DEVELOPMENT OF A MACHINE VISION SYSTEM FOR WEED CONTROL USING PRECISION CHEMICAL APPLICATION

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ABSTRACT

Farmers need alternatives for weed control due to the desire to reduce chemicals used in farming. However, conventional mechanical cultivation cannot selectively remove weeds located in the seedline between crop plants and there are no selective herbicides for some crop/weed situations. Since hand labor is costly, an automated weed control system could be feasible. A robotic weed control system can also reduce or eliminate the need for chemicals. Currently no such system exists for removing weeds located in the seedline between crop plants.

The goal of this project is to build a real-time, machine vision weed control system that can detect crop and weed locations, remove weeds and thin crop plants. In order to accomplish this objective, a real-time robotic system was developed to identify and locate outdoor plants using machine vision technology, pattern recognition techniques, knowledge-based decision theory, and robotics. The prototype weed control system is composed of a real-time computer vision system, a uniform illumination device, and a precision chemical application system. The prototype system is mounted on the UC Davis Robotic Cultivator, which finds the center of the seedline of crop plants. Field tests showed that the robotic spraying system correctly targeted simulated weeds (metal coins of 2.54 cm diameter) with an average error of 0.78 cm and the standard deviation of 0.62 cm.

Key Words : Weed Control, Machine Vision, Plant Identification, Robotic Sprayer

INTRODUCTION

A weed has been called "any plant growing in the wrong place at the wrong time and doing more harm than good". Weeds compete with the crop for water, light, nutrients and space, and therefore reduce crop yields and also affect the efficient use of machinery (Parish, 1990). A lot of methods are used for weed control. Among them, mechanical cultivation is commonly practiced in many vegetable crops to remove weeds, aerate soil, and improve irrigation efficiency, but this technique cannot selectively remove weeds located in the seedline between crop plants. The most widely used method for weed control is to use agricultural chemicals (herbicides and fertilizer products). In fact, the success of U.S. agriculture is attributable to the effective use of chemicals.

However, this heavy reliance on chemicals raises many concerns about social and environmental aspects. The current concern over the use of methyl bromide produces an example of some of the issues with the use of agricultural chemicals. Ferguson and Padula (1994) investigated the economic effects of banning methyl bromide (MB) for soil fumigants which has been widely used to control soil pests and protect stored commodities, since MB contributes to the depletion of the stratospheric ozone layer. They reported that the Environmental Protection Agency (EPA) might ban the use of MB by initiating action under the Clean Air Act that requires a phaseout of MB uses by the year 2001. They predicted that losses for tomato growers would be about $86 million per year if the available alternatives for tomatoes were used, while the net revenue loss would be about $100 million annually if no alternatives were available.

For processing tomatoes in California, the current cost for weed control is $50 per 0.4 ha (1 acre) for herbicides and $80 per 0.4 ha (1 acre) for hand weeding. According to the economic analysis for the prototype machine by D. C. Slaughter (1996), if a prototype robotic system could travel at 0.80 km/hr (0.5 mi/hr), the savings would justify a purchase price of over $110,000 per machine considering the current cost. This assumes a three-row machine for rows spaced 1.52 m (60 inches) apart, an operating period of 45 days per season, 60 percent of overhead and operating costs, no interest, and a five year machine life.

Thus, farmers need alternatives for weed control due to the desire to reduce chemical use and production costs. For some crop/weed situations there are no selective herbicides. Since hand weeding is costly, an automated system could be feasible. A robotic weed control system can reduce or eliminate the need for chemicals. Currently no such system exists for removing weeds located in the seedline between crop plants. In this project, a real-time robotic system was developed to identify and locate outdoor plants using machine vision technology, pattern recognition techniques, knowledge-based decision theory, and robotics.

There has been a lot of effort to control weeds non-chemically in order to reduce chemical costs in response to environmental pressure. These methods can be largely divided into cultural weed control methods, mechanical control methods, and biological control methods. In this project we would like to mainly focus on the mechanical control methods. These include hand pulling or hoeing, tillage, cultivation, burning, flame cultivation, and electrical devices (Cooperative Extension Service, 1995). There are some researchers who investigated non-chemical weed control methods (Parish, 1990, and Bond, 1992), but as Bond pointed out, few attempts have been made to selectively control weeds in the seed line.

However, with advances in image processing and machine vision technologies, many researchers have applied these techniques to agriculture to identify individual crop plants.

Slaughter and Harrell (1989) investigated the use of color information only in digital color images for the guidance of a robotic manipulator in the harvest of oranges. A color lookup table was implemented for real-time implementation of a robotic guidance system. Jia et al. (1990) investigated the feasibility of using machine vision technology to locate corn plants. Slaughter et al. (1992) developed an experimental precision cultivator (later named as the "UC Davis Robotic Cultivator") that could identify the center of the row under normal field conditions. The machine vision system identified the location of the seed line, then the offset between the current position and the desired position was adjusted by moving the toolbar laterally. The system was tested in tomato fields and preliminary test results indicated that the prototype could be operated at speeds exceeding 8.0 km/hr (5 mi/hr) while precisely positioning the cultivator over the row within +/- 1.02 cm 68% of the time, and +/- 2.03 cm 95% of the time. This precision UC Davis Robotic Cultivator is used as a guidance system for the robotic spraying system.

While initial research on the robotic cultivator was to find the center of the row, Tian and Slaughter (1993) developed and tested a computer vision algorithm in a laboratory environment to detect and locate individual tomato plants with images taken in commercial tomato fields. They used hue and excessive green (=2Green-Red-Blue) to get binary images by thresholding and extracted features such as compactness, elongation, and y-coordinate of centroid of leaves from binary images. With 28 field images, the algorithm was able to identify almost all the isolated tomato cotyledons, and determined the inward position of occluded cotyledons with the accuracy of 61.2%.

Further, Tian (1995) studied the feasibility of using a machine vision system as the sensor for an agricultural field robot to identify individual plants with images taken in the natural outdoor environment. The binary look-up table (LUT) technique was used in both segmentation and plant shape detection algorithms to promote high speed processing. He used the watershed method (Vincent and Soille, 1991) for separating the cotyledons from the occluding plants in the images, but it didn't work on some of the images. Tian reported problems associated with non-uniform illumination. He analyzed about 270 frames of field images in a laboratory environment and successfully identified between 61 to 82 percent of all the individual plants. However, he ended his research before developing the high speed algorithms needed for implementation in a real-time computer vision system for use in a commercial field.

Although there have been many efforts to control in-row weeds, no system has yet been completed as a real-time implement for a field use. There is a practical need for a real-time machine for weed control to eliminate or at least to reduce the use of agricultural chemicals. In this research, we are developing a "*real-time*" robotic system for weed control based upon algorithms developed previously by Tian and Slaughter (1993), and Tian (1995). The ultimate goal of this research is to develop new techniques of weed control for California tomato growers. Specifically, we would like to develop an intelligent real-time machine for weed control.

Objectives

The specific objectives are as follows:

1. To develop a new weed control system for seed-line weeds which is composed of a real-time computer vision system, implement controller and an implement for weed removal,
2. To implement the algorithms in real-time which were previously developed in laboratory environment for identifying crop plants and weeds in the seedline,
3. To develop an algorithm which can distinguish plants older and larger than those at the first true leaf stage,
4. To develop a uniform illumination device for field use with a real-time computer vision system to get high quality images, and
5. To evaluate the performance of a prototype system in commercial agricultural fields.

MATERIALS AND METHODS

Image Processing Hardware

The following equipment is used to develop and implement a real-time computer vision system:

- Compaq Model DESKPRO XE 560 with 60 MHz Pentium CPU,
- SHARP GPB-2 board: a hardware portion of image processing system for an IBM compatible computer,
- SHARP Incard: an accessory card handling three additional inputs (for example, red, green, and blue video signals) to the GPB-2 board for color image processing,
- SHARP AUXLUT Card: a daughter board to the GPB-2 for real-time look-up table conversion,

- COHU 2222-1340/0000 camera: a color video camera for high resolution NTSC (National Television System Committee) image acquisition,
- Softvision: an image processing algorithm development software package, and
- Microsoft C Compiler Version 7.0.

Machine Vision System

All research is being conducted with juvenile processing tomato plants grown in commercial tomato fields in northern California. The UC Davis Robotic Cultivator is utilized as a guidance system to find the center of a row. Each step, from taking field images to actuating the weed control device, is synchronized using an encoder (Danapar Brand, Danaher Controls Model HR6251000006), which is attached to a gage wheel on the toolbar of a tractor (Model 7800, John Deere Co.). This sensor generates a pulse whenever the tractor moves 0.13 mm forward. In order to obtain higher resolution from the encoder, an intermediate pulley is used between the encoder and the axle of the gage wheel. A SensorWatch™ microcontroller (TERN Inc.) is used to count the number of encoder pulses, and the location of the tractor is obtained by incrementing a counter. The SensorWatch™ is a C/C++ programmable 16-bit controller designed for data acquisition and control applications. The SensorWatch™ communicates via a RS-232 serial port to the Compaq computer containing the Sharp boards. The image size is 11.43 cm (4.5 in.) wide and 10.16 cm (4 in.) long, and a new image will be taken every 879 pulses (11.43 cm) using an asynchronous reset signal given to the color camera.

A robotic spraying system (Fig. 1) was developed with eight 12V DC solenoid valves (Capstan Ag Systems, Inc., Topeka, Kansas), a metal plate (13.97 cm x 6.35 cm x 0.48 cm) to align the valves, a stainless steel manifold (3.18 cm x 3.18 cm x 13.97 cm), a specially designed accumulator, and eight RHS® circuits for valve control. The robotic spraying system is mounted at the end of the tunnel about three image frames behind the camera.

For the valve nozzle, a nylon unslotted hex head screw (size 8-32, 1.27 cm long) was used with a center hole of diameter of 0.57 mm (#74 drill bit size) and was screwed into the center of the valve so that each valve would spray a 1.27 cm (0.5 in.) diameter circle with a 10 ms valve opening time at 103 kPa (15 psi) and a nozzle height of 10.16 cm (4 in.) above the ground. The eight solenoid valves (2.54 cm diameter) were aligned in two rows (four valves in each row) in order to allow the entire 10.16 cm (4 in.) wide seedline to be sprayed when they are all opened at the same time.

A uniform illumination device was developed using a specially designed cultivation tunnel which is attached to the end frame of an 'Alloway' cultivator and is composed of a C channel beam (10.16 cm wide, 60.96 cm long, and 0.48 cm thick), two dichroic halogen lamps (Iwasaki Electric Co. Model MR16CG, 12V

DC, and 50W), two flashed opal optical diffusers (Oriel Model No. 48030, 5.08 cm diameter and 2.2 mm thick), two metal side shields and front and rear rubber flaps. The two lamps were positioned at 60° relative to the optical axis of the camera. The two side shields were designed to block the sunlight and to minimize the amount of soil falling on top of the tomato plants during cultivation. Fig. 2 shows a uniform illumination device attached to the end of the UC Davis Robotic Cultivator.

Image Processing Algorithm

Upon receiving an asynchronous reset signal, the first step of image processing was to acquire an image of juvenile tomato plants from the field. A shutter speed of 1/500 second was used to keep images from blurring due to motion of the tractor and wind. The three channels of the SHARP Incard were used to input the red, green, and blue video components of an image and to digitize them. The actual size of an image was about 11.43 cm x 10.16 cm and was digitized into 256 x 240 pixels. After a color image was digitized and stored as a 24 bit color image in computer memory, the image was segmented into plant and non-plant regions using color information such as hue and saturation. In this step a Bayesian decision rule was applied to build a look-up table and the AUXLUT card was used for real-time conversion from a color image to a binarized image (white for plant leaves and black for background). This process required approximately 3 ms using the AUXLUT card in a Compaq XE 560 computer with a 60 MHz Pentium processor. After segmentation, the image was enhanced through a series of eight image processing steps including erosion and dilation to remove any digitization noise and to obtain a more realistic shape for the plant leaves. Fig. 3 shows an image of tomato seedlings in the field and Fig. 4 shows the segmented and enhanced image using the Sharp image processing boards.

Then, features were obtained for each plant leaf such as area, major axis, minor axis, centroid, elongation, compactness, the logarithm of the ratio of height to width (LHW), and the ratio of length to perimeter (LPT). Tian (1995) selected four features (elongation, compactness, LHW, and LPT) as the optimum subset among all features for tomato plant recognition. Elongation, compactness, LHW, and LPT are defined as follows:

$$\text{Elongation} = (\text{Major Axis} - \text{Minor Axis}) / (\text{Major Axis} + \text{Minor Axis}) \qquad (1)$$

$$\text{Compactness} = 16\text{Area} / \text{Perimeter}^2 \qquad (2)$$

$$\text{LHW} = \log_{10}\left(\frac{\text{Height}}{\text{Width}}\right) \qquad (3)$$

$$\text{LPT} = \frac{\text{MajorAxis}}{\text{Perimeter}} \qquad (4)$$

Using these features, plant leaves could be identified either as tomato cotyledons or as weeds for non-occluded leaves.

Table 1 shows execution times for each image processing step. For one frame of a 256 by 240 pixel image representing a 11.43 cm x 10.16 cm image, the image processing algorithm takes about 0.415 seconds to distinguish about 10 plant leaves in the image, and about 0.022 seconds to produce centroid information to be sent to the SensorWatch™, thus the prototype cultivator could travel at a continuous rate of 0.94 kilometers per hour. For this example, only the two features of elongation and compactness were used. Higher speed could be achieved simply by dedicating more image processing units to extract morphological features from the leaves in parallel since extracting features takes about 82% of the time for one image (Table 1).

Once the center of the weed leaves were located by the real-time computer vision system, the information was sent to the valve operating unit, the SensorWatch™ (TERN Inc.), which controlled the valve circuit. Then, an excited valve would spray the proper amount of agricultural chemical to remove weeds. A spraying time of 10 ms gives a flow rate of 0.098 L/min for each valve and an exit velocity from the nozzle of 6.4 meters per second. An accumulator is attached to the manifold in order to maintain constant flow rate independent of the number of valves opened simultaneously.

RESULTS AND DISCUSSION

The prototype machine vision system was tested in commercial tomato fields and images of tomato plants were acquired for future research. As of the date of this publication, all hardware has been constructed and an implementation of the real-time algorithm has been developed. The computer vision system, the uniform illumination device, and the precision chemical application system have been built. The algorithm for identifying crop plants and weeds in the seedline has been implemented in real-time for non-occluded plant leaves. However, performance of the prototype system was not obtained with tomato plants since most of tomato plants had already grown bigger than the cotyledon stage in commercial fields at the time of development, and an algorithm which can distinguish plants older and larger than those at the first true leaf stage was not completed at this stage.

In order to estimate the accuracy of the system, however, the prototype system was tested on tomato beds with metal coins of thickness 0.16 cm and diameter 2.54 cm, which were painted green in color. The coins were considered as "weeds" in the field and tacked on a 10.16 cm (4 in.) wide strip of cardboard using double sided tape in order to prevent them from changing their position. A look-up table was created with a few training images to identify the color of the coins. Eighty one coins were laid down on the bed in rows perpendicular to the tractor moving direction every 22.86 cm (9 in.) apart in a line of four or five coins. Their centroids were sprayed with a blue dye (Precision Laboratories, Inc. SIGNAL™) by the robotic spraying system after they were detected by the computer vision system, while the tractor was moving forward about 0.8 km/hr. Then, the distance was measured between the center of the coins and the center of the spray drops. The average error between the center of the coins and the spray drops was 0.78 cm and the standard deviation was 0.62 cm. Many sources of error were observed in the test. First of all, the encoder did not always work consistently (i.e., it did not generate the same number of the pulses for the same distance). This might be because there were clods and bumps on the bed where the gage wheel was traveling, or because the hardness of the soil was different from one field to another. There is also an intrinsic error due to the physical distance between the nozzle centers (1.27 cm). The distance between the center of the coins and the spray drops could be 0.64 cm even though the computer vision system correctly identifies the center of the coin.

In order to observe operation of the encoder on different ground surfaces, the robotic spraying system was used to spray all 8 valves every 22.86 cm (9 in.) apart both on the bed and on the paved road. The gage wheel pressure was about 138 kPa (20 psi). The distances between each of the two sprayed lines were measured, subtracted from 22.86 cm (9 in.) and considered as errors. The absolute values of these errors were taken and their mean and standard deviations were summarized in Table 2. The mean error and the standard deviation of the paved road were smaller than the ones from the dirt surface. This means that the encoder works more consistently on a smooth surface. The drops sprayed on the paved road seemed to be more aligned and uniform than the ones sprayed on the bed.

Future work

A more accurate method to measure the travel distance is needed since every operation is synchronized with travel distance. In order to accomplish the objective for distinguishing plants larger and older than those at the first true leaf stage, the morphological characteristics and texture of true leaves of tomato plants should be examined in more detail. A convex region of true leaves could be used for identifying them. The perimeter of true leaves could also be used to produce a feature since true leaves seem to have a longer perimeter than cotyledons. Also, faster and more accurate computer vision algorithms are needed for real-time use.

CONCLUSIONS

This study shows that

- A machine vision system for a real-time weed control was completed and tested in commercial tomato fields with a robotic spraying system as an implement.

- Using color information, the plant leaves were successfully extracted from a field image.
- The precision sprayer was able to spray the center of the targets (metal coins 2.54 cm in diameter) with the average error of 0.78 cm and the standard deviation of 0.62 cm.

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Table 1. Execution time for each image processing step. (unit: ms)

Step	Acquire image (one field)	Subsample by column	Binarize	Erode & Dilate	Extract features	Identify tomato	Total time
Time	16.70	5.39	2.97	28.79	339.12	21.80	414.77

Table 2. Performance of encoder on different ground surfaces. (unit: cm)

	Dirt surface	Paved road	Total
n	73	57	130
Mean	0.23	0.15	0.20
Std. Deviation	0.19	0.14	0.17

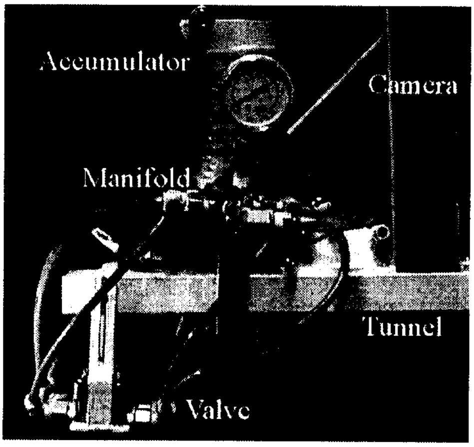

Fig. 1
Robotic spraying system.

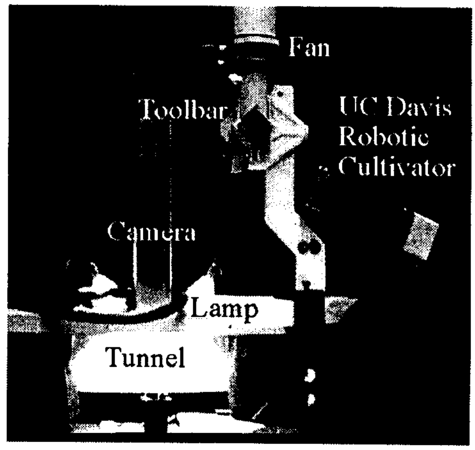

Fig. 2
Uniform illumination device attached to the UC Davis Robotic Cultivator.

Fig. 3
Image of tomato seedlings in a commercial field.

Fig. 4
Binary image processed by Sharp boards.