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Vision-based Guidance Line Detection in Row Crop Fields

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***Abstract*—A new method of vision-based guidance line detection is developed to find guidance line in row crop fields for agricultural machinery, which uses the mathematical morphology to process images and segment crops in images and to extract target crops. The guidance line is fit with the least-square method according to the centroids of individual target crops or/and the central points of several pixel rows of crops with a continuous region in image. The guidance line could be found easily in three kinds of row crop fields, such as individual crop plants with spacing in image, plants with continuous region in image, and plants with both features above. Then experiments were implemented by an agricultural robot in a vegetable field, and results showed that the algorithm enabled the robot to drive along crop row with a high accuracy ±29.5mm, and had an expected speed of image processing between 0.7s and 1.3s, which meets the needs of agricultural production. Therefore, the proposed algorithm has a good performance in accuracy and speed of image processing, and has robust performance for different crops.**

Keywords- machine vision; guidance; crop row; agricultural robot;image processing

I. INTRODUCTION

The navigation technologies based on GPS or machine vision have been chosen primarily for agricultural automated vehicles. The GPS-based technologies have a limitation on obtaining local information which may be very important to guide vehicles, and a set of precise GPS equipment is costly for agriculture applications[1,2]. But vision sensors have a significant advantage of precise correction with the local features of crops during vehicle navigation and have similar navigation processing of human operators. Especially for crops planted in rows, the increasingly in-depth researches based on machine vision have been performed on the relative position navigation according to crop rows.

The objective of this work is to research a new method of finding guidance line from crop rows in order to precisely guide the agricultural machinery. An overview of the vision-based detection methods of crop row and reasons for developing a new algorithm are introduced in Section 2. Then, the new method about how to detect crop row and then to find guidance line is presented in detail in Section 3. And the experimental results and analyses are illustrated in Section4. Finally, the conclusions are drawn.

II. AN OVERVIEW OF THE VISION-BASED DETECTION METHODS OF CROP ROW

In vision-based vehicle navigation systems, it is the key to find guidance information from crop row structure in order to precisely control vehicle or other operations. For that, many technologies and algorithms of image processing are researched to find guidance line from the row crops.

A binarization threshold method based on the Bayes classification technique was developed by Reid et al. to segment plants of the different stages and soil precisely in cotton field[3]. Schoenfisch and Billingsley handled the problem of plants lack in a row with two or three rows[4]. And Brivot et al. showed that it was good to segment plants, weeds and soil according to infrared images[5].

A Hough transform method was used by Marchant and Brivot to find the crop row from the field image[6]. And this method also was reported to identify crop plants such as cauliflower, sugar beet, corn in many other literatures[7-11]. Especially, it was successfully applied to detection of furrows in seed drill to provide driver assistance[12].

A segmentation of the 24 bit true color image into a binary image and a stochastic pattern recognition technique were used by Slaughter et al. to identify the cotton plants location among weeds[13]. A filter matched to the crop row spacing was employed by Hague et al. to extract the periodic amplitude variation of the image intensity and reduce the effects of partial shadow and weeds. And an EKF was used to track the position and direction of crop rows[14,15].

An original method was used by Søgaard et al. to localize the double spaced wheat rows. The grey-scale images were divided in several horizontal strips and each strip included several sub-strips with a width equal to the inter-row width. The gravity centre of the mean sub-strip of each strip gave rows position and an estimation of the relative accuracy[16].

A robust algorithm was described by S. Han et al. to obtain a guidance line. The algorithm included rows segmentation using the K-cluster algorithm, rows detection with the moment algorithm and guidance line selection based on the cost function[17].

An approach to row recognition introduced by Tijmen Bakker et al., was based on grey-scale Hough transform on the merged images resulted from three sections of the grey-scale image which caused less data and remained the information of three crop rows[18].

A row-detection algorithm based on a 3D crop elevation map from a stereovision image of crop rows was developed by M. Kise et al. for a stereovision-based agricultural machinery guidance system. The optional navigation points were searched from the 3D map[19].

Although there are different crop row detection methods for different prototypes, it still has a need for improving the robustness, accuracy and speed of crop row detection algorithm in agricultural practice. And a new and practical method is proposed in the next section.

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III. Detection of Guidance Line

A new method based on mathematically morphological image processing algorithms is presented to detect the guidance line in row crop fields. The more fundamental shape of an object can be obtained by the mathematical morphology due to the interaction of the object and structure elements[20]. So it has advantage of structure feature compared with the other space-domain or frequency-domain methods. According to this feature, the algorithm must have better robustness to noise and distortion during crop identification and as well the grey level differences and geometric differences are taken into account.

Fig. 1 shows the algorithm of guidance line detection based on mathematical morphology. The algorithm mainly includes two parts, one is crop segmentation and identification, the other is guidance line fitting.

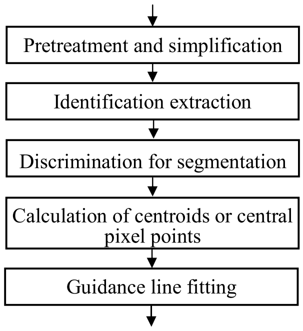


Figure 1. Algorithm of guidace line detection.

A. Crop Segmentation and Identification

This part includes image pretreatment and siplification, identication extraction and discrimination for segmentation.

1) Image pretreatment and siplification: Its purpose is to remove image noises and smaller regions in image to make the internal grey of targets more uniform and the texture more sparse so that it is easier to segment the targets from image. The reconstruction operation of mathematical morphology is used to siplify the images in this work. In a crop image, the texture and structure of crop plants may be too close to the soil or weeds due to the different lighting conditions and growing conditons, while bigger holes and edge grooves can appear in the inside of targets and destroy the integrity of targets, so it is difficult to segment targets in image. For that, the morphological reconstruction operation can be applied to eliminate holes and fill grooves.

2) Identification extraction: This step is to perform the identification extraction according to an uniform criteria of greyscale, color, texture and so on. Then a marked image is formed in which different regions of an imgae are marked and every marked region corresponds to the the main parts of the segmentation region.

3) Discrimination for segmentation: The crop edges have a stronger regularity because some information of crop row to be detected are known in advance such as crop size, inter-row spacing and/or intra-row spacing. So the following discriminants are established to detect crop reliably and accurately. The edge detection will not be implemented if the pixel detected is not satisfied the discriminants.

$$G(i,j)-G(i-L,j)>\varepsilon \qquad (1)$$

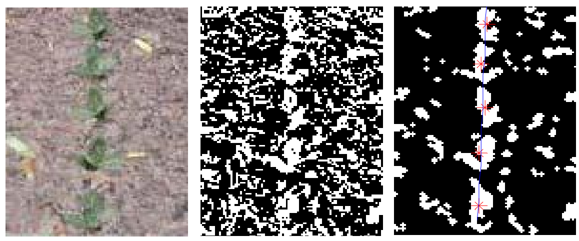
$$\text{and } G(i,j)-G(i+L,j)>\varepsilon \qquad (2)$$

$$\text{and } \overline{G}(i,j)=\frac{1}{9}\sum_{j+1}^{j-1}\sum_{i-1}^{i+1}G(m,n)>THR \qquad (3)$$

where $G(i,j)$ represents the gray value of the image pixel point (i,j), L the plant size (pixels) in image, ε a non-negative small integer, $\overline{G}(i,j)$ the average gray value of the 3×3 area around the pixel point (i,j), and THR the grayscale threshold. Therefore, the pixel points within the region where their size is less than L are implemented by edge detection according to the discriminants (1) and (2), and image is segmented by the discriminant (3).

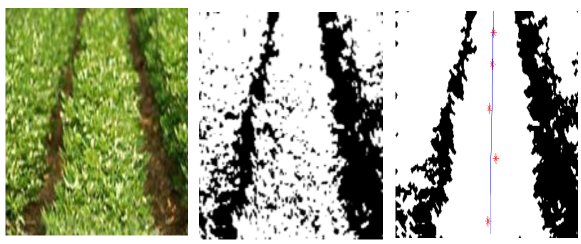
The examples using the algorithm of crop segmentation and identification are shown in Fig. 2, Fig. 3 and Fig. 4, which correspond to three kinds of crops fields including individual crop plants with spacing in image, crop plants with continuous region in image, and crop plants with both features above in image, relatively. While the sub-figures (a), (b) and (c) in Fig. 2, Fig. 3 and Fig. 4 represent the original color images, the binary images and the images processed by the algorithm, relatively.

From the binary image in Fig. 2(b), it shows that it is difficult to segment the crop plants directly due to the poor contrast between crop plants and background. But Fig. 2(c) obtained after the algorithm, is more convenient to find the plants. Although there is the poorest segmentation in Fig. 2, compared with Fig. 3 and Fig. 4, the target plants(in Fig. 2(c)) segmented by the algorithm can represent the shape and position of actual plants(in Fig. 2(a)). As for Fig. 3 and Fig. 4, they all show that they have a better performance of segmentation and identification than that of Fig. 2.



(a) (b) (c)

Figure 2. Example of individual plants with spacing in image.



(a) (b) (c)

Figure 3. Example of continuous plants image.

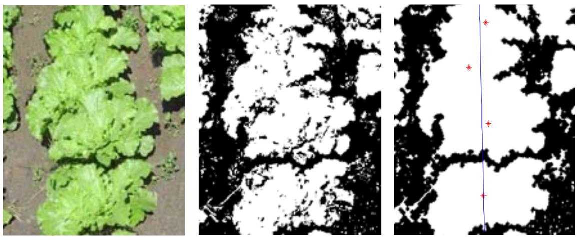


Figure 4. Example of plants image with individual and continuous parts.

B. Detection of Guidance Line

For the plants with bigger intra-row spacing, which means the regions of interest(ROIs) corresponding to crop plants separate each other with spacing in the image, the centroid of every ROI can be calculated. Then, the guidance line can be obtained by fitting the centoids of the relative ROIs with the least-square method, as shown in Fig. 2 (c).

For the plants with less spacing, which means that the ROIs are continuous in the image, the central point of pixels of the horizontal direction in near view scene of crop image is found out firstly. Then, the central points corresponding to the other several pixels of horizontal direction with equal spacing in real scene(unequal spacing in image) are found out. Finally, the guidance line can be calculated by fitting the central points with the least-square method(Fig. 3 (c)).

For the crop image, in which the ROI(s) in near view scene may be independent, but the ROIs in far view scene continuous, the centroids of seperate ROIs and central points of continuous ROIs are calculated respectively in the same way proposed above, and the guidance line is fitted according to the centroids and central points(Fig. 4 (c)).

Centroid pixel (x,y) of ROI corresponding to crop plant in image is calculated according to the following formula:

$$x=\frac{\sum_{j=1}^{m} j\sum_{k=1}^{n} f(j,k)}{\sum_{j=1}^{m}\sum_{k=1}^{n} f(j,k)} \qquad y=\frac{\sum_{j=1}^{m} k\sum_{k=1}^{n} f(j,k)}{\sum_{j=1}^{m}\sum_{k=1}^{n} f(j,k)}$$

$$(\, j=1,\cdots,m;\quad k=1,\cdots,n;)$$

Where, f(j, k) is the value of pixel point (j, k) in the image, it is 1 in the binary image; m and n are the number of the image pixels in horizontal and vertical direction respectively.

IV. EXPERIMENTS AND RESULTS

A. Experimental System Description

Experiments were done on an agricultural robot driven by DC motors via the sprocket reduction units and steered by controlling the speed difference between the left and right driving wheels. The speed difference of the two driving wheels was controlled by the row guidance controller according to the information about offset and heading angle of the platform relative to the guidance line

In order to capture images, a portable PC with AMD Turion 64 X2 TL-50 dual-core processors and a portable plug-in USB2.0 type image acquisition box were equipped in the robot. And a SONY CCD colorful camera with the 8mm-focus lens was used as the visual system.

The offset and heading angle of the robot relative to the crop row could be obtained by the machine vision, but any error of the camera position would result in errors of the provided data. Therefore, the camera calibration was carried out before experiments. The calibration method and algorithm, proposed by Zhang Zhengyou[21], were adopted in this work. Through the calibration, the position errors of camera were reduced and the resolution was determined for the following experiments.

The test scene was shown in Fig. 5. The vegetable plants were planted with 500mm inter-row distance which fit to the platform width and 150mm intra-row distance according the actual production. And the test speed of the robot platform was 0.2m/s, the maximum length of crop rows was 6m but the test distance only 4.5m. To eliminate the impact of the start of the robot on measurement, the experimental data were measured and calculated after the start about 1m. It is noted that the plants in the field were selected artificially with the similar size and height and planted along row.


Figure 5. Test scene in a vegetable field.

B. Results and Analyses

The offsets of plants relative to guidance line in images were obtained as the mentioned above. In order to measure the lateral differences, a small box containing the diluted white emulsion paint was placed in the rear cabin of the robot platform. When the robot moved, the paint dropped on the soil through the tube to record the robot's position (Fig. 5). The lateral differences might be measured and calculated by the difference between the distance from crop row to paint trace line and the fixed distance from the tube to the crop row. The offsets and heading angle derived from the detection of guidance line and the lateral difference with man-made measurement were shown in Fig. 6 according to the experiment of the robot in the field, where the abscissa axis indicated the number of test plants within 4.5m.

From the Fig. 6, the maximum heading angle was only 0.95º in the vegetable field(Fig.6 (a)). While the offsets of row guidance were within ±29mm and its mean -0.1mm, its standard deviation 15.7mm(Fig.6 (b)). The lateral differences were within ±29.5mm and its mean 3.4mm, its standard deviation 15.4mm(Fig. 6 (c)). Although there existed some conditions such as uneven field, man-made measure error, wheels sideslip due to soft and moist soil, etc. it was shown that the robot had good performance in following the crop row and had a high accuracy enough to guide itself. So, it can be indicated that the algorithm of guidance line detection has a good performance in accuracy.

During image processing, the processing times of images using the algorithm proposed were varied between 0.7s and 1.3s. So, it also shows that the algorithm has a good performance in speed of image processing.

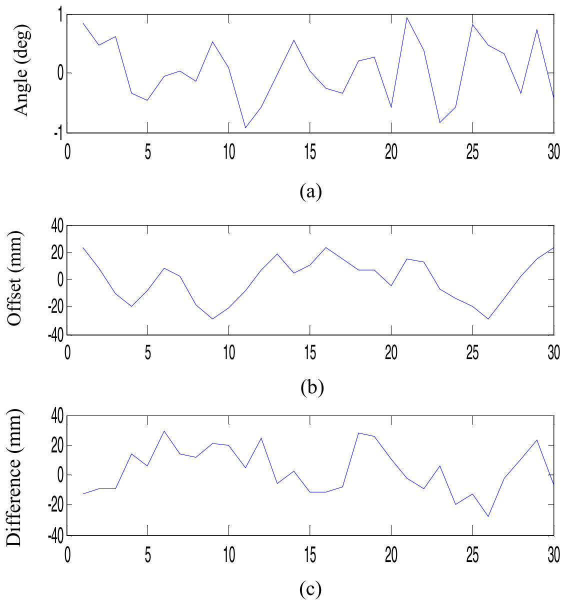


Figure 6. Results of field test.

V. CONCLUSIONS

A new machine vision-based algorithm using mathematical morphology approach is presented to process and segment images and then to find the guidance line from row crop image. The guidance line is fit by using the least-square method according to the centroids of individual target crops or/and the central points of several pixel rows of crops characterized as a continuous region in image. Experimental results showed that the algorithm ensured the robot platform had a high accuracy to drive along the crop row, which meets the needs of agricultural production. And it is indicated that the algorithm has a good performance in accuracy and image processing speed, and also has robust performance for different crops. Of course, the structural element in mathematical morphology has a significant impact on the results of morphological operations, it is needed to further study and improve how to select the size and shape of structural element relating to the practical application scenarios in order to obtain the best results.

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