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Research on Detection Method of Navigation Line for Ningxia Lycium Barbarum Garden

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Keywords：color difference model analysis, Genetic Algorithm, edge detection, navigation line detection.

ABSTRACT

At present, developing intelligent production equipment under “general self-moving host platform + operation module” mode is the urgent task to realize the healthy development of *L.barbarum* industry. The problem of edge detection between the plant column region and the soil region and the problem of navigation line detection are difficulties for precision visual navigation of self-moving platform. For the problem of edge detection between plant column and soil, optimized the coefficient of color differences model based on Genetic Algorithm. For the problem of navigation line detection for the known segmentation image, construct the parameterized trapezoidal template, and match the parameterized trapezoidal template and segmentation image. Made matching overlap as fitness function, and optimized the trapezoidal template parameters based on Genetic Algorithm, then extract trapezoidal midline from the optimized trapezoidal template as navigation line. It laid the foundation for precision navigation of self-moving platform under *L.barbarum* garden environment.

INTRODUCTION

Lycium barbarum (*L.barbarum*) is the most having local characteristics and advantageous industries in Ningxia, with broad development prospect. At present, in *L.barbarum* plant protection, fertilization, picking and other production links, it is generally low efficiency and strong labor intensity, becoming the bottle-neck that restricts industry development. Developing intelligent production equipment under “general self-moving host platform + operation module” mode is the urgent task to realize the healthy development of *L.barbarum* industry. Self-moving platform is the foundation for intelligent production of *L.barbarum*. In order to adapt to *L.barbarum* garden complex unstructured environment, self-moving platform need to have ability of adaptive navigation. To solve the navigation line detection problem for self-moving platform under *L.barbarum* garden environment is one of the key problems to realize precision navigation.

(Shen et al., 2003) dealt automatic detection of the cropland areas under the complicated background and introduced some knowledge-based approaches to implement the area detection. (Zhou et al., 2004), developed a predictive control method based on Kalman filtering for the problem of time lag produced mainly by robot vision system and the other signal processing exerting some negative effects on the autonomous navigation of the wheeled mobile robot. (Zhou et al., 2005) demonstrated a visual navigation system of agricultural mobile robot which included its system structure, the road recognition in filed environment, the estimation of pose relative to the tracked road, the improvement of real-time and robustness of navigation system, and a Kalman filter based lateral control algorithm. (Wang & Ji, 2006) put forward an assumption for cotton harvesting based on agricultural robot in view of the conjuncture. (Chen et al., 2009) proposed a new algorithm for crop rows detection for the problem of detecting and localizing the crop rows quickly and effectively for navigation of agricultural machines and developed navigation software in VC++ 6.0. (Zhou et al., 2014) developed the method that agricultural mobile robot acquire the navigation strategies through autonomous learning based on reinforcement learning and fuzzy logic. (Lin et al., 2015) proposed a method fusing edge detection and improved random sample consensus for winding orchard path detection and the algorithm was consisted of orchard road edge detection algorithm (REE) and improved RANSAC algorithm (IRANSAC) for the problem of the orchard road detection algorithm required to be improved. (Zaidner & Shapiro 2016) proposed a new data fusion algorithm for navigation that optimally fused the localization data from various sensors. (Bengochea-Guevara et al., 2016) developed an

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image-processing method capable of extracting the central crop row under uncontrolled lighting conditions in real time from images acquired with a reflex camera positioned on the front of the robot. Designed and developed two fuzzy controllers to achieve vision-guided navigation. Developed a method for detecting the end of a crop row using camera-acquired images. (Bai et al., 2016) proposed a method of automatic identification for motion target based on dual windows to reduce the visual feedback delay. (Liangxi et al., 2016) used color components to extract the target features of the inner and outside of the corn field respectively, and smooth the image using the moving average method with the set length. (Jiang et al., 2016) proposed an agricultural robot visual de-hazing method based on image segmentation map for the problem of navigation function failure which results in unable to effectively positioning and navigation. (Meng et al., 2016) constructed Cg component on the base of YCrCb color mode and selected the 2Cg-Cr-Cb factor to preprocess the image. (Liu et al., 2016) described a method of monocular visual recognition to navigate small vehicles between narrow crop rows. (Zhang et al., 2017) proposed a navigation method for weeding robot based on SUSAN corner and improved sequential clustering algorithm. (Zhai et al., 2017) presented a novel test method based on virtual reality for binocular vision based guidance system. (Narvaez et al., 2018) focused on the soil surface classification by implementing a visual system capable to distinguish between five usual types of off-road terrains for the problem of taking the proper guidance or control actions.

From what has been discussed above, in respect of agricultural robot vision navigation, environments are different for different agricultural and forest crops, so the detection methods for navigation line are vary. Moreover, problem of the navigation line detection under *L.barbarum* garden environment has not been studied. So, this paper focus on the problem of navigation line detection of self-moving platform under *L.barbarum* garden complex unstructured environment.

The problem of edge detection between the plant column region and the soil region and the problem of the navigation line detection are basis of precision navigation for self-moving platform. Suitable color difference model for image processing is the premise of edge detection. And for to this problem, optimized color difference model for image processing is constructed. For the problem of navigation line detection for the known segmentation image, parameterized trapezoidal template is constructed. The parameterized trapezoidal template is matched with segmentation image, and matching degree is used as fitness function. Trapezoidal template parameters are optimized based on genetic algorithm, and the middle line of trapezoid is extracted as the navigation line.

IMAGE ACQUISITION AND PROCESSING

Image Acquisition

L.barbarum garden images were collected on October 15, 2017. The site is located in the Tongxin north street *L.barbarum* garden in Xixia district, Yinchuan, Ningxia. The image acquisition equipment is a Redmi 3X camera. The image color space is RGB. The image is a JPG format. The size is 208x416 pixels as shown in Figure 1.

Fig. 1. *L.barbarum* garden image.

Image Processing Environment

The computer for image processing is TOSHIBA Satellite L800, and the processor is Intel(R) Core(TM) i5-3210M. The image processing tool is Matlab R2016a.

Navigation Line Detection Method

For the problem of navigation line detection, processing flow is as shown in Fig. 2.

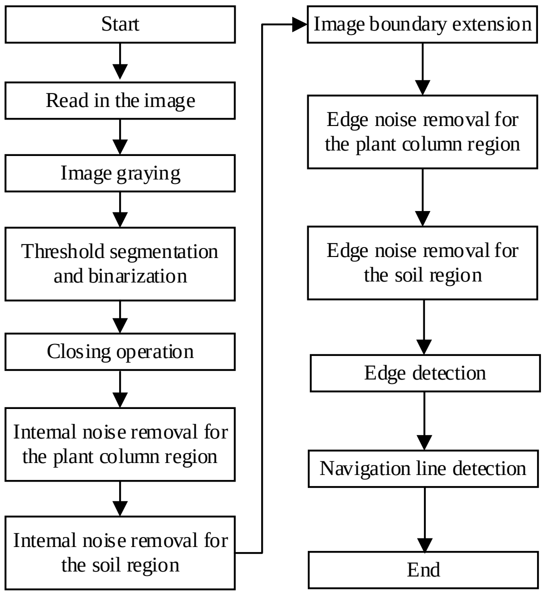

Fig. 2. Processing flow for navigation line detection.

CONSTRUCT COLOR DIFFERENCES MODEL BASED ON GENETIC ALGORITHM

Optimization Problem Analysis for Color Differences Model

Selection of color differences model for *L.barbarum* garden image processing directly affects the edge detection effect between the plant column region and soil region, then it affects the quality of the navigation line detection. Color difference model is constructed as shown in Eq. (1). Among them, x_1 is the coefficient of G component, x_2 is the coefficient of B component, x_3 is the coefficient of R component. As can be seen from Fig. 3, G component is greater than R component and B component in the plant column region, and G component is less than R component and B component in the soil region. To enhance contrast, coefficient at the front side of the G component is set as the plus sign, while coefficients at the front side of the R component and B component are set as the minus sign.

Fig. 3. Comparison diagram of each color component.

$$A = (x_1 * G) - (x_2 * B) - (x_3 * R). \quad (1)$$

For color difference model shown in Eq. (1), set the following constraints:

$$\begin{cases} 0.1 < x_1 < 1 \\ 0.1 < x_2 < 1 \\ 0.1 < x_3 < 1 \\ x_1 + x_2 + x_3 = 1 \end{cases}. \quad (2)$$

Therefore, Eq. (1) can be transformed into:

$$A = (x_1 * G) - (x_2 * B) - ((1 - x_1 - x_2) * R). \quad (3)$$

In Eq. (3), suitable color difference model coefficients are the basis of edge detection between the plant column region and the soil region. In order to determine the appropriate coefficients, a method of finding highest fitness coefficients through multiple evolutionary searching based on Genetic Algorithm is proposed.

Coefficient Optimization Flow Based on Genetic Algorithm

Coefficient optimization flow based on Genetic Algorithm is shown in Fig. 4.

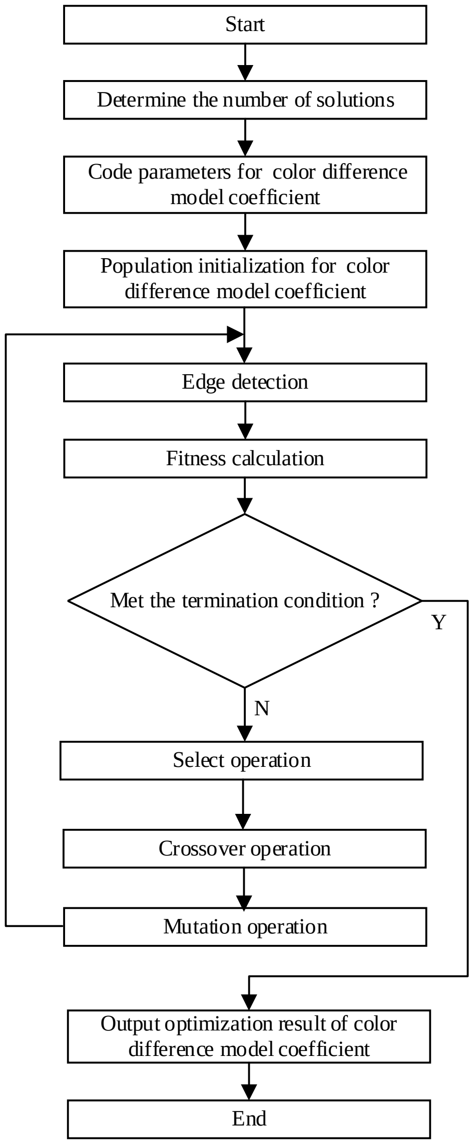

Fig. 4. Coefficient optimization flow.

Chromosome Coding

The encoding method has important influences on individual chromosome arrangement, the transformation of genotype of search space into phenotype of solution space, and operation of genetic operator. Therefore, coding method determines the efficiency of genetic evolution operation. Decimal coding is suitable for the optimization problem with high precision. So choose the decimal encoding method. The optimization problem has two variables. Each variable has its corresponding upper and lower limit. Its phenotype type is $x=[0.1,1;0.1,1;]$.

Fitness Function Construction

Images No. 1 to No. 1200 are selected as sample. Edges of image No. 1 between the plant column region and the soil region are manually calibrated. And manual image segmentation is performed, and with the plant column region "1" and the soil region "0". The manual calibration edge result of image No. 1 is shown in Fig. 5. The manual segmentation result of image No. 1 is shown in Fig. 6. The result is set as $figure1\#_{manual}$. In turn, images No. 2 to No. 1200 is processed using the above methods, getting $figure2\#_{manual}$ to $figure1200\#_{manual}$. Among them, images No. 1 to No. 1000 is the training set for optimization of color difference model coefficients. Images No. 1001 to No. 1200 is the test set for verifying the adaptability of the color difference model to edge detection and image segmentation between the plant column region and the soil region.

Fig. 5. Manual edge calibration result of image No. 1.

Fig. 6. Manual segmentation result of image No. 1.

Based the color difference model shown in Eq. (3), images of No. 1 to No. 1000 are processed follow the method shown in Fig. 2, getting the segmentation results between the plant column region and the soil region. These segmentation results respectively are $figure1\#_{cdm}$ to $figure1000\#_{cdm}$.

The closer image segmentation results $figure_{cdm}$ based on the color difference model shown in Eq. (3) and following method shown in Fig. 2 is to the manual calibration segmentation results $figure_{manual}$, the better are coefficients x_1 and x_2. To evaluate degree of proximity between $figure_{cdm}$ and $figure_{manual}$, evaluation function $f(x)_{evaluation}$ shown in Eq. (4) is constructed. The larger the value of evaluation function is, the closer is between $figure_{cdm}$ and $figure_{manual}$.

$$f(x)_{evaluation}=1-(figure_{manual}\oplus figure_{cdm}). \quad (4)$$

For images No. 1 to No. 1000, $f(x)1\#_{evaluation}$ to $f(x)1000\#_{evaluation}$ is performed using the method shown in Eq. (4) in sequence. To comprehensively evaluate the image segmentation adaptability of color difference model coefficients x_1 and x_2 to images No. 1 to No. 1000. Fitness function shown in Eq. (5) is constructed.

$$Fit(x)=f(x)average_{evaluation}+f(x)vaiance_{evaluation}, \quad (5)$$

In Eq. (5): $f(x)average_{evaluation}$ is the average of $f(x)1\#_{evaluation}$ to $f(x)1000\#_{evaluation}$. $f(x)vaiance_{evaluation}$ is the variance of $f(x)1\#_{evaluation}$ to $f(x)1000\#_{evaluation}$.

Selection Operator

Roulette selection method is used. The superior is selected and the inferior is eliminated according to the fitness of each individual. Individuals with strong vitality are selected to generate a new generation of population. The probability that each individual enters the next generation is equal to the ratio of its fitness value to the sum of individual fitness values of the whole population, namely:

$$P_i=f(x_i)\Big/\sum_{1}^{n}f(x_i), \quad (6)$$

In Eq. (6): $f(x_i)$ is the fitness value of the i chromosome. n is the population size.

Cross

The method of single point cross is used. The crossover probability is set 0.7. For each pair of pairs, the crossing point is randomly selected. Mutually exchange part of the chromosomes of two individuals.

Mutation

To maintain population diversity, effectively avoid premature puberty and improve local search results, method of basic bit variation is adopted.

Mutation probability is set as 0.01. For each locus of the individual, specify the variation points according to the mutation rate. Do the inverse of the genetic value, and it creates new individuals.

Selection of Control Parameter

The population size is generally selected as 20~100. After many experiments and comprehensive comparison of the optimal solution and the running time under different population size, eclectically select 50. The end algebra is set as 50.

Optimization Experiment and Result Analysis

Based on the method shown in Fig. 4, then color difference model coefficients were optimized. Fitness curve in process of iterative operations is shown in Fig. 7. The optimization results are shown in Eq. (7).

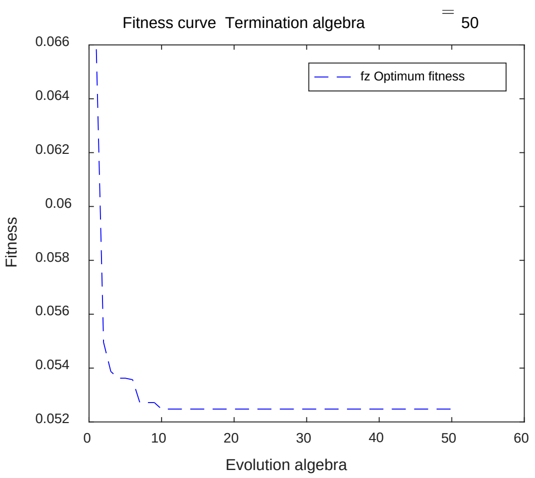

Fig. 7. Fitness curve.

$$\begin{cases} x_1 = 0.4750 \\ x_2 = 0.3401 \\ x_3 = 0.1849 \end{cases} . \tag{7}$$

So the color difference model is:

$$A = (0.4750 * G) - (0.3401 * B) - (0.1849 * R) . \tag{8}$$

Image graying is carried out for image No. 1 based on Eq. (8), and the result is shown in Fig. 8. Threshold segmentation is performed by the average gray value of all pixels, and then binarization is performed, as shown in Fig. 9. The results of a closing operation using a flat disk structure element with a radius of 8 pixels for the image shown in Fig. 9 are shown in Fig. 10. It can be seen from Fig. 10 that there are noises in the plant column region. These noises mainly are bare surfaces. Some of them are inside the image. Also some of them are at the edge of the image. There are also noises in the soil region. These noises mainly are weeds. Some of them are inside the image. Also some of them are at the edge of the image. The internal noises in the plant column region are removed by using the method of filling internal hole. The image is then inverted. In the same way, the internal noises in the soil region are removed by using the method of filling internal hole. The image is then inverted. The result of internal noises removal is shown in Fig. 11. To remove the edge noise in the plant column region and the soil region, two pixels is expanded outward for the image shown in Fig. 11, with the edge noise change into internal noise. Then these edge noises are removed by the method of removing the internal noise. Finally, the extended element is deleted. The result is shown in Fig. 12. The edge detection effect for image No. 1 is shown in Fig. 13.

Fig. 8. Grayscale image.

Fig. 9. Threshold segmentation and binarization image.

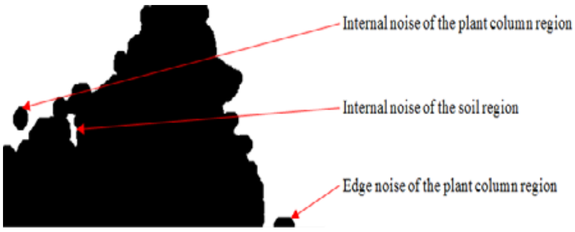

Fig. 10. Result of closing operation.

Fig. 11. Image with internal noise removed.

Fig. 12. Image with edge noise removed.

Fig. 13. Edge detection result of image No. 1.

To further verify the adaptability of the color difference model shown in Eq. (8) to images of *L.barbarum* garden, image segmentation and edge detection is performed for images No. 1001 to No. 1200. The precision evaluation coefficients are calculated for images No. 1001 to No. 1200 based on Eq. (4). The minimum of the precision evaluation coefficient is 84.38%. The average of the precision evaluation coefficient is 96.32%.

The edge detection effects for partial image of the test set are shown in Fig. 14 to18. Edge detection results of manual detection and detection based on color difference model are compared. The red line represents the edge detection results of manual detection, and the blue line represents the result of detection based on color difference model. Among them, the image shown in Fig. 14 was acquired in the morning. The image shown in Fig. 15 was acquired in the forenoon. The image shown in Fig. 16 was acquired at noon. The image shown in Fig. 17 was acquired in the afternoon. The image shown in Fig. 18 was acquired just before sunset.

Fig. 14. Edge detection effect for image acquired in the morning.

Fig. 15. Edge detection effect for image acquired at forenoon.

Fig. 16. Edge detection effect for image acquired at noon.

Fig. 17. Edge detection effect for image acquired in the afternoon.

Fig. 18. Edge detection effect for image acquired just before sunset.

At present, the manual production operation links and the production operation links by manually driven mechanical equipment basically begin after dawn and end before dark. It can be seen from the precision evaluation coefficients and Fig. 14 to18 that the edge detection method proposed in this paper for visual navigation of self-moving platform basically covered the time period of the current production link, and has a very high degree of similarity to manual edge detection. This method also has a strong adaptability to shadow problems. Therefore, this color difference model has high adaptability to normal production operation time during the day and it can be used as the color difference model for image processing of *L.barbarum* garden.

NAVIGATION LINE DETECTION BASED ON PARAMETERIZED TRAPEZOIDAL TEMPLATE MATCHING

Parameterized Trapezoidal Template Construction

For segmentation image shown in Fig. 12, navigation line detection is the key problem for realizing precision navigation of self-moving platform. For this problem, reverse the segmentation image shown in Fig. 12, getting the reverse image $figure_{reverse}$ shown in Fig. 19. Among them, the white region is the soil and the black region is the plant column.

Fig. 19. Reverse image.

Match the parameterized trapezoidal template with reverse image, and set up the coordinate system as shown in Fig. 20. As can be seen from Fig. 20, the more overlap area between the trapezoid ABCD and the soil region, the higher matching degree of the trapezoid ABCD with the soil region. The middle line EF of trapezoid can be used as the navigation line. Therefore, the appropriate trapezoid ABCD can realize detection of navigation line. For this problem, parameterized trapezoidal template image $figure_{tem}$ is constructed.

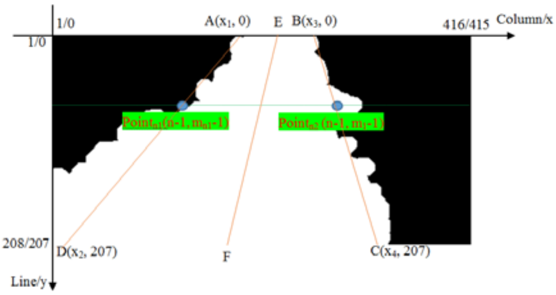

Fig. 20. Coordinate system.

The intersection point coordinate of line AD with each line of parameterized trapezoidal template image $figure_{tem}$ is $Point_{n1}(n-1, m_{n1}-1)$. The intersection point coordinate of line BC with each line of parameterized trapezoidal template image $figure_{tem}$ is $Point_{n2}(n-1, m_{n2}-1)$. Therefore, parameterized trapezoidal template image is as follows:

$$figure_{tem}(n,m) = \begin{cases} 0 & 1 < m \le m_{n1} \\ 1 & m_{n1} < m < m_{n2} \\ 0 & m_{n2} \le m \le 416 \end{cases} . \tag{9}$$

In Eq. (9): n is the line coordinates of $Point_{n1}$ and $Point_{n2}$ in parameterized trapezoidal template image $figure_{tem}$, $n = 1, 2......208$. m is the column coordinates of $Point_{n1}$ and $Point_{n2}$ in parameterized trapezoidal template image $figure_{tem}$, $m = 1, 2......416$.

Assume that that four vertices of the trapezoid respectively are $A = (x_1, 0)$, $B = (x_3, 0)$, $C = (x_4, 207)$ and $D = (x_2, 207)$. Therefore,

$$m_{n1} = round(((x_2 - x_1)/207) * n + x_1) + 1 . \tag{10}$$

$$m_{n2} = round(((x_4 - x_3)/207) * n + x_3) + 1 . \tag{11}$$

It can be seen from Eq. (9), (10) and (11), finding the appropriate x_1, x_2, x_3 and x_4 is the key to the detection of navigation line.

Parameter Optimization Based on Genetic Algorithm

In order to determine the appropriate x_1, x_2, x_3 and x_4, look for excellence through multiple evolutionary searching based on Genetic Algorithm. Fitness function was constructed as shown in Eq. (12).

$$Fit(x) = 1 - (figure_{tem} \oplus figure_{reverse}) . \quad (12)$$

Roulette selection method is used. Method of single point cross is used. The crossover probability is set as 0.7. Method of basic bit variation is adopted. Mutation probability is set as 0.01. The population size and end algebra are respectively set as 50 and 150. The range of parameter variables is $x = [0.1, 415; 0.1, 415; 0.1, 415; 0.1, 415;]$. For the segmentation image of image No. 1 shown in Fig. 12, optimization experiment is carried out for trapezoidal template parameter. Fitness curve in process of iterative operations is shown in Fig. 21. The optimization results are shown in Eq. (13). The optimized parameterized trapezoidal template is shown in Fig. 22.

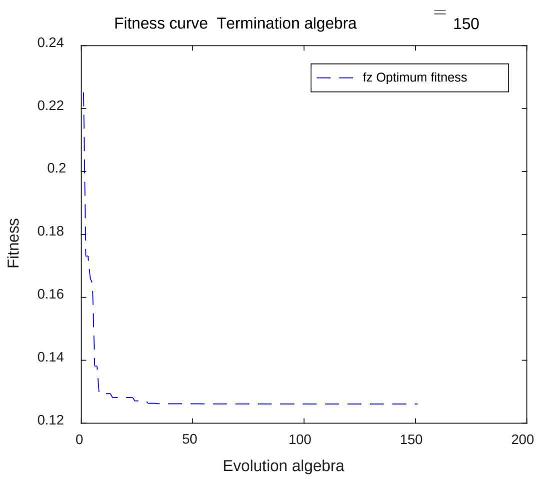

Fig. 21. Fitness curve.

Fig. 22. Optimization results of trapezoidal template parameter.

$$\begin{cases} x_1 = 181.3223 \\ x_2 = 10.4566 \\ x_3 = 259.5956 \\ x_4 = 345.9005 \end{cases} . \quad (13)$$

Based on the above method, 20 images were randomly selected and optimization experiments were performed for trapezoidal template parameters. The optimization results are shown in Table 1. As can be seen from Table 1, the minimum percentage of matching of the parameterized trapezoidal template with segmentation image is 88.16% and the average is 91.34%, with a high degree of matching. Meet requirements for navigation line detection.

Table 1. Optimization results of trapezoidal template parameters.

Image sequence number	x_1	x_2	x_3	x_4	Percentage of matching
1	176.5125	46.8304	240.7952	335.3600	94.56%
2	201.3444	72.6597	239.7939	414.4284	92.47%
3	169.5349	91.7949	289.7914	407.9326	95.05%
4	156.2334	14.2146	302.2391	387.3961	88.16%
5	202.4452	82.4461	279.1046	411.5560	93.23%
6	130.9304	13.1376	249.0815	382.0804	89.57%
7	172.4655	70.6770	257.0032	413.2467	93.95%
8	122.4316	8.4202	355.2650	414.3350	89.68%
9	187.9868	25.7939	287.3892	397.9202	90.34%
10	217.7839	95.0194	290.6596	412.8216	92.62%
11	170.3042	62.9686	347.9932	414.6471	90.54%
12	213.9713	41.3159	287.6142	376.2585	89.21%
13	143.1168	17.0638	299.7048	404.6258	90.12%
14	109.0300	54.5439	295.8282	414.6873	91.12%
15	209.6624	55.4347	271.3466	372.1471	91.59%
16	169.9996	64.2158	289.3950	403.9838	92.59%
17	144.9867	47.0770	258.0229	374.9712	92.43%
18	200.1198	99.8104	295.0767	372.2529	90.63%
19	186.9539	119.0306	388.7853	413.1715	89.26%
20	183.6998	75.1299	230.5802	365.3589	89.58%
		Average			91.34%

Based on the optimization parameters shown in Table 1, trapezoidal template was used to detect the navigation line for the 20 images, and detection effects for four out of 20 images are shown in Fig. 23 to 26. As can be seen, it can stably and reliably detect navigation line of *L.barbarum* garden based on optimized parameterized trapezoidal template.

Fig. 23. Detection effect of image No. 1.

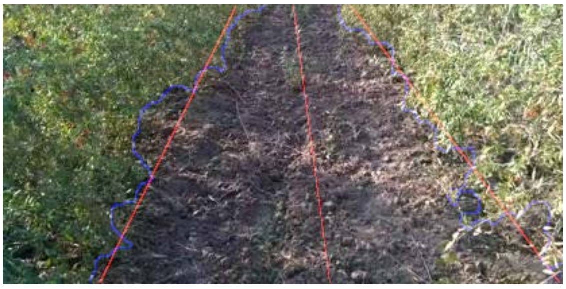

Fig. 24. Detection effect for image No. 6.

Fig. 25. Detection effect for image No. 15.

Fig. 26. Detection effect for image No. 20.

CONCLUSIONS

(1) For the problem of color difference model for RGB image processing in *L.barbarum* garden, a method based on genetic algorithm for constructing color difference model is proposed.

(2) A kind of color difference model ($A=(0.4750*G)-(0.3401*R)-(0.1849*B)$) which is suitable for image processing in *L.barbarum* garden is proposed.

(3) Experiments show that image processing based on the color difference model proposed in this paper can effectively detect edges between the plant column region and the soil region.

(4) For the problem of navigation line detection for the known segmentation image, proposed a method which match the parameterized trapezoidal template with segmentation image and extract the middle line of trapezoid as the navigation line.

(5) For the problem of trapezoidal template parameter optimization, an optimization method based on genetic algorithm which uses matching degree of the parameterized trapezoidal template with segmentation image as fitness function is proposed, with the average matching degree reaching 91.34%.

(6) The navigation line detection method proposed in this paper can effectively detect the navigation line of *L.barbarum*. It laid the foundation for precision navigation of self-moving platform under *L.barbarum* garden environment.

In the future, to comprehensively improve the adaptability of the self-moving platform to the complex unstructured environment of *L.barbarum* garden and realize navigation in all-weather and whole-life cycle of *L.barbarum*, there are still some problems in edge detection that need to be further studied. Details are as follows:

(1) Ningxia has some days with windy and dusty weather, and there are also a few days with heavy fog. In view of these extreme weather conditions, the edge detection is a difficult problem.

(2) Links of winter fertilizing and spring pruning are respectively in early winter and early spring. During these periods, *L.barbarum* has dropped its leaves, and it is a difficult problem to realize edge detection.

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寧夏枸杞園自主移動平臺導航線檢測方法研究

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摘 要

當前發展“通用自主移動承載平臺+作業模組”模式下的智慧化生產作業裝備是實現枸杞產業健康發展的迫切任務。株列與土壤區域邊緣檢測及導航線檢測問題是自主移動平臺精准視覺導航的難點。針對株列與土壤邊緣檢測問題，基於遺傳演算法優化了色差模型係數。針對已知分割圖像檢測導航線問題，構建參數化梯形範本，以參數化梯形範本圖像與分割圖像匹配，以匹配重疊度為適應度函數，基於遺傳演算法優化梯形範本參數，以優化後的梯形範本提取梯形中線作為導航線，為自主移動平臺枸杞園環境下精准導航奠定了基礎。