Regard the single connected regions with smaller areas as noise points, and fill the corresponding pixel values with zero to become the background. Finally, the number of all simply connected domains in the image is counted as the total number of rice seeds.

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2.4.2 Position and Area Statistics

To identify germinated seeds, it is necessary to extract the positional and area information of seeds before and after segmentation. First, both the images containing rice seeds with sprouts/roots and those containing only seed portions undergo grayscale conversion and threshold segmentation to obtain binary images. The connected components in each image are then extracted, with the centroid coordinates ((x, y) positions) and pixel counts (connected component area) being recorded for each individual connected region. Each connected component and its corresponding centroid and area are assigned unique identifiers. For images containing seeds with sprouts/roots, the centroids are denoted as (x_d^i, y_d^i), where $1 \le i \le 50, 1 \le d \le 7$, and the areas are represented as $S_d^i, 1 \le i \le 50, 1 \le d \le 7$, where i indicates the seed number and d represents the day. Similarly, for images containing only seed portions, the centroids are expressed as (x_d^j, y_d^j), $1 \le j \le 50, 1 \le d \le 7$, and the areas are denoted as S_d^j, where$1 \le j \le 50, 1 \le d \le 7$, with j representing the seed number and d indicating the day.

To better observe the extracted seed characteristics, three randomly selected seeds were analyzed for their centroid positions and area (pixel count) changes from day 1 to day 5, as shown in Table 1. The first seed remained ungerminated, with its centroid position and area staying constant throughout. In contrast, the second and third seeds both germinated, demonstrating noticeable changes in both centroid positions and areas over the observation period.

Table 1 Centroid and area characteristics of partial seeds during days 1-5.

Days / Seeds	Seed 1		Seed 2		Seed 3	
	Centroid	Area	Centroid	Area	Centroid	Area
Day 1	(141,934)	6903	(320,727)	7036	(771,1754)	6822
Day 2	(141,934)	6903	(321,729)	7308	(772,1752)	7214
Day 3	(141,934)	6903	(326,734)	7956	(775,1746)	7907
Day 4	(141,934)	6903	(331,733)	8923	(778,1742)	8872
Day 5	(141,934)	6903	(334,736)	12769	(785,1740)	11846

2.5 Germination Determination

During the image acquisition process, the germination tray and camera maintain a fixed relative position. The system determines seed germination by calculating dynamic changes in positional coordinates and projected area across consecutive daily images. When either the displacement magnitude or area change ratio exceeds predefined thresholds, the seed is identified as germinated. For day d, the germination status of the $i \in \{1,2,\dots,50\}$ is determined through the following steps:

(1) The calculation for the i-th seed on day d involves summing three minimum absolute differences: between its x-coordinate and all x-coordinates x_d^j in the seed-only image, between its y-coordinate and all y-coordinates y_d^j, and between its area S_d^k and all areas S_d^j, with the calculation formula expressed as

$$D_d^i = \begin{cases} 1, \min\limits_{1 \le k \le 50} \left(\left|x_d^i - x_d^k\right| + \left|y_d^i - y_d^k\right| + \left|S_d^i - S_d^k\right|\right) \le \sigma \\ 0, \min\limits_{1 \le k \le 50} \left(\left|x_d^i - x_d^k\right| + \left|y_d^i - y_d^k\right| + \left|S_d^i - S_d^k\right|\right) \le \sigma \end{cases} \quad (2)$$

Here, D_d^i indicates whether the i-th seed has germinated on day d, x_d^j represents the x-coordinate of the i-th seed on day d, y_d^i denotes the y-coordinate of the i-th seed on day d, and S_d^i stands for the area of the i-th seed on day d. The parameter σ represents the error margin, and through repeated experiments, it was found that setting the error parameter to 1 yields the best results.

(2) The criterion for determining whether the i-th seed has germinated on day d is as follows: if D_d^i equals 1, the seed is considered ungerminated; if D_d^i equals 0, the seed is considered germinated.

Figure 3 (left) and Figure 3 (right) show the visualization results of the centroid and area for the radicle part and the seed-only part when d is 3, respectively. The red line outlines the area, while the blue dot represents the centroid. It is clearly observed that seeds 1, 2, and 4 have germinated, as both their area and centroid changed before and after segmentation of the seed region. In contrast, seed 3 did not germinate, as its area and centroid remained unchanged before and after segmentation.

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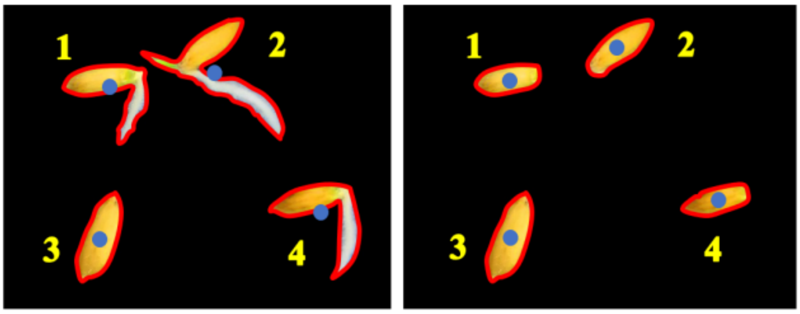

Figure 3 Germination detection results.

3. Experimental Design

3.1 Dataset and Experimental Setup

The experiment used the rice variety Hualiangyou 6, with 150 seeds selected as experimental samples. These seeds were evenly divided into three groups of 50 seeds each, placed in three separate germination boxes, and then incubated in a germination chamber at a constant temperature of 26°C. The image acquisition setup consisted of a camera, a stand, and a light source. Images were captured at 24-hour intervals over seven consecutive days, with the first acquisition time set as Day 0. During each image capture, the positions of both the camera and the germination box remained consistent. All experiments used the open-source OpenCV image library for image processing.

3.2 Results and Analysis

To verify the effectiveness of the proposed method, a comparison was made between manual detection and the proposed method in three groups of rice seed germination experiments, as shown in Table 2,3,4. The results indicate that there were minor discrepancies between the proposed method and manual detection on the first day, primarily because the germination characteristics of rice seeds were too subtle to be accurately distinguished by the algorithm at this early stage. However, from the second to the seventh day, the results of the proposed method closely matched those of manual detection. The average results across the three groups revealed that the germination recognition accuracy of the proposed algorithm had an error margin of less than 1% compared to manual statistics, demonstrating the accuracy and reliability of the proposed method for rice seed germination detection.

Table 2 Manual vs. algorithm recognition results (Group 1).

Days	Manual Count (seeds)	Algorithm Count (seeds)	Error Rate (%)
0	0	0	0
1	1	3	4
2	38	39	2
3	48	50	2
4	48	50	2
5	48	50	2
6	48	50	2
7	48	50	2

Table 3 Manual vs. algorithm recognition results (Group 2).

Days	Manual Count (seeds)	Algorithm Count (seeds)	Error Rate (%)
0	0	0	0
1	3	5	2
2	42	42	0
3	50	50	0
4	50	50	0
5	50	50	0
6	50	50	0
7	50	50	0

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Table 4 Manual vs. algorithm recognition results (Group 3).

Days	Manual Count (seeds)	Algorithm Count (seeds)	Error Rate (%)
0	0	0	0
1	4	7	6
2	47	48	2
3	49	49	0
4	49	49	0
5	49	49	0
6	49	50	2
7	49	50	2

4. Conclusions

Seed germination detection is highly time-consuming and labor-intensive. To address this issue, this study proposes an image processing-based germination recognition method specifically for rice seeds. By utilizing color information to segment the seed region from the radicle and shoot regions, germination is identified based on changes in seed area and position before and after segmentation. Experimental results demonstrate that the automatic recognition outcomes of this method closely align with manual statistical results, indicating its strong practical applicability. Future research could focus on enhancing algorithm robustness and extending the method to germination recognition for multiple rice seed varieties. Method closely align with manual statistical results, indicating its strong practical applicability. Future research could focus on enhancing algorithm robustness and extending the method to germination recognition for multiple rice seed varieties.

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