Adaptive target spray system based on machine vision for plant protection UAV

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Abstract: Aiming at solving drawbacks of traditional spraying systems such as uniform spraying mode which is prone to waste of chemical pesticides and cannot be mounted on UAV, this paper designed a machine vision based system to identify crop coverage for target spraying by UAV. This research built a hardware device of the system using Raspberry Pie as the main controller, and then analyzed the grayscale processing effect of the ultra-green method, ultra-green and Ultra-red method, standard deviation index method in sunny and cloudy days. The result is that the Ultra-green and Ultra-red method has a better grayscale effect. Therefore, a spraying decision model based on rice canopy coverage calculation was constructed in this research. According to the rice canopy coverage, the system adjusts the spray nozzles to full, half, and no-spray states. The rice canopy identification model is evaluated in this paper based on four indicators: relative error of coverage, grayscale time, segmentation time, and total time. The experimental results show that the comprehensive performance of the ultra-green and ultra-red-maximum entropy is excellent, with the performance indexes of 5.43 ms, 11.356 ms, 11.356 ms, 4.409 ms, and 15.765 ms. Water-sensitive paper droplet distribution experiments show that the system can reduce unnecessary agent waste and provide a reference for the application of machine vision technology to target spraying by plant protection UAV.

Keywords: plant protection UAV, target spraying, raspberry pie, rice canopy coverage, threshold segmentation
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1 Introduction

With the advancement of agricultural modernization, Chinese agriculture is transitioning to green, stable and sustainable development[1]. Now, excessive use of pesticides has threatened human health, brought about related problems such as ecological environment damage, food safety, etc. At present, China is vigorously promoting plant protection equipment, and provide professional technical guidance to improve the efficiency of pest control and the use of pesticides, not only to ensure the quality of agricultural products but also to solve environmental pollution and other issues[2]. In recent years, China's plant protection UAV equipment has developed rapidly, whether it is in the amount of equipment or the actual operating area is at the forefront of the world. In September 2019, DJI Agriculture announced that its operating area in China will exceed 130,000 square kilometers in 2019[3]. The use of plant protection UAV aerial spraying can provide more accurate and efficient spraying technology, and target spraying is an effective method for precise spraying of crops[4]. Giles D K and others have developed a precision application system based on machine vision, which can identify the crop width through the machine vision guidance system and automatically adjust the nozzle rotation to match the width of the target plant. This reduced spray rate by 66 to 80 percent and increased spray deposition efficiency on target plants by 2.5 to 3.7 times. However, it cannot adjust the application rate according to crop coverage[5]. Zhou W combined machine vision and target spray technology to design a variable spray system for the target. The system uses a camera to collect images in real time and send them to the processor for image processing. According to the processing results, it determines whether there are crops and the size of the crop area to determine whether to spray and the size of the spray flow. However, the variable spray for the target is realized without considering its atomization characteristics[6].

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Wang LH and others designed a precision spray control system for UAV, which uses support vector machines to process and identify empty blocks of farmland images captured by drones. The test results show that compared with the system without image recognition, the system has a significant reduction effect. However, the nozzles are only open and closed, and the spray state is not complete[7]. Lei T and others developed a system to accurately measure the density of weeds, the size of weed branches, and the size of weeds and achieve the target application of pesticides through machine vision. The system can quickly identify weeds, crops, and soil areas, to effectively carry out target applications[8]. Miranda-Fuentes and others designed a wind-driven targeting sprayer. The sprayer uses multiple ultrasonic sensors to detect whether there is an olive tree canopy at different heights and then controls the opening and closing of the corresponding nozzles to spray the target. This sprayer helps to reduce the pesticide dosage used in the olive canopy, but the above two sprayers are not suitable for spraying on UAV[9].

Most of the current variable and target spray systems are more spray equipment applied to the ground. There are few systems suitable for plant protection UAVs, and problems such as the inability to apply pesticides basis on the coverage of crops in the operating area. According to the development direction and actual demand for modern agriculture in china, this research designed an adaptive target spray system based on machine vision for plant protection UAV. Through the camera mounted on the UAV cloud platform to collect the field image during the operation, the corresponding spray nozzle spray state changes after the crop coverage is calculated, to achieve variable spraying of the target to improve the efficiency of pesticide use.

2 Materials and methods

2.1 Design of target spray system for UAV

This system mounts cameras, flow sensors, and microcontrollers on the UAV, the realization method is that the system collects the field image through the camera, and then the controller calculates the crop coverage after performing operations such as grayscale and threshold segmentation on the image. According to the coverage of crops, the corresponding spray state of the nozzle is determined, and the PWM signal of the corresponding duty ratio is output to the solenoid valve to control the spray flow. This system selects Raspberry Pi as the main controller, which is a microprocessor-based on the Linux system, with 1.4 GHz 64-bit 4-core CPU, wireless network card, and Bluetooth 4.2. It has the advantages of small size and good performance. The camera is fixedly connected to the plant protection UAV using a pan-tilt, responsible for collecting image information of field crops, and is connected to the main control through the CSI interface. The main controller controls the micro-diaphragm pump and the spray head to transport the liquid medicine from the medicine box to the spray head for atomization and spraying. The physical diagram of the system is shown in Figure 1.

The specific working process of the system is as follows. The system collects crop images through the camera mounted on the UAV, calculates the crop coverage information after processing by the CPU, makes the corresponding spray decision, and transmits it to the diaphragm pump to achieve the target spray. The flow sensor detects the spray flow in real-time to achieve the purpose of precise application. The control process mainly includes image acquisition and processing, and centrifugal nozzle control of the solenoid valve.

1. Power 2. Wind pressure transducer 3. Microcontroller 4. Sprinkler 5. Pesticide box 6. Solenoids valve 7. Micro diaphragm pump 8. Camera 9. Pan-tilt 10. Flow sensor

Figure 1 Physical map of the system

2.2 Image recognition model of rice canopy

The rice canopy image collection site is the teaching and scientific research base of South China Agricultural University. During the operation of plant protection UAV, the rice canopy images were captured through the camera. The shooting was performed under sunny and poor cloudy conditions with good lighting conditions. The camera is perpendicular to the ground, the height from the ground is 2 m, the image resolution is 320×240, and 50 images are collected in each of the two weather conditions.

After the image is collected, a set of recognition models need to be established for processing. The rice canopy extraction and recognition model needs to undergo image graying and image segmentation. The purpose of image graying is to establish areas with different gray levels in the image, to divide the target and background according to different thresholds[10]. In this paper, the ultra-green method, ultra-green and Ultra-red method, standard deviation index method are used to gray the image. The calculation formula of the ultra-green method is as follows:

$$E=\begin{cases}0 & (G<R, G<B, G<120)\\ 2G-R-B & (\text{other})\end{cases} \tag{1}$$

The calculation formula of the ultra-green and Ultra-red method:

$$E=3G-2.4R-B \tag{2}$$

The calculation formula of the standard deviation index method:

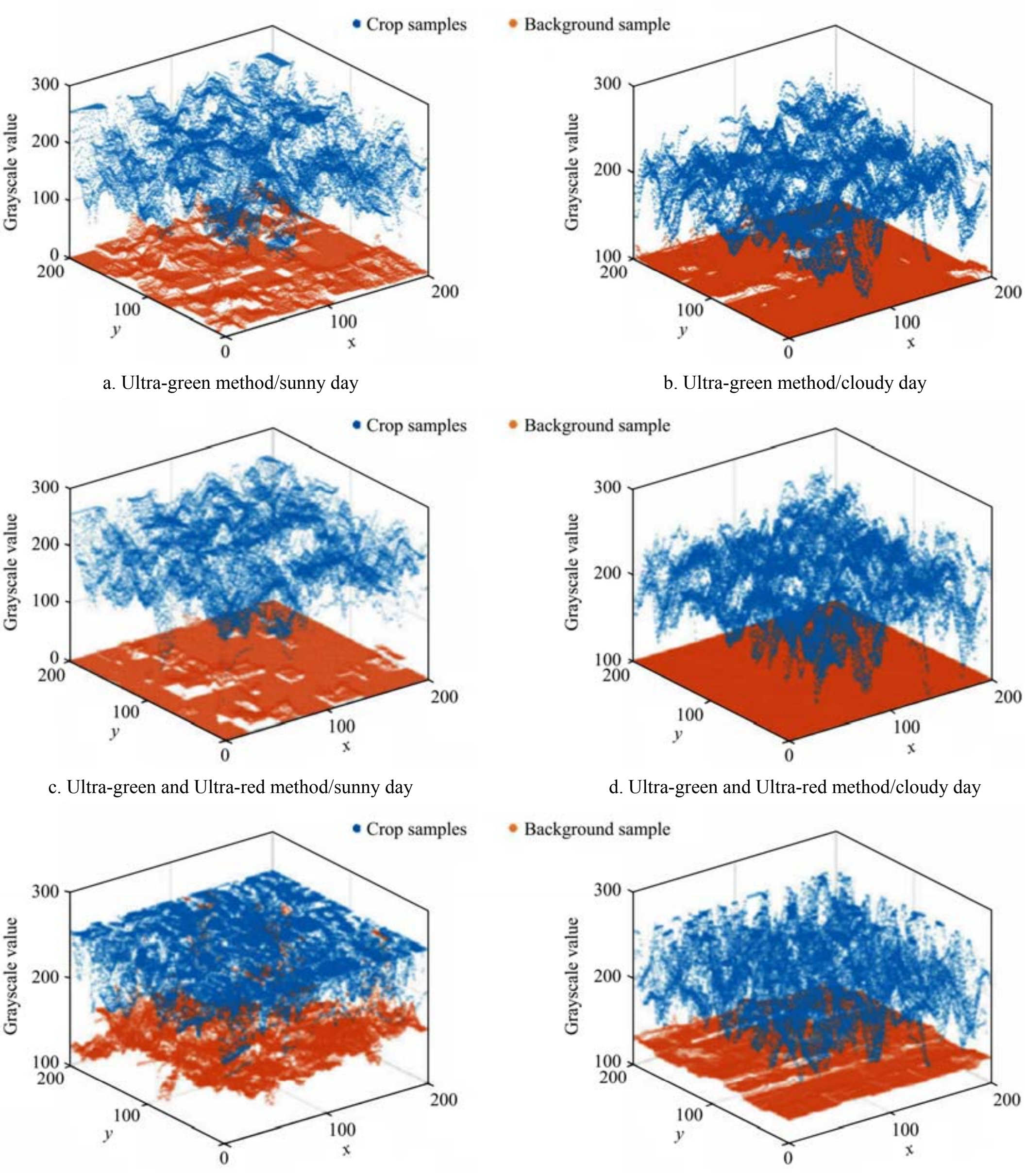
$$E=128\times\left(\frac{G-R}{G+R}+1\right) \tag{3}$$

In the formula (1), (2), (3): E represents the gray value, R, G, and B represent the red, green, and blue components in the corresponding RGB color space[11]. At the same time, in order to cope with different weather to enhance the practicability and accuracy of the system, this article sets sunny and cloudy conditions to ensure that the system can accurately segment the target and the background. In the experiment, to select the RGB channel combination with good grayscale effect, the complete image of the rice canopy collected on sunny and cloudy days was randomly intercepted, and all the images of the crop area and all of the background area were arranged and stitched into 200×200 pixels. The sample image is shown in Figure 2.

Figure 3 shows the distribution of gray values of the target and background after using the ultra-green method, ultra-green and Ultra-red, standard deviation index methods on sunny and cloudy days, respectively.

a. Sunny day-Crop b. Sunny day-Background c. Cloudy-Crop d. Cloudy-Background

Figure 2 Sample images of crops and background under different light conditions



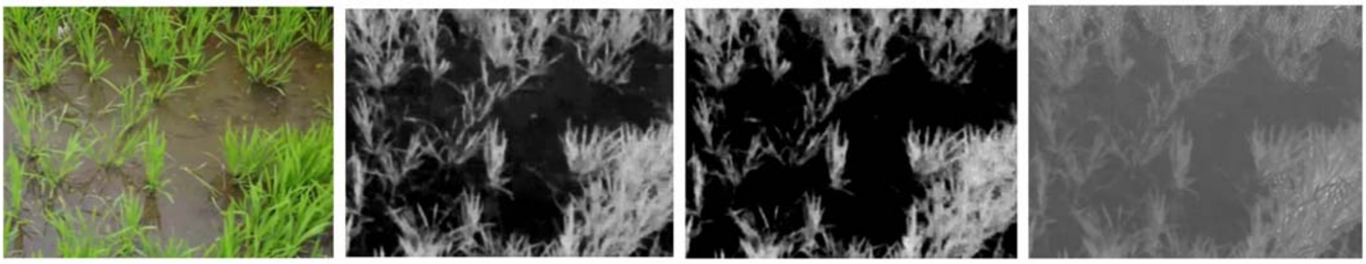
a. Ultra-green method/sunny day b. Ultra-green method/cloudy day

c. Ultra-green and Ultra-red method/sunny day d. Ultra-green and Ultra-red method/cloudy day

e. Standard deviation index method/sunny day f. Standard deviation index method/cloudy day

Figure 3 The distribution map of the gray value of the target and background under different weather for each channel combination

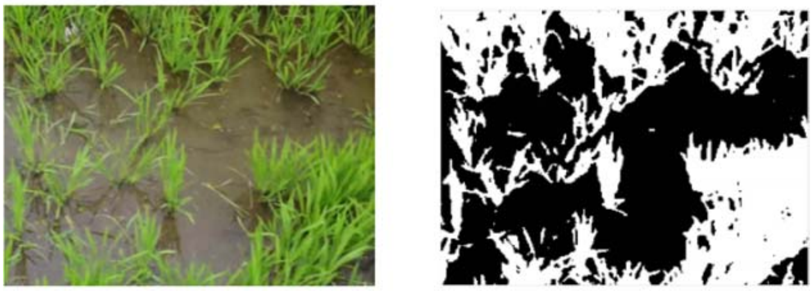
In Figure 3, the blue part represents the crop sample, and the orange part represents the background sample. It can be seen from the figure that except for the overlap between the crop sample and the background sample in the standard deviation index method on a sunny day, the gray value distribution of the crop sample and the background sample of the ultra-green method and the ultra-green and Ultra-red method is quite different. They can separate the crop from the background well, which is helpful for rapid target extraction. At the same time, the influence of light intensity on the experimental results can be found. On sunny days with good light conditions, the gray value is mostly near 200. On cloudy days with slightly poor lighting conditions, the gray value is mostly around 100, which is significantly lower than the result of sunny days. After preliminary experiments, three feasible methods were determined to continue the image processing verification experiment. The results are shown in Figure 4.



a. Color image b. Ultra-green method c. Ultra-green and Ultra-red method d. Standard deviation index method

Figure 4 Color images and grayscale images comparison

After the image is grayscaled, image segmentation is performed to divide the target and background into different sub-regions. At present,traditional image segmentation methods include threshold method[12], edge detection method[13], area method[14,15] and so on. The threshold segmentation method is easy to calculate and has high operating efficiency, and it is widely used in image segmentation[16]. Therefore, this system uses the threshold segmentation method. In this paper, the collected rice canopy images are processed by three commonly used threshold segmentation algorithms: gray average method, OTSU, and maximum entropy method. Adobe Photoshop software was used to manually segment the rice canopy and background in the acquired image[17] as a standard image to evaluate the accuracy of the three algorithms. The division diagram of each method is shown in Figure 5.



a. Original image b. Manual segmentation

c. Ultra-green/gray average d. Ultra-green/OTSU e. Ultra-green/maximum entropy

f. Ultra-green and ultra-red/gray average g. Ultra-green and ultra-red/OTSU h. Ultra-green and ultra-red/maximum entropy

i. Standard deviation index/gray average j. Standard deviation index/OTSU k. Standard deviation index/maximum entropy

Figure 5 Comparison of images segmentation methods

In Figure 5, the white is rice and the black is the ground background. The horizontal comparison shows that under the same graying process, the gray average and OTSU method in the process of image segmentation is relatively complete, but the effect is not as good as the maximum entropy method. By comparing with the standard image of manual segmentation, it can be found that the maximum entropy method is more perfect in processing details.

2.3 Target spraying decision model

The key to the adaptive target spray system is the establishment of the target spray decision model. The calculation method of rice canopy coverage is to use the binary image obtained by image segmentation above to calculate the percentage of rice canopy pixels in the entire image pixels.

The calculation formula is as follows:

$$P_V = \sum_{x=0}^{m}\sum_{y=0}^{n} f(x,y) \tag{4}$$

$$P_{VS} = m \times n \tag{5}$$

$$GC = \frac{P_V}{P_{VS}} \times 100\% \tag{6}$$

where, m, n represents the length and width of the entire image pixel; (x, y) represents the two-dimensional coordinates in the binary image; $f(x, y) = 0$ represents the background area, and $f(x, y) = 1$ represents the crop area. GC represents rice canopy coverage; P_V represents rice canopy area pixel values, and P_{VS} represents pixel values contained in the entire image[18,19].

According to the calculated rice canopy coverage, the nozzle of the UAV applies the corresponding spray treatment. In this paper, three spray strategies of no spray, half spray, and full spray are used. When the rice canopy coverage is less than 10%, it is set to the non-sprayed state, because it is likely that the area is empty or the rice is not developed. When the coverage is 10%~50%, it is set to the half spray state, when the coverage is greater than 50%, it is set to the full spray state. In this way, spraying pesticides according to the actual situation of the target object can largely save the use of pesticides and avoid waste.

In the experiment, the sampling interval of the camera can be determined according to the relationship between the captured image and the actual area, the actual area of the captured image, the camera's FOV (Field Of View), the shooting height, and other parameters.

$$L_a = 2H_a \tan\frac{\theta}{2} \tag{7}$$

$$D_a = \frac{3}{4}L_a \tag{8}$$

$$S_a = L_a D_a \tag{9}$$

In the formula, L_a is the actual length; H_a is the shooting height; θ is the camera FOV; D_a is the actual width, and S_a is the actual area.

The FOV of the camera of this system is 72.4°, and the operating height of the UAV is 2 m. According to formulas (7), (8), and (9), it can be calculated that L_a=2.93m, D_a=2.20 m, S_a= 6.43 m^2, meanwhile the sampling interval of the camera is t_{cy}.

$$t_{cy} = \frac{D_a}{v} - t_{cj} \tag{10}$$

In the formula, t_{cj} represents the time required to collect one frame of the image, and v is the flight speed of the UAV during operation.

Since L_a=2.93 m, considering the size of a single nozzle and the normal operating height of the UAV, the system decided to use two nozzles to be mounted on both ends of the UAV to spray. Therefore, when calculating the coverage, the captured image is divided into two areas according to the central axis to calculate the coverage respectively.

In the actual operation process, the system will have the problem of time delay caused by software and hardware transmission processing. This system needs to design the camera and nozzle installation positions to eliminate this effect. The specific relationship is shown in Figure 6.

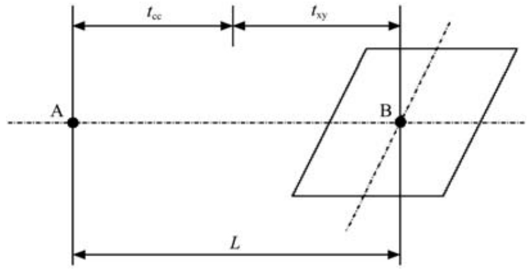


Figure 6 System physical map

Among them, point A is the center of the spray bar, point B is the center of the optical axis of the camera, L is the longitudinal distance between the spray bar and the camera, t_{cc} is the image acquisition and processing time, and t_{xy} is the time from the system to the solenoid valve responding. It can be seen from Figure 6 that the distance between the camera and the spray bar should satisfy formula 11.

$$L \geq v(t_{cc} + t_{xy}) \tag{11}$$

When L satisfies the above conditions, the time delay problem of the system can be solved, and the nozzle can accurately perform different spraying states in the corresponding area.

3 Results and analysis

3.1 Recognition results and analysis of rice canopy images

To finally determine the image recognition algorithm required for the experiment, the 100 images collected were used to combine experiments with the ultra-green method, ultra-green and Ultra-red method, standard deviation index method, and gray average, OTSU, and maximum entropy method. The results obtained are shown in Table 1.

Computer processing can produce errors, so process a photo 10 times and take the average as the final result. From the data in the table, it can be concluded that the relative error of the coverage rate of the ultra-green/maximum entropy method is the smallest, only 5.26%, and the ultra-green and Ultra-red/maximum entropy method is also less than 6%, and the image segmentation effect is good. The relative error of the coverage rate of the ultra-green and Ultra-red/OTSU method is the largest, reaching 33.89%. In terms of total time, the shortest total time of the ultra-green and Ultra-red/OTSU method is 14.276 ms, and the total time of the ultra-green and Ultra-red/maximum entropy method is close to it, which is 15.765 ms. Out of comprehensive considerations, Ultra-green and Ultra-red methods are finally used for grayscale processing, and the maximum entropy method is used as the processing algorithm for threshold segmentation.

Table 1 Performance index table of various image processing algorithms

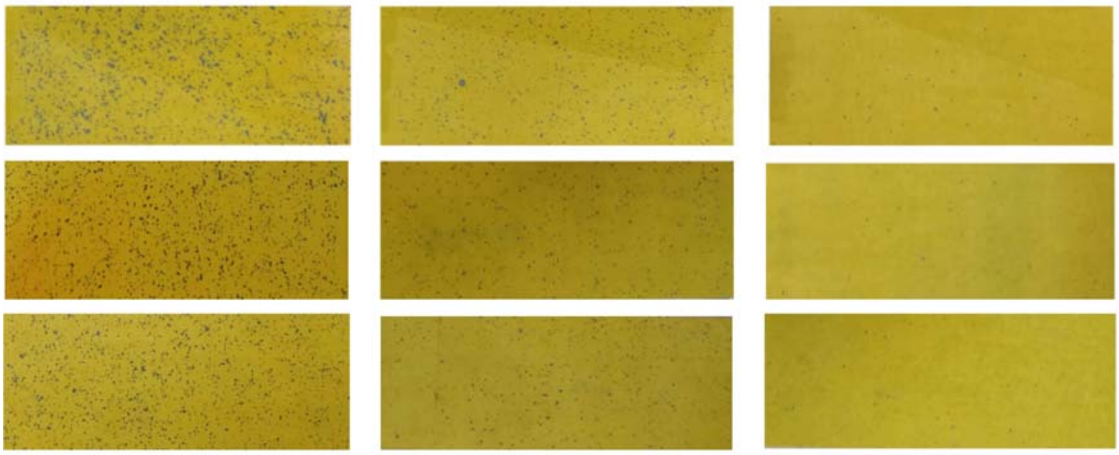
Image processing algorithm	The relative error of c overage/%	Time-consuming for grayscale/ms	Time-consuming for segmentation/ms	Total time /ms
Ultra-green/gray average	17.98	15.321	25.777	41.089
Ultra-green/OTSU	25.93	15.426	7.485	22.911
Ultra-green/maximum entropy	**5.26**	15.266	11.679	26.945
Ultra-green and Ultra-red/gray average	24.26	11.586	16.286	27.872
Ultra-green and Ultra-red/OTSU	33.89	11.985	2.291	**14.276**
Ultra-green and Ultra-red/maximum entropy	5.43	**11.356**	4.409	15.765
Standard deviation index/gray average	13.77	749.543	19.875	769.418
Standard deviation index/OTSU	21.58	740.262	**1.247**	741.509
Standard deviation index/maximum entropy	5.90	738.856	9.998	748.854

3.2 Results and analysis of target spray test

The selected test site is located in the teaching and research base of South China Agricultural University, Tianhe District, Guangzhou City, Guangdong Province. During the experiment, the flying height of the UAV is set to 2 m and the flying speed is 3 m/s. Water-sensitive paper with a specification of 3 cm×8 cm was arranged in the full spray area, half spray area, and no spray area respectively, which was used to detect the deposition amount and distribution uniformity of spray droplets of the UAV nozzle. After the UAV operation was completed, the water-sensitive paper was marked and put into a sealed bag, and three repeated tests were carried out.

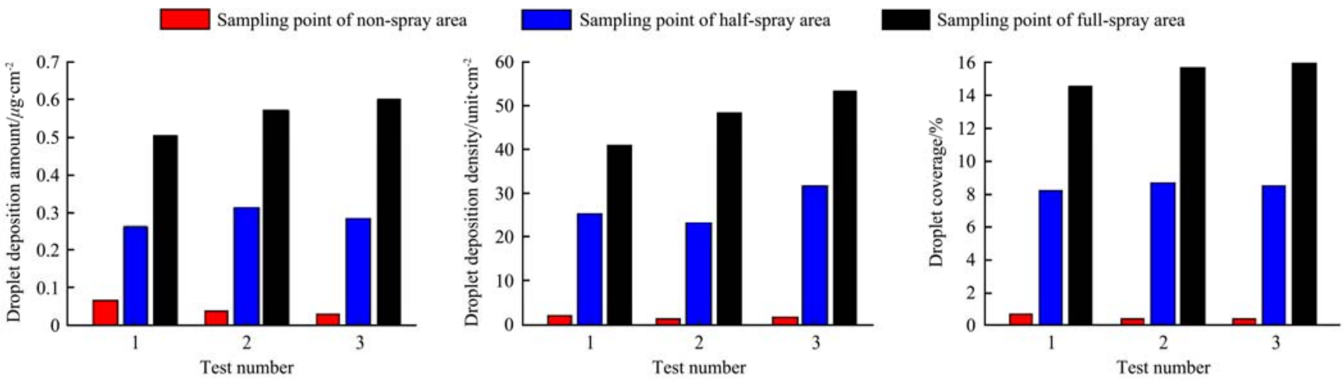
After the test, the water-sensitive paper was taken out of the sealed bag and scanned. The scanning results of the water-sensitive paper at sampling points in the full spray, half spray, and no spray areas are shown in Figure 7.

It can be seen from Figure 7 that with the reduction of rice canopy coverage, the number of fog droplets deposited on the water-sensitive paper is also decreasing, indicating that the UAV's nozzle can adjust the spray state according to the image collected by the camera. The deposition effect of spray droplets on crop objects is an important indicator for evaluating the quality of field operations[20]. To accurately and quantitatively reflect the distribution of the droplets, the software DepositScan is used to calculate the droplet deposition amount, droplet deposition density, and droplet coverage of the water-sensitive paper scan map. The results are shown in Figure 8.



a. Full spray area b. Half spray area c. No spray area

Figure 7 Scanning result of water-sensitive paper



a. Droplet deposition amount b. Droplet deposition density c. Droplet coverage

Figure 8 Calculation results of water-sensitive paper

It can be seen from Figure 8 that the results of the three repeated experiments are similar, and the droplet deposition amount, droplet deposition density, and droplet coverage are all consistent with the three spray states. At the same time, in areas with low rice canopy coverage, the sprinklers should be closed, but the data shows that there is still a small number of droplets deposited in this area. This shows that there is a small amount of drift in the fog.

4 Conclusions

1) By combining technologies such as target spraying and machine vision, this research designed an adaptive target spraying system for plant protection UAV based on machine vision. Moreover, the expected design function is realized, the waste of pesticides is reduced and the environmental pollution caused by overuse is avoided.

2) A rice canopy image recognition model was established. First, three different methods were used to perform image gray-scale processing under different lighting conditions in sunny and cloudy days. After analysis and comparison, the differences in gray value distribution of various methods were obtained. In the image segmentation algorithm, the maximum entropy method is better by comparing various segmented images. Experiments have proved that the relative error of the coverage rate of the three methods: ultra-green/maximum entropy, ultra-green and Ultra-red/maximum entropy, and standard deviation index/maximum entropy is less than 6%. They are at one level. The total time spent on image processing is 14.276 ms and 15.765 ms for the two methods of ultra-green ultra-red/OTSU and Ultra-green ultra-red/maximum entropy respectively. However, factors such as excessive soil moisture can also increase the noise in image segmentation, thereby affecting the expected effect of background segmentation. These influencing factors need to be added in subsequent research.

3) The target spray decision-making model was established, and the rice canopy coverage was calculated through the images collected by the camera mounted on the UAV, to change the working state of the nozzle of the UAV. According to the analysis of the target spray test results, in the full spray, half spray, and non-spray areas, the droplet deposition amount, droplet deposition density, and droplet coverage can be distinguished. It can meet the needs of UAV in the field.

4) The research object of the target spray system in this paper is rice, but rice is still in the seedling stage before the tillering stage. The plant spacing is too large, and the rice canopy has not yet been formed. It is not possible to control spray based on canopy coverage at this stage. Therefore, this system is suitable for rice fields where the plant canopy grows more obviously after the tillering stage. The UAV sprays the target according to the canopy coverage.

5) In the follow-up related research, we should also consider updating multiple processing algorithms and improving the processing performance of the main controller to improve the response speed and accuracy of the entire system. At the same time, field crops other than rice can be considered to increase the application range of the system.

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