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***An ASABE Meeting Presentation***

***Paper Number: 131596766***

# Development of a High-Efficient Weeding Robot in the Crop Fields

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**Written for presentation at the**

**2013 ASABE Annual International Meeting**

**Sponsored by ASABE**

**Kansas City, Missouri**

**July 21 – 24, 2013**

***Abstract.*** *A novel high-efficient weeding robot was developed, which could perform inter-row and intra-row weed control simultaneously. A machine vision based system was constructed to guide the robot to move along the crop line. The robot was driven by two geared motors. Intra-row weeds were distinguished from the crops by utilizing infrared sensing technology and the plant spacing information. A microcontroller based control system was designed and fabricated to remove intra-row weeds mechanically and inter-row weed by direct herbicide application. Experiments showed that the prototype of the weeding robot was able to walk along the crop line with an accuracy of ±5 cm and realize weeding operations.*

***Keywords.*** *mechanical weed control, direct herbicide application, intra-row, inter-row, autonomous navigation*

# Introduction

Excessive use of herbicides has caused serious environmental pollution. Alternative methods for weed control have been extensively studied (Srinivasan, 2006). One of the potential ways to reduce chemicals is to employ precision techniques for various types of agricultural operations so that chemicals can be used where they have an optimal effect in a minimum quantity. Besides, mechanical weed control is also a promising method available in some operations to abandon the use of chemicals.

While there is sufficient equipment available to control the weeds between the crop rows, weed control within the crop row still requires a lot of manual labor, for this type of weeding is much more difficult in discriminating weeds from crops (Bakker et al., 2006). However, the required labor for hand weeding is expensive. The development of suitable mechanized weeding methods is an imperative. With the development of automated planters, crops are usually sowed with precision drills, meaning that the interplant spacing in rows becomes precise enough for the usage in discriminating weeds and crops.

Researchers have already developed different applications for autonomous weed control (Slaughter et al., 2008). Haff et al. (2011) designed an autonomous tomato weeding device. It utilized X-Ray technology in the discrimination of in-row weeds, based on the difference in signal strength between and background. Bjorn Astrand et al. (2002) developed an agricultural mobile robot with vision-based perception for mechanical weed control. A method for corn plant detection and plant center position estimation using stereo vision was reported by Jin and Tang (2009). Cordill et al. (2011) developed and tested an intra-row mechanical weeding machine for corn, which applied a sensing arrangement of four laser transmitter-receiver pairs in extracting stalks from weeds. Staab et al. (2009) developed a precision weed control system to autonomously detect, identify and map weed species in the seedline of directly-seeded processing tomatoes and to apply a precise and lethal spray to the weed foliage.

So far, weeding applications developed are limited to either inter-row or intra-row weed control, which is inefficient. The main objective of this research was therefore to develop a novel high-efficient weeding robot with light and flexible structure, which could perform inter-row and intra-row weed control simultaneously. The specific objectives were to 1) design a mechanical structure of the robot wish a set of weeding mechanisms for both inter-row and intra-row weed control 2) develop a machine vision based navigation system that is capable of guiding the robot to move along the crop line 3) work out with an intra-row weed recognition algorithm for intra-row weeding.

# Materials and Methods

### Mechanical Design

An efficient weeding robot was developed as shown in figure 1. It was designed for weed control when corn plants were V2-V3 growth stages, as weeding application at that early stage would minimize weed competition. The distance between rows in crop fields is about 500 mm, which restricts the physical width of the robot to about 700 mm. The length of the robot was 1000 mm, and the height was 590 mm (not including the navigation camera).

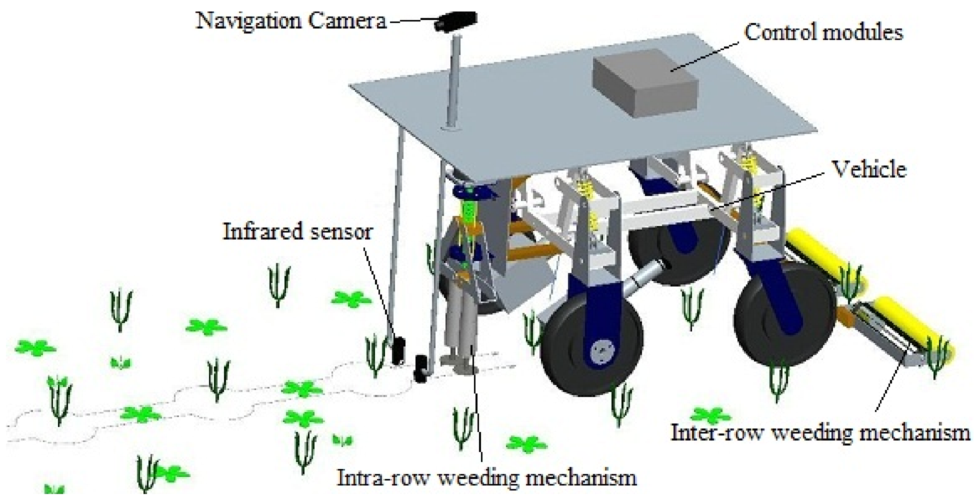
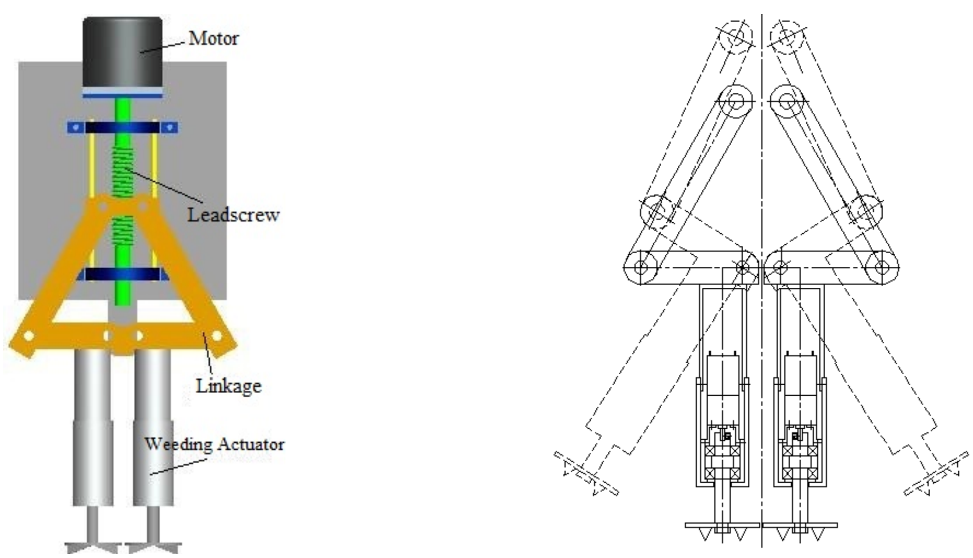



**Figure 1. Schematic description of the weeding robot.**

The vehicle, equipped with double wishbone suspension, as a platform for carrying the weeding tools and control modules, was driven by two geared motors. A machine vision based navigation system was constructed to guide the robot to move along the crop line. Intra-row weeds were distinguished from the crops by utilizing the plant spacing information, and a microcontroller based control system was designed and fabricated to remove intra-row weed mechanically and inter-row weed by direct herbicide application.

*Intra-row weed removal mechanism*

The intra-row weed removal mechanism was developed, as shown in figure 2(a). It consisted of a motor, a lead crew, a linkage, two weeding actuators, etc. Figure 2(b) displays diagrammatic movement of the mechanism. Motor drove the leadscrew rotation, boosting the linkage movement, then led the weeding actuators ‘open’ or ‘close’. If the intra-row weeds were detected, the weeding actuators would close, making the bottom cutters insert into the soil and cut off the roots. If plants were detected, the weeding actuators would open to avoid them.




**(a) structure** **(b) diagrammatic movement**

**Figure 2. Intra-row weed removal mechanism**

*Inter-row weeding mechanism*

The inter-row weeds were eliminated by direct herbicide application, which was more efficient and simpler. The structure of the inter-row weeding mechanism is shown in figure 3. There were two of them placed on both sides in the back of the robot.

Surface of the hobbing was inserted with barbed blades, and it rotated to cut off the weeds driven by the motor inside. The roller was wrapped in a layer of sponge dipped with herbicides. After weeds were cut by the hobbing, pesticide would be smeared on the damaged surface of the weed leaves.

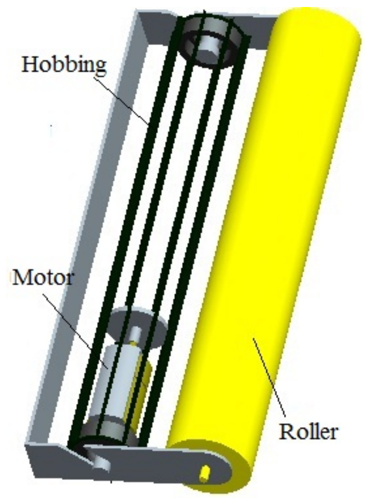



**Figure 3. Inter-row weeding mechanism**

## Machine vision based navigation system

For the navigation system, images were captured from a forward-looking camera (Model 0776, 3Com Inc.) directed downward at an angle of 55 degrees below the horizontal, which was mounted on the top of the robot, 800 mm above the ground, as shown in figure 1. The camera generated 320 × 240 color images at 48 fps. Smaller resolutions were selected to minimize image processing effort. The camera was pre-calibrated for lens distortions.

Image processing was performed using a laptop with an Intel(R) Core(TM) 2 Duo T8100 @2.10GHz central processing unit (CPU) connected through a USB 2.0 interface. Processing software was implemented in Microsoft Visual C++6.0 using the OpenCV library (version 1.0).

Schematic description of the machine vision based navigation system arrangement is shown in figure 4. The main steps of the image processing are mainly divided into two parts: vegetation segmentation and extraction of navigation data.

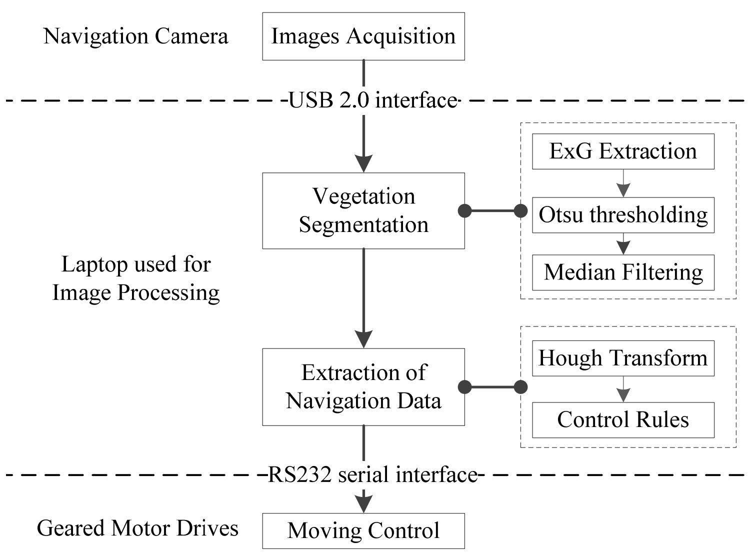



**Figure 4. Schematic description of machine vision based navigation system.**

### *Vegetation Segmentation*

In order to extract the navigation data for guiding the robot to move along the crop line, it is necessary to discriminate vegetation from other elements of the scene (i.e. soil, residues) at first. The normalized excess green index (ExG) introduced by Woebbecke et al. (1995) was used with some modifications, which made the algorithm insensitive to the intensity of the light source as well as the viewing and illumination angles (Gee et al., 2008).

$$\text{ExG} = \begin{cases} 0 & \text{if}(\ g < r \parallel g < b\ ) \\ 2g\text{-}r\text{-}b & \text{Otherwise} \end{cases} \tag{1}$$

$$r = \frac{R}{R+G+B},\ g = \frac{G}{R+G+B},\ b = \frac{B}{R+G+B} \tag{2}$$

where r, g and b are the normalized RGB coordinates ranging from 0 to 1.

The grey level image was transformed into a binary image using Otsu method, based on analysis of the histogram resulting from the gray level image calculation. Then, a median filter was applied to the segmented images to eliminate random noise in the image. In the resulting binary image, vegetation from both weeds and crops was black and the rest, coming from soil, stones and residues, was white.

*Extraction of navigation data*

In order to control the moving of a mobile robot, the offset λ, and the heading angle θ, of the camera relative to the row structure should be acquired. On the basis of the binary image, the next step was to detect the crop rows in the image. The Hough transform as a relatively fast and robust method for finding lines, especially if the lines cover the whole image, was used in our case. Therefore, all pixels coming from the crops contributed to the line and all pixels from the weeds are just noise.

Normally we parameterize lines by its equations in the image space, e.g. y=ax+b, where slope a and intercept b are coefficients to be determined. Then a point in the original image is transformed to a locus of points in the (a, b) plane corresponding to all of the lines passing through that point. If we convert every nonzero pixel in the input image into such a set of points in the output image and sum over all such contributions, then lines that appear in the input (i.e., (x, y) plane) image will appear as local maxima in the output (i.e., (a, b) plane) image. Because we are summing the contributions from each point, the (a, b) plane is commonly called the accumulator plane.

In the OpenCV library, the equation for such a line is presented in polar coordinates (ρ, φ): ρ= x cosφ+ y sinφ (Bradski et al., 2008). The function cvHoughLines2 was used to acquire the coordinates of the maximum value in the Hough plane. Then the arguments were linear transformed to the navigation data (offset λ and heading angle θ), as shown in figure 5, where parameter height and width referred to the size of the image (320 × 240).

$$\theta = \begin{cases} -\varphi\ , & \varphi < \pi/2 \\ \pi - \varphi, & \pi/2 < \varphi < \pi \end{cases} \tag{3}$$

$$\lambda = \begin{cases} \left|\rho - \frac{1}{2} width \cdot \cos\varphi - \frac{1}{2} height \cdot \sin\varphi\right|, & \left(\frac{\varphi - \frac{hight}{2}\sin\theta}{\cos\theta}\right) < \frac{width}{2} \\ -\left|\rho - \frac{1}{2} width \cdot \cos\varphi - \frac{1}{2} height \cdot \sin\varphi\right|, & \left(\frac{\varphi - \frac{hight}{2}\sin\theta}{\cos\theta}\right) > \frac{width}{2} \end{cases} \tag{4}$$

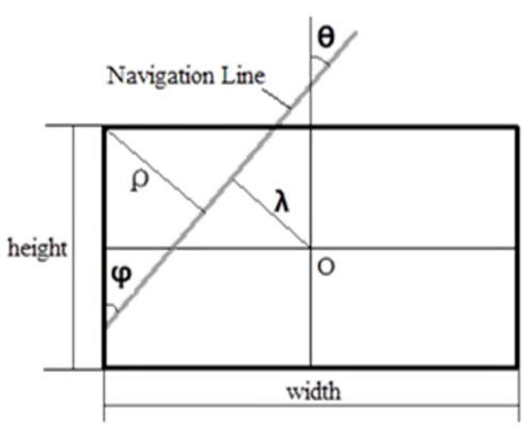



Figure 5. The extraction of navigation data.

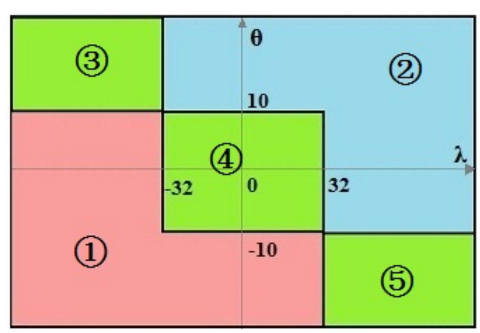



Figure 6. Control rules of navigation.

Afterwards, the navigation data would be processed by a certain rule, which is illustrated in figure 6, then transmitted to two geared motor drives via RS232. Figure 6 shows a plane formed by offset λ and heading angle θ, where the arguments (λ: 32 pixels, θ: 10 degrees) are selected as thresholds (determined empirically through tests). The moving of the robot is then controlled according to the coordinates in the plane, where the lower left region 1 (colored red) refers to turning right, the upper right region 2 (colored blue) refers to turning left, and the rest, region 3, 4and 5, colored green, refer to moving forward.

### Intra-row weeds recognition system

The intra-row weed recognition system is based on an algorithm which applies infrared sensing technology and plant spacing information to determine the location of the weeds in the row, so that the intra-row weed removal mechanism could treat them.

An infrared beam sensor (Longge Inc., Guangzhou, China), with a maximum detection distance of 300mm, was mounted in the front, 50mm ahead of the intra-row weed removal mechanism. The transmitter was placed at a distance of 100 mm (±50 mm on both sides of the crop plant, determined empirically through tests) from the receiver to prevent leaves from touching the device. Besides, to avoid contacting the soil surface, the bottoms of the devices were kept at an approximate height of 30 mm. The outputs of the sensor were pulled high with resistors, which resulted in an active-low sensing arrangement. The signals were conditioned using Schmitt-Triggers. Therefore, only if the sensor passes crops or weeds, would the trigger output high voltage. Otherwise, output low.

In row crops, using the assumption that crops are sowed with approximate drills with a distance of 250mm normally distributed, the interplant spacing information could be extracted to discriminate between crops and weeds. When the robot moved along the crop line at a certain speed, the high voltage output corresponded to the locations of plants (crop/weed). Once the locations of plants (crop/weed) were found, the distance between the plants and previous crop could be calculated.

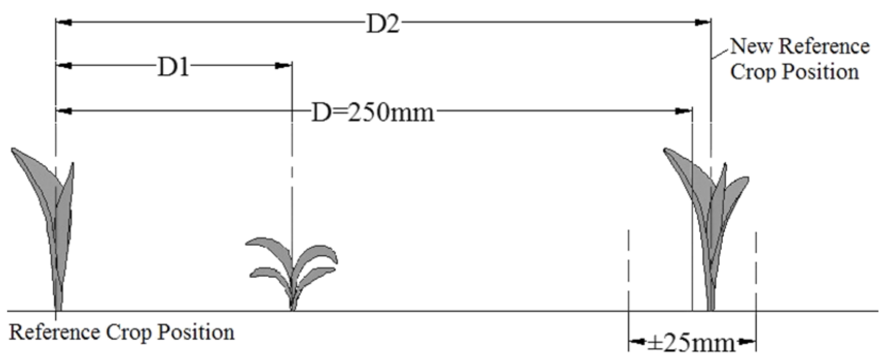



**Figure 7. Intra-row weeds detection using infrared sensing technology and plant spacing information.**

Figure 7 shows the schematic description of intra-weed detection using infrared sensing technology and plant spacing information. The plant whose distance away from the previous crop nearest to the assuming constant spacing is considered as crop, otherwise marked as weed. The algorithm assumes that the first plant detected by the sensor is a reference crop, and the distance between the reference crop and next plants are calculated (D1, D2). The plant who at the D±25mm distance away from the reference crop is determined as crop (±25mm is used to offset the inaccuracies in the drilling of the crop, which usually cause variation in crop plant spacing). The detected crop is then marked as a new reference crop, and the algorithm continues processing as above. If there is a skip in a row section and a corn plant is not planted, the position exactly at the constant spacing distance of 250mm away from the previous crop is then assumed as the new reference crop plant.

In practical operation, the transmitter emits infrared signals continuously during walking along the row. When a high voltage returns, the optical encoder position of the moment will be recorded. Then the above process is applied with the difference of the optical encoder positions, which is related to the distance between plants. The flowchart of the overall processing for intra-row weed discrimination utilizing infrared sensing technology and plant spacing information is shown in figure 8.

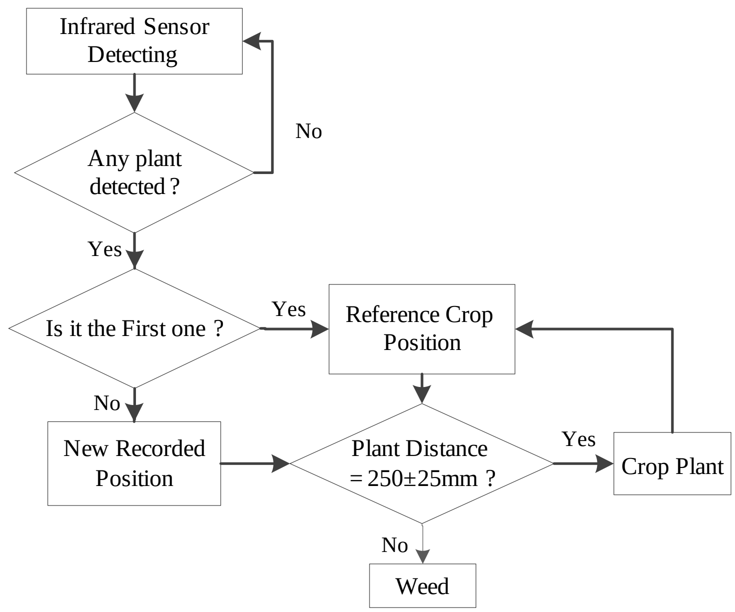



**Figure 8. Flowchart of the overall processing for intra-row weed discrimination.**

## Results and discussion

Figure 9 gives an example of image processing of the navigation system, which shows that the modified excess green index improved the contrast of the test areas of the interest between the plants and background, and the Hough transform was successful in extracting the navigation line from the image.

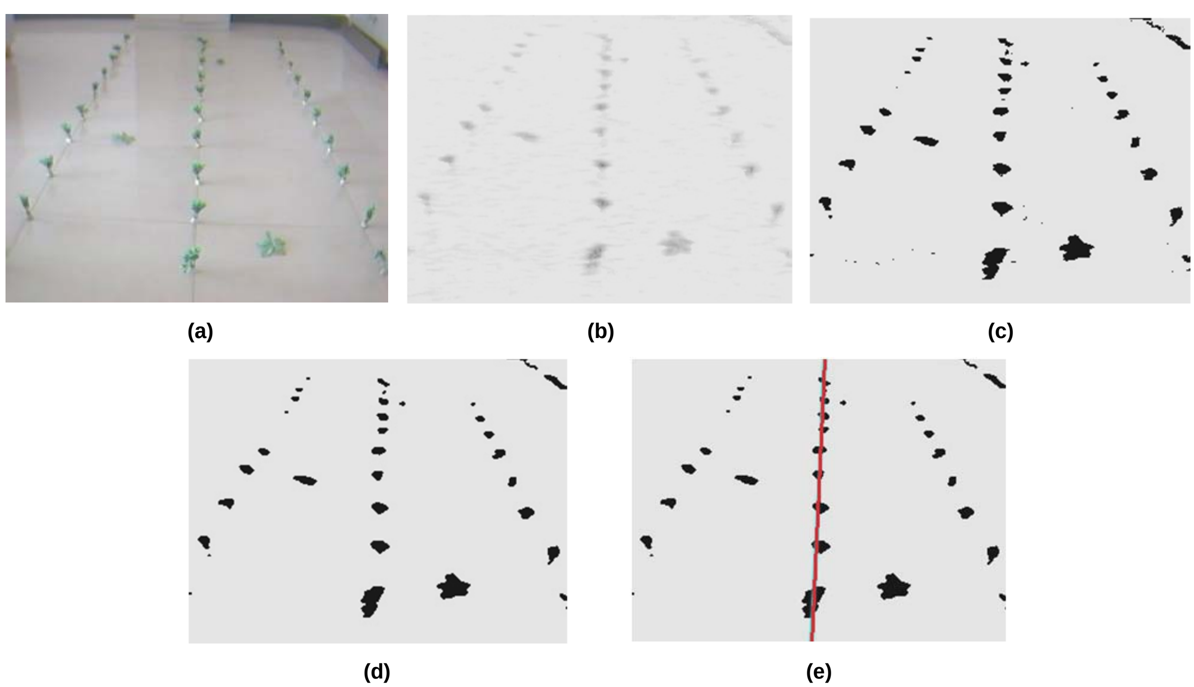



**Figure 9. Example results of image processing: (a) raw image, (b) modified excess green index, (c) binary image created with the Otsu's method, (d) binary image after median filter, (e) navigation line extracting**

Afterwards, the result (ρ=165, φ=3) returned from the example of image processing was processed by the rule from Fig.6. The final navigation data (λ=-1.1, θ=3) belonged to the green region, which meant moving forward.

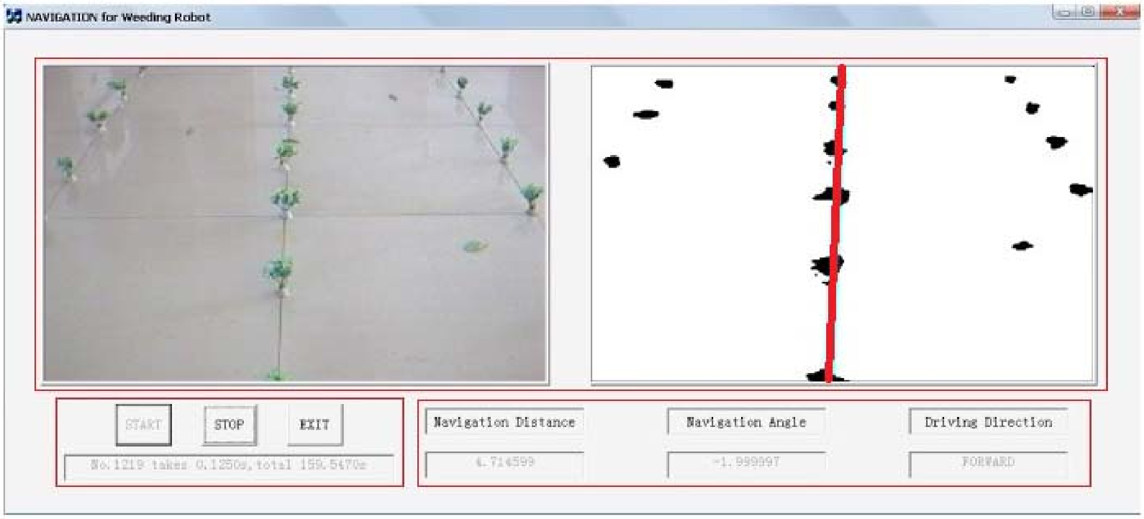



**Figure 10. Interface of vision navigation of weeding robot**

A screen-shot of the software interface of the machine vision based navigation system for weeding robot is demonstrated in figure 10. The two upper windows show separately the last frame acquired and the processed image according to it. The bottom left four windows form a control panel showing the number of fragments processed and the time consuming, and the bottom right six windows display the current navigation data and control instruction.

Experiments show that the average time consuming of each thread processing (from image acquisition to the extraction of the navigation data) is 125ms, which guarantees that robot could adjust the position and orientation continuously, and manage weed control effectively. Figure 11 shows a navigation test of the robot in the laboratory. The data of the robot pose were collected, as shown in table 1.

**Figure 11. Control experiment of weeding robot**

**Table 1: Data of Robot Pose**

| Sequence Number | Offset $\lambda$(pixel) | Angle $\theta$(degree) | Control Instruction | Time Consuming(ms) |
|---|---|---|---|---|
| Adjustment process of turning right | | | | |
| 1 | -38.118664 | -1.000003 | Right | 125 |
| 2 | -35.118664 | -1.000003 | Right | 141 |
| 3 | -32.000000 | 0.000000 | Right | 125 |
| 4 | -29.285401 | -1.999997 | Forward | 125 |
| 5 | -24.000000 | 0.000000 | Forward | 125 |
| Adjustment process of turning left | | | | |
| 1 | 36.849841 | 5.000000 | Left | 125 |
| 2 | 34.981025 | 4.000000 | Left | 125 |
| 3 | 32.061040 | 3.000000 | Left | 141 |
| 4 | 26.981025 | 4.000000 | Forward | 125 |
| 5 | 24.061040 | 3.000000 | Forward | 140 |

## Conclusion

This paper presented a development of a novel high-efficient weeding robot with light and flexible structure, which could perform inter-row and intra-row weed control simultaneously. It mainly elaborated the mechanical design of the robot, and the algorithms for the machine vision based navigation and intra-row weeds recognition.

It showed that the modified excess green index was successful in discriminating vegetation from the background and the Hough transform was feasible for extracting the navigation line from the image, besides the infrared sensing technology and plant spacing information used in the intra-row weed recognition system were shown to have promising performance in determining the location of the weeds in the row.

Through indoor tests, the whole weeding robot has been verified to be able to walk along the crop row and manage weed control effectively. More work is needed in extensive test of different field conditions.

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