DESIGN AND EXPERIMENT OF FILM LAYING QUALITY MONITORING SYSTEM FOR COTTON PRECISION PLANTER
/
棉花精量播种机铺膜质量监测系统设计与试验

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ABSTRACT
To realize real-time monitoring of film laying process of cotton precision planter and improve intelligent level of cotton precision planter, based on advanced morphological filtering method and graphical programming of Labview software, a film laying quality monitoring system of cotton precision planter is designed. Using the Vision Assistant visual assistant, the system uses a color extraction function to convert colors to grayscale images. It uses LOOKup Table function and FFT filter function to perform grayscale transformation, binarization and advanced morphological filtering on it respectively. It then uses basic morphology to acquire various components in the plastic film image. It realizes the monitoring of parameters such as the width of the daylighting surface, the side length or seam length of the mechanical damaged part, and the width of the film edge covering soil. The performance test results of the film laying quality monitoring system showed that the system worked stably and reliably, the average monitoring accuracy of the width of the lighting surface and the width of the film edge covering soil reached more than 95%, and the average monitoring accuracy of the side length or the length of the seam at the mechanical damage part reached more than 88%. It solved the problems of difficulty in recognizing the similarity between the plastic film and the background interferer (soil, etc.) and could accurately detect the quality of the cotton film in real time. It effectively improved the operation quality and working efficiency of the cotton precision planter and met the practical requirements of film laying monitoring.

摘 要
为了实现棉花精量播种机铺膜作业过程的实时监测，提高棉花精量播种机智能化水平，基于高级形态学滤波方法，采用 Labview 软件图形化编程，设计了棉花精量播种机铺膜质量监测系统。系统运用 Vision Assistant 视觉助手，使用颜色提取函数将彩色转换为灰度图像，通过 LOOKup Table 函数和 FFT 滤波函数分别对其进行灰度变换、二值化与高级形态学滤波，再运用基本形态学获取地膜图像中的各个成分，实现对采光面宽度、机械破损部位的边长或缝长、膜边覆土宽度等参数监测。铺膜质量监测系统台架性能试验结果表明：该系统工作稳定可靠，采光面宽度、膜边覆土宽度平均监测精度达到 95%以上，机械破损部位的边长或缝长平均监测精度达到 88%以上，解决了地膜与背景干扰物（土壤等）相近识别难度大等问题，能实时准确地检测棉花铺膜质量，有效提高了棉花精量播种机的作业质量和工作效率，满足铺膜监测实际要求。

INTRODUCTION
Cotton is the main economic crop in Xinjiang. According to statistics, in 2021, Xinjiang's cotton planting area reached 2.61 million hm^2 (accounting for 83% of the country), and its output was 5.13 million t (accounting for 89% of the country) (*National Bureau of Statistics of the People's Republic of China, 2011; Bureau of Statistics of Xinjiang Uygur Autonomous Region Xinjiang statistical Yearbook, 2021*). Xinjiang has become the largest cotton producing region in China. At present, cotton planting has generally adopted the technique of mulching precision cave-seeding. Among them, mulching film has the functions of increasing soil temperature and preserving soil moisture, improving soil and inhibiting weeds, which has become a key means to reduce diseases and insect pests and increase crop yield (*Zhai Z.Q. et al., 2022; Zhang S., 2008; Xing J.F. et al*).

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Due to the harsh working environment in the field, the working parts are more complex, easy to appear film tearing, insufficient lighting surface and other problems. Drivers understand the quality of the film needs to stop, relying on the naked eye to judge. If the fault cannot be found and indicated in time, it will seriously affect the yield and benefit of cotton, and it is difficult to meet the current demand for rapid detection of film laying quality. Therefore, it is of great practical significance to realize real-time monitoring of film laying quality of cotton precision planter to improve operation quality and promote mechanization informatization.

With the continuous development and improvement of science and technology, in modern agricultural production, intelligence is an important development direction of agricultural machinery equipment, and has become a new trend of sustainable agricultural development (*Kong Y.L. et al., 2012*). The detection technology of plastic film mainly includes ultrasonic technology (*Zhang Q. et al., 2013*), polarized light technology (*Zhang C. et al., 2017; Peng B. et al., 2015*), infrared technology (*Zhang D.W. 2019; Lu L. et al., 2015*), low altitude drone imaging (*Banerjee B. et al., 2020; Adão T. et al., 2017*), machine vision (*Zhang X., 2020*), etc. Among them, ultrasonic technology is easily disturbed by external environmental noise and produces misjudgment; The precision of polarized light technology is not high and its performance is unstable; Infrared technology and low altitude drone imaging are easily affected by ambient temperature and humidity, and the maintenance cost is high; Machine vision plays the role of "eyes". Based on the color, contour and distribution characteristics, the specific area of the target or non-target crop is expanded and corrode to achieve the purpose of highlighting. It has the characteristics of high precision, fast speed and non-destructive, which is widely used in various fields and has a broad prospect (*Li Q.L. et al., 2020; Qin C.B. et al., 2019; Diao Z.H. et al., 2014; Hou J.L. et al., 2020*).

With the increasing maturity of machine vision technology *(Bu L.X. et al., 2020)*, it has also developed rapidly in farmland plastic film recognition, and scholars have carried out a lot of research on it. Lu et al. was based on spectral characteristics to extract geomembrane information from the influence of Landast satellite time series (*Lu L. et al., 2014*). Liang Changjiang et al (*Liang C.J. et al., 2019*) used the traditional image segmentation algorithm to identify the farmland plastic film image collected by the UAV, and the results showed that the iterative threshold segmentation algorithm had the best effect; Zhang Xuejun et al (*Zhang X.J. et al., 2021*) optimized Faster R-CNN convolution neural network and used double threshold algorithm to reduce the influence of threshold on model performance; Wu Xuemei et al (*Wu X.M. et al., 2020*) put forward a recognition method based on color characteristics, using pulse coupled neural network to realize the recognition of plastic film in different periods. *Zhai Zhiqiang et al* proposed a method for detecting the coverage of cotton field surface residues before sowing based on pixel blocks and machine learning (*Zhai Z.Q. et al., 2022*). Most of the above-mentioned documents are in the stage of algorithm research and are not combined with hardware. They are all based on the recognition of plastic film images under experimental conditions. There are high requirements for the recognition environment, and the related technologies are still immature. And it is reported that the quality monitoring of film laying has not been explored yet. Therefore, it is necessary to carry out further research on real-time monitoring technology of film laying quality aiming at the complex operating environment of cotton precision planter.

In order to realize real-time monitoring of film laying quality of cotton precision planter, an advanced morphological filtering method is proposed to realize film laying image recognition. In this study, Labview is used to build and develop the quality monitoring system of film laying, and the performance tests are carried out to improve the precision sowing quality of cotton.

MATERIALS AND METHODS

Image acquisition system

The film laying image acquisition system of cotton precision planter includes high-definition network camera (Logitech, C920e), bracket and upper computer. Among them, the camera's field of view angle is 72°, the acquisition capacity is 30 frames/s, and it can automatically zoom and expose. It has the characteristics of clear image, strong adaptability and low cost. The software and hardware of the upper computer are configured as Windows 11 64-bit system, with 16 GB of RAM, Intel Core i9-12900H CPU, and 2.50 GHz main frequency. LabView software is selected for graphical programming, and Vision Assistant is used for image morphology processing. It has a complete image processing function library, rich and powerful functions, and can process images efficiently and quickly (*Hou Z.F. et al., 2022; Zhang, X.W. et al., 2022*).

The shooting object distance is 80 cm (that is, the height of the camera from the ground), and keep the camera vertically downward, the image size is 1280 pixels × 960 pixels, image format is. jpg; Get high-quality images.

The upper computer collects, processes, identifies and displays the film image once through the camera to obtain real-time film samples, so as to realize online monitoring of film laying quality. The image acquisition system is shown in Figure 1.

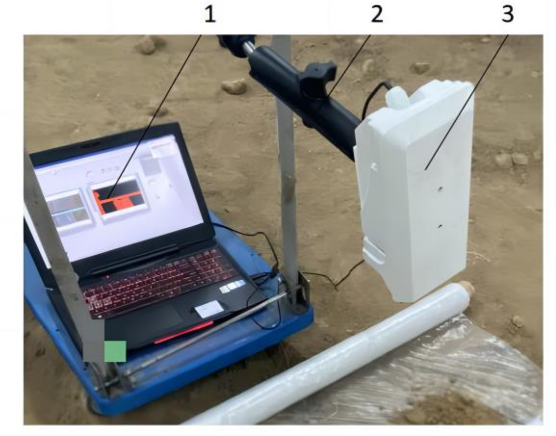

Fig. 1 - Image acquisition system

1. Upper computer; 2. Bracket; 3. HD network camera

Image data acquisition and processing

- **Image data acquisition**

The experimental area of this study is located in the cotton planting area of Tiemenguan City, Xinjiang, China. It is covered with plastic film to sow cotton all year round. The cotton variety is Xinluzao 78. The image acquisition time was April 20, 2022, as shown in Figure 2. The camera was connected with the host computer through USB interface, and the image acquisition system described in this paper was used to collect the film image in real time. The corresponding physical size of the ground was 60 cm×45 cm, a total of 50 near-ground original images of the sampling area were taken. The software interface is shown in Fig. 3.

(a) Test area scenario *(b) Sampling area image*

Fig. 2 - Schematic diagram of study area

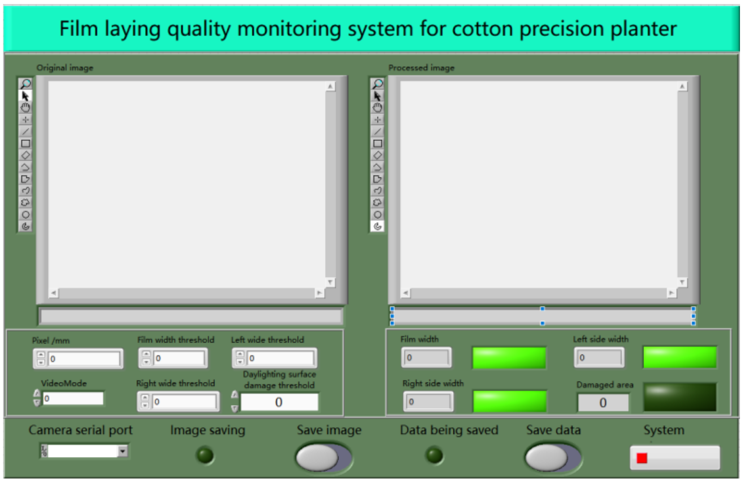

Fig. 3 - Software diagram

Figure 4 shows the collected film image samples, mainly including film and soil. This paper mainly realizes the recognition of the above two components, and constructs a quantitative model to judge the film laying quality of cotton precision planter.

Fig. 4 - Physical picture of plastic film sample

- **Image recognition process**

The image system collects the film image of the mechanized film laying process. Because the surface of the residual film is attached with soil, soil reflection and other phenomena, it is necessary to accurately identify the film and the main components of soil from the complex image. The image collected in this study is RGB image, and the RGB components of the original image are obtained, and then the color is converted into gray image using color extraction function; It uses the LOOKup Table function to transform its gray level and filter it through the FFT filter function. Then it is binarized and advanced morphological filtering. Basic morphology is used to obtain the recognition results of each component in the film image. The image recognition process is shown in Figure 5.

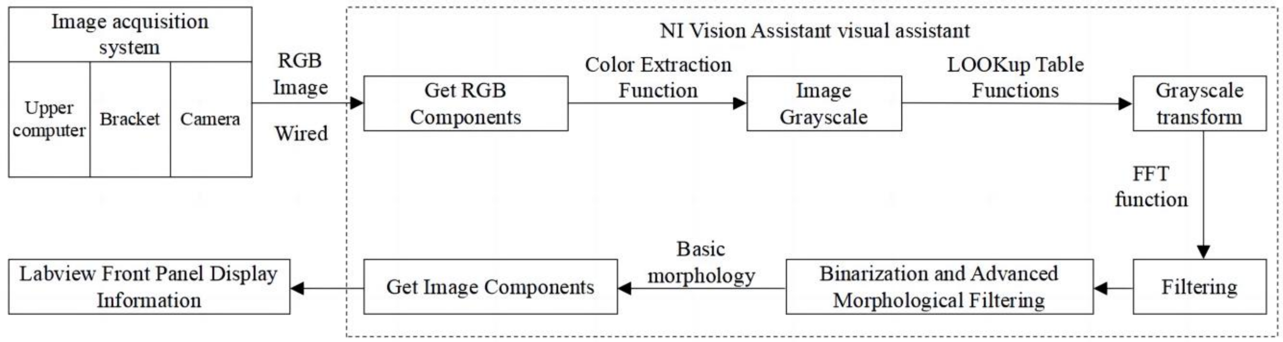

Fig. 5 - Flow chart of image recognition

- **Image preprocessing**

The effect of image preprocessing directly affects the recognition error of subsequent film sample images. In order to facilitate feature extraction and improve recognition accuracy, it is necessary to carry out color plane extraction, filtering, threshold segmentation and morphological analysis on image samples.

(1) Color plane extraction

Since the background of the film sample image is gray soil, the debugging shows that extracting the red plane can better highlight the film contour and eliminate background interference. First, the color image is converted into a grayscale image through the color extraction function, and then the Lookup Table function is used for grayscale transformation.

In this paper, the commonly used color feature RGB is selected in image processing, and the color moments in the color feature are statistically analyzed to achieve effective classification of the film sample image. The color distribution information is mainly concentrated in the first moment (Mean), second moment (Variance) and third moment (Skewness). The first order moment uses the first order origin moment (mean value) to reflect the overall shading procedure of the image. The larger the value, the brighter the image; The second order moment uses the square root of the second order center distance (standard deviation) to reflect the color distribution range of the image. The larger the value, the wider the color distribution range.

The cubic root (deviation) of the third-order center distance is adopted for the third-order moment to reflect the symmetry of image color distribution (*Chen M. et al., 2021*).

Then the calculation formula of the first moment, second moment and third moment is:

$$\begin{cases} \delta_a = \dfrac{1}{B}\sum_{b=1}^{B} P_{ab} \\ \mu_a = \sqrt{\left(\dfrac{1}{B}\sum_{b=1}^{B}\left(P_{ab}-\delta_a\right)^2\right)} \\ \eta_a = \sqrt[3]{\left(\dfrac{1}{B}\sum_{b=1}^{B}\left(P_{ab}-\delta_a\right)^3\right)} \end{cases} \tag{1}$$

where:

δ_a—the color mean value of the a-th color channel of all pixels;

P_{ab}—the color value of the b- th pixel on the a-th color channel;

μ_a—the standard deviation of the a color channel;

η_a—the color deviation of the a color channel.

Grayscale image is shown in Figure 6.

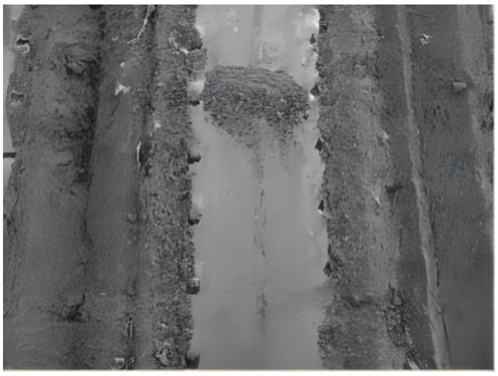

Fig. 6 - Grayscale image

(2) Image filtering

Image filtering has the characteristics of improving image quality, enhancing recognition effect and enriching details. As the surface of the plastic film is attached with soil, soil block, and reflection, it increases the difficulty of treatment. To this end, FFT function and efficient morphological filtering are used first, and details are highlighted. This method can effectively highlight the details of the film, strengthen the high-frequency information such as the contour and edge of the target, and sharpen the image. The filtering effect is shown in Figure 7.

Fig. 7 - Filtered image

(3) Threshold segmentation

The image segmentation is divided into different sub-regions according to the parameters such as image gray level and shape, so as to ensure that the parameters are similar in the same region and show obvious differences between different regions (*Gao L., 2016*). The automatic threshold segmentation method is based on the gray histogram of the image to determine the gray threshold, and has strong applicability.

The minimum uniformity measurement method supported by Ni Vision (LabView built-in visual development kit) (*Jiang L.L. et al., 2019*) is selected (assuming that the image is divided into target A and background B, and the pixel value distribution of the same category should be uniform). The class uniformity can be measured by variance. Then the algorithm steps are as follows:

Given the initial threshold *S*, the pixel values of the image to be segmented are expressed in m (width) and n (height) respectively. Then the calculation formula of gray mean value and intra-class variance corresponding to D_1 and D_2 after segmentation is:

$$\begin{cases} \mu_1 = \dfrac{1}{N_{D_1}} \sum\limits_{(x,y)\in D_1} f(x,y) \\ \mu_2 = \dfrac{1}{N_{D_2}} \sum\limits_{(x,y)\in D_2} f(x,y) \\ \sigma_1^2 = \sum\limits_{(x,y)\in D_1} \left(f(x,y)-\mu_1\right)^2 \\ \sigma_2^2 = \sum\limits_{(x,y)\in D_2} \left(f(x,y)-\mu_2\right)^2 \end{cases} \tag{2}$$

It selects the threshold that meets the condition λ^*, and ensures that the image is divided into D_1 and D_2, and meet the following requirements:

$$\begin{cases} \left[P_1\sigma_1^2 + P_2\sigma_2^2\right]_{\lambda=\lambda^*} = \min\left(P_1\sigma_1^2 + P_2\sigma_2^2\right) \\ P_1 = \dfrac{N_{D_1}}{mn} \\ P_2 = \dfrac{N_{D_2}}{mn} \end{cases} \tag{3}$$

where:

μ_1—the gray mean value corresponding to D_1;

μ_2—the mean gray value corresponding to D_2;

σ_1—the intra-class variance corresponding to D_1;

σ_2—the intra-class variance corresponding to D_2;

$F(x, y)$—the gray level at any point (x, y) on the original image;

N_{D1}—the number of pixels in category 1;

N_{D2}—the number of pixels in category 2;

P_1—the distribution probability in the Class 1 image;

P_2—the distribution probability in the class 2 image.

The film image processing after threshold segmentation is shown in Figure 8.

Fig. 8 - Threshold segmentation image

(4) Morphological analysis

After thresholding, the binary image is processed by mathematical morphology denoising method, and then eroded and expanded. It also performs an open operation (local modification) to remove unnecessary information (noise, overlapping areas, etc.) from the image.

At the same time, it guarantees not to destroy the details of the image edge contour, and improves the accuracy of the algorithm (*Tai H.J., 2019; Kang S., et al., 2021*). Then the gray-level morphology processing formula is as follows:

$$\begin{cases}(f\Theta b)(x,y)=\min\limits_{(s,t)\in bN}\{f(x+s,y+t)-b_N(s,t)\}\\ [f\oplus b](x,y)=\min\limits_{(s,t)\in bN}\{f(x-s,y-t)+b_N(s,t)\}\\ f\circ b=(f\Theta b)\oplus b\end{cases} \tag{4}$$

where:

$(f\Theta b)(x,y)$—gray-level morphological corrosion treatment;

f—the original image correlation matrix;

Θ—consistent with corrosion operation;

min—the minimum value operation symbol;

b_N—the structure range element;

（s，t）—the coordinate element;

$(f\oplus b)(x,y)$—gray-level morphological expansion processing;

$f\circ b$—an open operation processing of gray-level morphology;

$\circ$—an open operation symbol;

$\oplus$—the expansion operation compliance;

b—a non-flat structural element.

The film image processing after morphological analysis is shown in Figure 9. It uses the particle analysis function of NI Vision Assistant to obtain the sample coordinate value. It obtains the image data such as the width of the lighting surface of the plastic film, the length of the side or seam of the mechanical damaged part, and the width of the soil covering on the film side through calculation.

Fig. 9 - Morphological analysis image

Performance test design of monitoring system

With reference to the national machinery industry standard JB/T 7732-2006 "Film Planter" (*National Agricultural Machinery Standardization Technical Committee, 2007*) and the national agricultural industry standard GB/T5262-2008 "Operation quality of film planter" (*National Agricultural Machinery Standardization Technical Committee, 2009*), the evaluation index of the film laying quality of cotton precision planter is determined. On the measured plot, five survey areas are randomly and equidistant along the diagonal, with each survey area having a width of 1 working width and a length of 10 m.

Take 5 measuring points at random in each measuring area and measure the width of the lighting surface (within the range of (B-300 mm) to (B-150 mm)), which is qualified (B is the width of the film), the side length or seam length of all mechanical damaged parts of the film on the lighting surface in each measuring area, and the width of the soil covering on the film side (between 50 and 100 mm, which is qualified).

Then the calculation formula of the qualified rate of the width of the lighting surface, the mechanical damage degree of the lighting surface, and the qualified rate of the width of the covering soil at the edge of the film is as follows (*Feng W.H., 2012*):

$$\begin{cases} S_a = \dfrac{N_1}{N_2} \times 100\% \\ Sc = \dfrac{1000 \sum_{i=1}^{n} L_i}{LB} \\ S_d = \dfrac{N_d}{N_o} \times 100\% \end{cases} \quad (5)$$

where:

S_a—the qualified rate of daylighting surface width, %;

N_1—the number of qualified points of daylight surface width;

N_2—the total number of points measured for the width of the daylighting surface;

S_c—the mechanical damage degree of the daylighting surface, mm/m²;

L_i—the side length or seam length of the ith mechanical damaged part in the survey area, mm;

L—the length of the survey area, m;

B—the average value of the film width of the mining surface in the survey area, mm;

S_d—the qualified rate of the width of soil covering on the membrane side, %;

N_d—the number of qualified points for the width of soil covering on the membrane side;

N_o—the total number of measuring points.

The qualified rate of the width of the daylight surface, the mechanical damage degree of the daylight surface, and the qualified rate of the width of the covering soil beside the film calculated by formula (5) are compared with the preset theoretical values to determine the quality of the film. If the monitoring value is greater than the threshold, the alarm will be given, and vice versa, it will work normally.

In order to verify the accuracy of the monitoring system, a bench test bench was built in the State Key Laboratory of Soil and Plant Machinery System Technology of the Chinese Academy of Agricultural Mechanization. The test was carried out in July 2022, and the accuracy monitoring test of the width of the daylighting surface, the length of the side or seam of the mechanical damaged part, and the width of the film side covering soil were carried out respectively. The polyethylene transparent agricultural film with a film thickness of 0.005 mm was selected as the test sample, without adhesion and damage. The test device includes bench, trolley, monitoring system, tape measure, etc. The test bench is shown in Figure 10.

Fig. 10 - Test bench

- **Daylighting surface width monitoring test**

The purpose of the test was to evaluate the accuracy of the image acquisition system in the monitoring system in monitoring the width of the daylight face (that was, the accuracy of the monitoring of the qualified points of the width of the daylight face, and then calculate the qualified rate of the width of the daylight face).

In the test, the lighting surface width of 130, 170, 210, 250 and 290 mm was set respectively. Start the system, open the data and image saving button, and move forward 5 m.

Select 3 time points randomly from the monitoring test results of the width of each daylighting surface, and call up the images and data corresponding to each time point. Record the actual value and monitoring value in the test table, and calculate the monitoring error of the width of the daylighting surface.

- **Monitoring test for side length or seam length of mechanical damaged parts**

In order to evaluate the accuracy of the monitoring of the side length or seam length of the mechanical damaged part of the system (that was, the accuracy of the monitoring of the mechanical damage degree of the daylighting surface), the artificial damage of the plastic film in the test was set as 15, 20, 25, 30 and 35 mm for the side length or seam length of the mechanical damaged part, and the repeatability test was conducted for 3 times. The monitoring accuracy was calculated by comparing the side length or seam length of the mechanical damaged part with the actual value, and the average value of three tests was taken as the monitoring test result of the side length or seam length of the mechanical damaged part.

- **Monitoring test on the width of soil covering at the edge of the membrane**

In order to further evaluate the accuracy of the system's monitoring of the width of soil covering at the edge of the membrane (that was, the number of qualified points of the width of soil covering at the edge of the membrane, and then calculate the qualified rate of the width of soil covering at the edge of the membrane), the width of soil covering at the edge of the membrane was set as 130, 160, 190, 220, and 250 mm respectively in the test. Start the system, open the data and image saving button, and move forward 5 m. In this test, three time points were randomly selected from the monitoring test results of the width of the soil covering around the membrane, and the corresponding images and data of each time point were retrieved. The actual values and monitoring values were recorded in the test table, the monitoring accuracy of the width of the soil covering around the membrane was calculated, and the average value of three tests was taken as the monitoring test results of the width of the soil covering around the membrane.

RESULTS AND ANALYSIS

The monitoring test results of different daylighting surface widths were shown in Table 1. The test showed that the monitoring range of daylighting width was 94.12%~97.60%, and the average monitoring accuracy was 95.99%. The side length or seam length monitoring test results of different mechanical damaged parts were shown in Table 2. The results showed that the monitoring range of side length or seam length of mechanical damaged parts was 85.71%~93.33%, and the average monitoring accuracy was 88.74%. The results of the monitoring test on the width of soil covering at different membrane edges were shown in Table 3. The results showed that the monitoring range of the width of the covering soil beside the membrane was 95.00%~96.82%, and the average monitoring accuracy was 95.61%.

Table 1

Test results of daylighting width monitoring

Actual daylighting surface width/mm	Monitoring daylighting surface width/mm	Monitoring accuracy/%	Average monitoring accuracy/%
130	124	95.38	95.99
170	160	94.12	
210	217	96.67	
250	244	97.60	
290	301	96.20	

Table 2

Monitoring test results of side length or seam length of mechanical damaged parts

Side length or seam length of the actual mechanical damage part/mm	Monitor the side length or seam length of mechanical damaged parts/mm	Monitoring accuracy/%	Average monitoring accuracy/%
15	13	86.67	88.74
20	22	90.00	
25	28	88.00	
30	28	93.33	
35	40	85.71	

Table 3

Results of monitoring test on the width of soil covering around the membrane

Actual width of soil covering at the membrane edge / mm	Monitoring the width of soil covering at the edge of the	Monitoring accuracy/%	Average monitoring accuracy / %
130	136	95.38	95.61
160	152	95.00	
190	181	95.26	
220	227	96.82	
250	261	95.60	

The average monitoring accuracy of the width of the daylighting surface and the width of the film edge covering soil was more than 95%, and the average monitoring accuracy of the edge length or the length of the seam at the damaged part of the machinery was more than 88%. The analysis of its error mainly includes two aspects: The first is that due to the influence of natural light intensity, the daylighting surface reflects too brightly, and the morphological analysis has not completely realized identification; Second, in image segmentation, some areas are identified as soil or impurities. After the segmentation error is accumulated into image recognition, the average recognition rate is reduced accordingly. However, the monitoring accuracy of the width of the daylighting surface, the width of the film edge covering soil, and the edge length or the length of the seam at the damaged part of the machine meet the requirements of the monitoring system. The above results show that the quality monitoring system of film laying of cotton precision planter can accurately judge the width of daylight surface, the width of film edge covering soil, and the side length or seam length of mechanical damaged part, which can be used for evaluation and reference of film laying quality.

CONCLUSIONS

This paper designs a kind of film laying quality monitoring system suitable for cotton precision planter, puts forward an advanced morphological filtering method to realize film laying image identification, and tests the monitoring performance of the monitoring system on the width of daylight surface, the edge length or seam length of mechanically damaged parts and the accuracy of film edge covering width.

(1) A high-definition network camera with clear image and strong adaptability is adopted and a film laying quality monitoring system is designed based on LabView software graphic programming. The system uses the Vision Assistant visual assistant to quickly collect, process, identify and display plastic film images to obtain real-time plastic film samples. It realizes the monitoring of parameters such as the width of the daylighting surface, the side length or the length of the seam at the damaged part of the machine, and the width of the film edge covering soil. It also has alarm and storage functions of data such as alarm information and data monitoring information, and can accurately detect the quality of cotton film laying in real time.

(2) The software system uses a color extraction function to convert colors to grayscale images. It uses the LOOKup Table function to perform grayscale transformation and FFT filter function to binarize it and filter it with advanced morphology. It then uses the basic morphology to obtain the recognition results of each component in the plastic film image. The system solves the problems of difficulty in recognizing the similarity between the plastic film and the background interferer (soil, etc.), and accurately identifies the main components of the plastic film and the soil.

(3) The bench test of the film laying quality monitoring system of cotton precision planter showed that the average monitoring accuracy of the width of the daylighting surface and the width of the film edge covering soil was more than 95%, and the average monitoring accuracy of the edge length or the length of the seam at the damaged part of the machinery was more than 88%. The system works stably and reliably and meets the requirement of quality monitoring of cotton precision burrowing film laying.

Further field tests are carried out to further verify the performance and reliability of the system monitoring, and other programming languages are considered to be introduced, and the development characteristics of other high-level programming languages are taken into account in LabView. This can fully measure analysis and processing, enrich the functional modules, improve the accuracy and adaptability of the algorithm, and enhance the monitoring performance and image data processing capabilities of the system.

This will collect more diversified data to enhance the robustness and adaptability of the model, ensure more stability, reduce monitoring accuracy errors, and improve the environmental adaptability and operational reliability of the system. In the future, high-precision Beidou positioning technology and mobile Internet technology can be combined to form field film laying quantity maps, operation quality status maps and variable film filling prescription maps. This provides support for improving the film laying quality of cotton precision planters and automatically sets film laying parameters, which makes the system functions more in line with actual production conditions and adapts to different operating scenarios.

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