COMPUTER VISION-BASED CORN STALK IMAGE RECOGNITION RESEARCH
/
基于计算机视觉的玉米秆图像识别研究

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ABSTRACT
The utilization of machine vision and image processing techniques enables the recognition of corn stalks in complex field conditions, thereby enhancing the efficiency and accuracy of corn stalk identification. Initially, images of corn stalks are captured using a camera, followed by Gaussian filtering to effectively reduce noise within the images. Subsequently, RGB and HSV color segmentation is applied to the corn stalk images to isolate the component V, which most distinctly differentiates the corn stalks from the background. Threshold segmentation is then conducted on component V, establishing a threshold range to identify and extract the corn stalks from the background. Morphological operations are employed to enhance the fullness of the image. Finally, grid division is performed, using the coverage area of the straw as a feature to assign density values to corn straw in various sub-regions, ultimately generating a distribution grade map of corn straw. The results indicate that when the straw coverage rate ranges from 25% to 80%, the discrepancy between the corn straw recognition rate obtained through threshold segmentation and the manually measured straw coverage rate is less than 5%, satisfying the requirements for subsequent real-time variable spraying of corn straw decomposition agents.

摘要
运用机器视觉和图像处理的方法可实现玉米秸秆田间复杂条件下的识别，提高玉米秸秆田间识别效率和精度。首先通过摄像头对田间玉米秸秆进行采集，将采集到的田间玉米秸秆图像进行高斯滤波处理，有效消除图像中的噪音；然后对玉米秸秆图像进行 RGB 和 HSV 颜色分割，找出玉米秸秆与背景区分最明显的分量 V；再对分量 V 进行阈值分割处理，设定阈值范围，将玉米秸秆从背景中识别提取出来，运用形态学运算，使图像更加饱满；最后进行网格划分，以秸秆覆盖率面积作为特征，将不同子区域内的玉米秸秆密度进行赋值，生成玉米秸秆的分布等级图。结果表明：秸秆覆盖率为 25%~80%时，通过阈值分割的玉米秸秆识别率与人工测量的秸秆覆盖率结果误差小于 5%，能够满足后续玉米秸秆腐解剂实时变量喷施作业要求。

INTRODUCTION
During the 14th Five-Year Plan period, several forward-looking research directions have been strategically identified to encourage the exploration and development of new concepts, theories, and methods. These efforts are intended to promote innovation in scientific research paradigms and interdisciplinary integration. With the rapid advancement of technology, machine vision has become increasingly important not only in industry but also in agriculture and forestry, placing higher demands on its application in complex environments. Currently, employing machine vision to identify various plants and fruits has emerged as a prominent research focus. In China, the vast grain output and abundant straw resources have led to traditional practices that primarily involve burning straw for fuel. This approach results in a low resource utilization rate and contributes significantly to environmental pollution *(Chang, 2022a; Chang, 2022b; Kurumayya, 2025).*

In alignment with the priority development areas outlined in the National Natural Science Foundation of China's "14th Five-Year Plan" and the "Five-way Comprehensive Utilization of Straw" initiative, this study employs a treatment method that integrates machine vision technology with straw fertilization.

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The application of variable spraying of decomposers facilitates the decomposition of corn straw and its subsequent return to the field, thereby improving the efficiency of straw resource utilization. *Su Boni et al*. employed median filtering, mean filtering, and Wiener filtering to address salt-and-pepper noise in strawberry images. Their findings indicated that median filtering provided the most effective denoising results. Jinli Diamond utilized 14 texture features for the identification and localization of cucumbers; however, this approach requires substantial computational resources, rendering it impractical. Consequently, ongoing enhancements are necessary *(Wang et al., 2021; Su et al., 2018; Gao, 2022; Yang et al., 2023; Niu et al., 2025)*.

Research on the identification of corn stalks remains incomplete and has yet to achieve full automation. This paper initiates an investigation into the identification of corn stalks. Initially, corn stalk images undergo processing through an image preprocessing method. Subsequently, a color space model, in conjunction with morphological processing operations, is employed to execute threshold segmentation, effectively isolating the corn stalks from the background. The variable spraying device is then regulated based on the percentage of the corn stalk coverage area, facilitating the decomposition and return of corn stalks to the field (*Niu et al.*, 2024; *Ding et al., 2022a; Ding et al., 2022b; Deng, Wang, & Zhang, 2020; Niu et al., 2024)*.

MATERIALS AND METHODS

Experimental conditions

The corn stalk images were collected in Heping Village, Xiangyang District, Jiamusi City, Heilongjiang Province. The data collection occurred from September to October 2022, between 09:00 and 15:00. A mobile phone was utilized for capturing the images, which were taken under natural light conditions. To enhance data diversity and improve the model's generalization ability, images of corn stalks were gathered under various environmental conditions and distribution scenarios. Subsequently, the collected images underwent manual screening, resulting in the selection of those with stalk distribution percentages of 20% to 33%, 33% to 50%, 50% to 66%, 66% to 80%, and 80% to 90%. The selected images are presented in Figure 1. To further enhance the model's recognition accuracy, additional corn stalk images were sourced from the internet and incorporated into the self-captured image set. The flowchart illustrating the research on the identification of corn stalks in the field soil background is depicted in Figure 2 *(Wang; Dongxiang MA, 2023; Yasin et al., 2025)*.

Fig. 1 - Image of corn straw collection

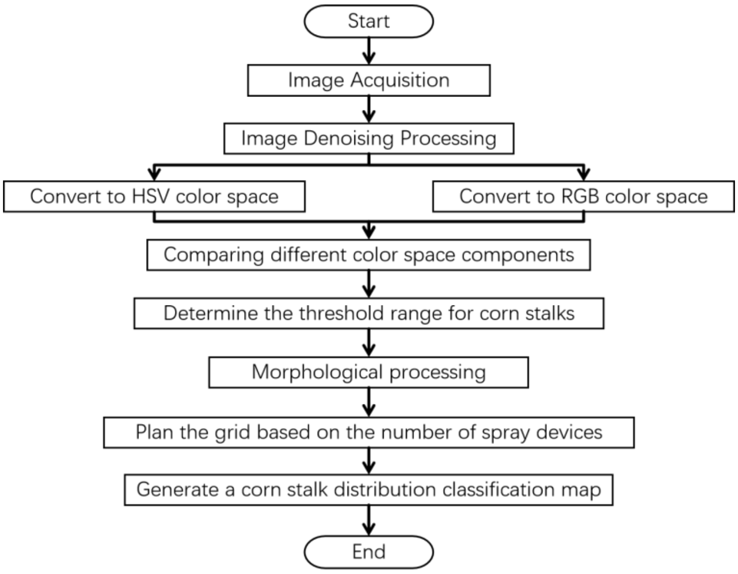


Fig. 2 - Flow chart of corn straw identification

Image color segmentation method

Images of corn stalks were captured using a camera. These images were subsequently analyzed and processed with PyThon-OpenCV, initially converting them into the RGB color space. Following this, the images were transformed into the HSV color space, allowing for a comparison with the RGB color space to identify the color component that provided the most effective separation between the corn stalks and the soil background. The corn stalks were isolated from the background using threshold segmentation, after which morphological processing techniques were employed to enhance the representation of the corn stalks *(Liu et al., 2024*).

Image filtering processing

This paper employs a denoising method that integrates Gaussian filtering with median filtering. Initially, Gaussian filtering is applied to the image prior to color space conversion. This technique utilizes the Gaussian function to smooth the image by computing the weighted average of pixels within a specified neighborhood around each pixel, thereby mitigating the impact of noise and effectively reducing high-frequency noise. The mathematical representation is provided in Equation (1), and the resulting image is illustrated in Figure 3. Subsequently, before the binarization process, median filtering is performed for further denoising. In this step, the median value of the pixel intensities within a defined area surrounding the central pixel replaces the original pixel value, effectively eliminating salt-and-pepper noise or impulse noise. The corresponding expression is detailed in Equation (2), and the processed image is depicted in Figure 4 *(Shah et al., 2022; Suneetha & Reddy, 2021; Latorre-Carmona, 2024)*.

$$(x)=\frac{1}{2\pi\sigma^2}\mathrm{e}^{-\frac{x^2+y^2}{2\sigma^2}} \quad (1)$$

$$\hat{f}(x,y)=\underset{(i,j)\in S_{(x,y)}}{\mathrm{median}}\{g(i,j)\} \quad (2)$$

Fig. 3 - Gaussian filter denoising process

Fig. 4 - Median filter denoising process

Color space model

The RGB color space is the most widely recognized method for representing colors, with its color space model illustrated in Figure 5. Any color F in a color image can be created by mixing the three primary colors: R (red), G (green), and B (blue) in varying proportions, as expressed in Equation (3) *(Togban & Ziou, 2025; Mengibar-Rodriguez & Chamorro-Martinez, 2022)*:

$$F=r[R]+g[G]+b[B] \quad (3)$$

where: R - red component; G - green component; B - blue component.

This color space accurately represents colors, as it has not been converted to other color spaces, resulting in minimal loss of image information. Following image processing, the image is subsequently processed through the RGB color space, with the outcome depicted in Fig. 6.

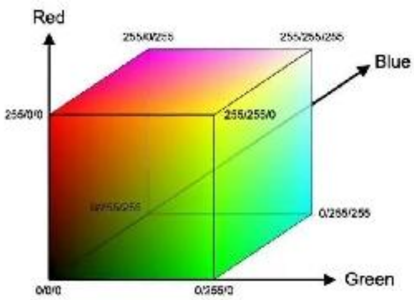
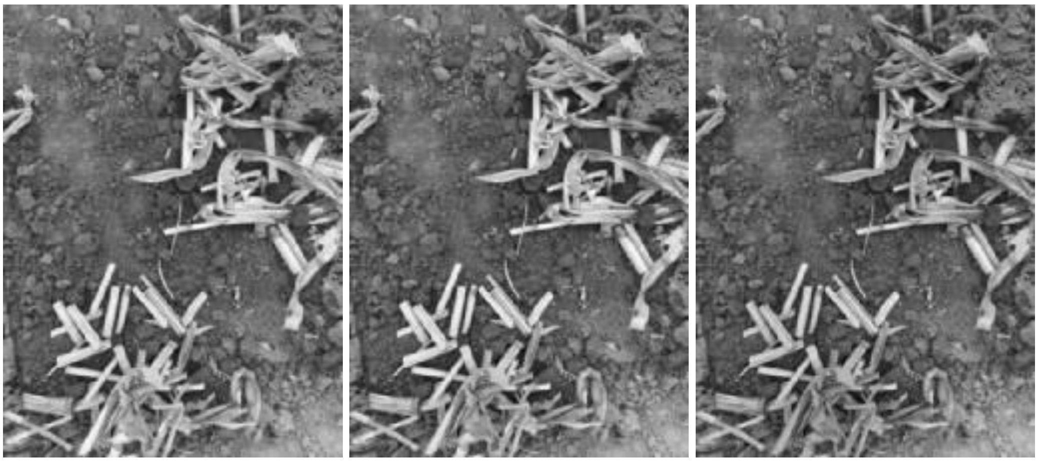


Fig. 5 - RGB color space model



(a) R component (b) G component (c) B component

Fig. 6 - RGB component map

The HSV color space is a color model defined by the attributes of Hue, Saturation, and Value, commonly referred to as a hexagonal cone model. The representation of this color space is illustrated in Fig. 7 *(Kamiyama & Taguchi, 2021; Yan, Li, & Hirota, 2021)*.

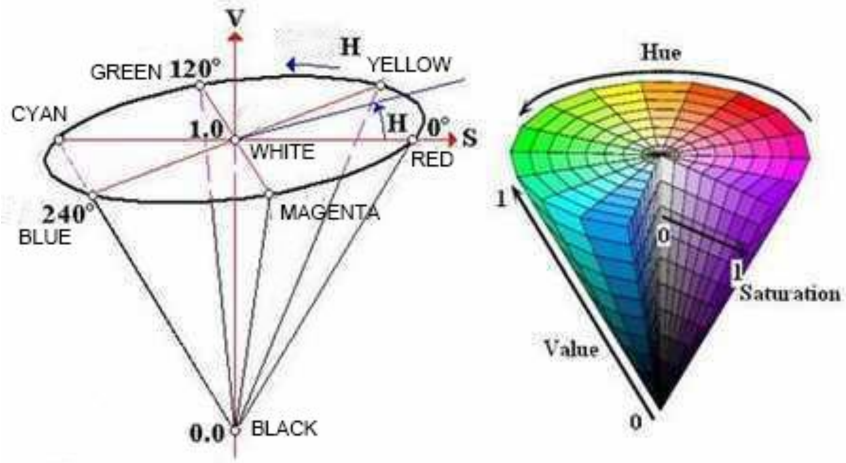


Fig. 7 - HSV color space model

The conversion relationship expression between this model and the RGB color space model is shown in Equation (4), that is:

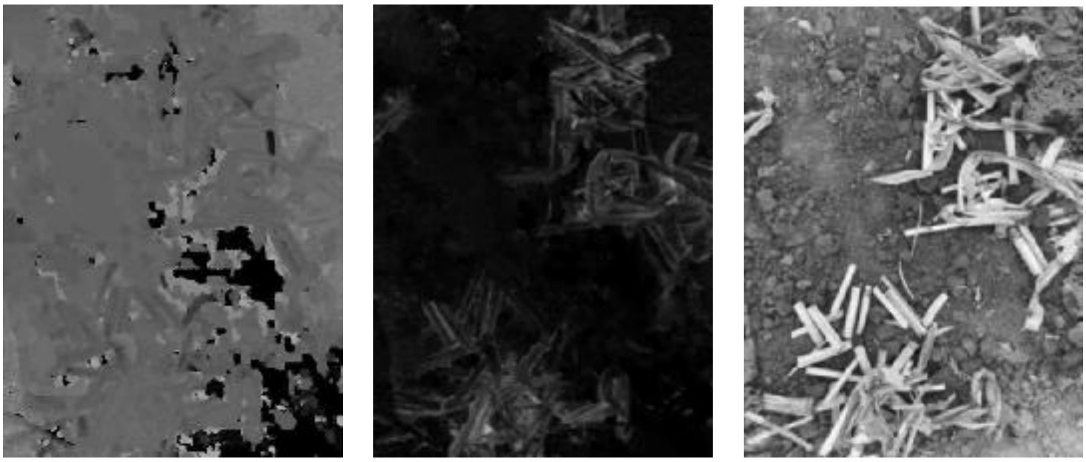
$$H=\begin{cases} 0^{\circ}, & \text{if Max} = \text{Min} \\ 60^{\circ}\times\frac{G-B}{\text{Max}-\text{Min}}+0^{\circ}, & \text{if Max} = \text{R and G} > \text{B} \\ 60^{\circ}\times\frac{G-B}{\text{Max}-\text{Min}}+360^{\circ}, & \text{if Max} = \text{R and G} < \text{B} \\ 60^{\circ}\times\frac{G-B}{\text{Max}-\text{Min}}+120^{\circ}, & \text{if Max} = \text{G} \\ 60^{\circ}\times\frac{G-B}{\text{Max}-\text{Min}}+240^{\circ}, & \text{if Max} = \text{B} \end{cases} \tag{4}$$

$$S=\begin{cases} 0, & \text{if Max} = 0 \\ \frac{\text{Max}-\text{Min}}{\text{Max}}=1-\frac{\text{Min}}{\text{Max}}, & \text{otherwise} \end{cases} \tag{5}$$

$$V=\text{Max} \tag{6}$$

where: Max - the maximum among R, G, and B;
Min - the minimum among R, G, and B

Subsequently, the preprocessed image undergoes processing in the HSV color space. A comparison is made between the components of the RGB color space model and those of the HSV color space model to identify the component that most effectively distinguishes corn stalks from the background. The diagram of the HSV color space components is presented in Fig. 8.



(a) H component (b) S component (c) V component

Fig. 8 - HSV component map

By comparison, it can be seen that among the six components, the differences between the corn stalks and the soil background in component V are more obvious.

Research on recognition algorithms

As indicated in Section 2, the V component exhibits the most pronounced distinction effect. Consequently, threshold segmentation is applied to the V component, enabling the identification of corn stalks through this method.

The image acquisition process using industrial cameras is influenced by various unstable factors, including perspective, distance, light source, reflection, occlusion, and shadow, which can significantly affect image recognition outcomes. Additionally, noise interference may occur during both the acquisition and transmission of images. Consequently, preprocessing the images is essential to eliminate this noise and ensure the accuracy of subsequent results.

Image smoothing processing

To mitigate the effects of image noise generated during acquisition and transmission on image processing, it is essential to perform denoising prior to processing to enhance the resolution of image features. Image denoising involves applying filtering techniques to smooth the image, recalculating the value of each pixel to align it more closely with the values of neighboring pixels.

The commonly used image smoothing processing methods are as follows:

Mean filtering

Mean filtering is a linear filtering algorithm that employs a template to conduct convolution operations on the target image. This method replaces the value of each target pixel with the average pixel value of its surrounding neighborhood, thereby enhancing denoising effects and making the desired target more prominent.

$$(x,y)=\frac{1}{M}\sum_{(k,l)\square N} f(i,j) \tag{7}$$

Median filtering

Median filtering is a technique that employs a template to execute convolution operations on a target image. This process replaces the pixel value at a given point with the median of the pixel values within its neighborhood. Consequently, the surrounding pixel values are adjusted to approximate the true values, effectively eliminating isolated noise points.

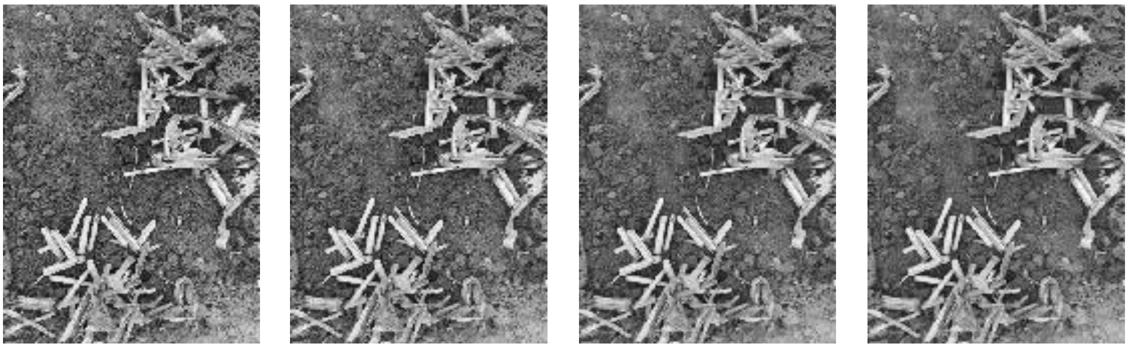
$$\hat{f}(x,y)=\underset{(i,j)\in S_{(x,y)}}{\text{median}}\{g(i,j)\} \tag{8}$$

Gaussian filtering

Gaussian filtering involves the weighted averaging of the entire image. The value of each pixel is determined by the weighted average of its own value and those of neighboring pixels. When the mean μ is 0:

$$(x)=\frac{1}{2\pi\sigma^2}e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{9}$$

In Gaussian filtering for denoising, the value of σ is crucial, as it dictates the dimensions of the filter template. A larger template results in increased blurring of the edge information of the particles. This article compares the denoising effects of three different templates $3\times3(\sigma=0.65)$, $5\times5(\sigma=1.43)$, $7\times7(\sigma=1.79)$, with the results illustrated in Figure 9.



Grayscale image 3×3 Template 5×5 Template 7×7 Template

Fig. 9 - Gaussian filtering effect

Comparative analysis of the experimental effects of Gaussian filtering reveals that an increase in template weight significantly suppresses image noise. When utilizing templates of the same size, a comparison of various filtering processes demonstrates that $5\times5(\sigma=1.43)$ template Gaussian filtering effectively reduces noise while preserving edge information, resulting in favorable outcomes.

Image grayscale processing

The image data captured by industrial cameras is typically in color, comprising a combination of three channel vectors. For instance, in the RGB color model, each color channel ranges from 0 to 255. Consequently, color images require substantial storage space, which significantly impacts the speed of image processing. In contrast, grayscale images consist of a single channel without color, also ranging from 0 to 255. In the case of a binary grayscale image, white is represented by 255 and black by 0.

Common image grayscale conversion algorithms:

Single-channel component method

According to the requirements, one of the R, G, or B components in the color image is taken as the gray value of the image.

$$V_{gary1}=R \tag{10}$$

$$V_{gary2}=G \tag{11}$$

$$V_{gary3}=B \tag{12}$$

Maximum value method

The maximum brightness among the R, G, and B components in the color image is taken as the gray value of the grayscale image.

$$V_{gary}=\max(R, G, B) \tag{13}$$

Average value method

Take the average luminance of the R, G, and B components in the color image as a gray value.

$$V_{gary}=(R, G, B)/3 \tag{14}$$

Weighted average method

Based on their importance and other indicators, the three components are weighted and averaged with different weights.

$$V_{gary}=(\omega_r*R+\omega_g*G+\omega_b*B)/3 \tag{15}$$

where: $\omega_r, \omega_g, \omega_b$ - respectively the weights of R, G, and B.

Research shows that the grayscale effect of the image is the best when the following conditions are met. That is:

$$V_{gary} = 0.299 * R + 0.578 * G + 0.114 * B \tag{16}$$

The following figure is the grayscale image, as shown in Figure 10.

Fig. 10 - Image binarization

Image binarization processing

Color images captured by industrial cameras are converted into grayscale images. Following this, image binarization processing transforms the grayscale images into black-and-white images. Image binarization involves assigning pixel grayscale values of 0 or 255, thereby creating a pronounced black-and-white effect throughout the image and decreasing the overall data size.

A comparison of the preprocessing results presented in Figures 9 and 10 reveals that the application of image smoothing effectively removes target information while eliminating noise interference. The image processed through Gaussian filtering exhibits distinct edges, free from noise or artifacts, thereby facilitating subsequent image processing.

Morphological processing

Following the threshold segmentation of corn stalks, the desired outcome is frequently not attained. Consequently, morphological operations must be employed to enhance the completeness of the target. Morphology is among the most prevalent techniques in image processing. Its fundamental principle involves utilizing a specific structural element to measure or extract corresponding shapes or features from the input image, thereby facilitating further image analysis and target recognition. The commonly employed morphological processing methods are illustrated in Figure 11.

Image erosion

The erosion operation serves to "shrink" the selected area, effectively removing edges and speckles. It smooths the edges of the image area and reduces the number of pixels within that area; however, this process may result in the disconnection of adjacent components.

Image dilation

Dilation is the process of expanding a selected area, which smooths the edges of the image region, increases the pixel count within that region, and may connect previously unconnected components. However, regions that were originally separate will remain distinct and will not merge, despite any pixel overlap.

Open operation

The procedure for the opening operation involves initially executing the erosion operation, followed by the expansion operation. This sequence effectively eliminates isolated and small points, smooths rough edge lines, and ensures that the original area remains largely unchanged, akin to a "deburring" effect.

Closing operation

The procedure for the closed operation involves initially executing the expansion operation, followed by the erosion operation. This sequence effectively connects cavities within the area and merges isolated points outside into a single entity. The overall appearance and area of the region remain largely unchanged, akin to the effect of "filling the gaps."

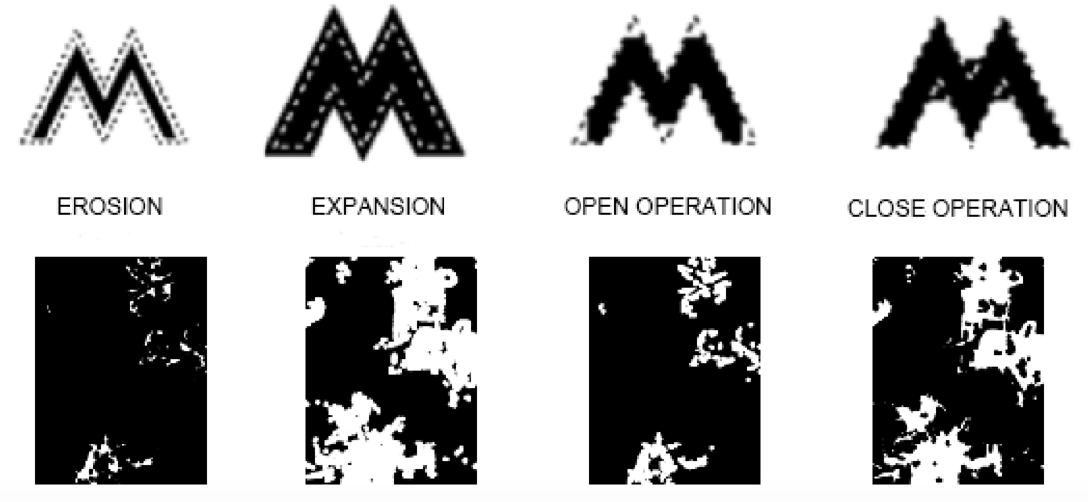


Fig. 11 - Morphological processing methods

This paper employs the closed operation method for image processing. This approach fills the gaps between corn stalks without thickening the edge contours, thereby connecting scattered targets within the image. As a result, the operational complexity is diminished, and efficiency is enhanced.

Image threshold segmentation method

The threshold is established based on specific requirements, incorporating various restrictive conditions to isolate the target from the image background. Threshold segmentation primarily relies on the disparity in gray values between the target and other objects within the background. This method filters the pixels in the image that satisfy the criteria determined by the gray values of the target pixels, thus enabling the segmentation of target features.

Fixed threshold segmentation

Fixed threshold segmentation represents the most basic and straightforward method of threshold segmentation. The underlying principle involves establishing a gray value, denoted as T. If the gray value of a pixel is less than T, it is assigned a value of 0 (i.e., black). Conversely, if the gray value exceeds T, it is assigned a value of 255 (i.e., white).

$$(x)=\begin{cases} 0, & x<T \\ 255, & x>T \end{cases} \tag{17}$$

Large law threshold segmentation

The OTSU method was introduced by Japanese researcher Nobuyuki Otsu in 1979. This method binarizes and segments images by identifying threshold pairs that maximize the inter-class variance between the foreground and background, thereby minimizing the likelihood of misclassification. However, the effectiveness of this segmentation diminishes when there is a substantial area difference between the target and the background, or when the gray levels of the target and background exhibit significant overlap.

Interval threshold segmentation

In a manner akin to fixed-threshold segmentation, the fixed threshold is modified to an interval threshold. If a pixel's threshold falls within this interval, its gray value is assigned a value of 255 (i.e., white). Conversely, if a pixel's threshold does not reside within the specified range, its gray value is designated as 0 (i.e., black).

The working environment described in this paper is complex, influenced by various factors, including light conditions, shooting angle, the presence of weeds, and the timing of straw collection, all of which affect straw color. Consequently, this study employs the interval threshold segmentation method to analyze the acquired images.

RESULTS

Experimental verification

Images of corn stalks in the field were captured using cameras. A total of fifteen images, representing varying coverage rates of corn stalks, were obtained and subsequently compared with the manually measured straw coverage rates.

Among the 15 selected images, the straw coverage rates were categorized into ranges: three images each for 20% - 33%, 33% - 50%, 50% - 66%, 66% - 80%, and 80% - 90%. The results of the two measurements are summarized in Figure 12. The figure illustrates that the corn stalk recognition algorithm developed in this study exhibits higher measurement accuracy within the straw coverage range of 25% to 80%, achieving an error of less than 5%.

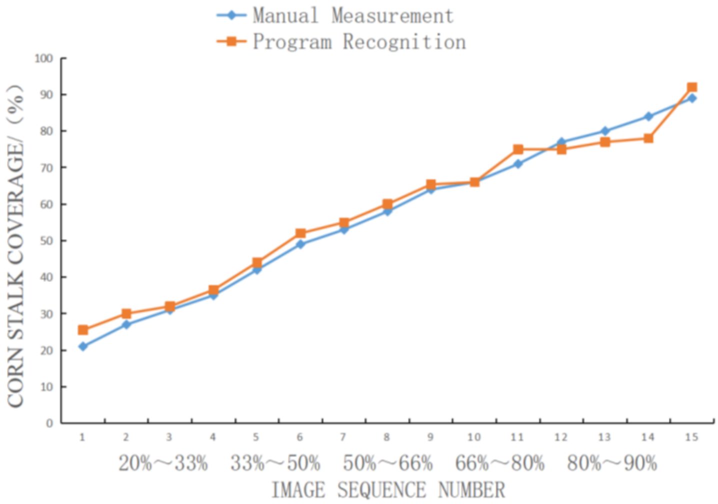


Fig. 12 - Straw cover comparison curve

Corn stalk identification

Heilongjiang Province, recognized as China's leading corn-growing and corn-producing region, generates a substantial quantity of corn stalks. Following the autumn harvest, a portion of these stalks is recycled and reused; however, a significant number are either burned or left to decay in the fields, representing a considerable waste of resources. Corn stalks are abundant in organic matter and contain various nutrients essential for plant growth. The effective utilization of these nutrients can significantly enhance soil fertility and decrease reliance on chemical fertilizers. Consequently, the decomposition and utilization of corn stalks hold considerable research significance.

Following the autumn harvest, corn stalks are crushed by harvesters and dispersed across the fields. The crushing is relatively uniform, resulting in a brownish-yellow color that contrasts markedly with the black soil characteristic of Northeast China. Consequently, this study employs color and area as the primary features for segmentation.

First, images of straw distribution in the field are captured using a camera. These images undergo several processing steps, including grayscale conversion, denoising, binarization, morphological processing, and grid division. Ultimately, a straw distribution grade map is generated, as illustrated in Figure 13.

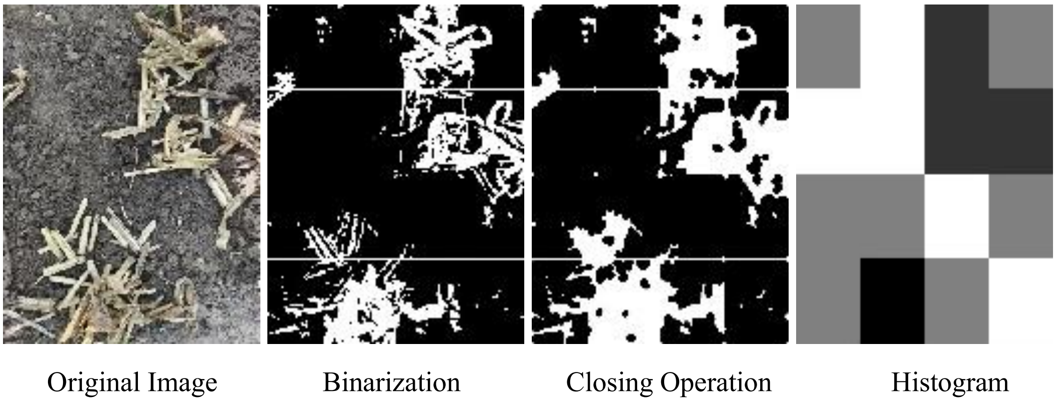


Fig. 13 - Corn straw identification

The figure illustrates that within each small cell, an increase in the area of straw corresponds to a progressively darker color of the cell. The classification is divided into four grades. If the straw area within a small cell is less than 5% of the total cell area, it is deemed to contain no straw. When the straw area comprises 5% to 33% of the cell area, it is categorized as level 1. If the straw area constitutes 33% to 66% of the cell area, it is classified as level 2. Finally, when the straw area exceeds 66% of the cell area, it is designated as level 3.

CONCLUSIONS

The HSV color space was chosen for this study after comparing three color models: RGB, HSV, and L*a*b*. Subsequently, the color images were converted to grayscale. To mitigate noise in the images, Gaussian filtering and median filtering techniques were employed. Among three threshold segmentation methods—fixed threshold, OTSU threshold, and interval threshold—the interval threshold method was selected based on its suitability for the actual working environment. The analysis focused on the color and shape characteristics of corn stalks, utilizing color as the segmentation feature to distinguish the stalks from the background. Area was then used as a feature to create a distribution grade map of the corn stalks. The corn stalk recognition algorithm, which relies on interval threshold segmentation, is straightforward and exhibits targeted effectiveness. When the straw coverage rate ranges from 25% to 80%, the recognition accuracy remains high, with an error margin of less than 5%.

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