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Weed detection using image processing under different illumination for site-specific areas spraying

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ABSTRACT

Large area bold type spraying of chemical herbicide is not only a waste of herbicides and labor, but also leads to environmental pollution and food quality problems. Traditional methods have the problems of high light and sample quality etc requirements. Therefore, accurately identifying weeds and precisely spraying are important strategies for promoting agricultural sustainable development. To avoid the influence of different illumination on images, this paper adopts the color model and then proposes component to gray images; the vertical projection method and the linear scanning method are combined to quickly identify the center line of the crop rows; the classic Weeds Infestation Rate (WIR) is modified to decrease the computational complexity and the improved horizontal scanning method is taken to calculate within cells; finally, Modified Weeds Infestation Rate (MWIR) is used to realize real-time decision through the minimum error ratio of Bayesian decision under normal distribution. The experimental results show that the accuracy of this algorithm is 92.5%, which exceeds the BP algorithm and SVM algorithm.

1. Introduction

China is a developing agriculture country, and agricultural development is closely related to its economic and social development. In the long-term management of agricultural production, weeds are always a strong threat to crops. Weeds hold the features of fast growth rate, larger growth increment, competing water, fertilizer, space with different stages of crops, which are harmful for crops growth (Xu, 2013). In addition, farmland weeding also affects the harvest speed, increases the operating costs and reduces economic benefit (Zhang et al., 2011). In China, farmland weeds are about 1500 kinds, of which there are 38 kinds of swart weeds, 94 kinds of regional weeds and 364 kinds common weeds (Wei et al., 2012). According to the Ministry of Agriculture and Plant Protection Station statistics, the amount of labor used in farmland weeding is up to 20–30 million labor days, farmland weeding accounts for 1/3–1/2 of the total workload of farm employment, and that causes an average of 13.4% of food losses and about 17,500 kiloton per year (Wu, 2010).

At present, China mainly adopts large bold type chemical herbicide spraying which cannot accurately determine the distribution of crops and weeds, therefore, it results in not just low utilization rate of herbicides, but also some serious problems like environmental pollution, chemical pesticide residue, weeds resistance, and ecological and safety of agricultural products. Besides, it goes against the concepts of human health, green environmental protection, and accurate and efficient modern agriculture. In modern precision agriculture research, to accurately identify the distribution of crops and weeds, and to spray on the weeds area only with the aid of vision technology can not only control weeds effectively, guarantee the quality of the crops and yield, but can effectively reduce the effects of chemical herbicide on the ecological environment. Therefore, accurate weeds identification is the obvious developmental trend of "precision agriculture" (Wu, 2010).

In consideration of the overall efficiency and cost, weeds identification mainly adopts computer vision method at home and abroad currently. It includes color-based identification, shape-based identification, texture-based and location-based identification. Li (2014) extracted a variety of distinguishing features of field crops through the ground imaging spectrometer data, and then combined multi-feature for weeds identification through SVM, whose result showed the weeds identification precision was high. What should be mentioned is that the training samples should be consistent, and there are higher requirements for the training samples in this method. Huang et al. (2013) took the three leaf stage, three rows of corn field image as the research objects, through establishment of mapping relation between actual field corn line width and line width images to determine the coverage scope

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0168-1699/

based on identification rate and speed, and they got the weeds identification of 89.2%. However, this method is only applicable to equally spaced line width crops as three leaf stage. Yang and Li (2014)) used the BP neural network to identify weeds, and the weeds identification precision was higher. But the accuracy can be affected by the selection of training samples. Manh et al. (2001) detected the end of leaves, and deformed the model to match the blade. However, this method is only limited to the unobstructed blade edge. Gebhardt and Khbauch (2007) used morphological method to achieve images segmentation and obtain weeds leaf images, then they used the color and texture features for weeds identification. Their weeds identification rate was about 90%. But, there are problems like the complex calculation, slow identification speed, and poor real-time capability in this method. Tellaeche et al. (2011) combined basic suitable image processing techniques to extract cells, and used Support Vector Machines to determine if a cell must to be sprayed. But, this method is only applied to green plant characteristics is apparently.

Many traditional chemical herbicides spraying methods are no longer suited to modern agricultural development. "Precision agriculture" will become the future trend of agricultural development, and weeds identification is an important part of it (Zhao et al., 2003). Based on the studies in China and abroad, this paper aims at the effect of field illumination on images segmentation, converting the *RGB* images to *YCrCb* color model, and adopting the *Cg* component that is unrelated to different illumination for images graying; for the histogram of *Cg* component has double peak properties, this study utilizes global threshold method for images binary; to quickly identify the center line of the crop rows, this study combines the vertical projection method with the linear scanning method; to reduce the correlation and computational complexity between each component, the Weeds Infestation Rate (WIR) is improved to the Modified Weeds Infestation Rate (MWIR), and the improved horizontal scanning method is taken for calculating MWIR within the cells; Finally the minimum error ratio of Bayesian decision under normal distribution is used to realized online variable spraying. Flow chart is shown in Fig. 1.

2. Image acquisition and preprocessing

2.1. Image acquisition

In this paper, the 1300 images were taken in the experimental plot in north campus of Northwest A&F University, May to July, 2013; they were taken in different light conditions (sunny, cloudy), periods and plots; they were collected by manual collection. Also, The camera was fixed on the console. The image size is $4208 * 3120$ and format is *JPEG*. Acquired images are shown in Fig. 2.

2.2. The selection of color space

Color is an important characteristic of the plant identification. Because the images in this paper were under different light conditions, which can be easily affected by many environmental factors, therefore, in order to more accurately identify crops and guarantee the accuracy of identification algorithm, appropriate color feature vector selection is critical and a suitable color space is the prerequisite.

Color space, also known as color model, uses the coordinate system or subspace to describe colors (Meng et al., 2014). At present, the most commonly used color space models are *RGB*, *HSI* and *YCrCb*. For *RGB* color space model, all sorts of colors are gotten by *R* (red), *G* (green), *B* (blue) three color channels transformation and mutual superposition. All colors that humans can perceive can be expressed by color space model (Yang and Zhu, 2010), but the three color channels are highly correlated, which are more sensitive to the changes of lightness (Meng et al., 2014). Because the images of this paper were easily affected by lightness, it could result in information uncertainty of images segmentation and reduce the accuracy of images segmentation precision by using the *RGB* color space model for images processing. *HSI* color space model uses *H* (hue), *S* (saturation) and *I* (intensity) to represent. In different light conditions, *H* component is not obvious and can identify objects in different colors, so it is more suitable for processing images that are sensitive to illumination changes. However, the *H* and *S* color components are nonlinear transformation by *R*, *G*, *B* component, which have singular point, so it can affect images segmentation precision and computational complexity (Lin and Hu, 2012). In *YCrCb* color space model, *Y* represent rightness, *Cr* and *Cr* represent red and blue concentration offset component. In this color space model, the luminance and chrominance are separated, which is more suitable for processing images that are sensitive to illumination changes. Because the farmland images are mainly green component, the *YCrCb* color space model lacks the differences of green signal and light brightness, so this paper adopted the *Cg* component to describe the green crops features (Meng et al., 2014). *Cg* component can be obtained by matrix transformations from *RGB* color space model. Thus, conversion algorithm was simpler and calculation was smaller. The conversion formula is as shown in formula (1) Ghazali et al., 2012.

$$\begin{bmatrix} Y \\ Cg \\ Cr \end{bmatrix} = \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix} + \begin{bmatrix} 65.481 & 128.553 & 24.966 \\ -81.085 & 112 & -30.915 \\ 112 & -93.786 & -18.214 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}. \quad (1)$$

2.3. Image preprocessing

Gray images contain only luminance information, no color information. In order to extract the plant characteristics and process images accurately, color images must be converted to gray images (Liu et al., 2013). Due to the different light conditions of images acquisition, this paper selected the *YCrCb* color space model with the introduction of *Cg* component gray images. Conversion results are as shown in Fig 7(b), (f), (j).

When being converted to gray images, the gray images can be binary to segment crops and soil background. As shown in Fig. 8 (a), (d), (g), the histogram of the images has double peak properties in which it is better to use global threshold (He et al., 2008).

In the process of images acquisition, some factors such as insufficient light, uneven exposure can result in images noise. Meanwhile, there were still many dummy white pixels such as plant shadows, plant residues after binary processing, which would affect the accuracy of WIR. Therefore, removing the noise pixels was necessary. After experimental comparison (Liu et al., 2013), it was found the effect of median filter was remarkable in pulse interference, salt and pepper noise, and Gaussian template for Gaussian noise effect was obvious. So, this paper mainly adopted median filter, supplemented by Gaussian template.

3. Identification of the center line of crop rows

At present, line detection algorithms mainly include Hough transform and perspective method. Hough transform uses the duality of point-line, that is to say, after transforming the line in the original images space coordinate system into the points in the parameter space, and then accumulating and counting all the possible points that falling on boundary line to finally complete the detection task (Duan et al., 2010). By using the global feature of an image, the robustness of the Hough transformation is strong,

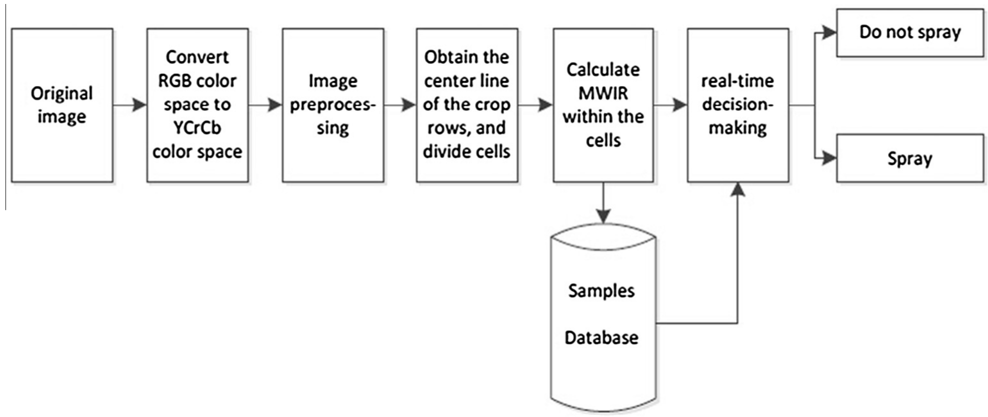
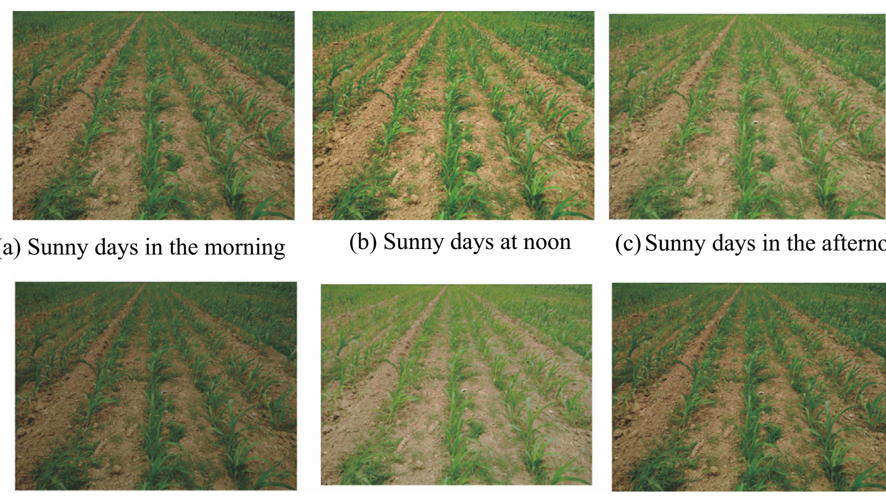


Fig. 1. Bayesian decision-based weeds identification under different illumination.



(a) Sunny days in the morning (b) Sunny days at noon (c) Sunny days in the afternoon

(d) Cloudy days in the morning (e) Cloudy days at noon (f) Cloudy days in the afternoon

Fig. 2. Different times farmland images in sunny days and cloudy days.

but statistical calculation is taken in its parameter space with larger calculation and longer processing time (Yuan et al., 2005). Perspective mainly uses the character of crops in the images plane converge a point to obtain perspective point, which can be the access to the center line of crop rows (Pla et al., 1997). Although this method can be accurately positioned to images that contain incomplete crop rows, when dealing with the edge of the farm images, it cannot accurately calculate the position of the crop rows because the length of the crop line is insufficient (Tellaeche et al., 2008). Aiming at the shortcomings of above line detection algorithms, this paper combined the vertical projection method and linear scanning method, firstly vertical projection method was used to obtain the number and scope of the crop rows, then the image bottom and top pixels were taken as two endpoints of a line, by moving the location of the endpoint to obtain different lines, then selected the line which contains the most white pixels as the center line of crop rows.

3.1. Vertical projection method

Projection is mainly detecting based on projection distribution features in some direction, and the projection direction should be horizontal, vertical, diagonal and so on. It is often uses for binary images segmentation and images analysis.

Provided binary image $bw(i,j)$, the size of image is $W * H$, where, W denote the width of images, H denote the height of images, let $P_x(i)$ denote all the non-zero pixels of the i column in the horizontal projection direction; let $P_y(j)$ denote all the non-zero pixels of the j row in the vertical projection direction. As shown in formula (2) and (3).

$$P_x(i) = \sum_{j=1}^{W} bw(i,j), \quad i = 1,2,\ldots,H \tag{2}$$

$$P_y(j) = \sum_{i=1}^{H} bw(i,j), \quad j = i,2,\ldots,W. \tag{3}$$

Because of the shooting angle and distance in the processing of acquisition images, the crop rows often intersect to the top or outside of the top images, therefore, this method cannot be taken to process images directly (Yuan et al., 2005). Assuming that there is a horizontal rectangle area in the bottom and top images, crop rows and horizontal rectangular area will intersect. Therefore, the distribution of crop rows in the top of images and the bottom of images could be obtained by using vertical projection in horizontal rectangle area. In this paper, firstly $W * 50$ size of horizontal rectangular area were selected in the top and bottom of images respectively. Then vertical projection within the horizontal rectangle area was used to obtain the distribution scope of the crop rows. Horizontal rectangular area and vertical projection result are shown in Fig. 3, where the white pixels present crops; black pixels present soil; the blue line curve is the crop vertical projection graph.

Fig. 3. Crop vertical projection.

3.2. Linear scanning algorithm

Firstly, supposed the size of image is $W * H$. Then, the number of crop rows and the scope of each crop rows were got through vertical projection method, n denoted the number of the crop rows, P_{iTL} denoted the left top boundary of i column of crop rows, P_{iTR} denoted the right top boundary of i column of crop rows, P_{iBL} denoted the left bottom boundary of i column of crop rows, P_{iBR} denoted the right bottom boundary of i column of crop rows.

Linear scanning algorithm flow chart is shown in Fig. 4.

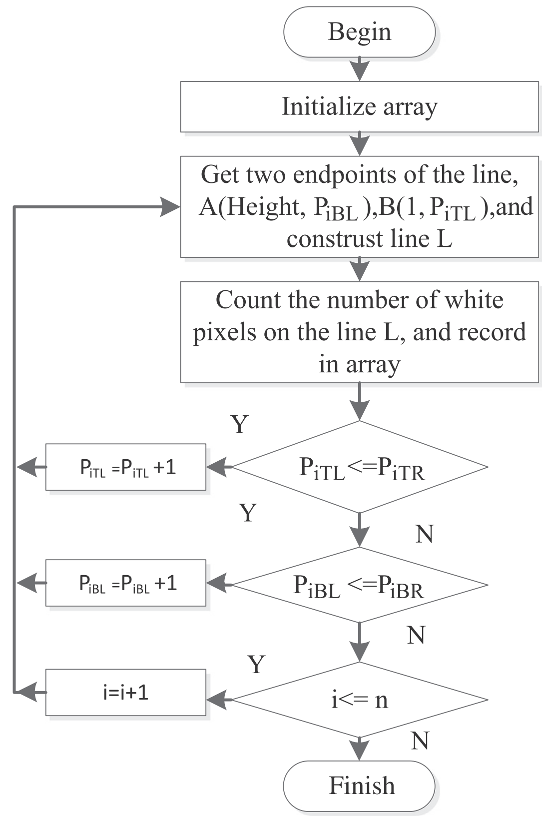


Fig. 4. Linear scanning crop line detection algorithm.

4. Extraction of Weeds Infestation Rate

4.1. Division of grid cells

To further calculate weeds coverage area and crop coverage area within the cells, farmland images should be divided into cells. Vertical line of grid cells can be obtained by Sections 3.1 and 3.2, namely the farmland images can be divided into grid shape by the center line of crop rows (As shown in Fig. 5(b) red[2] lines). Horizontal lines of the grid cells were divided according to the traveling speed of agricultural machinery. The speed of the tractor is about 18 Km/h, namely 5 m/s. The horizontal lines are as shown in formula (4).

$$y = ku \tag{4}$$

where in the farmland, $u = 5m$, $k = 1, 2, \ldots, n$; in images, u was set 340 pixel. According to the references, the value of u did not need to change (Tellaeche et al., 2008). The selection of n is according to the height of the images. In this paper, n is set to 9. When the cells rises, the cells of above images will disappear, therefore, cells in the below picture is the only thing to be dealt with.

4.2. Calculation and modification of the classic Weeds Infestation Rate

Some factors like sowing omitting, jitter and center lined deviation often lead to the heterogeneous spatial distribution of weeds in the farmland. What's more, the irregular distribution of the crops and the similar spectral signature (color) between crops and weeds will make weeds detection be a difficult task. Domestic and foreign scholars had made a lot of research in the parameter of WIR, for instance, Alberto (Tellaeche et al., 2008) used corn farmland as a research object, put forward the classic WIR, which uses a vector $\vec{X}$ to represent had two components; $\vec{X}_1$ is weeds coverage; $\vec{X}_2$ is weeds threat. Formula is as shown in formula (5) and (6).

$$\text{Weeds coverage}: \quad \vec{X}_1 = \frac{C_{iw}}{A_{ic}} \tag{5}$$

$$\text{Weeds threat}: \quad \vec{X}_2 = \frac{C_{iw}}{C_{ic}}\left(1 - \frac{C_{is}}{A_{ic}}\right). \tag{6}$$

For C_{iw} is weeds coverage area of cell, A_{ic} s the full area of cell, C_{ic} is crop coverage area of cell, C_{is} is soil coverage of cell. By formula (5) and (6), correlation between weeds coverage and weeds threat were higher; the weeds threat (WIR) formula involved many parameters, and the parameter calculation was complex. Therefore, this paper modified the formula of weeds threat based on Alberto WIR by removing the parameter A_{ic} and C_{is} in formula (6). The modified component is as shown in formula (7).

$$\text{Weeds threat}: \quad \vec{X}_2 = \frac{C_{iw}}{C_{ic}}. \tag{7}$$

For C_{iw} is weeds coverage area of cell, C_{ic} is crop coverage area of cell. Compared formula (6) and (7), the MWIR (Modified Weeds Infestation Rate) involved less parameters, and calculation was easier, which reduced the correlation between two components.

4.3. Extraction of MWIR

The cells of MWIR can be calculated by the horizontal scanning method after the division of grid cells. As shown in Fig. 6, bottom left of the figure regarded as origin of coordinates $O(0,0)$, i marks row number of cells, j marks column number of cells. Using the cell G_{12} as a example. Obtaining the parameters of formula (5) and (7), such as weeds coverage area, crop coverage area were through improved horizontal scanning method. Improved horizontal scanning method is as follows.

(1) According to Sections 3.1 and 3.2, the center line of the crop rows can be achieved, that is linear a, let linear a as a reference, scan a certain width of the pixel to the right, marks linear b, width according to the experience, the total of pixel marks C_{icl}.

[2] For interpretation of color in Fig. 5, the reader is referred to the web version of this article.

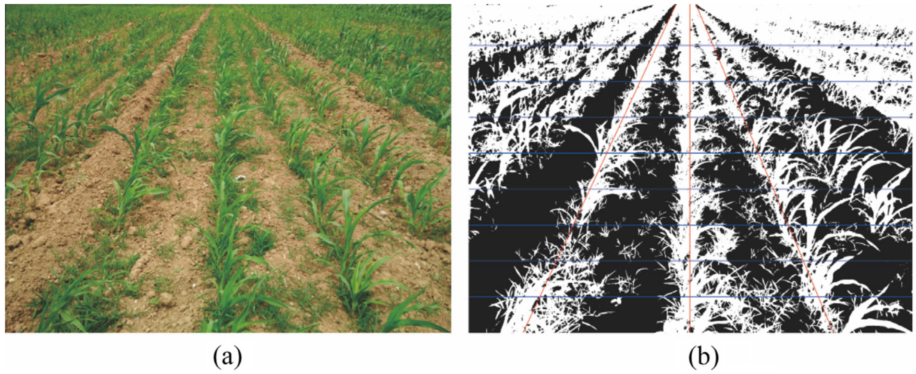


Fig. 5. Cells in the images.

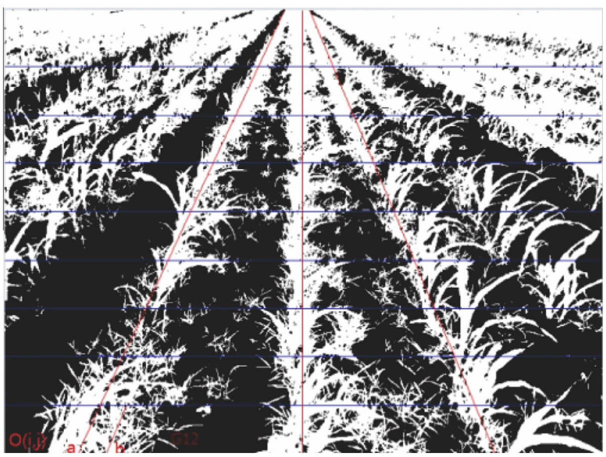


Fig. 6. Algorithm diagram.

(2) Let linear b as a reference, continue scanning to the right, k is a height of cell.
(3) Whether k is greater than or equal to 0, if it to continue, otherwise ending the current image scanning.
(4) If the pixel is white, then the $C_{icl} = C_{icl} + 1$, otherwise $k = k - 1$, switch to (2).

Through the above steps, the crop coverage area of cell of the left part can be got, which marks as C_{icl}. According to the same principle, the crop coverage area of cell of the right part can be got, which marks as C_{icr}. So the crop coverage area of cell is the sum of C_{icl} nd C_{icr}. The total of white pixels of the cell could be got according to the binary images (for Section 2.3 the white pixels present crops and weeds), which marks as S_i. The full area of cell can be got according to Section 4.1, marks as A_{ic}. Therefore, crop coverage area, weeds coverage area and soil coverage area are as shown in formula (8)–(10).

$$\text{Crop coverage area}: \quad C_{ic} = C_{icl} + C_{icr} \tag{8}$$

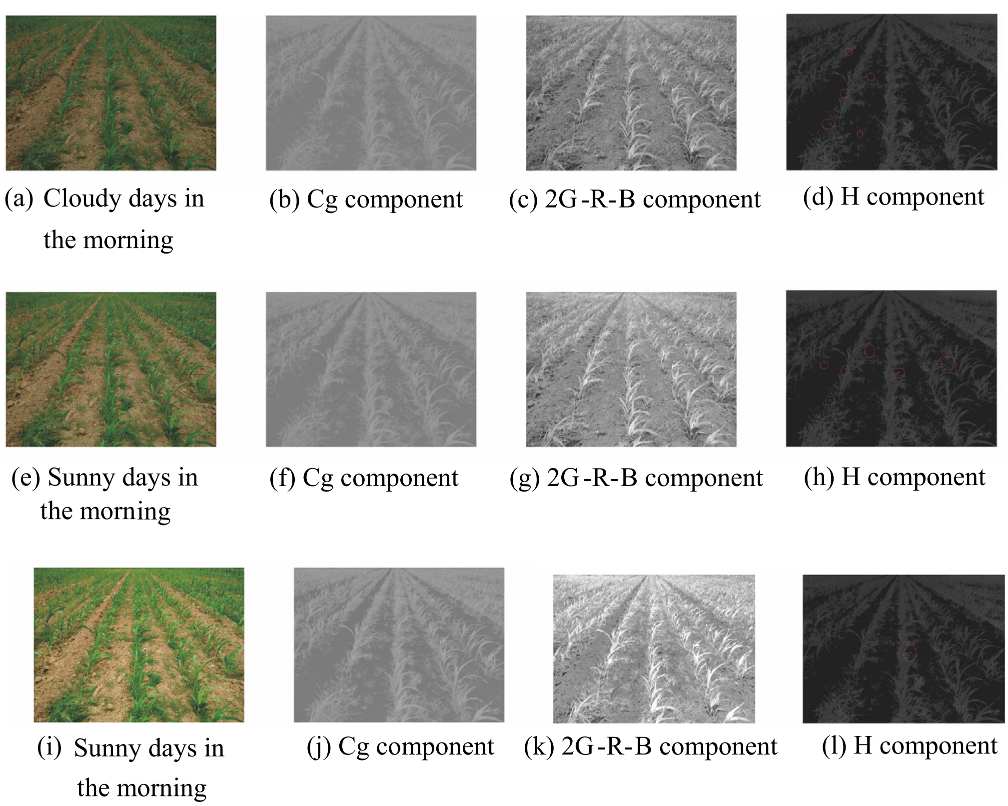


Fig. 7. The component of each color space.

Table 1
The time consumption of each color space.

Time consumption/s	Cg component	$2G-R-B$ component	H component
Cloudy days in the morning	0.175	0.372	1.039
Sunny days in the morning	0.163	0.341	1.084
Sunny days at noon	0.164	0.353	1.052

$$\text{Weeds coverage area}: \quad C_{iw} = S_i - C_{ic} \tag{9}$$

$$\text{Soil coverage area}: \quad C_{is} = A_{ic} - S_i. \tag{10}$$

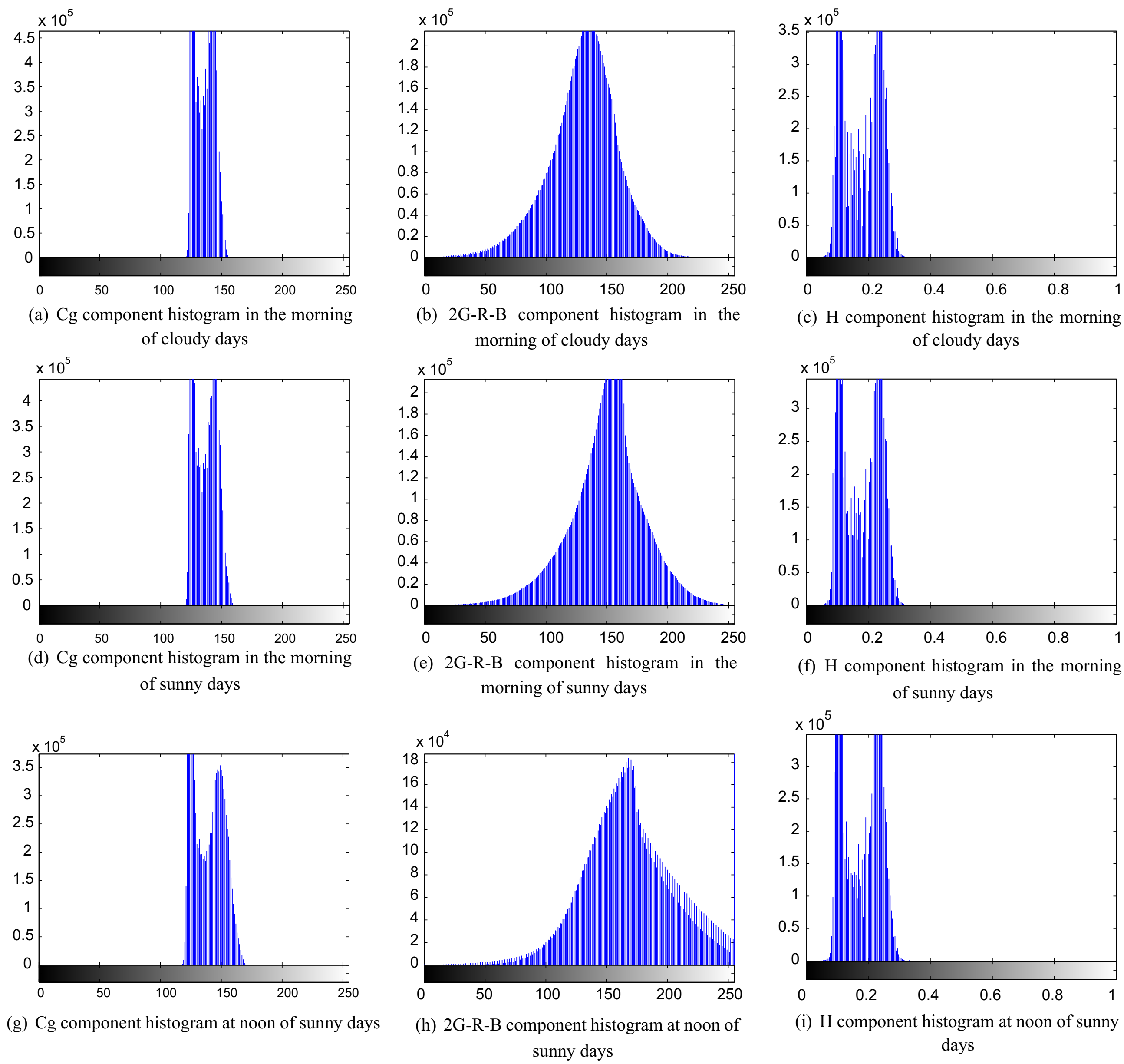
5. Minimum error ratio of bayesian decision under normal distribution

After extracting two components (weeds coverage, weeds threat) within cells which can provide decision support for variable spraying. This paper makes decisions using the minimum error ratio of Bayesian decision under normal distribution.

Our approach works in two stages: (1) performing a training process, termed off-line. The related parameters of normal distribution is calculated by statistic and analysis the data in the MWIR database; (2) performing a decision making process, termed on-line. Decision is made based on the minimum error ratio of Bayesian decision under normal distribution.

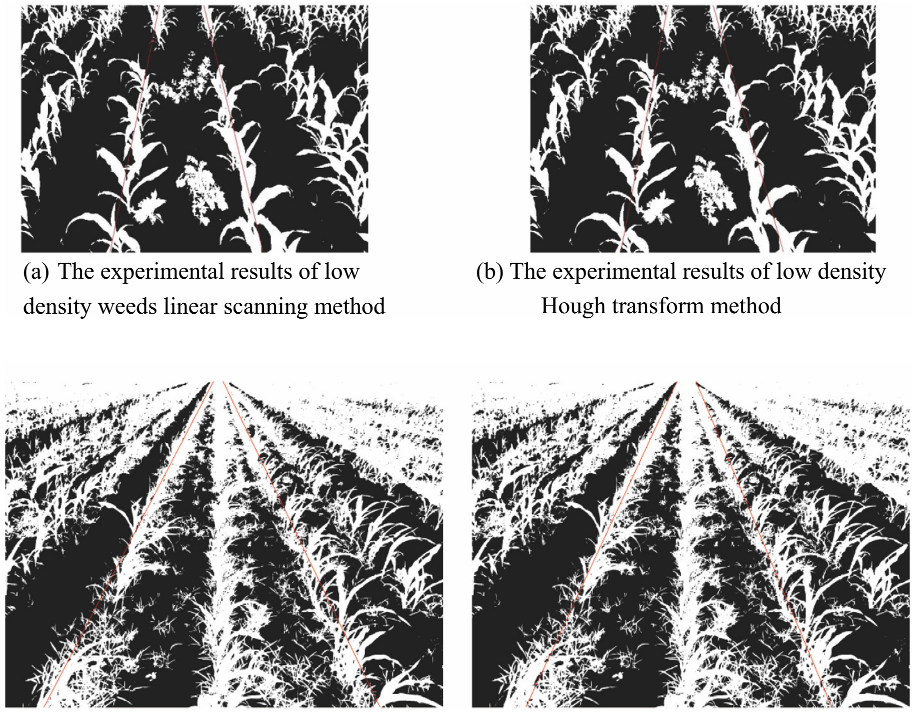
Off-line: 1300 images were segmented, and then were divided to 5800 cells. Crop science postgraduates of agricultural college which had the experience of images analysis classified artificially. The number of need spraying of the cells are 4705 (mark as y), on the contrary, it are 1095 (mark as n). Therefore, the prior probabilities are $P(W_n) = 0.8112$, $P(W_y) = 0.1887$.

Cells that need spraying and not were counted and analyzed, represent set X^y and X^n respectively, that are $X^y = \{x_1^y, x_2^y, \ldots x_{n_y}^y\}$, $X^y = \{x_1^n, x_2^n, \ldots x_{n_n}^n\}$, each of which contains two components $x = (x_{i1}, x_{i2})$, namely MWIR (formula (5) and (7)). The normal



(a) Cg component histogram in the morning of cloudy days
(b) 2G-R-B component histogram in the morning of cloudy days
(c) H component histogram in the morning of cloudy days
(d) Cg component histogram in the morning of sunny days
(e) 2G-R-B component histogram in the morning of sunny days
(f) H component histogram in the morning of sunny days
(g) Cg component histogram at noon of sunny days
(h) 2G-R-B component histogram at noon of sunny days
(i) H component histogram at noon of sunny days

Fig. 8. The histogram of each color space.



(a) The experimental results of low density weeds linear scanning method

(b) The experimental results of low density Hough transform method

(c) The experimental results of high density weeds linear scanning method

(d) weeds linear scanning method Hough transform method

Fig. 9. Experiment result of the identification of the center line of crop rows use different density weeds and different algorithms.

distribution parameters of the set X^y and X^n ere calculated respectively. Where i is y (need spraying) or n (not need spraying).

$$\text{Mean}: \quad u_i = \frac{1}{n_i}\sum_{j=1}^{n_i} x_j^i = \frac{1}{n_i}\left(x_1^i + x_2^i + \ldots + x_{n_i}^i\right) \tag{11}$$

$$\text{Covariance}: \quad \sum_i = \frac{1}{n_i}\sum_{j=1}^{n_i} x_j^i * (x_j^i)^T - u_i * u_i^T \tag{12}$$

$$\sum_i^{-1} \text{ is the transpose of } \sum_i \tag{13}$$

$$\left|\sum_i\right| \text{ is the determinant of } \sum_i. \tag{14}$$

Through the off-line, related parameters of normal distribution can be obtained. Next, on-line variables decision was made through the discriminant function of the minimum error ratio of Bayesian decision under normal distribution.

On-line: The discriminant function of the minimum error ratio of Bayesian decision under normal distribution is as shown in formula (15).

$$g_i(\vec{x}) = -\frac{1}{2}(\vec{x} - \vec{u}_i)^T \sum_i^{-1} (\vec{x} - \vec{u}_i) - \frac{d}{2}\ln 2\pi - \frac{1}{2}\ln\left|\sum_i\right| + \ln P(W_i). \tag{15}$$

Parameters can be calculated in off-line, that is u_i, $\sum_i$, $\sum_i^{-1}$, $|\sum_i|$. Where i is y (need spraying) or n (not need spraying). Finally, the decision was made whether or not to spray was by comparing $g_y(\vec{x})$ and $g_n(\vec{x})$.

6. Experimental results and analysis

6.1. Image gray processing

To detect the accuracy and efficiency, this paper used the algorithm of this paper, $2G - R - B$ in RGB color space model and H component in HSI color space model to gray farmland images in sunny morning sunny noon and cloudy morning. Experimental results are shown in Fig. 7. The algorithm running time is as shown in Table 1.

From Fig. 7, $2G - R - B$ component does not distinguish weeds within rows from soil in farmland images, also, the corresponding histogram has not exist the peaks and troughs. H component can distinguish green crop form soil, however, the figure contains noise

Table 2
Different algorithm of linear parameters.

	Low density weeds this paper's method	Low density weeds Hough transform method	High density weeds this paper's method	High density weeds Hough transform method
k(left)	−3.390	−3.6583	−1.9135	−2.1436
b(left)	950.2	1025.3	3827.95	4224.12
k(right)slope	2.8250	3.0699	2.0656	2.2121
b(right)	−1044.3	−1095.2	4316.2	4843.6
Time consumption/s	0.501	0.553	0.565	0.565

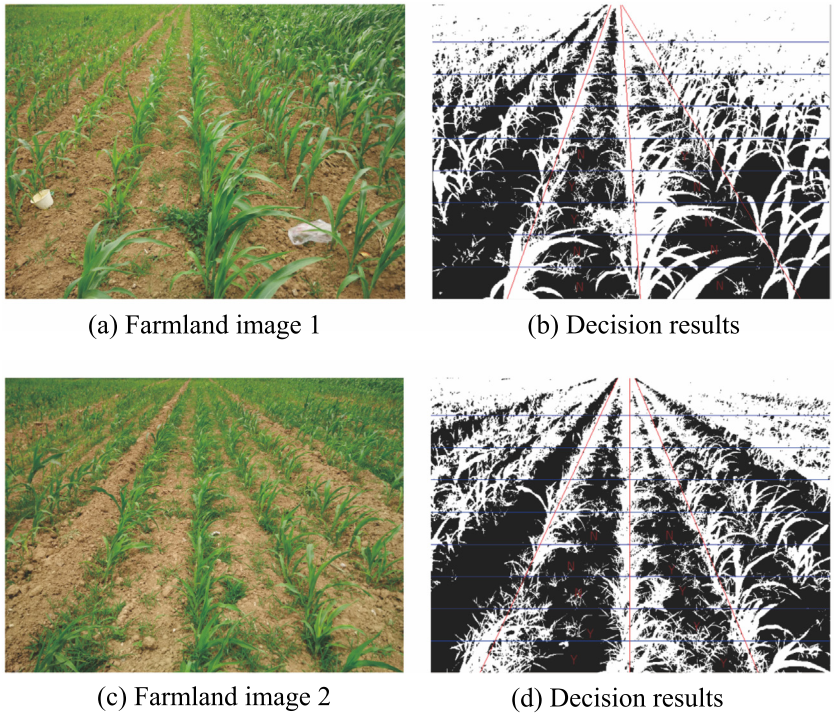


Fig. 10. Farmland images and decision results.

points, as shown in the oval of Fig. 7(d), (h) and (l). Also *RGB* color space transformed into *HSI* color space need a long time. *Cg* component can distinguish green crop form soil, the corresponding histogram does not exist the peaks and troughs, meanwhile the transformation needs less time. Compared to the experimental results of sunny days in the morning, sunny days at noon, cloudy days in the morning, it can be found *Cg* component is not sensitive to different light, and is suitable for using threshold to target extraction. Also, the time efficiency is higher at the same time, so it can be used for green crop identification.

6.2. Identification of the center line of crop rows

To detect the accuracy and efficiency, this paper used the algorithm of this paper and the Hough transform method to identify the center line of crop rows. The experimental subject is inter-tillage stage maize (high density weeds, low density weeds). Tested result of two kinds of algorithm is shown in Fig. 9. The algorithm running time is as shown in Table 2. In Table 2, k denote slope, b denote intercept.

As can be seen from Fig. 9, both the algorithm of this paper and the Hough transform method can correctly identify the center line of the crop rows when there are fewer weeds in corn fields. But when a lot of weeds in corn fields, the accuracy of this paper algorithm decreases, and the Hough transform method can still correctly identify the center line of the crop rows; However, in terms of time consumption, the algorithm of this paper takes less than Hough transformation. When there are a lot of weeds in corn fields, the causes of the low precision is the weeds within crop rows. This paper made the preliminary study in the identification of the center line of crop rows, also needs further study in terms of accuracy to improve the detection accuracy and time efficiency.

6.3. Minimum error ratio of Bayesian decision under normal distribution

This paper used the discriminant function of the minimum error ratio of Bayesian decision under normal distribution to make decision by 100 groups of experimental data. The experimental result is as shown in Fig. 10 and Table 3.

Compared with the decision results and artificial decision results, the correct rate of decision is 92.5%. From the experimental results, only a small part such as sixth and eighth appeared mistakes. By analyzing the experimental results, the main reason is that noise removal was not complete in images pre-processing, and it was deviated from the center line when using the linear scanning method to identify the center line of the crop rows etc.

In order to verify the effectiveness of the proposed method, 15 images were selected firstly, then 80 cells were got after dividing grid cells, and extracted NWIR. Compared these methods and methods proposed by this paper, Back Propagation (BP) algorithm

Table 3
Experimental results.

Number	Weeds coverage	Weeds threat	This paper results	Human decision-making results
1	0.2185	1.0525	Y	Y
2	0.2157	0.8183	N	N
3	0.2376	1.1276	Y	Y
4	0.1840	0.8561	N	N
5	0.3621	1.7164	Y	Y
6	0.1850	1.0961	Y	N
7	0.1779	0.8636	N	N
8	0.1954	0.9822	N	Y
9	0.2081	1.7646	Y	Y
10	0.2054	0.8102	N	N
...	...	...	...	...
90	...	...	...	...
91	0.1358	0.6474	N	N
92	0.2859	2.2009	Y	Y
93	0.2201	0.8312	N	N
94	0.2752	1.8532	Y	Y
95	0.1802	0.8382	N	N
96	0.3035	2.1336	Y	Y
97	0.3353	2.0452	Y	Y
98	0.2936	1.3899	Y	Y
99	0.1643	0.7948	N	N
100	0.2081	1.7616	Y	Y

and support vector machines (SVM) algorithm, the correct decisions of BP algorithm is 88.5%; SVM is 94%; this paper is 92.5%. Analyzing the results, decision accuracy of this paper algorithm is relatively high. The main reasons are: (1) BP algorithm needs to set the number of hidden layers and hidden nodes based on empirical value, however, the selection of hidden nodes lacks of the theoretical guidance, and depends on the number of training samples and samples noise, so the choice of samples has a great influence on BP network. Meanwhile BP algorithm is easy to form local minima and can affect the global optimization. BP algorithm would have a tendency to forget old samples when training new samples. (2) Although the accuracy of SVM algorithm is higher, it solved support vector by quadratic programming, however, solving vector would involve calculation of order matrix, when is very big, it would lead to space efficiency problem. (3) For this method, parameters can be calculated according samples database in the off-line stage, and realize online variable decision. This method is real-time, and its accuracy is relatively high.

7. Conclusion

Accurate weeds identification and precision spraying are the main trend of modern agricultural development, this article, based on the farmland environmental information, aiming at the feature that farmland images are susceptible to different illumination, uses the *YCrCb* color model, adopts *Cg* component to gray images that in the morning, noon and afternoon of sunny days and cloudy days, to avoid the influence of different farmland environments on image segmentation, then the global threshold method was taken for images binary and de-noising at the same time. This paper combined vertical projection method with linear scanning method to identify the center line of the crop rows, and divided the grid cells. Based on the former parameters of the classic Weeds Infestation Rate (WIR), this study improved it and reduced the computational complexity, then it was calculated by the improved horizontal scanning method within cells. Finally online variable spraying was realized that by the minimum error ratio of Bayesian decision under normal distribution. The experimental results show that the accuracy of this algorithm is 92.5% which exceeds BP algorithm and SVM algorithm. In the next stage, we will consider the status when the crop grows large and the weed can be seed behind the crop. And this technique can be used in real time application.

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References

Duan, R.Q., Zhao, W., Huang, S.L., Chen, J.Y., 2010. Fast line detection algorithm based on improved Hough transformation. Chin. J. Sci. Instrum. 31 (12), 2774–2779.
Gebhardt, S., Khbauch, W., 2007. A new algorithm for automatic rumex obtusifolius detection in digital images using colour and texture features and the influence of image resolution. Precision Agric. 8 (1–2), 1–13.
Ghazali, K.H.B., Ma, J., Xiao, R., Lubis, S.A., 2012. An innovative face detection based on YCGCR color space. Phys. Procedia 25.
He, D.J., Geng, N., Zhang, Y.K., 2008. Digital Image Processing. Xian University of Electronic Science and Technology Press.
Huang, S.K., Qi, L.J., Zhang, J.H., Wang, J., 2013. An identification algorithm of weeds among multi-row corn based on the mapping of the corn rows width. Chin. J. China Agric. Univ. 18 (1), 165–171.
Li, Y., 2014. Svm-based weed identification using field imaging spectral data. Chin. J. Remote Sens. Inform. 29 (1), 40–50.
Lin, W.M., Hu, Y.T., 2012. Image segmentation method based on YUV color space for tomato harvesting robot. Chin. J. Trans. Chin. Soc. Agric. Mach. 43 (12), 176–180.
Liu, Z.Z., Xu, X.Y., Wu, Q.F., 2013. A novel *k*-nearest neighbor algorithm based on *i*-divergence criterion. ICIC Express Lett. 4 (2), 343–348.
Manh, A.-G., Rabatel, G., Assemat, L., Aldon, M.-J., 2001. Weed leaf image segmentation by deformable templates. J. Agric. Eng. Res. 80 (2), 139–146.
Meng, Q.K., He, J., Chou, R.C., Ma, X.D., Si, Y.S., Liu, M.Z.G., 2014. Color image segmentation method based on RGB color space. Chin. J. Acta Opt. Sinica 34 (7), 180–186.
Pla, F., Sanchiz, J.M., Marchant, J.A., Brivot, R., 1997. Building perspective models to guide a row crop navigation vehicle. Image Vis. Comput. 15 (6), 465–473.
Tellaeche, A., Xavier, P., Burgos-Artizzu, Pajares, G., Ribeiro, A., 2008. A vision-based method for weeds identification through the bayesian decision theory. Pattern Recogn. 41 (2), 521–530.
Tellaeche, A., Pajares, G., Burgos-Artizzu, X.P., Ribeiro, A., 2011. A computer vision approach for weeds identification through support vector machines. Appl. Soft Comput. 11 (1), 908–915.
Wei, S.H., Wan, Z.X., Wang, K.J., Qiang, S., 2012. The application and prospects of weeds in computer science. Chin. J. Weed Sci.
Wu, L.L., 2010. Research on identification for in-field weed/corn seedlings by digital image processing. Ph.D. thesis, Huazhong Agricultural University.
Xu, Y., 2013. Research on weed detection method for corn seedling stage. Master's thesis, Agricultural University.
Yang, H.Q., Li, M.G., 2014. An evaluation model for the field weed control based on bp neural network. Chin. J. Shandong Univ. Technol. (Nat. Sci. Ed.) 28 (2), 70–74.
Yang, J., Zhu, L., 2010. Color image segmentation method based on RGB color space. Chin. J. Jisuanji Xian Dai Hua (8), 147–150.
Yuan, Z.Y., Mao, Z.H., Wei, Q., 2005. Orientation technique of crop rows based on computer vision. Chin. J. China Agric. Univ. 10 (3), 69–72.
Zhang, K., Wang, X.Y., Wang, Z.Q., 2011. Harmful of field weeds and control technology. Chin. J. Modern Agric. 31 (1), 12–13.
Zhao, C.J., Xue, X.Z., Wang, X., Chen, L.P., Pan, Y.C., Meng, Z.J., 2003. Advance and prospects of precision agriculture technology system. Chin. J. Trans. CSAE 19 (4), 7–12.