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Guidance Line Recognition of Agricultural Machinery Based on Particle Swarm Optimization under Natural Illumination

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Abstract: In farmland with complex environment, guidance line recognition of agricultural machinery based on machine vision is subjected to illumination variation, weed noise, etc. In addition, the conventional path detection algorithms have the drawbacks of low processing speed and poor anti-interference. The visual navigation path detection under natural environment was conducted. Firstly, to reduce the influence of illumination changes on the quality of image segmentation, *Cg* component was constructed on the base of YCrCb color mode and the $2Cg-Cr-Cb$ factor was selected to preprocess the image. Secondly, the clustering segmentation of the image was performed based on improved K-means algorithm to achieve the respective clusters of soil and green crop information. Then, the weed interference information in the binary image was eliminated by morphological filtering algorithm so as to obtain the complete and clear crop information. Finally, according to the characteristics of the crop rows in the image, linear equation constraints of crop rows were established. An algorithm of crop lines detection based on particle swarm optimization (PSO) was designed. Experiment results showed that the image segmentation based on $2Cg-Cr-Cb$ gray image can effectively identify crop from soil background under different illumination conditions. The segmentation images were less affected by change of illumination and no background noise was contained. The guidance line recognition method based on PSO can quickly and accurately detect the navigation line. Furthermore, it had good fitness for different crops and nice adaptability for different crop growth stages in the farmland. Compared with conventional guidance line recognition algorithms, the designed algorithm had the advantages of high speed and good robustness.

Key words: agricultural machinery; machine vision; guidance line recognition; color mode; particle swarm optimization algorithm

0 Introduction

The automatic navigation technology of agricultural machinery can effectively improve the efficiency of agricultural production and extend the working hours, so that the work intensity of agricultural laborer will be significantly reduced [1-2]. At present, the research on automatic navigation of agricultural machinery is mainly focused on machine vision and global positioning system (GPS) [3-4]. Compared with GPS, machine vision has the advantages of rich information, non-contact measurement, high real-time and excellent cost performance, which has become one of the research focuses in the field of precision agricultural at home and abroad.

The key technologies of agricultural machinery navigation based on machine vision include guidance line detection and navigation control. Navigation line recognition is the basis of vision-based navigation of agricultural machinery. The efficiency and accuracy of navigation system can be significantly improved by fast and accurate extraction of guidance line. The changes of natural light and the performance of guidance line detection algorithm are the main factors to affect the navigation line identification. In the aspect of illumination variation, literatures [5-9] choose

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different color space and use color factor for image preprocessing, which can effectively reduce the influence of illumination change on image segmentation. In the aspect of navigation line identification, literatures [10 – 15] adopted Hough transforms, least square method, random algorithm and well-ordered subset method to detect crop lines. However, these methods have the problems of high computational complexity, sensitivity to weed noise, low detection accuracy and poor adaptability, which can not meet the requirements of precision and real-time of agricultural machinery navigation system.

Particle swarm optimization (PSO) algorithm is a kind of intelligent evolutionary algorithm, which employ individual collaboration to find the optimal solution of the problem. At present, the particle swarm optimization algorithm is mainly used for obstacle avoidance and path planning in visual navigation system, but there is little research on guidance line recognition. As yet, there is no paper adopting particle swarm optimization algorithm for crop lines identification. Literatures [16 – 17] adopted particle swarm optimization algorithm to detect lane. The lane detection algorithm introduced a deformable line model with road geometry characteristics to describe the road structure and utilized likelihood density probability for evaluating how correctly road images match the model. A posterior probability function was constructed and the parameters of lane model were optimized by using particle swarm optimization algorithm. According to the parameters of lane model, the equation of lane was obtained. The road is a structured environment and the lane has regular shape features. However farmland is a non-structural environment, so that the lane detection method based on PSO is not suitable for navigation line identification of agricultural machinery.

This paper mainly focuses on reducing the influence of illumination variation on image processing and improving the performance of guidance line detection algorithm. To improve the adaptability of image processing to the change of illumination, Cg component is constructed on the base of YCrCb color mode and $2Cg - Cr - Cb$ factor is selected to preprocess the image. In order to increase the real-time and accuracy of guidance line recognition, a new algorithm based on particle swarm optimization algorithm is proposed to detect crop lines. According to the features of crop rows in the image, a constraint model for crop linear equation is established. Particle swarm optimization algorithm is adopted to search the optimal crop lines on the basis of constraint model, and then the guidance line is calculated.

1 Image preprocessing

Image preprocessing is the process of converting color images into gray images under a specific color space and the choice of color space has an important influence on the following image processing. At present, the commonly used color spaces are RGB, HIS and YCrCb. The RGB color space contains R (red), G (green), B (blue) three color channels, which have a strong correlation and are sensitive to the change of brightness. Therefore, the RGB color space is not suitable for processing the image under illumination change conditions. The HIS color space consists of three components, which are hue, saturation and intensity. H component is unsusceptible to illumination variation and can identify objects in different colors, so it is more suitable for processing images that are sensitive to illumination changes. But the transform between H component and RGB color space is nonlinear, which is easy to cause the image distortion[18]. The YCrCb color space, also known as YUV color space, is a kind of encoding method used for color TV signal transmission. Y is the luminance component and Cb and Cr are the blue-difference and red-difference chrominance components. In particular, Cb is proportional to $B - Y$ and Cr is proportional to $R - Y$[19 – 20]. Due to the separation of luminance and chrominance, YCrCb color space is more suitable for processing images that are sensitive to illumination changes.

Green component plays a very important role in farmland image, but YCrCb color space is short of the chrominance that describes the difference between green component and luminance. Therefore, in this paper, the Cg component that is proportional to $B - Y$ is introduced to describe the features of green crop mode. A $2Cg - Cr - Cb$ factor is constructed to preprocess the crop image.

The conversion formula between RGB and YCrCb is shown in formula (1).

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \begin{bmatrix} 0 \\ 128 \\ 128 \end{bmatrix} + \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ -0.169 & -0.331 & 0.5 \\ 0.5 & -0.419 & -0.081 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{1}$$

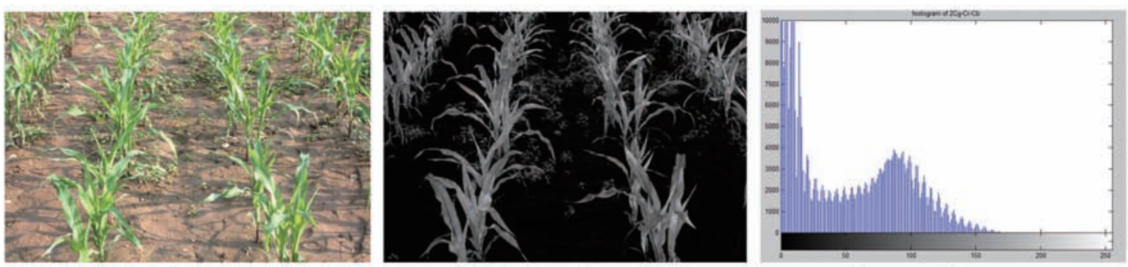
The formula for the Cg component is shown below.

$$Cg = 128 + [\, -0.299 \quad 0.413 \quad -0.114 \,] \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{2}$$

According to ITU − R BT. 601 − 6 standard, the Cg component is normalized, as shown in formula (3).

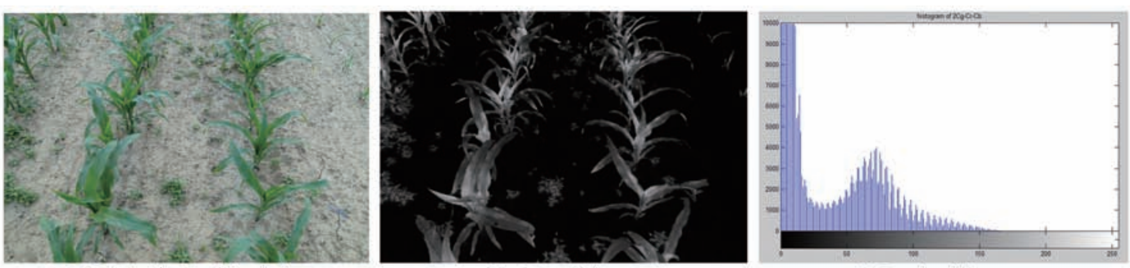
$$Cg = 128 + [\, -0.362 \quad 0.5 \quad -0.138 \,] \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{3}$$

As can be seen from the formula (3), the transform relationship between Cg and R, G, B is linear, which has the advantages of simple calculation and high conversion speed. In this paper, a number of maize pictures were collected under different environment, as shown in Fig. 1a and Fig. 2a. $2Cg - Cr - Cb$ factor is used to convert color images to gray images, as shown in Fig. 1b and Fig. 2b. Furthermore, the histograms of gray-scale images are calculated, as shown in Fig. 1c and Fig. 2c. As can be seen from the results, the gray images of maize are clear and complete and there is a significant contrast between crop and soil. The histograms show obvious peaks and valleys, which are suitable for image segmentation.



(a) Original image of sunny day (b) Gray-scale image (c) Gray-level histogram

Fig. 1 Results of corn image conversion in sunny day



(a) Original image of cloudy day (b) Gray-scale image (c) Gray-level histogram

Fig. 2 Results of image conversion in cloudy day

2 Image segmentation and weeds filtering

Image segmentation plays a crucial rolein crop lines recognition, which separates the crop information from soil background. K-means clustering is a kind of unsupervised image segmentation method, which has the advantages of simple calculation, fast processing, and high efficiency in the processing of large data. Compared with threshold segmentation method, the K-means clustering algorithm has a better effect, even if there is no significant gray level difference between the crop and the background or the gray scale of each object has a large overlap[21-22]. K-means clustering algorithm takes sample distance as the similarity evaluation index and defines that the class is composed of samples, which are close to each other. The best clustering is obtained through the iteration, when the objective function is minimized. In this paper, the similarity evaluation function and objective function for clustering algorithm are defined as formula (4) and formula (5).

$$d(x_i, x_j) = \sqrt{\sum_{k=1}^{d} (x_{ik} - x_{jk})^2} \tag{4}$$

$$E = \sum_{i=1}^{n} \sum_{p \in X_i} \| p - m_i \|^2 \tag{5}$$

Where x_i and x_j are two points in d-dimensional; $d(x_i, x_j)$ is euclidean distance between x_i and x_j; X_i is the i-th clustering subset; m_i is mean of clustering X_i; p is a sample of clustering X_i; n is number of clustering; E is sum of squares of the difference between all objects and the corresponding cluster centers in the data space.

The selection of initial cluster center has an important influence on the convergence rate of clustering algorithm, when the number of clusters is determined. In general, the initial clustering centers are randomly selected in conventional K-means clustering algorithm and the minimum time consuming of image segmentation is uncertain. In order to decrease the time consumption of image segmentation, an improved clustering algorithm is proposed in this paper. Firstly, peaks and troughs of gray histogram are detected. Secondly, data corresponding to the peaks and troughs are selected as the initial cluster center. The convergence speed of the clustering algorithm is improved by establishing the optimal initial clustering center. Due to the image noise, some of the random interference points in the histogram may be regard as peaks and troughs. For removing the random interference points, Gauss filter algorithm is used to smooth the histogram.

The conventional clustering algorithm and the improved clustering algorithm are adopted for image segmentation, when the number of clustering is 2. The running environment of algorithm is VS2010 and segmentation images are shown as Fig. 3a and Fig. 3b. It can be seen from the results that the image segmentation effect of the two algorithms are similar. In the aspect of time consumption, the convention algorithm is 25.7 ms and the improved algorithm is 14.1 ms. Compared with traditional clustering algorithm, the improved algorithm has a better real time performance. In addition, there are some weeds in the image segmentation, which will affect the crop lines detection. Therefore, the morphological filtering algorithm is used to filter weed noise. In this paper, the 2×2 square elements are used for dilation and the disk elements with radius of 4 for erosion. The morphological filtering effect is shown as Fig. 3c. It can be seen that weed is basically eliminated and crop information is preserved.

(a) Image segmentation based on conventional K-means algorithm

(b) Image segmentation based on improved K-means algorithm

(c) Binary image after weeds filtering

Fig. 3 Image segmentation and weed filtering

3 Crop rows identification and guidance line detection based on PSO

3.1 The principle of PSO algorithm

Particle optimization algorithm (PSO) is a kind of heuristic algorithm based on swarm intelligence, which emphasizes cooperation among individual particles to search the optimum location. The basic principle of particle swarm optimization algorithm is as follows[23].

Assuming the particles search in an n-dimensional space, a particle can be defined as $\boldsymbol{x}_i = (x_{i1}, x_{i2}, \cdots, x_{in})$, which is considered as a candidate solution to the problem. The velocity of a particle is defined as $\boldsymbol{v}_i = (v_{i1}, v_{i2}, \cdots, v_{in})$ and the formula of particle swarm optimization algorithm is as follows.

$$v_{id}(k+1) = wv_{id}(k) + c_1\mathrm{rand}_1(P_{idbest}(k) - x_{id}(k)) + c_2\mathrm{rand}_2(P_{gdbest}(k) - x_{id}(k)) \tag{6}$$

$$x_{id}(k+1) = x_{id}(k) + v_{id}(k+1) \tag{7}$$

Where $P_{idbest}(k)$ is individual best position of a particle; $P_{gdbest}(k)$ is globally best position of particle swarm; c_1 and c_2 are acceleration factors; w is inertia factor; k is number of iterations; rand_1 and rand_2 are random number between 0 and 1.

3.2 Crop rows recognition and guidance line identification

Particle swarm optimization algorithm was used to detect lane in literatures [16 - 17]. For the line feature of crop rows is similar to that of lane, the particle swarm optimization algorithm can also be used for crop lines detection. In order to recognize the crop lines quickly and accurately, a linear equation constraint model is established according to the feature of crop rows in the image. The parameters of crop lines are calculated by PSO algorithm on the base of linear equation constraint model. The linear equation constraint model of crop row is defined as follows.

(1) Due to mechanized planting, the crop rows are parallel to each other and the distance between the crop rows seem to be greater at the bottom of the image than at the top because of camera perspective.

(2) Crop lines start from the bottom and end at the top of the image. The linear equation of a crop row can be determined by 2 pixels, which are on the bottom and top edges of the image.

(3) Taking image center line as boundary, the image is divided into two parts and a rectangular coordinate based on the lower left corner of the image is established. The slope of a crop line is positive when crop row is on the left of image center line, and vice versa. If the crop row is in the center of the image, it is coincident with the center line.

According to the above constraints, particle swarm optimization algorithm is used to detect crop lines, when the image height and width are determined. The specific steps of crop lines detection algorithm are as follows.

(1) It is assumed that in an image with $Height \times Width$ pixels, the starting point of a crop line is $(x_0, 0)$ and the end point is $(x_1, Height)$.

(2) Vertical projection method is adopted to detect crop number N and location information (P_{nL} and P_{nR}). P_{nL} is the left edge position of the n-th ($n = 1, 2, \cdots, N$) crop row and P_{nR} is the right edge position. If $N \geqslant 1$, at least one crop row is included in the image and step (3) is performed. Otherwise the program ends.

(3) Initialize crop rows counter $num = 1$, position storage array $Pos[N][2]$ and distance threshold d. $Pos[n][0]$ and $Pos[n][1]$ are used to store P_{nL} and P_{nR}, which are the location of the n-th crop row.

(4) Initialize the particle number m, accelerating factors c_1 and c_2, inertia factor w, the maximum iterations l and termination threshold t. The fitness function $f = T$ is established and T represents the number of target pixels within a certain range (d range) of candidate crop line.

(5) If $Pos[num][1] \leqslant \frac{Width}{2}$, a crop row is on the left of image center line, then $x_0 \in [Pos[num][0], Pos[num][1]]$, $x_1 \in [Pos[num][0], Width/2]$. If $Pos[num][0] \geqslant \frac{Width}{2}$, a crop row is on the right of image center line, then $x_0 \in [Pos[num][0], Pos[num][1]]$, $x_1 \in [Width/2, Pos[num][1]]$. If $Pos[num][0] < \frac{Width}{2} < Pos[num][1]$, the crop row coincident with image central line, then $x_0, x_1 \in [Pos[num][0], Pos[num][1]]$.

(6) The starting point x_0 and end point x_1 of the line is selected to constitute a particle (x_0, x_1), which is regarded as a candidate crop line. Initialize particle swarm optimization.

(7) The personal best position and global best position of particle swarm are obtained by calculating the fitness of each particle. The velocity and position of particles are updated according to formulas (6) and (7).

(8) If PSO algorithm reaches the maximum number of iterations or meet the requirement of termination threshold, the parameters of a crop line (x_0, x_1) is determined and the equation of crop line can be calculated. Otherwise return step (7).

(9) $num = num + 1$. if $num \leqslant N$, return step (5). Otherwise perform step (10).

(10) The navigation line equation is obtained by using the nearest two crop lines of the image center line.

The combination of linear model and particle swarm optimization algorithm for navigation line identification has two obvious advantages. Firstly, the linear model of crop rows has little relationship with the crop species and growth stages, so that the crop lines recognition algorithm can be adapted to different environments. Secondly, particle swarm optimization algorithm has the advantages of high precision and fast convergence, which can effectively improve the accuracy and real-time performance of navigation line detection.

4 Experimental results and discussion

In this paper, the experiments included static and dynamic experiment. Static experiment was performed in laboratory by using a computer for image processing and analysis. Dynamic experiment was carried out on experimental platform for navigation path tracking.

The computer used in static experiment was Lenovo Y460 with Intel Core (TM) i3 2.4 GHz processor, 2 GB of memory and a Windows 7 system . The image processing program was realized by C/C + + language, which runs on the platform of VS2010. The experimental platform of agricultural implement is shown in Fig. 4. The hardware used in the guidance system mainly consisted of a color video camera, an industrial computer, a lateral displacement controller (PLC), a GPS receiver, a hydraulic system, and an weeding implement. The camera used for machine vision was an OKAC1310 color video camera with bmp format picture output and resolution of 640 × 480. The industrial computer was a PPC – 5152 – D525 industrial panel PC with Intel Atom D525 2.8 GHz processor, 2 GB of memory, and a Windows XP system. Navigation program was developed by C/C + + language, whose run environment was VS2010. A GPS system is installed on the experimental platform. It is used to record the location information of navigation system.

Fig. 4 Experimental platform

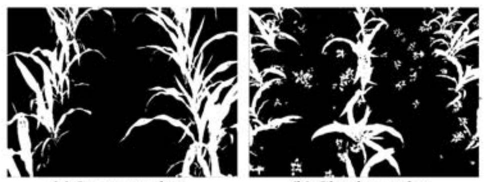
4.1 Adaptability of $2Cg - Cr - Cb$ to illumination changes

To verify the influence of illumination changes on image segmentation, crop images under different environment were converted into YCrCb, HIS and RGB color space. The $2Cg - Cr - Cb$ factor, H component and $2G - R - B$ factor were used for images gray-scale processing. OTSU threshold method was applied to image segmentation. The crop images in a sunny day (about 80 000 lx illumination intensity) and cloudy day (about 6 500 lx illumination intensity) were acquired, as shown in Fig. 5.

(a) Sunny weather (b) Cloudy weather

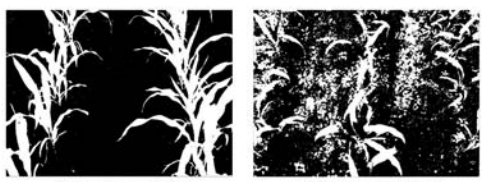
Fig. 5 Corn images under different weather conditions

Fig. 6 shows the corn binary images based on $2Cg - Cr - Cb$ gray image under sunny and cloudy conditions. It can be seen that illumination changes have little effect on image segmentation. The segmentation results based on $2Cg - Cr - Cb$ gray image are complete and clear under various weather conditions. Fig. 7 shows the corn binary images based on H component under sunny and cloudy weather conditions. As can be seen, crop information is clearly and completely separated from soil background in sunny days. However, there is a lot of noise in binary image under cloudy condition. The image noise is caused by nonlinear transformation between RGB and HIS color space. Fig. 8 shows the corn binary images based on $2G - R - B$ gray image in sunny and cloudy days. The segmentation result is good in cloudy day, whereas the crop information was incomplete on a sunny day. This is because the R, B, G components are coupled to each other and sensitive to the changes of illumination.



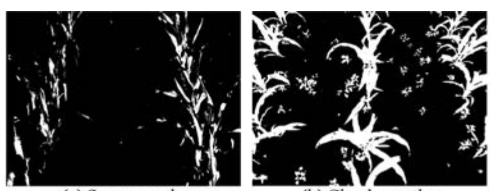
(a) Sunny weather (b) Cloudy weather

Fig. 6 Image segmentation effects based on $2Cg - Cr - Cb$ gray image



(a) Sunny weather (b) Cloudy weather

Fig. 7 Image segmentation effects based on H component



(a) Sunny weather (b) Cloudy weather

Fig. 8 Image segmentation effects based on $2G - R - B$ gray image

According to the above experiments, we can make a preliminary evaluation of the performance of the 3 image preprocessing methods. In order to verify the universal validity of $2Cg - Cr - Cb$ factor under different light intensities, 60 crop images were acquired in three illumination range (20 images were collected in each illumination range). A method proposed by George was adopted to evaluate the quality of image segmentation[24]. The evaluation criterion of image segmentation is relative segmentation error rate, which is defined as follows.

$$E_{seg}^{AB} = 1 - \frac{\sum_{j,k=1}^{m,n} I^A(j,k) \cap I^B(j,k)}{\sum_{j,k=1}^{m,n} I^B(j,k)} \tag{8}$$

Where I^A and I^B are the segmentation images based on A and B algorithms; E_{seg}^{AB} is relative segmentation error rate of I^A to I^B; i and j are the row and column number of a pixel; m and n are the width and height of image.

It can be seen from formula (8), in 2 segmentation algorithms, the larger relative segmentation error rate is, the greater deviation between the relative segmentation pixels and the common pixel set is. Fig. 9 shows the curves of relative segmentation error rate in 60 images.

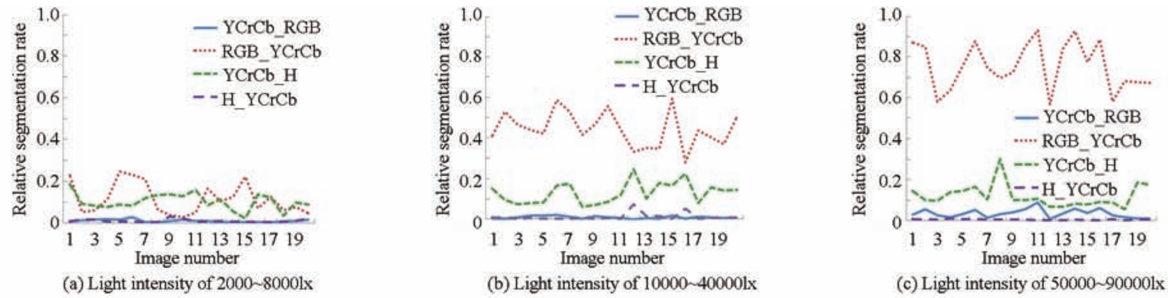


Fig. 9 Relative error curves of image segmentation under different illumination conditions

In Fig. 9 the meaning of curve YCrCb_RGB is the relative segmentation error rate of $2Cg - Cr - Cb$ factor to $2G - R - B$ factor. The curve YCrCb_H stands for the relative segmentation error rate of $2Cg - Cr - Cb$ factor to H component. The curve RGB_YCrCb represents the relative segmentation error rate of $2G - R - B$ factor to $2Cg - Cr - Cb$ factor. The meaning of curve H_YCrCb is the relative segmentation error rate of H component to $2Cg - Cr - Cb$ factor. As can be seen from Fig. 9, the curve RGB_YCrCb is larger than YCrCb_RGB under different illumination conditions. The difference between the two curves increases with the increase of light intensity. This is due to the higher intensity of light, the more lack of crop information in the segmentation image based on $2G - R - B$ factor (Fig. 8a). The curve H_YCrCb is less than YCrCb_H under different light conditions. For the background noises are regard as target pixels (Fig. 7b), and the target pixels in the segmentation image based on H component is more than that based on $2Cg - Cr - Cb$ factor. The relative error rate of $2Cg - Cr - Cb$ factor to H component is less than that of the H component to $2Cg - Cr - Cb$ factor, when the common set of pixels is determined.

Experimental results show that $2Cg - Cr - Cb$ factor could improve the adaptability of image processing to illumination variation. Compared with $2G - R - B$ factor[5-6] and H component[7-8], the $2Cg - Cr - Cb$ factor is more suitable for image preprocessing. The segmentation images based on $2Cg - Cr - Cb$ factor could preserve more crop information and do not introduce any background noise under different illumination conditions.

4.2 Performance test of guidance line detection algorithm

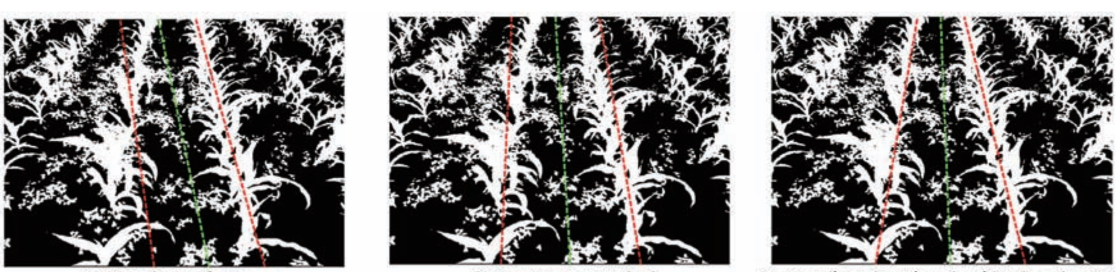
In order to verify the accuracy, real-time and adaptively of different guidance line detection algorithms, 60 crop images under three growth stages were acquired (20 images were collected at each growth stage). The Hough transform, least square method and crop lines recognition algorithm based on particle swarm optimization were used to detect guidance line. According to the numbers of images that guidance lines were accurately identified and the time consumption under different crop growth stages, the performance of the three algorithms was compared. Crop images with 640 × 480 pixels were used for guidance line detection. The Hough transform and least square method were standard algorithms without optimization. The guidance line detection steps of Hough transform and least square method included gray scale transform, image segmentation, feature points detection, feature points classification, crop lines recognition and navigation line identification. The guidance line detection steps of the algorithm proposed in this paper included gray transform, image segmentation, crop location detection, crop lines detection and navigation path recognition. In the standard Hough transform algorithm, $\theta \in [-90°, 90°]$, $\rho = [-800, 800]$. In particle swarm optimization algorithm $w = 0.5$, $c_1 = c_2 = 1$, $d = 5$, and particles number was initiated to 50. The termination condition of PSO was defined as $l = 100$ or $t > 4\,000$, which could be adjusted according to the type of crop or different growth stages. Number of images that navigation lines were identified by the three algorithms and time consumption under different growth stages are shown in Tab. 1.

Tab. 1 Number of images that navigation path were extracted and time consumption under different growth phases

Guidance line detection algorithm	The height range of crop/cm			Time of image processing/ms
	10 ~ 15	20 ~ 25	30 ~ 35	
Hough transform	20	18	16	196.2
Least square method	20	17	14	119.6
Algorithm of this paper	20	20	19	88.4

As can be seen from Tab. 1, the accuracy of Hough algorithm and least square method is less than the algorithm proposed in this paper. This is because the weed noise and the scattered growth of maize leaves are detected as feature points of crop. The existence of inaccurate feature points leads to the deviation of crop row detection. The algorithm proposed in this paper directly identity crop rows in binary image without feature point detection. Therefore, the algorithm is less affected by weed noise and maize leaves. One image detection failure of the algorithm is due to high weed density, which leads to crop rows position detection failure. In the aspect of real time, the time consumption of the algorithm proposed in this paper is less than Hough transform and least square method. This is due to the existence of the feature point detection, and the time consumption of Hough transforms and least square method increase. The time consumption of feature point detection is about 40ms in an image with 640 × 480 pixels. The algorithm proposed in this paper does not include feature point detection and the overall time consumption is less than Hough transform and least square method. Fig. 10 shows the guidance line detection results of different algorithms, when the height of crop is about 20 ~ 25 cm. The green dotted line in image is the guidance line and red lines are the crop lines, which are the nearest crop rows from the center of image. Tab. 2 illustrates the parameters of the crop lines and guidance lines.

As can be seen from Fig. 10, all of the three algorithms could detect the guidance line. Compared with the algorithm of this paper, the accuracy of Hough transforms and least square method in crop lines detection is low. It is due to the spread of maize leaves and weed noise. In Tab. 2, parameter k is the slope and b is the intercept. The guidance line parameters detected by Hough transform are $k = -5.40$ and $b = 2\,484.60$. The guidance line slope of least square method is -18.26 and the intercept is $2\,697.87$. The guidance line slope of the algorithm proposed in this paper is -28.22 and the intercept is $11\,347.36$. The guidance lines parameters of the three algorithms are different. It can be seen that the algorithm of this paper has strong anti-interference of weed noise, yet the Hough transform and least square method are susceptible to noise interference. The experimental results demonstrated that the crop lines detection algorithm based on PSO had better accuracy, real time and adaptability than Hough transforms and least square method.



(a) Hough transforms (b) Least square method (c) Crop lines detection algorithm based on PSO

Fig. 10 Guidance line detection results of different algorithms

Tab. 2 Results of liner parameter comparison

Guidance line detection algorithms	Parameters of left crop row		Parameters of right crop row		Parameters of guidance line	
	k	b	k	b	k	b
Hough transform	−8.17	2 745.47	−4.03	2 354.96	−5.40	2 484.60
Least square method	25.19	−6 312.70	−6.62	3 743.09	−18.26	2 697.87
Algorithm of this paper	6.60	−1 547.50	−4.52	2 582.03	−28.22	1 1347.36

4.3 Performance comparison of different crop lines recognition algorithms

In addition to standard Hough transform and least square method, the literatures [14 − 16] also proposed other methods for crop row and lane recognition. In this paper, the different methods are compared with the crop lines identification method based on particle swarm algorithm.

(1) Real-timeof crop lines detection

Literature [14], a random method was used for crop lines detection. The time consumption of the algorithm is greatly related to the selection of random points. If the random points are selected appropriately, the crop lines could be identified quickly. Otherwise, you need to continue to select the random points. Moreover, the method did not limit the maximum number of random point selection, which leaded to the maximum time consumption of the algorithm uncertain. In this paper, the proposed algorithm establishes termination condition, which is the maximum number of iterations, to limit the time consumption in a certain range. In addition, the method of literature [14] is essentially a kind of stochastic optimization, which does not include optimization strategy and search direction. The algorithm of this paper is a kind of orientation search, which follows a certain strategy to make the particles to the best direction. If the number of random points selection and iteration times of particle swarm algorithm are the same, the probability of searching the most optimal crop lines with the algorithm in this paper is larger than that of the random algorithm. Therefore, the time consumption of the algorithm proposed in this paper is less than the random algorithm.

Literature [16] adopt particle swarm algorithm to extract lane. All the pixels in the image were calculated by posterior probability function. In an image with $M \times N$ pixels, calculation the fitness of a particle needs to traverse $M \times N$ pixels. In the algorithm of this paper, for the same image, calculation the fitness of a particle needs to traverse $M \times 2d$ pixels. d is distance threshold, which is less than N. Under the condition of the same particles number and iterations, the real-time of the algorithm proposed in this paper is higher than the method of literature [16].

(2) Accuracy of crop lines detection

The algorithm of literature [15] took the prior knowledge of crop row-structure to define feature points detection threshold. Under the condition that the threshold remains constant, the accuracy of crop lines identification may change, when the method is used to recognize different crop rows. In this paper, the proposed algorithm recognizes the crop lines on the base of the linear model of crop rows. The accuracy of the algorithm is not affected by crop species.

In addition, the algorithms of literatures [14 − 15] need to extract crop feature points before detecting crop lines. The weed noise and dispersed growth leaves may be detected as crop feature points, which decrease the accuracy of line detection. In this paper, the algorithm does not include feature detection step and directly recognize crop lines on the basis of binary image. The accuracy and anti-interference ability of the algorithm are higher than methods proposed in literatures [14 − 15].

4.4 Adaptability of crop lines recognition algorithm

The algorithm proposed in this paper was adapted to detect different crop rows, such as soybean, wheat and cabbage. Each kind of crop was captured 30 images. Compared with maize, crops with leaf growth concentration are more easily identified. The algorithm can accurately identify different crops lines. Fig. 11 shows the detection results of different crop. Experimental results show that the crop lines detection algorithm based on particle swarm algorithm can correctly identify different crops lines, which has a strong adaptability.

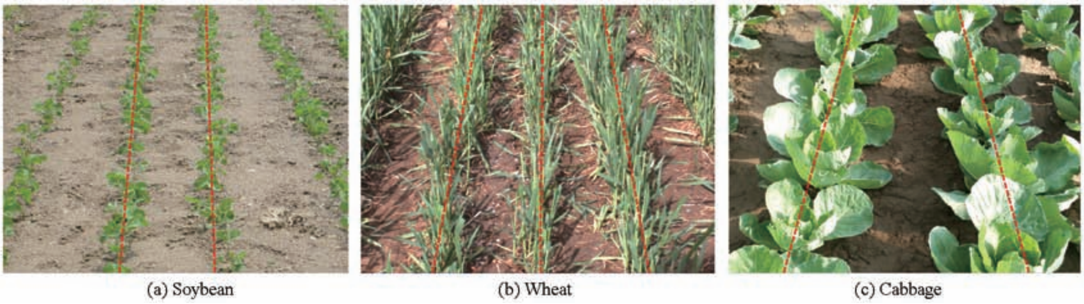


Fig. 11 Detection results of different crop

4.5 Experiment on navigation tracking

To test the dynamic performance of the guidance system, experiments were carried out at a corn field. The length of experimental field was approximately 20 m and crops were sown in rows with 0.6 m inter-row spacing. The height of corn was about 20 cm and guidance system run at the speed of 0.6 m/s, 1.0 m/s and 1.4 m/s respectively. A GPS mounted on implement was used to record the location information of agricultural implement. The GPS worked at 2 Hz. In order to improve the reliability of the experimental data, 5 repeat tests were performed at each velocity. The max lateral deviation is used as the performance evaluation index of the navigation system. The max lateral deviation that is the maximum and the max lateral deviation that is the minimum are selected to form a group, when the navigation speed is the same. Fig. 12 shows the path tracking results at three different speeds. Fig. 12a and Fig. 12d, Fig. 12b and Fig. 12e, Fig. 12c and Fig. 12f respectively constitute a group at the same speed.

The maximum lateral deviations are 5.7 cm and 5.4 cm, and average lateral deviations are 2.2 cm and 2.18 cm at the speed of 0.6 m/s. The maximum lateral deviations are 7.5 cm and 6.8 cm, and average lateral deviations are 3.3 cm and 2.4 cm at the speed of 1.0 m/s. The maximum lateral deviations are 9.6 cm and 8.7 cm, and average lateral deviations are 3.7 cm and 3.3 cm at the speed of 1.4 m/s. The experimental platform can effectively remove the inter row weeds and does not damage the crops, when the maximum lateral deviation is less than 15 cm. Therefore, the crop lines detection algorithm of this paper could meet the precision requirements of agricultural machinery navigation and has a good dynamic performance.

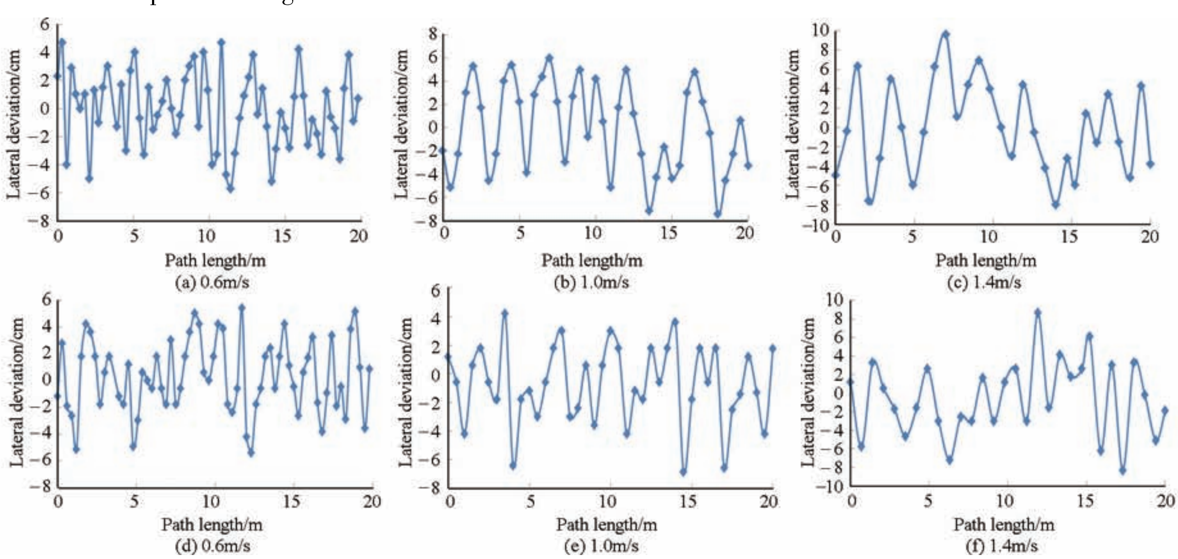


Fig. 12 Experimental results of guidance line tracking in different speed

5 Conclusion

(1) The Cg component that is independent of illumination was constructed on the base of YCrCb color mode. A $2Cg-Cr-Cb$ factor was selected to preprocess the image, which improved the adaptability of the image processing to illumination changes. The experimental results showed that the image segmentation based on $2Cg-Cr-Cb$ gray image could effectively identify the crop from the soil background

under different illumination conditions. The segmentation result was less affected by the change of illumination.

(2) An improved K-means clustering algorithm was proposed in this paper. In the precondition of guaranteeing image segmentation quality, the real time performance of image segmentation algorithm was improved.

(3) According to the features of crop rows in the image, linear equation constraints of crop rows were established. A crop lines detection algorithm based on particle swarm optimization (PSO) was first proposed. Compared with conventional method, the crop lines recognition algorithm based on PSO could quickly and accurately detect the navigation line. The proposed algorithms not only had high adaptability to different crops, but also meet the requirements of agricultural machinery navigation.

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自然光照下基于粒子群算法的农业机械导航路径识别

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摘要：针对农业机械视觉导航线提取易受光照变化影响及常规导航线识别算法实时性低、抗干扰能力差等问题，对自然光照条件下基于机器视觉的农业机械导航路径识别技术进行了研究。首先，在 YCrCb 颜色模型的基础上构建与光照无关的 Cg 分量，选择 $2Cg-Cr-Cb$ 特征因子对图像进行灰度化处理，以降低光照变化对图像分割的影响；然后，采用改进 K-means 聚类方法进行图像分割，将绿色作物信息从土壤背景中分离出来，并通过形态学滤波方法滤除二值图像中存在的杂草干扰信息；最后，根据图像中作物行的特点建立作物行直线方程约束模型，利用粒子群算法对作物行直线进行寻优求解，进而得到导航线。实验结果表明，不同光照条件下对 $2Cg-Cr-Cb$ 灰度图像进行图像分割，可以清晰完整地将作物从土壤背景中分离出来，分割图像受光照变化影响较小并且不会引入背景噪声；基于粒子群算法的导航线检测方法可以快速准确地提取出导航路径，对于不同农田作物和作物不同生长阶段具有较高的适应性，相比于常规导航线识别算法具有实时性高、鲁棒性好等优点。

关键词：农业机械；机器视觉；导航路径识别；颜色模型；粒子群算法

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Guidance Line Recognition of Agricultural Machinery Based on Particle Swarm Optimization under Natural Illumination

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Abstract: In farmland with complex environment, guidance line recognition of agricultural machinery based on machine vision is subjected to illumination variation, weed noise, etc. In addition, the conventional path detection algorithms have the drawbacks of low processing speed and poor anti-interference. The visual navigation path detection under natural environment was conducted. Firstly, to reduce the influence of illumination changes on the quality of image segmentation, Cg component was constructed on the base of YCrCb color mode and the $2Cg-Cr-Cb$ factor was selected to preprocess the image. Secondly, the clustering segmentation of the image was performed based on improved K-means algorithm to achieve the respective clusters of soil and green crop information. Then, the weed interference information in the binary image was eliminated by morphological filtering algorithm so as to obtain the complete and clear crop information. Finally, according to the characteristics of the crop rows in the image, linear equation constraints of crop rows were established. An algorithm of crop lines detection based on particle swarm optimization (PSO) was designed. Experiment results showed that the

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image segmentation based on $2Cg - Cr - Cb$ gray image can effectively identify crop from soil background under different illumination conditions. The segmentation images were less affected by change of illumination and no background noise was contained. The guidance line recognition method based on PSO can quickly and accurately detect the navigation line. Furthermore, it had good fitness for different crops and nice adaptability for different crop growth stages in the farmland. Compared with conventional guidance line recognition algorithms, the designed algorithm had the advantages of high speed and good robustness.

Key words: agricultural machinery; machine vision; guidance line recognition; color mode; particle swarm optimization algorithm

引言

利用农业机械自动导航技术可以有效提高农田作业效率,延长工作时间,将劳动者从繁重的农业生产中解放出来[1-2]。目前,农业机械自动导航领域的研究主要集中在机器视觉技术和卫星定位(GPS)技术两种方式上[3-4]。与 GPS 技术相比机器视觉技术具有获取信息量丰富、非接触测量、实时性好、性价比高等优点,已经成为国内外精细农业研究领域的一个热点。

基于机器视觉的农业机械导航涉及的关键技术主要包括:导航路径检测和路径跟踪控制。其中,导航路径检测是视觉导航的基础,快速准确地提取导航基准线可以提高导航系统的工作效率和作业精度。自然光照变化和导航线检测算法自身的鲁棒性是影响农业机械视觉导航路径识别效果的主要因素。对于自然光照问题,文献[5-9]选择不同的颜色空间,通过颜色特征因子对图像进行预处理,有效降低了光照变化对图像分割的影响。在导航线检测方面,文献[10-15]分别采用 Hough 变换、最小二乘法、随机算法和良序子集法提取作物行直线,但这些方法均存在计算复杂度高、对杂草噪声敏感、检测精度低和适应性差等问题,难以满足农业机械自主导航对精度和实时性的要求。

粒子群优化算法是一种基于群体的智能进化方法,通过个体间的协作来寻找问题最优解。目前,粒子群算法在视觉导航方面多用于避障和路径规划,而用于导航路径识别的研究较少并且在农业机械导航线提取方面没有发现相关报道。文献[16-17]采用粒子群算法对车道线进行检测。通过线性变形模型描述车道线结构,选择似然估计概率评价道路图像与模型的匹配程度,构造后验概率函数,利用粒子群算法优化车道线模型参数,实现车道线提取。但道路环境为结构化环境,车道线具有规则的形状特征,而农田为非结构环境,所以该方法应用于农业导航线提取有一定的局限性。

本文着重在降低光照信息对图像处理的影响和导航路径检测算法上开展研究。利用 YCrCb 颜色模型构建与光照无关的 Cg 分量,选择 $2Cg - Cr - Cb$ 特征因子进行图像灰度化处理,以提高图像处理对光照变化的适应能力;为提高导航路径识别算法的实时性与检测精度,提出一种基于粒子群算法的作物行检测与导航线提取方法。根据作物行在图像中的特点,建立作物行线性方程约束模型,在此基础上利用粒子群算法搜索最优作物行直线,进而得到导航路径。

1 图像预处理

图像预处理是指在特定的颜色空间(模型)下,将彩色图像转换为灰度图像的过程。其中,颜色空间的选择关系到后续图像的处理,目前常用的颜色空间主要包括 RGB、HIS、YCrCb 颜色空间。RGB 颜色空间各基色具有很强的相关性,对亮度变化敏感,不适合处理对光照变化敏感的图像。HIS 颜色空间亮度与色度信号相分离,H 分量受光照变化影响很小且可以识别不同颜色的物体,但 H 分量与 RGB 转换关系为非线性容易造成图像失真,同时存在计算量大、耗时多等问题[18]。YCrCb(亦称 YUV 模型)颜色空间是用于彩色电视信号传输的一种编码方式,Y 表示亮度,Cr 和 Cb 为色度信号与光照无关,分别表示 RGB 输入信号红色分量和蓝色分量与亮度信号之差[19-20]。YCrCb 颜色空间亮度信号与色度信号相分离,适合处理易受光照变化影响的图像。

农田作物图像中绿色分量占很大比重,但 YCrCb 颜色空间缺少对绿色分量与信号亮度之差的描述。因此,本文引入 Cg 分量(RGB 信号绿色部分与亮度之差)来描述绿色作物特征,构建 $2Cg - Cr - Cb$ 特征因子对农田作物图像进行灰度化。

RGB 与 YCrCb 颜色空间转换公式为

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \begin{bmatrix} 0 \\ 128 \\ 128 \end{bmatrix} + \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ -0.169 & -0.331 & 0.5 \\ 0.5 & -0.419 & -0.081 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{1}$$

Cg 分量对应绿色信号与亮度之差

$$Cg = 128 + \begin{bmatrix} -0.299 & 0.413 & -0.114 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (2)$$

根据 ITU－R BT.601－6 标准对 Cg 进行归一化处理得到

$$Cg = 128 + \begin{bmatrix} -0.362 & 0.5 & -0.138 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (3)$$

由式(3)可以看出，Cg 分量与 R、G、B 分量转换关系为线性，具有计算简单、转换速度快等优点。本文采集不同环境下玉米图片，利用 $2Cg - Cr - Cb$ 因子对图像进行灰度化处理并计算出灰度图像所对应的直方图，如图 1、2 所示。由处理结果可以看出，不同环境下玉米灰度图像清晰完整且与土壤对比度明显，直方图呈现明显波峰波谷，具有良好的分割特性。

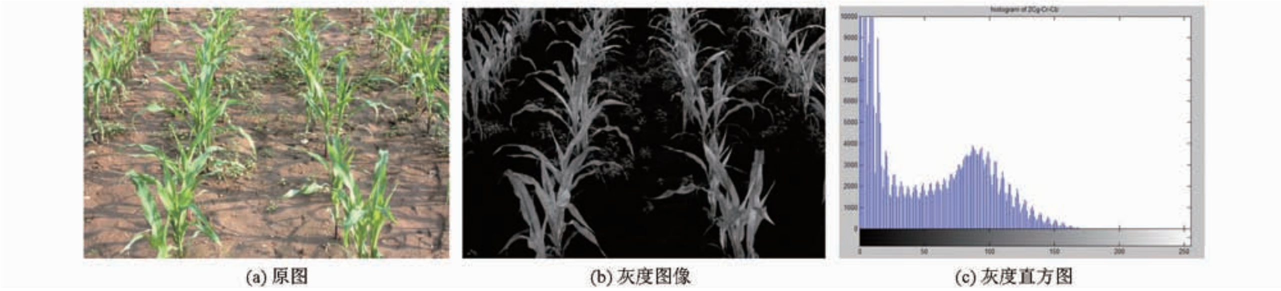


图 1　晴天环境下玉米图像转换结果

Fig. 1　Results of corn image conversion in sunny day

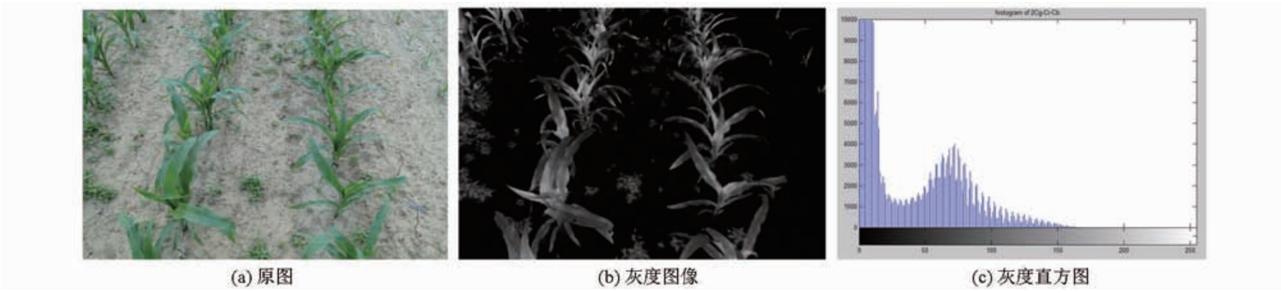


图 2　阴天环境下玉米图像转换结果

Fig. 2　Results of image conversion in cloudy day

2　图像分割与噪声滤除

图像分割是导航路径识别的关键环节，主要作用是将作物信息从土壤背景中提取出来。K-means 聚类算法是一种非监督图像分割方法，具有简单、快速、处理大数据时相对可伸缩和高效率等优点。相比于阈值分割方法，聚类分割算法对作物与背景不存在明显灰度差异或者各物体灰度范围有较大重叠的图像也具有良好的分割效果[21－22]。K-means 算法将样本距离作为相似性评价指标，认为类是由距离靠近的样本组成，通过迭代使目标函数最小以获取最佳聚类。本文聚类分割算法使用的相似性评价指标函数和目标函数为

$$d(x_i, x_j) = \sqrt{\sum_{k=1}^{d} (x_{ik} - x_{jk})^2} \quad (4)$$

$$E = \sum_{i=1}^{n} \sum_{p \in X_i} \| p - m_i \|^2 \quad (5)$$

式中　x_i、x_j——d 维空间的两个点

$d(x_i, x_j)$——x_i、x_j 的欧氏距离

X_i——第 i 个聚类子集

m_i——聚类 X_i 均值

p——聚类 X_i 中样本

n——聚类个数

E——数据空间中所有对象与相应聚类中心的均方和之差

在聚类个数确定的前提下，初始聚类中心的选择对算法的收敛速度有着重要的影响。常规 K-means 聚类算法是随机选择初始聚类中心，造成图像分割的最小耗时无法保证。本文对 K-means 算法进行改进，通过确定最佳初始聚类中心提高聚类算法的收敛速度。主要思路是在 $2Cg - Cr - Cb$ 灰度直方图中检测直方图的波峰波谷，选取波峰值所对应的数据为初始聚类中心。由于图像噪声的影响，直方图中常出现类似波峰的随机干扰点，影响计算机波峰自动检测。为去除随机干扰点，可以采用高斯滤波对直方图进行平滑处理。

在聚类个数为2的情况下,分别利用常规聚类算法和改进聚类算法进行图像分割(运行环境为VS 2010),如图3a、3b所示。在分割效果上,2种算法接近;在算法耗时上,常规算法为25.7 ms,改进算法为14.1 ms,后者实时性比前者有所提高。此外,分割图像中除作物信息外还存在一些杂草噪声,杂草噪声的存在将对后续作物行直线检测造成影响。本文采用形态学滤波算法进行噪声滤除,先用2×2结构元素进行膨胀操作,然后用半径为4的圆盘结构进行腐蚀操作,滤波效果如图3c所示,可以看出杂草噪声被基本消除,作物行信息得到保留。


(a) 常规K-means图像分割　(b) 改进K-means图像分割　(c) 杂草滤除后二值图像

图3　图像分割与杂草去噪

Fig. 3　Image segmentation and weed filtering

3　基于粒子群算法的作物行识别与导航路径检测

3.1　粒子群优化算法原理

粒子群优化算法(Particle swarm optimization, PSO)是一种基于群体的演化算法,通过个体间的协作与竞争,实现复杂空间最优解搜索,算法基本原理如下[23]:

设粒子群在一个 n 维空间中搜索,粒子可以表示为 $\boldsymbol{x}_i=(x_{i1},x_{i2},\cdots,x_{in})$,是问题的一个解,$\boldsymbol{v}_i=(v_{i1},v_{i2},\cdots,v_{in})$ 表示粒子速度,则PSO算法公式为

$$v_{id}(k+1)=wv_{id}(k)+c_1\mathrm{rand}_1(P_{idbest}(k)-x_{id}(k))+c_2\mathrm{rand}_2(P_{gdbest}(k)-x_{id}(k)) \tag{6}$$

$$x_{id}(k+1)=x_{id}(k)+v_{id}(k+1) \tag{7}$$

式中　$P_{idbest}(k)$——粒子个体最优位置

$P_{gdbest}(k)$——整个粒子群全局最优位置

c_1、c_2——加速度系数

w——惯性因子　k——迭代次数

rand_1、rand_2——0~1之间2个随机数

3.2　作物行直线检测与导航路径识别

文献[16-17]采用粒子群算法对车道线进行检测,由于农田作物行具有与车道线相似的线性特征,因此可以通过粒子群算法对作物行直线进行提取。为快速、准确地获取作物行直线,本文根据图像中作物行的特点建立作物行线性方程约束模型,在此基础上利用粒子群算法对直线参数进行寻优求解。作物行直线方程约束模型具体内容如下:

(1)由于机械化播种,生长出的作物行表现为小曲率曲线或者近似直线并且作物行间相互平行。但受相机投影模型影响,图像中的作物行呈现出近大远小的特点,即作物行在图像底端较粗且行间距离较大,而在图像顶端较细且距离较小。

(2)作物行起始于图像底边,终止于图像顶边,生长具有连续性,其直线方程可以通过底边和顶边上的2个像素点确定。

(3)以图像中心线为界,将图像分为左、右两部分,以图像左下角为原点建立直角坐标系,图像中心线左侧作物行直线斜率为正,右侧作物行直线斜率为负,图像中间作物行与中心线重合。

根据上面约束条件,在图像宽度和高度固定的条件下,本文采用粒子群算法对作物行直线进行检测,具体步骤如下:

(1)设图像高度为 $Height$,宽度为 $Width$,作物行直线起点坐标为 $(x_0,0)$,终点坐标为 $(x_1,Height)$。

(2)利用垂直投影法计算作物行个数信息 N 和位置信息 P_{nL}、P_{nR},P_{nL}、P_{nR} 分别表示第 n($n=1,2,\cdots,N$)条作物行两侧边缘位置。如果 $N\geqslant1$(图像中包含作物行)执行步骤(3),否则程序结束。

(3)初始化作物行个数计数变量 $num=1$、位置信息存储数组 $Pos[N][2]$ 和直线距离阈值 d。其中,$Pos[n][0]$、$Pos[n][1]$ 分别用来存储第 n 条作物行位置信息 P_{nL}、P_{nR}。

(4)初始化粒子个数 m、加速度系数 c_1、c_2、惯性因子 w、最大迭代次数 l 和终止阈值 t。建立适应度函数 $f=T$,T 表示距离候选直线一定范围(d 范围)内目标点个数,T 越大表示直线越接近作物行中心线。

(5)如果 $Pos[num][1]\leqslant\frac{Width}{2}$(中心线左侧作物行),则 $x_0\in[Pos[num][0],Pos[num][1]]$,$x_1\in[Pos[num][0],Width/2]$;如果 $Pos[num][0]\geqslant\frac{Width}{2}$(中心线右侧作物行),则 $x_0\in[Pos[num][0],$

$Pos[num][1]]$，$x_1 \in [Width/2, Pos[num][1]]$；如果 $Pos[num][0] < \frac{Width}{2} < Pos[num][1]$（与中心线重合的作物行），则 x_0、$x_1 \in [Pos[num][0], Pos[num][1]]$。

（6）选择直线起点、终点横坐标 x_0、x_1 构成一个粒子，利用 (x_0, x_1) 表示一条候选作物行直线，初始化粒子群。

（7）计算每个粒子适应度，设置粒子自身最优位置和全局最优位置，利用式（6）、（7）对粒子速度和位置进行更新。

（8）如果达到最大迭代次数或满足终止阈值，则输出参数 (x_0, x_1)，然后利用两点式得到作物行直线；否则返回步骤（7）继续迭代。

（9）$num = num + 1$，如果 $num \leqslant N$ 则返回步骤（5），否则执行步骤（10）。

（10）利用距离图像中心线最近的两条作物行直线计算得到导航路径方程。

将作物行线性模型与粒子群算法相结合进行导航路径识别具有以下两方面优点：首先，作物行线性模型与作物种类和生长阶段无关，使路径识别算法可以适应不同环境；其次，粒子群算法具有精度高、收敛速度快等特点，可以有效提高路径识别算法的准确性与实时性。

4　实验结果与分析

本文设计的实验包括静态实验和动态实验。静态实验是在实验室中利用计算机进行图像处理和分析；动态实验是在农田环境下利用实验平台进行导航跟踪测试。

静态实验的计算机型号为联想 Y460，采用 Intel Core（TM）i3 2.4 GHz 处理器，2 GB 内存，Windows 7 操作系统。图像处理程序基于 C/C + + 语言开发，运行环境为 VS 2010；动态实验平台如图 4 所示，主要由视觉传感器、工控机、PLC 控制器、液压系统和除草机具组成。视觉传感器采用 OKAC1310 彩色相机，输出为 RGB 格式的 bmp 图片，图像尺寸为 640 像素 ×480 像素。工控机型号为 PPC - 5152 - D525，采用 Intel Atom D525 2.8 GHz 处理器，2 GB 内存，Windows XP 操作系统。导航程序基于 C/C + + 语言开发，运行环境为 VS 2010。在实验平台上安装 GPS 系统，采集导航系统运动轨迹信息，用于导航效果评价。

4.1　光照适应性实验

为测试光照变化对图像分割效果的影响，将不同环境下玉米图像分别转换到 YCrCb、HIS、RGB 颜色空间，利用 $2Cg - Cr - Cb$ 因子、H 分量、$2G - R - B$ 因子对图像进行灰度化处理并进行图像分割。选择晴天（光强约 80 000 lx）和阴天（光强约 6 500 lx）条件下的玉米图像，如图 5 所示。

图 4　实验平台

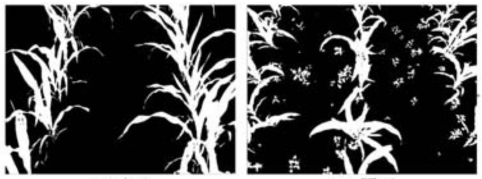
Fig. 4　Experimental platform

(a) 晴天　(b) 阴天

图 5　不同天气条件下玉米图片

Fig. 5　Corn images under different weather conditions

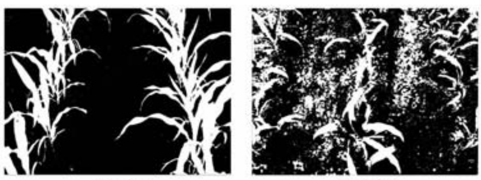
图 6 为 YCrCb 颜色空间下使用 $2Cg - Cr - Cb$ 因子进行图像灰度化后的图像分割，可以看出分割效果受光照变化影响很小，不同天气条件下作物图像分割清晰完整。图 7 为 HIS 颜色空间下 H 分量分割效果图，晴天条件下作物图像完整的从土壤背景中分割出来，阴天环境下分割图像存在大量噪声点，影响后续图像的处理。其中，噪声点的产生是由于 RGB 与 HIS 颜色空间转换关系为非线性导致的。图 8 为 RGB 颜色空间下基于 $2G - R - B$ 灰度图像的图像分割，阴天环境下分割效果良好，但在晴天环境下作物信息缺失，无法完整地表达原始作物特征，这是由于 R、B、G 3 个分量相互耦合且对光照变化敏



(a) 晴天　(b) 阴天

图 6　基于 $2Cg - Cr - Cb$ 灰度图像的分割效果

Fig. 6　Image segmentation effects based on $2Cg - Cr - Cb$ gray image



(a) 晴天　(b) 阴天

图 7　基于 H 分量的分割效果

Fig. 7　Image segmentation effects based on H component

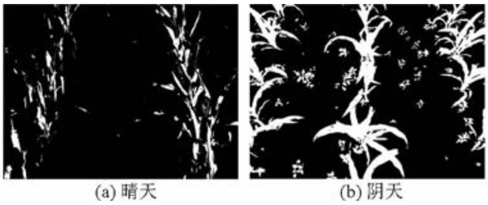


图8 基于 $2G-R-B$ 灰度图像的分割效果

Fig. 8 Image segmentation effects based on $2G-R-B$ gray image

感造成的。

通过上面实验可以在直观效果上对3种图像预处理方法的性能做出初步评价。为进一步验证 $2Cg-Cr-Cb$ 因子在不同光照强度下具有的普遍有效性，本文在3种光照范围内共采集60幅作物图像（每种光照范围内采集20幅）。选择 George 的评价方法[24]，通过图像相对分割错误率对基于 $2Cg-Cr-Cb$ 因子、H 分量、$2G-R-B$ 因子的分割图像进行质量评价。图像相对分割错误率为

$$E_{seg}^{AB}=1-\frac{\sum_{j,k=1}^{m,n} I^{A}(j,k)\cap I^{B}(j,k)}{\sum_{j,k=1}^{m,n} I^{B}(j,k)} \tag{8}$$

式中 I^A、I^B——利用方法A和方法B得到的分割图像

E_{seg}^{AB}——图像 I^A 对图像 I^B 的相对分割错误率

i、j——像素行号、列号

m、n——图像宽度、高度

由式(8)可以看出，2种分割算法对比中，相对分割错误率越大，其相对分割的像素与两者分割的公共像素集偏离程度越大。图9为60幅作物图片相对分割错误率对比曲线。

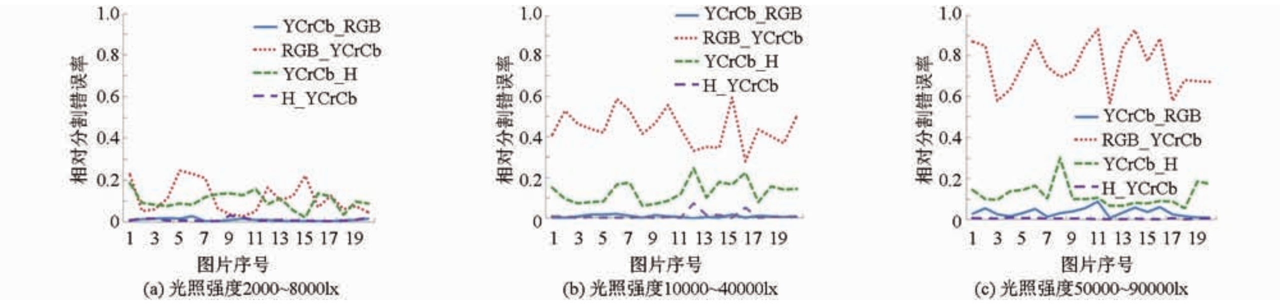


图9 不同光照条件下图像相对分割错误率曲线

Fig. 9 Relative error curves of image segmentation under different illumination conditions

图9中 YCrCb_RGB 曲线、YCrCb_H 曲线分别表示 $2Cg-Cr-Cb$ 法对 $2G-R-B$ 法和 H 分量法的相对分割错误率；RGB_YCrCb 曲线、H_YCrCb 曲线分别表示 $2G-R-B$ 法和 H 分量法对 $2Cg-Cr-Cb$ 法的相对分割错误率。由图9可以看出，不同光照范围内 RGB_YCrCb 曲线均大于 YCrCb_RGB 曲线，并且随着光强的增加呈现不断上升的趋势，这是由于光照强度越高 $2G-R-B$ 法分割图像中作物信息缺失越多导致的（图8a）。H_YCrCb 曲线在不同光照环境下均小于 YCrCb_H 曲线，这是因为背景噪声的存在（图7b）使 H 分量分割图像中目标像素多于 $2Cg-Cr-Cb$ 分割图像中目标像素，在公共像素集一定的条件下，H 分量法对 $2Cg-Cr-Cb$ 法的相对分割错误率小于 $2Cg-Cr-Cb$ 法对 H 分量法的相对分割错误率。

上述实验表明，相比于 $2G-R-B$ 法[5-6]和 H 分量法[7-8]，采用 $2Cg-Cr-Cb$ 因子进行图像灰度化处理，可以在不同光照环境下使分割图像保留足够多的绿色作物信息，有效提高了图像处理对光照变化的适应能力，同时在分割图像中不会引入背景噪声。

4.2 导航路径检测算法性能测试

为测试导航线检测算法的准确性、实时性以及对作物不同生长时期的适应性，本文采集3个生长阶段的玉米图像共60幅（每个阶段采集20幅）。利用标准 Hough 变换、标准最小二乘法和本文算法进行作物行检测与导航路径识别，根据可以准确获取导航路径信息的图像数量和获取导航路径信息的平均耗时，对3种算法性能进行对比。3种算法均为标准算法，未进行相关优化，处理图像尺寸为640像素×480像素。Hough 算法和最小二乘法的检测步骤为：灰度变换、图像分割、特征点检测、特征点归类、作物行提取、导航路径识别；粒子群算法检测步骤为：灰度变换、图像分割 、作物位置检测、作物行提取、导航路径识别。Hough 算法中，$\theta\in[-90°,90°]$，$\rho=[-800,800]$，量化精度0.5°。粒子群算法中，初始化粒子个数为50，惯性系数 $w=0.5$，学习因子 $c_1=c_2=1$，距离阈值 $d=5$，终止条件为 $l=100$ 或者 $t>4\,000$，其中 t 根据作物种类或者生长时期不同可进行适当调整。表1为3种方法在作物不同生长阶段下准确提取导航路径信息的图像数量与平均耗时（不包括灰度化、图像分割耗时）。

表 1　作物不同生长阶段导航路径信息检测结果与耗时

Tab. 1　Number of images that navigation path were extracted and time consumption under different growth phases

检测算法	作物高度范围/cm			平均耗时/ms
	10～15	20～25	30～35	
Hough 方法	20	18	16	196.2
最小二乘法	20	17	14	119.6
粒子群算法	20	20	19	88.4

由表 1 可以看出，在准确率方面，Hough 算法与最小二乘法的准确率低于本文算法，这是因为杂草噪声和分散生长的玉米叶片（随着玉米的生长，叶片变宽且向外分散生长趋势增加）被误检测为作物特征点，引入了干扰噪声，导致作物行检测存在偏差。本文方法直接在二值图像基础上进行作物行检测，受杂草噪声和玉米叶片干扰很小，其中一幅图像检测失败是因为杂草密度很高与作物行连成一片，导致作物位置检测环节出现错误。在实时性方面，粒子群算法的平均耗时少于前面 2 种方法，这是由于特征点检测环节的存在，使 Hough 变换和最小二乘法总体耗时增加（对于一幅 640 像素×480 像素的图像，特征点检测耗时约为 40 ms）。粒子群算法没有特征点检测环节，所以在算法整体耗时上少于 Hough 变换和最小二乘法。图 10 为玉米高度在20～25 cm 范围内，3 种方法检测结果，红色虚线表示作物行直线，绿色虚线表示导航路径。表 2 为 3 种方法得到的作物行直线与导航线参数。

由图 10 可以看出，3 种方法均可以提取出作物行直线与导航线，但 Hough 变换与最小二乘法提取的作物行直线与粒子群算法相比存在一定误差（主要由于玉米叶片的分散生长和杂草噪声造成）。表 2 中 Hough 变换的导航线斜率为 -5.40，截距为 2 484.60；最小二乘法的导航线斜率为 -18.26，截距为 2 697.87；粒子群算法的导航线斜率为 -28.22，截距为 11 347.36。通过比较可以看出，Hough 变换和最小二乘法与粒子群算法相比在导航线参数上存在较大偏差。

上述实验表明，本文提出的导航线识别算法与标准 Hough 变换和标准最小二乘法相比具有检测速度快、准确率高等特点，同时对不同生长时期的作物具有良好适应性。

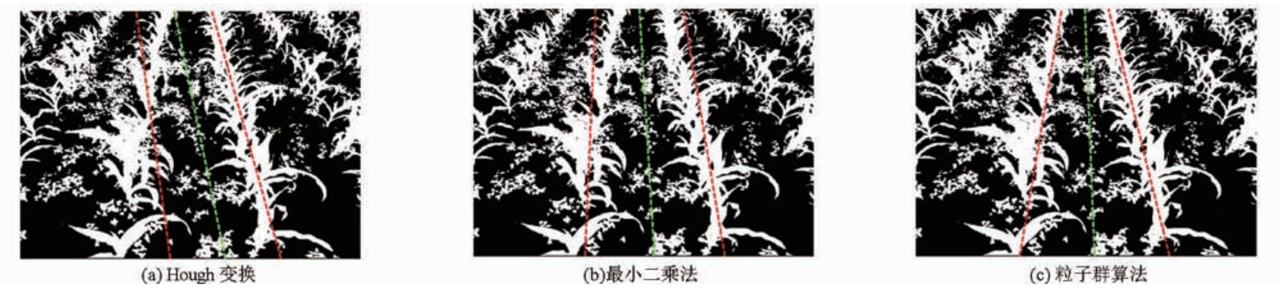


图 10　不同算法导航线检测结果

Fig. 10　Guidance line detection results of different algorithms

表 2　不同算法作物行直线及导航线参数比较

Tab. 2　Results of liner parameter comparison

检测算法	左侧作物行		右侧作物行		导航路径	
	斜率 k	截距 b	斜率 k	截距 b	斜率 k	截距 b
Hough 变换	-8.17	2 745.47	-4.03	2 354.96	-5.40	2 484.60
最小二乘法	25.19	-6 312.70	-6.62	3 743.09	-18.26	2 697.87
粒子群算法	6.60	-1 547.50	-4.52	2 582.03	-28.22	11 347.36

4.3　作物行直线检测算法性能对比

除标准 Hough 变换、最小二乘法外，文献[14-16]也分别提出了用于作物行检测和车道线识别的方法，本文将这 3 种方法与基于粒子群算法的作物行检测方法在性能上进行定性的比较：

（1）实时性

文献[14]采用随机方法进行作物行直线检测，该算法的耗时与随机点的选择具有很大关系，随机点选择恰当，可以很快得到作物行直线；否则需要不断地进行随机点选择，且该方法没有限定随机点选择的最大次数，导致算法最大耗时具有不确定性。本文方法通过设置终止条件（最大迭代次数）使算法最大耗时保证在一个确定范围内。此外，文献[14]的方法本质上是一种随机寻优（不具有寻优策略和寻优方向），本文算法是一种定向寻优（按照一定策略使粒子向最优方向前进）。在随机点选择次数（假设文献[14]规定了随机点选择次数）与粒子群算法运算次数相同的条件下，本文算法搜索到

最优作物行直线的概率大于随机算法，也就表示本文算法在时间消耗上小于随机算法。

文献[16]采用粒子群算法进行车道线提取，该方法后验概率函数中图像所有的像素点都参与运算，对于 $M\times N$ 的图像，计算1个粒子适应度要遍历的像素个数为 $M\times N$。本文算法中，对于 $M\times N$ 的图像，计算1个粒子适应度要遍历的像素个数为 $M\times 2d$（d 表示距离阈值，远小于 N）。因此，在粒子个数和最大迭代次数相同的条件下，本文算法实时性要高于文献[16]的方法。

（2）准确性

文献[15]的方法需要结合垄宽先验知识设置作物特征点检测阈值，在特征点检测阈值一定的条件下，利用该算法对不同作物进行直线提取，算法的准确性会发生改变。本文算法通过构建作物行线性模型进行直线提取，算法的准确性不会受到作物种类影响。

此外，由于文献[14－15]进行作物行直线提取前需要获取作物特征点，导致一些杂草噪声和向外分散生长的叶片被误检测为作物特征点，影响直线检测的准确性。本文方法不包括特征点检测环节，直接在二值图像基础上进行直线检测，受杂草噪声和叶片干扰很小，算法的准确性和抗干扰性高于前面2种方法。

4.4 作物行适应性检测实验

利用本文算法分别对不同类型作物行进行直线检测，检测作物包括大豆、小麦和圆白菜，每种作物各采集30幅图片。与玉米相比，这些作物叶片生长集中更易于检测，所以本文算法能够全部准确识别出作物行直线。其中，图11是3种代表性图像。实验表明，基于粒子群算法的作物行检测方法能够正确识别出不同类型作物行直线，具有较强的适应性。

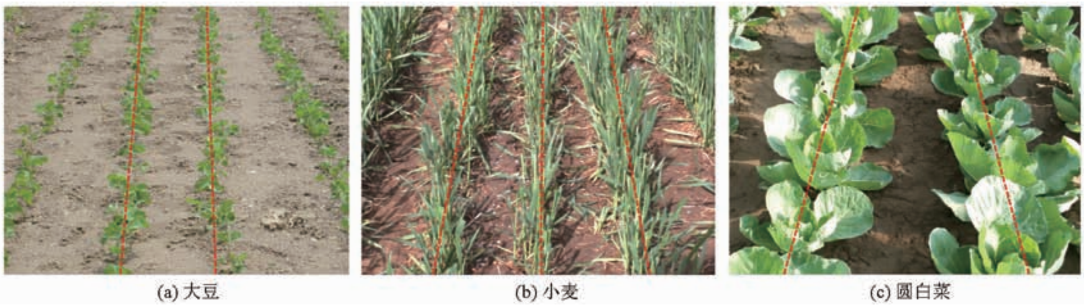


图11 不同作物直线检测结果

Fig. 11 Detection results of different crop

4.5 导航跟踪实验

利用本文的导航线提取方法分别在0.6、1.0、1.4 m/s速度条件下进行导航路径跟踪实验，以评价算法的动态性能。实验对象为中耕期玉米，行间距60 cm，平均高度约25 cm，行走路径长度20 m，GPS采集频率2 Hz。为提高实验数据的可靠性，每种速度条件下进行5次重复实验，并在每种速度条件下选出最大横向偏差最大的一次和最大横向偏差最小的一次作为一组。路径跟踪结果如图12所示，图12a与图12d、图12b与图12e、图12c与图12f分

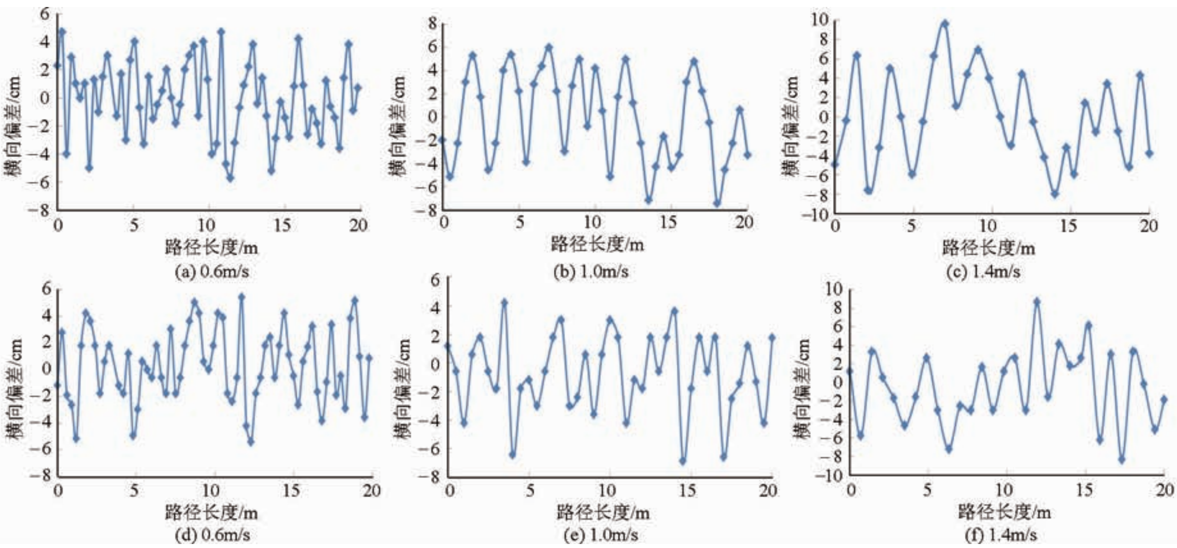


图12 不同速度条件下导航路径跟踪实验结果

Fig. 12 Experimental results of guidance line tracking in different speed

别构成相同速度条件下的一组。0.6 m/s 时最大横向偏差分别为 5.7 cm、5.4 cm,平均横向偏差分别为 2.2 cm、2.18 cm;1.0 m/s 时最大横向偏差分别为 7.5 cm、6.8 cm,平均横向偏差分别为 3.3 cm、2.4 cm;1.4 m/s 时最大横向偏差分别为 9.6 cm、8.7 cm,平均横向偏差分别为 3.7 cm、3.3 cm。本文实验平台导航作业过程中最大横向偏差小于 15 cm 时,可有效除去行间杂草,不会损伤作物。因此,本文提出的导航线检测方法能满足农业机械田间自主导航作业的精度要求,具有良好的动态性能。

5　结论

(1)利用 YCrCb 颜色模型构建与光照无关的 Cg 分量,选择 $2Cg-Cr-Cb$ 特征因子对图像进行预处理,提高了图像处理对光照变化的适应能力。实验结果表明,不同光照条件下基于 $2Cg-Cr-Cb$ 灰度图像的图像分割,可以将作物信息清晰完整地从背景中分离出来,分割效果受光照变化影响较小。

(2)通过对 K-means 聚类分割方法进行改进,在保证图像分割质量的前提下缩短了分割时间,使图像处理算法整体实时性提高。

(3)首次提出了利用作物行线性模型与粒子群算法相结合进行农业机械导航线提取的方法。此方法在二值图像基础上直接进行直线提取,具有抗干扰性强、算法复杂度低等特点。实验结果表明,相比于常规方法本文算法可快速、准确地提取出作物行直线与导航路径,对不同作物具有较高的适应性,能较好地满足农业机械田间自主导航作业要求。

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