

ANALYSIS OF VISUAL NAVIGATION EXTRACTION ALGORITHM OF FARM ROBOT BASED ON DARK PRIMARY COLOUR

基于暗原色的农田机器人视觉导航提取算法分析

Zhongkun Hou ¹

Department of Mechatronics and Information Engineering, Sichuan College of Architectural Technology,
Deyang City, Sichuan Province / China

*Tel: 15963582573; E-mail: akun501@163.com

DOI: <https://doi.org/10.35633/inmateh-62-23>

Keywords: dark primary colours, farmland, robot, visual navigation, extraction algorithm

ABSTRACT

With the development of information technology, precision agriculture has also ushered in new development prospects. The use of farm robots to accurately identify the navigation path is of great significance for achieving accurate positioning of agriculture. In this study, when analysing the extraction algorithm of farm robot visual navigation based on dark primary colours, a method for pre-processing and edge detection of farmland images based on dark primary colours is proposed. At the same time, the least square method of linear fitting is used for the navigation path of agricultural robot, and then the fitting program is executed. On this basis, combined with the actual situation of outdoor farming and greenhouse cultivation of crops, the effectiveness of the robotic visual navigation extraction algorithm was verified. The research results show that for any form of farmland cultivation, image extraction technology based on dark primary colours can effectively distinguish between soil and crops, and the visual navigation path of farm robots fitted with least squares is basically linear, which is consistent with the commonly used crops for farm planting. The legal route is basically the same, and then the effectiveness of the extraction algorithm is verified. It is hoped that this study will provide a certain reference and reference for the analysis of the field navigation robot visual navigation extraction algorithm based on dark primary colours.

摘要

随着信息技术的发展, 精准农业也迎来了新的发展前景。使用农业机器人准确识别导航路径对实现农业的精确定位具有重要意义。本文在分析基于深色原色的农用机器人视觉导航提取算法的基础上, 提出了一种基于深色原色的农田图像预处理和边缘检测方法。同时, 线性拟合的最小二乘法用于农用机器人的导航路径。执行拟合。在此基础上, 结合野外耕作和温室大棚栽培的实际情况, 验证了机器人视觉导航提取算法的有效性。研究表明, 对于任何形式的农田耕作, 基于深色原色的图像提取技术都可以有效地区分土壤和农作物, 配备最小二乘法的农场机器人的视觉导航路径基本上是线性的, 这与通常的做法是一致的。用于农作物种植的农作物。合法路径基本相同, 然后验证了提取算法的有效性。希望这项研究为基于深色原色的野外导航机器人视觉导航提取算法的分析提供一定的参考和借鉴。

INTRODUCTION

Agriculture is the basis for human survival, an important guarantee for human food and clothing, and plays an important role in economic prosperity and social stability. With the development of social economy, the development of agricultural modernization is steadily advancing. One of the most important signs of agricultural modernization is the increasing degree of agricultural mechanization (Teshome and Degu, 2019). With the rapid development of information technology, agricultural mechanization is moving to the next new development stage, namely, agricultural precision. The so-called precision agriculture refers to relying on information technology and computer technology such as artificial intelligence to achieve the precise development of agriculture. Among them, farmland cultivation is the most important and basic part of agriculture, and is a part of the vigorous development of precision agriculture (Srbnovska and al., 2015). Machine vision has been widely used in the development of precision farming technology. Field robot is of great significance for accurate identification of navigation path and accurate positioning.

¹ As. PhD. Lec. Zhongkun Hou

Machine vision refers to the use of cameras and other sensors to collect images, and to simulate human visual functions through image processors. After completing a series of image acquisition and simulation function operations, extract and understand relevant information from the images, and finally use the relevant information for monitoring and control (Sun T.H., Tien F.C. and Tien F.C., 2016). Farm robot visual navigation is relatively low in cost and easy to operate. It has no special requirements for operators and agricultural scale, and has good applicability, so it is widely used in farm cultivation. In addition, in the visual navigation of farm robots, the extraction of navigation lines is the most critical content, which is the key to determine the navigation accuracy and speed of farm robots.

In this study, when analysing the field navigation robot visual navigation extraction algorithm based on dark primary colours, a method for pre-processing and edge detection of farmland images based on dark primary colours is proposed. At the same time, the least square method in linear fitting is used to extract the navigation lines. Farm robot navigation path to fit. On this basis, combined with the actual planting conditions of outdoor farmland cultivation and greenhouse cultivation of crops, the effectiveness of the robot visual navigation extraction algorithm was verified.

The innovation of this research lies in the use of dark primary colour prior theory for grayscale pre-processing of farmland images, which can quickly perform grayscale processing on the image, and can effectively distinguish crops and soil in farmland images. At the same time, the research also focused on the practical application of extraction algorithms, combining the method with the actual farmland cultivation, and by combining the actual conditions of outdoor farmland cultivation and greenhouse cultivation of crops, the effectiveness of the robotic visual navigation extraction algorithm was verified.

This research mainly includes four parts. The first part is the application of the prior theory of dark primary colours by domestic and foreign scholars and the research of robot visual navigation. The second part is the research of the field navigation robot visual navigation extraction algorithm based on the dark primary grayscale processing, including the use of dark primary colour images for grayscale pre-processing and edge detection, and the least square method in linear fitting to extract the navigation path. The third part is to verify the effectiveness of the robotic visual navigation extraction algorithm in combination with the actual planting conditions of outdoor farmland cultivation and greenhouse cultivation.

Aimed at the inaccuracy of the Gaussian algorithm in the dark primary colour prior theories, Li A *et al.* proposed a method to improve the image clarity based on the dark channel, and verified this by analysing the factors affecting the image colour shift. Regarding the effectiveness of the method, the results show that this method can effectively solve the problem of image migration in light-coloured areas (Li A., Fang Z and Mi B., 2018). In the study of coal dust and smoke images, Mingben D.U *et al.* proposed an image enhancement algorithm based on dark primary color prior theory. Based on the image degradation model, the image denoising technology is realized. The experimental results show that the image denoising technology can optimize and enhance the image quality. (Mingben D.U., *et al.*, 2015). Xiao JS *et al.* proposed an image denoising algorithm based on the dark primary colour prior theory to overcome the colour distortion and halo effect of the sky, accurately estimate the overall atmospheric light in the sky area, and use the median filter technology to obtain detailed Edge information to effectively estimate the transmission image (Xiao J.S. *et al.*, 2017). Liu H.B. *et al.* proposed an image defogging method based on the a priori theory of dark primary colours, and changing the grey value of the image through linear mapping, thereby improving the medium transmittance in foggy and large sky areas. This method can achieve faster image processing speed (Liu H.B., Yang J. and Wu Z.P., 2015). When studying the single image denoising algorithm, Alharbi EM *et al.* proposed an atmospheric light estimation algorithm based on the dark primary colour prior theory. By improving the attenuation image contrast, etc., the effectiveness of the algorithm in estimating atmospheric light was verified (Alharbi E.M., Ge P. and Wang H., 2016).

When studying the visual navigation of autonomous mobile robots, Kurashiki K. *et al.* proposed an image-based road boundary tracking control law, and designed an interactive model of robot motion and image features. This method reduces a priori information and improves the map scalability (Kurashiki K, *et al.*, 2015). Rômulo T Rodrigues and others proposed a method of improving robot visual positioning based on artificial potential field when researching robot visual navigation, which connects the features in robot visual images with potential energy to promote the robot to advance. The research results show that this method has good performance (Rômulo T. Rodrigues, *et al.*, 2018). Phalak Y. *et al.*, when studying robot navigation, combined with the parabolic geometry in mathematical tools, proposed a method of navigation using image processing, and finally proposed a system expansion based on the actual experimental results

of the combination of static and dynamic (Phalak Y. et al., 2018). Kamaev A.N. et al. used the point cloud computing algorithm and the algorithm to establish the point cloud correspondence to provide navigation data for the aircraft when studying the navigation problem of the automatic launch vehicle. The test results show that this method can make the aircraft always follow the navigation trajectory (Kamaev A.N. and Karmanov D.A., 2018). When studying the visual navigation path of coloured cotton robots, Li D. et al. proposed a field navigation path extraction method based on horizontal spline segmentation, and obtained the connected domain of cotton valley by detecting the connected domain in the horizontal spline. Planning the navigation path for the coloured cotton robot finally verified the accuracy and effectiveness of the method (Li D., Xu S. and Zheng Y., 2017). Kumar B. et al. proposed a robot path navigation method using RF communication and wireless audio and video transmission when studying the mobile navigation of autonomous robots. By installing a navigation embedded system inside the robot, the robot can help the robot to achieve autonomous mobile navigation. The actual test verifies the effectiveness of the method (Yang H., Gao L. and Tang N., 2019). Delaune J. et al. proposed a vision-assisted inertial navigation system for autonomous space robot landing when studying the running path of autonomous space robot. Image processing is performed through data fusion to accurately control the navigation path of space robot (Delaune J. et al., 2016).

It can be seen that the relevant research at home and abroad mainly includes the application of dark primary colour prior theory in image processing and the application of related methods in robot navigation (Wang B., He J.L., Zhang S.J. and Li L.L., 2020). Among them, the dark primary colour prior theory is mainly used in image processing, and robot visual navigation also mainly depends on the research on related image features. The related researches are less concerned with the navigation research of farm robots, so this study analyses and studies the visual navigation of farm robots based on dark primary colours.

MATERIALS AND METHODS

Dark primary grayscale processing

In the process of visual navigation of farm robots, in order to quickly and accurately extract image features, it is necessary to pre-process the images in visual navigation. In general, for the visual navigation of farm robots, one of the main problems is that the farm environment is complex and changeable, the colours are complicated, the farm contains a lot of colour image information, and the amount of related data is huge. (Tai J.J., Li H.T., Du Y.F., Mao E.R., Zhang J.N. and Long X.J., 2020) Extracting relevant image information and pre-processing it is beneficial to quickly extract navigation information, so that farm robots can better perform farm operations.

In farmland images, the colours of most crops are more vivid colours such as green, and there are fewer crops that are darker. (Guo Y.B., Zhang X.G. and Zhang C., 2020). Therefore, according to the principle of dark primary colours, if the image includes objects with bright colours or bright surfaces, it also includes objects or surfaces with darker colours, for the three RGB values in the images of these objects or surfaces, there must be a channel with a very small value, and the corresponding dark primary colour image is also greyer. Therefore, for crop images or soil images in farmland, there must be a kind of grey state. In order to promote the application of farm robot visual navigation in agricultural operations, this study grey-scales the dark primary colours of the corresponding farm road images based on the grey-levelling rules and the principle of dark primary colours. First, a mathematical method is used to define the dark channel.

The dark channel of each pixel of the farmland image can be expressed as follows.

$$I^{dark}(x, y) = \min_{c \in \{r, g, b\}} I^c(x, y) \quad (1)$$

Among them, $I^{dark}(x, y)$ represents the dark primary colour channel of the pixel coordinate (x, y) ; $I^c(x, y)$ is the colour channel of the pixel coordinate (x, y) . On this basis, traverse all the pixels included in the farmland image I , and compare the size of the three colour channel values of each pixel; the three colour channels can be expressed as: $I^r(x, y)$, $I^g(x, y)$, $I^b(x, y)$, before comparing the three colour channel values. It is necessary to calculate the grey value of each pixel according to formula (1), and finally obtain the dark primary grey image I_{dark} . In order to evaluate the image processing effect in the visual navigation process of farm robots, MATLAB is used to process farm images, and the corresponding image running time and normalized histogram characteristics are obtained, as shown in Figures 1 and 2.



Fig. 1 - Gary scale conversion results

Figure 1 is a comparison between an unprocessed image and a grey-scale image, where Figure 1(a) is the original image of a typical crop, Figure 1(b) is a dark-primary grey-scale image, and Figure 1(c) is the image after 2G-R-B grayscale processing. It can be seen from the figure that the green crops and soil can be clearly distinguished from the original image of typical crops. The dark primary colour grayscale image processing time is only 0.532s, and compared to the original image, it can also be clearer. Crop and soil are distinguished from it. 2G-R-B grayscale processing image takes longer time than dark primary grayscale processing image, which is 4.267s. Compared with the original crop image and gray processing image, the difference between soil and green crop is not obvious. Although the two can be distinguished to some extent, the performance of the green crops is not obvious enough, and the reflection is not accurate enough.

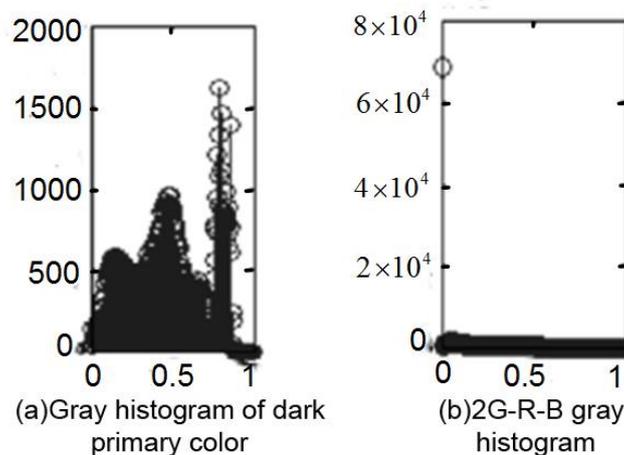


Fig. 2 - Histogram features of grey level processing

Figure 2 is a comparison of the normalized histogram features of agricultural image grey-scale processing. Figures 2(a) and 2(b) are the histogram characteristics of dark primary grayscale processing and the histogram characteristics of 2G-R-B grayscale processing, respectively. It can be seen from the figure that the histogram characteristics of agricultural crop images processed by the dark primary grayscale are more obvious, there are more obvious peaks and troughs, and they range from 0 to 2000; while for the 2G-R-B grayscale processing, as far as crop histograms are concerned, their characteristics are relatively insignificant, and there are no obvious fluctuations. The maximum value is between 6×10^4 and 8×10^4 , while the remaining small disturbances are mostly concentrated around zero.

Farmland image edge detection based on dark primary grayscale processing

On the basis of grey-scale processing of crop images, edge detection is performed on the images in a derivation manner. For the crops in the farmland, the edges between them and the farmland background can reflect the trend of the crops to a certain extent. Therefore, the detection of the edge parts of the crops is helpful for the farmland robot to extract important navigation feature points, so as to better perform visual navigation. This study takes a binary image as an example.

The biggest feature of the edge of a binary image is that the pixel value along the edge of the image always remains the same, while the pixel value perpendicular to the edge of the image changes.

In general, the differentiation mainly uses differential algorithms, and for the processing of digital images, differential approximation is often used to solve differential operations. Commonly used edge detection differential operators include first-order differential operators and second-order differential operators. Among them, the binary image with different edges and its first derivative curve are shown in Figure 3. It can be seen from the figure that all different image forms obtain the maximum value of the first derivative at the edge, and edge detection can be performed on the crop image on this basis. This is the principle of the first-order differential operator used for edge detection, namely the correlation between the image gradient and the first derivative is used for detection.

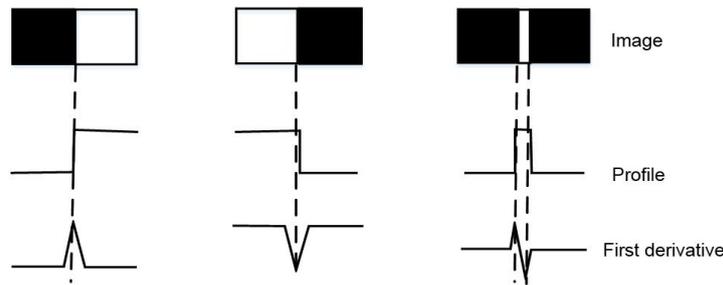


Fig. 3 - Image edge type and its first derivative curve

Assuming that the continuous image function is $f(x, y)$, the gradient at the point (x, y) can be defined as shown in the following formula.

$$\nabla f(x, y) = \left[\frac{\partial f(x, y)}{\partial x} \quad \frac{\partial f(x, y)}{\partial y} \right]^T = [G_x \quad G_y]^T \quad (2)$$

Where G_x is the gradient in the x direction; G_y is the gradient in the y direction. Further, the gradient modulus corresponding to the gradient vector can be expressed by Euclidean distance, as shown in the following formula.

$$|G(x, y)| = \sqrt{G_x^2 + G_y^2} \quad (3)$$

Similarly, the gradient modulus can also be expressed as a checkerboard distance as follows.

$$|G(x, y)| = |G_x| + |G_y| \quad (4)$$

The gradient direction corresponding to the gradient vector can be expressed as follows.

$$\theta(x, y) = \arctan\left(\frac{G_y}{G_x}\right) \quad (5)$$

The main idea of the first-order differential operator to detect the edge of the crop image is to set a suitable modulus threshold. If there is a gradient modulus value in a certain part of the image that exceeds this threshold, you can set the pixel of the image as the edge point. If otherwise, it belongs to a non-edge point, and the related expression is shown in the following formula.

$$g(x, y) = \begin{cases} 1, & G(x, y) > T \\ 0, & \text{Others} \end{cases} \quad (6)$$

When performing edge detection on farm crop images, several differential operators are mainly used, namely Roberts operator and Sobel operator.

Among them, the Roberts operator belongs to one of the first-order differential operators, and its main idea is to use the difference to approximate the gradients G_x and G_y in the x direction and the y direction, and the related expressions are as follows.

$$\begin{aligned} G_x &= f(x+1, y+1) - f(x, y) \\ G_y &= f(x+1, y) - f(x, y+1) \end{aligned} \quad (7)$$

The Roberts operator includes corresponding convolution templates, as shown in Table 1 and Table 2.

Table 1

Convolution template 1 of Roberts operator

-1	0
0	1

Table 1 is a convolution template of Roberts operator. Among them, the two diagonal numbers are 0, 0, and -1, 1. When using Roberts operator to detect edge of farm crop image, calculating the gradient amplitude is actually calculating the adjacent pixel value on the diagonal difference between. The same is true for another convolution template of Roberts operator. It can be seen from Table 2 that the convolution template is a transpose of another convolution template, and the two diagonal numbers are 1, -1, and 0, 0, respectively. Therefore, Roberts operator can be used to detect vertical and horizontal edges of crop images, and then extract image edge information.

Table 2

Convolution template 2 of Roberts operator

0	-1
1	0

The Sobel operator is also one of the first-order differential operators, and the gradients G_x and G_y in the x direction and the y direction are approximated by the difference as shown in the following formula.

$$\begin{aligned}
 G_x &= [f(x-1, y-1) + 2f(x, y-1) + f(x+1, y-1)] \\
 &\quad - [f(x-1, y+1) + 2f(x, y+1) + f(x+1, y+1)] \\
 G_y &= [f(x+1, y-1) + 2f(x+1, y) + f(x+1, y+1)] \\
 &\quad - [f(x-1, y-1) + 2f(x-1, y) + f(x-1, y+1)]
 \end{aligned}
 \tag{8}$$

The convolution templates corresponding to the Sobel operator are shown in Table 3 and Table 4.

Table 3

Convolution template 1 of Sobel operator

-1	-2	-1
0	0	0
1	2	1

Table 3 is a convolution template of the Sobel operator. The convolution operator mainly includes -2, -1, 0, 1, and 2, and the three 0s are arranged horizontally. Table 4 is another convolution template of Sobel operator, which is transposed from template 1. The convolution operator in this template also includes -2, -1, 0, 1, and 2, the difference is that the operator's three 0s are arranged vertically. In the edge detection of farm crop images, the Sobel operator has a better effect when detecting the oblique edges of the image, and can effectively reduce or even suppress the image noise.

Table 4

Convolution template 2 of Sobel operator

-1	0	1
-2	0	2
-1	0	1

In order to enable the field robot to realize automatic navigation during visual navigation, the navigation curve is fitted on the basis of extracting corresponding navigation feature points. Generally, the seeding method is mostly used in agricultural planting, and its path is basically straight or straight in the local range of the direction of agricultural machinery. Therefore, the least square method in linear fitting is used in this study to achieve navigation fitting. Assuming that the coordinate of the navigation feature point is $(x_i, y_i) (i=1, 2, \dots, n)$, the fitting equation can be obtained as shown in the following formula.

$$f(x) = ax + b \quad (9)$$

Among them, a and b both represent fitting coefficients. The residual sum of squares of the fitted equation is further obtained as shown in the following formula.

$$E = \sum_{i=1}^n [f(x_i) - y_i]^2 = \sum_{i=1}^n (ax_i + b - y_i)^2 \quad (10)$$

To minimize the value of E , the fitting coefficient a , b needs to satisfy the following conditions.

$$\begin{cases} \frac{\partial E}{\partial a} = 2 \sum (ax_i + b - y_i) x_i = 0 \\ \frac{\partial E}{\partial b} = 2 \sum (ax_i + b - y_i) = 0 \end{cases} \quad (11)$$

Further obtain the result shown in the following formula, and find the a , b to obtain the corresponding navigation line equation.

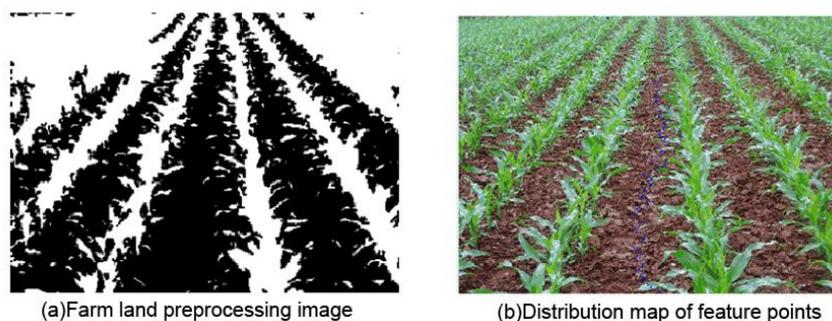
$$\begin{bmatrix} \sum_{i=1}^n x_i^2 & \sum_{i=1}^n x_i \\ \sum_{i=1}^n x_i & n \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} \sum_{i=1}^n x_i y_i \\ \sum_{i=1}^n y_i \end{bmatrix} \quad (12)$$

RESULTS

Real agricultural robots play an important role in the visual navigation effect measurement of agricultural crops. Based on the grayscale processing of farmland crop images, the first-order differential operator is used for edge detection and feature point extraction to obtain the visual navigation effect of farm robots when planting crops in outdoor farmland and the visual navigation effect of farm robots when planting crops in Dapeng. The experiment also analyzes the measurement results of the agricultural robot in the corresponding crop vision navigation path.



Fig. 4 - Real agricultural robots



(a) Farm land preprocessing image

(b) Distribution map of feature points

Fig. 5 - Processing of farmland crop lines

Figure 5 is the relevant situation of the green crops planted in a certain outdoor farmland. Figure 5(a) is the result of the dark primary grayscale pre-treatment of the green crops planted in the original farmland. It can be seen from the figure that in the image of the dark primary grayscale processing, the distinction between soil and green crops is more obvious, where green plants become black after grayscale processing,

and the soil becomes white after grayscale processing. On the basis of the grey processing of dark primary colours, the navigation feature points are extracted by linear fitting, and the distribution map of the navigation feature points as shown in Figure. 5(b) is obtained. As can be seen from the figure, most feature points fall in the navigation within the path. It is more in line with the straight path of the seeding method commonly used when planting crops.

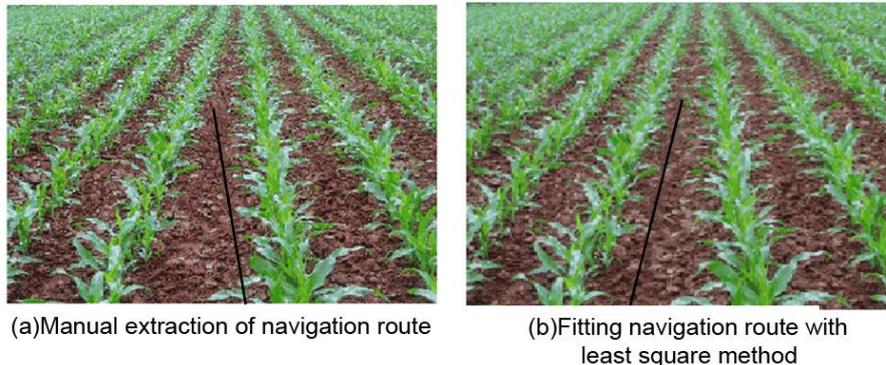


Fig. 6 - Comparison of navigation of farmland crops

After extracting feature points from outdoor farmland plants, the least square method was used to extract the navigation route, and compared with the result of manually extracting the navigation route, the results shown in Figure 6 were obtained, both Figure 6(a) and Figure 6(b). The same piece of outdoor farmland is planted with the same green crops. Among them, Figure 6(a) is a manually extracted navigation route. As can be seen from the figure, the navigation line is basically located on the navigation path, but there are some routes that deviate from the navigation path. Figure 6(b) is the navigation route obtained by fitting the least squares method based on the grey processing of dark primary colours. As can be seen from the figure, compared to the manually extracted navigation line, the route is basically the same as the actual sowing method used in sowing is consistent with the navigation path, which is located at the edge of two rows of crops. This shows that using the least square method of linear fitting to determine the visual navigation path of the farm robot has a good effect.

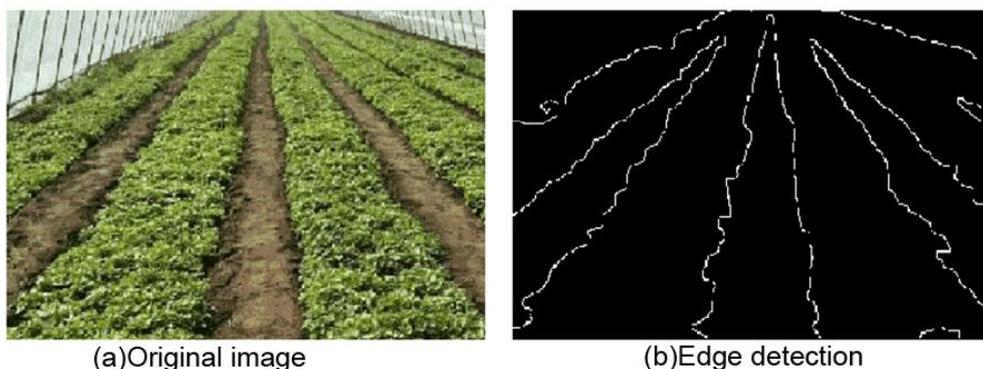


Fig. 7 - Comparison of original farmland image and edge detection results

Figure 6 is the relevant situation of the green crops planted in a greenhouse, and Fig. 7(a) is the crop image taken in the greenhouse environment. It can be seen from the figure that the light intensity in the greenhouse environment is very different from that in the normal environment. Compared with the light in the normal environment, the light in the greenhouse environment is darker, and the soil of the crops is also darker, so the brightness of the crop colour is closer to the soil colour. This kind of environment brings great difficulties to image recognition, which will directly affect the accuracy of image recognition during the navigation of agricultural machinery. This is also the focus of this research. Under the visual effect of agricultural robots, the edge detection results in the greenhouse are shown in Figure 7(b).

As can be seen from Figure 7(b), through edge detection, the image edge extraction algorithm based on dark primary colours proposed in this study successfully identified the boundary between crops and planting soil clearly, and this boundary is strict. According to the law of vision, the real display is carried out. As the distance of vision increases from near to far, the boundary between crops and planting soil gradually approaches. From this result, this study proposes that the image processing technology based on dark primary colour images can normally simulate the visual effect during the recognition process, and on this basis, it can further navigate the trajectory of the agricultural robot.

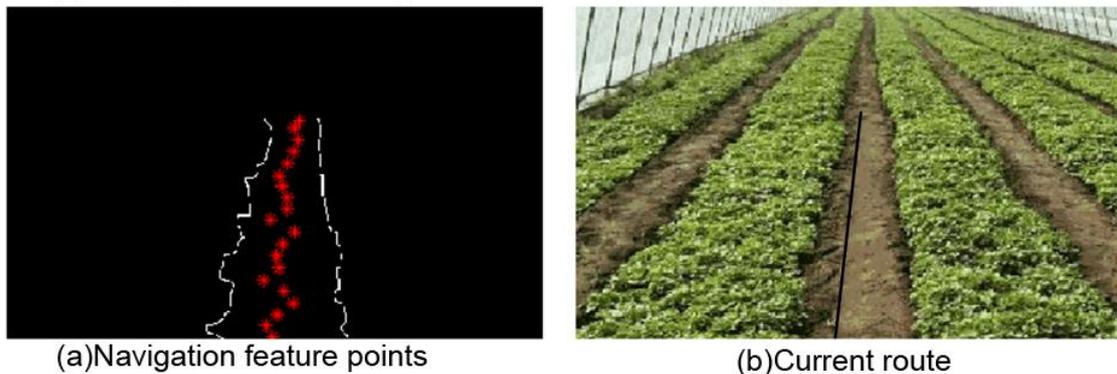


Fig. 8 - Navigation lines extracted when the row spacing of crops is wide

Figure 8 is the result of using linear fitting to route the crops in the greenhouse. The feature points need to be extracted before navigation. Among them, Figure 8(a) represents the feature points extracted by linear fitting at a wide line spacing, and only one line is used as the research object when extracting feature points. In order to distinguish from the results of edge detection, red is used when extracting feature points line. It can be seen from the figure that the feature points extracted by linear fitting are mostly distributed on the same straight line, which is basically consistent with the path when crops are planted by the seeding method in agricultural planting. Between the straight line where the feature points are located and the line spacing edge detection line there is a more obvious distinction. Figure 8(b) represents the visual navigation results of the farmland robot based on feature point extraction. It can be seen from the figure that the robot is completely advancing along the navigation line when performing agricultural planting operations, and is consistent with the straight line of the seed planting. This verifies the effectiveness of linear fitting for feature point extraction and farm robot visual navigation.

CONCLUSIONS

In the visual navigation of the farm robot, extracting the navigation line is the most critical content, which determines the navigation accuracy and speed of the farm robot. Based on the analysis of vision navigation circuit of field robot, a vision navigation extraction algorithm based on dark primary color is proposed in this paper. After the dark primary colour grayscale processing of the farmland plant image, the image is edge detected, and the least square method in linear fitting is used to extract the farmland navigation feature points, and then the robot visual navigation path is formed. On this basis, combined with the actual situation of outdoor farming and greenhouse cultivation of crops, the effectiveness of the robotic visual navigation extraction algorithm was verified. The results show that the crop images of outdoor crops processed by dark primary colours are more clearly distinguished, and most of the feature points fall within the navigation path. Compared with the manually extracted navigation lines, the least square method is used to fit the farm robot the visual navigation route is basically the same as the navigation method of the sowing method used in actual planting. The navigation route is located at the edge of two rows of crops. When the crops are planted in the greenhouse, the edge detection effect of the crop image is relatively good, the crops and the soil are clearly separated, and the linearly fitted robot visual navigation line is basically a straight line. On the whole, the visual navigation route of the farm robot based on the dark primary colours is basically the same as the conventional planting route of the seeding method used in agricultural cultivation. This study verifies the effectiveness of the field navigation robot visual navigation extraction algorithm based on dark primary colours, but its wide applicability needs further study.

REFERENCES

- [1] Alharbi E.M, Ge P., Wang H., (2016), A Research on Single Image Dehazing Algorithms Based on Dark Channel Prior. *Journal of Computer and Communications*, Vol.04, Issue 2, pp.47-55, USA;
- [2] Delaune J, Le Besnerais G, Voirin T., (2016), Visual-inertial navigation for pinpoint planetary landing using scale-based landmark matching. *Robotics & Autonomous Systems*, Vol.78, pp.63-82. Netherlands;
- [3] Guo Y.B., Zhang X.G., Zhang C., (2020), Adaptability test of dry farming tillage technique in northern China and study of key techniques. *INMATEH Agricultural Engineering*, Vol.61, Issue 2, pp. 273-280, Romania;
- [4] Kamaev A.N., Karmanov D.A., (2018), Visual navigation of an autonomous underwater vehicle based on the global search of image correspondences. *Computer Optics*, Vol.42, Issue 3, pp.457-467. Russia;
- [5] Kurashiki K., Aguilar M., Soontornvanichkit S., (2015), Visual Navigation of a Wheeled Mobile Robot using Front Image in Semi-Structured Environment. *Journal of Robotics and Mechatronics*, Vol.27, Issue 4, pp.392-400. Japan;
- [6] Li A., Fang Z., Mi B., (2018), An Improved Defogging Algorithm Based on Dark Colour Theory Combined with Self-Adaptive Threshold Mechanism. *Journal of Control Science & Engineering*, Issue 2, pp.1-10, USA;
- [7] Li D., Xu S., Zheng Y., (2017), Navigation Path Detection for Cotton Field Operator Robot Based on Horizontal Spline Segmentation. *International Journal of Information Technology & Web Engineering*, Vol.12, Issue 3, pp.28-41, USA;
- [8] Liu H.B., Yang J., Wu Z.P., (2015), A fast single image dehazing method based on dark channel prior and Retinex theory. *Zidonghua Xuebao/Acta Automatica Sinica*, Vol.41, Issue 7, pp.1264-1273. China;
- [9] Mingben D.U., Lichao C., Lihu P., (2015), Enhancement algorithm for fog and dust images in coal mine based on dark channel prior theory and bilateral adaptive filter. *Journal of Computer Applications*, Vol.35, Issue 5, pp.1435-1438, China;
- [10] Phalak Y., Charpe G., Paigwar K., (2018), Omnidirectional Visual Navigation System for TurtleBot Using Paraboloid Catadioptric Cameras. *Procedia Computer Science*, Vol.133, pp.190-196, Netherlands;
- [11] Rômulo T. Rodrigues, Basiri M, Aguiar A.P., (2018), Feature Based Potential Field for Low-Level Active Visual Navigation. *Third Iberian Robotics Conference*, Vol.693, pp.791-800, Switzerland;
- [12] Srbínovska M., Gavrovski C., Dimcević V., (2015), Environmental parameters monitoring in precision agriculture using wireless sensor networks. *Journal of Cleaner Production*, Vol.88, Issue 1, pp.297-307. Netherlands;
- [13] Sun T.H., Tien F.C., Tien F.C., (2016), Automated thermal fuse inspection using machine vision and artificial neural networks. *Journal of Intelligent Manufacturing*, Vol.27, Issue 3, pp.639-651, Netherlands;
- [14] Tai J., Li H.T., Du Y.F., Mao E.R., Zhang J.N., Long X.J., (2020), Rapid design of maize ear harvester header based on knowledge engineering. *INMATEH - Agricultural Engineering*, Vol.61, Issue 2, pp.263-272, Romania;
- [15] Teshome F.B., Degu Y.M., (2019), Design of Combined Press Tool for the Manufacturing of Rice Thresher Blade (Case Study at Amhara Agricultural Mechanization and Food Science Research Centre-Ethiopia). *International Journal of Engineering Science*, Vol.3, Issue 4, pp.90-107, England;
- [16] Wang B., He J.L., Zhang S.J., Li L., (2020), Non-destructive testing of soluble solids content in *Cerasus humilis* using visible / near-infrared spectroscopy coupled with wavelength selection algorithm. *INMATEH Agricultural Engineering*, Vol.61, Issue 2, pp.251-262, Romania;
- [17] Xiao J.S., Gao W., Zou B.Y., (2017), Image Dehazing Based on Sky-Constrained Dark Channel Prior. *Tien Tzu Hsueh Pao/Acta Electronica Sinica*, Vol.45, Issue 2, pp.346-352, China;
- [18] Yang H., Gao L., Tang N., (2019), Experimental Analysis and Evaluation of Wide Residual Networks Based Agricultural Disease Identification in Smart Agriculture System. *EURASIP Journal on Wireless Communications and Networking*, Vol.1, pp.292. USA.