A Computer Vision Based Robotic Harvesting System for Lettuce

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***Abstract*—Harvesting lettuces is a challenging task in agriculture. In the paper, we propose a computer vision based robotic harvesting system for lettuce in hydroponic farms. In these farms, lettuces are grown in holes evenly located on parallel plastic tubes. Therefore, the problem of estimating locations of lettuces' stems can be simplified by estimating the hole locations instead. In particular, locations of holes covered by lettuces are estimated based on uncovered holes and/or tubes' edges which are found by using Hough transforms. A robot manipulator and a servo controlled gripper are used for the harvesting task. Experiment results show that the system, with the mean location error of 0.83 mm (typical cases) and maximum error of 9.62 mm, can efficiently perform harvesting task in real word environments.**

***Index Terms*—lettuce, computer vision, robotic, harvest, hydroponic farms**

I. Introduction

Products harvesting is one of the most challenging tasks in agriculture due to its time and manpower consuming as well as short harvesting periods. The problem is more significant for developing countries where agriculture is still underdeveloped and lacking of advanced automation technologies. Therefore, automatic agricultural products harvesting has attracted a lot of researchers for decades [1], [2]. Lettuce, which can be grown as a year-round crop in controlled environments, is one of the most popular hydroponic crops for both commercial and home growers. Hydroponic crop has several advantages such as no full sun requirement, good grow even in low light and temperatures, simple and unchanged nutrient solutions, etc. Therefore, it is a demand for automatic lettuce harvesting solutions for hydroponic farms to mitigate the labor load and to allow flexible and timely harvesting [3].

Computer vision, machine learning and deep learning have been employed in lots of works [4]-[10] to tackle the problems of object detection and distance estimation. In [11] the authors developed a platform for phenotypic analysis of millions of lettuces using aerial images. The system is capable of counting lettuces heads and classifying lettuces sizes with high accuracy (98%), as well as mapping lettuce size distribution. Recently a robotic harvesting system has been developed for iceberg lettuce which utilize deep learning to tackle the classification and localization problems [12]. The system achieves 91% of lettuce localization success and 1.5 % of false positive (with a 2 cm localization tolerance). Ref. [13] reported the average localization errors in depth, width, and height of 0.4 cm, 1.2 cm, and 2.8 cm, respectively for a sweet pepper harvesting robot.

The paper describes a computer vision based robotic harvesting system for lettuce in hydroponic farms where lettuces are grown in holes evenly located on fixed parallel tubes. For such special growing pattern, the hole centers are estimated instead of the lettuces' stems. In particular, centers of holes covered by lettuces are estimated based on uncovered holes and/or tubes' edges which are found by using Hough transforms. The problem of lettuce maturity classification, however, is not considered in the paper due to the fact that the variation of lettuce maturity, for hydroponic farms, is insignificant in practice. For the harvesting task, a robot manipulator and a servo controlled gripper are used. The rest of the paper is organized as follows. Section II presents the computer vision system. Section III discusses the robot manipulator while Section IV details the experiment setup and results. Conclusions are given in Section V.

II. Computer Vision System

In hydroponic farm, lettuces are grown on long plastic tubes which are arranged in parallel and at a fixed height from the floor as shown in Fig. 1. As can be seen in the figure, estimating locations of lettuces' stems is a nontrivial task since, being seen from above, the stems are covered by leaves and lettuces are not point reflected. To this end, we proposes a simple yet effective method to predict locations of lettuces' stems based on the special arrangement of the lettuces. In practice, lettuces are grown in holes which are evenly located (20 cm apart in this study) on the tubes as can be seen in Fig. 2. Therefore, we estimate the hole centers instead of directly estimating the stems' locations. Experiment results show that the proposed method can work well in real world scenario.

In the paper, we consider three real-world situations. Most of the time the robot can see (at least) two uncovered holes when it moves along the tubes as illustrated in Fig. 3 and Fig. 4. When the robot starts at a

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tube's end, it can see only one hole (Fig. 5) or even no hole (Fig. 6). For simplicity, we assume that the robot only sees a tube at a time. In practice, several tubes can be observed simultaneously thus the system can exploit the advantage of extra information.

Figure 1. Parallel plastic tubes.

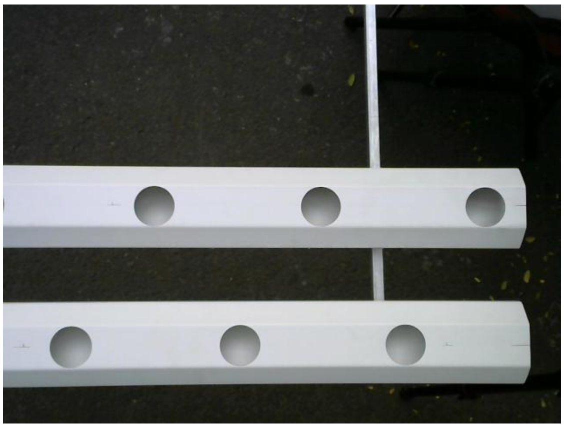

Figure 2. Evenly located holes on parallel tubes.

A. Robot Detect Two Uncovered Holes

The hole center (x, y), which is covered by a lettuce, is estimated based on the centers (x_1, y_1), (x_2, y_2) of the two adjacent uncovered holes as well as the fact that these holes are evenly located as depicted in Fig. 3. The uncovered holes in images are found using the circular Hough transform [14]. The center of the covered hole is estimated as follow:

$$\begin{cases} x = 2x_2 - x_1 \\ y = 2y_2 - y_1 \end{cases} \quad (1)$$

Another way to estimate the center (x, y) of the covered hole is based on the center (x_2, y_2), the distance d_1 (known a priori) between holes and the direction vector (v_x, v_y) of the tube estimated by its parallel long edges (using the standard Hough transform [15]) as shown in Fig. 4. In particular, the hole center coordinates (x, y) are computed from the following equations:

$$\begin{cases} \sqrt{(x - x_2)^2 + (y - y_2)^2} = d_1 \\ \dfrac{y - y_2}{x - x_2} = \dfrac{v_y}{v_x} \end{cases} \quad (2)$$

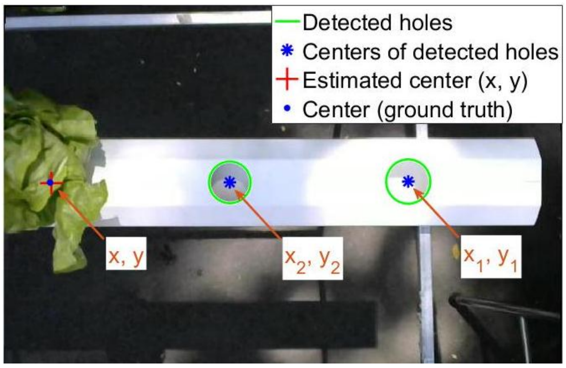

Figure 3. Estimate of center (x,y) of covered hole using centers (x_1,y_1) and (x_2,y_2) of two adjacent uncovered holes.

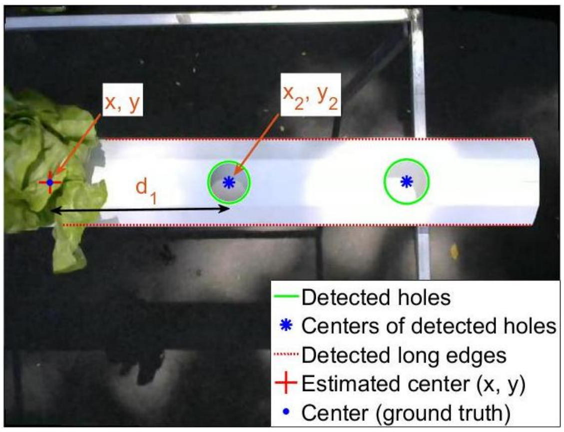

Figure 4. Estimate of center (x,y) of covered hole using center (x_2,y_2) of adjacent uncovered hole, distance d_1 and direction vector.

Before detecting lines, colour images are first binarized using the Otsu's method [16]. The binary images are then filled holes and applied morphological open operation [17]. Finally the Canny technique [18] is employed for edge detection.

B. Robot Detect One Uncovered Holes

This case is similar to the latter one in Section II.A. The hole center (x, y), which is covered by a lettuce, is estimated based on the center (x_1, y_1) of the adjacent uncovered hole, the distance d_1 (known a priori) between holes and the direction vector (v_x, v_y) of the tube estimated by its parallel long edges as shown in Fig. 5. In particular, the hole center coordinates (x, y) are computed from the following equations:

$$\begin{cases} \sqrt{(x - x_1)^2 + (y - y_1)^2} = d_1 \\ \dfrac{y - y_1}{x - x_1} = \dfrac{v_y}{v_x} \end{cases} \quad (3)$$

C. Robot Detect No Uncovered Holes

The hole center (x, y), which is covered by a lettuce, is estimated based on the center (x_1, y_1) of the tube's end, the distance d_2 (known a priori) between the first hole and the tube's end as well as the direction vector (v_x, v_y) of the tube estimated by its parallel long edges as shown in Fig. 6. In particular, the hole center coordinates (x, y) are computed from the following equations:

$$\begin{cases} \sqrt{(x-x_1)^2+(y-y_1)^2} = d_2 \\ \dfrac{y-y_1}{x-x_1} = \dfrac{v_y}{v_x} \end{cases} \tag{4}$$

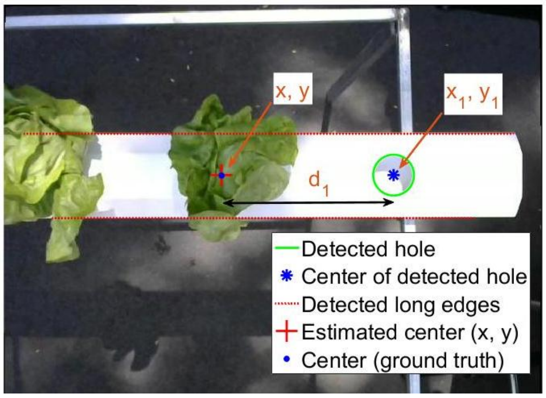

Figure 5. Estimate of center (x, y) of covered hole using center (x_1, y_1) of adjacent uncovered hole, distance d_1 and direction vector.

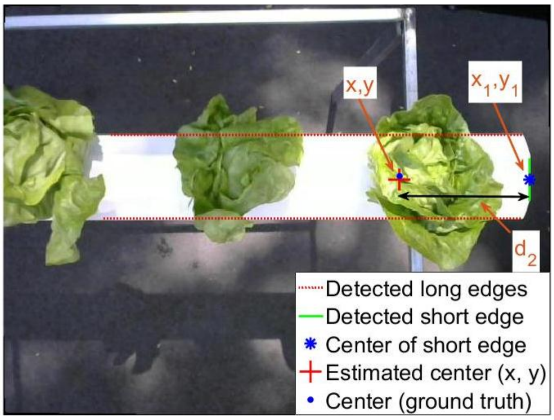

Figure 6. Estimate of center (x, y) of covered hole using center (x_1, y_1) of tube's end, distance d_2 and direction vector.

In this case, the detection of tube's edges is more challenging than that of previous cases because more part of the tube's edges are covered by the lettuces while the remaining parts might not be easily segmented due to uneven sunlight on the floor as can be seen in Fig. 6. To this end, the color image is first converted to the HSV (Hue, Saturation, Value) space then the tube is segmented by carefully manipulating the color components. Holes filling, morphological open operation and Canny edge detection are then applied before detecting lines using Hough transform. Fig. 7 shows intermediate results of the process.

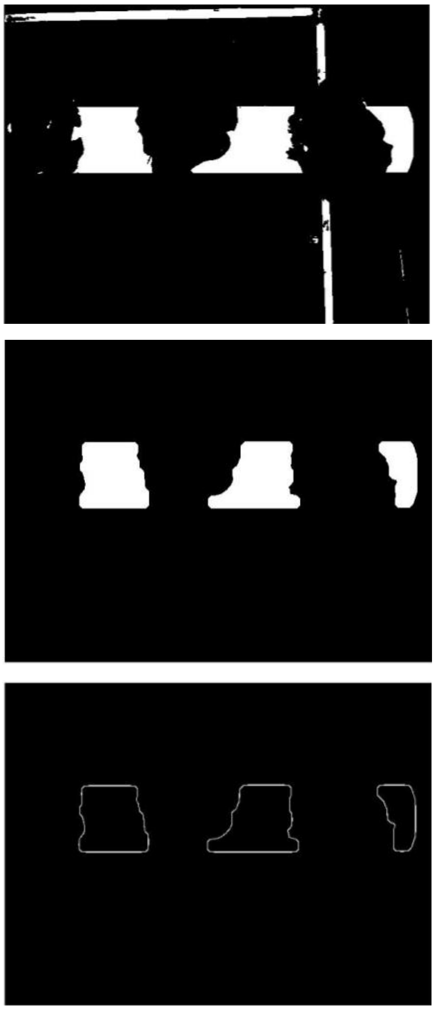

Figure 7. Images after segmentation (top), hole filling and morphological open (middle) and Canny edge detection (bottom).

III. Robot Manipulator

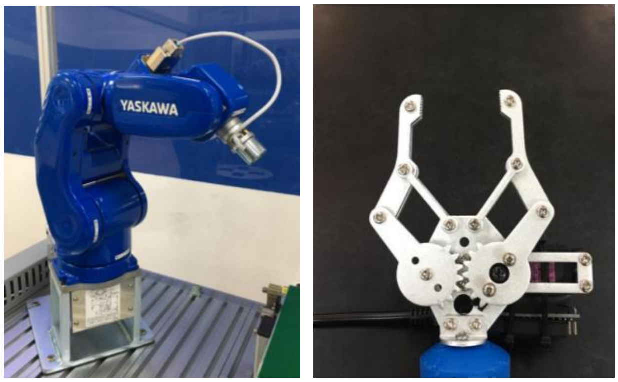

Figure 8. Yaskawa 6 DOF MotoMini manipulator (left) and servo controlled gripper (right).

A Yaskawa 6 DOF MotoMini robot with a servo controlled gripper as depicted in Fig. 8 is utilized to perform the harvesting task. Coordinate systems were chosen as illustrated in Fig. 9. Table I presents the MotoMini specifications. The Denavit - Hartenberg parameters are given in Table II and Table III.

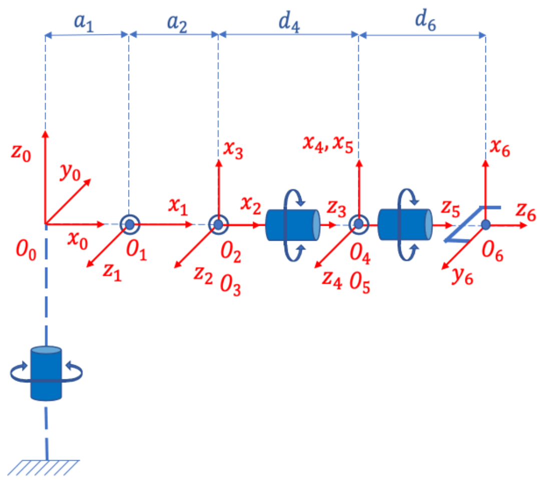

Figure 9. Coordinate frames of robot arm.

TABLE I. MOTOMINI ROBOT SPECIFICATIONS

Item	Value
# Controlled axes	6
Maximum payload	0.5 kg
Horizontal reach	350 mm
Vertical reach	495 mm
Weight	7 kg
Repeatability	± 0.02 mm

TABLE II. LINK PARAMETERS

Link	a_i	d_i	α_i	θ_i
1	a_1	0	90^0	θ_1
2	a_2	0	0^0	θ_2
3	0	0	90^0	θ_3
4	0	d_4	-90^0	θ_4
5	0	0	90^0	θ_5
6	0	d_6	0^0	θ_6

TABLE III. ROBOT PARAMETERS

Parameters	*Value (mm)*
a_1	20
a_2	165
d_4	165
d_6	148

The lettuce's 2D position (hole center) and tube's orientation estimated in the previous section are combined with a priori knowledge of the tubes' plane (at a fixed height and parallel to the plane O0x0y0 of the robot's coordinate system) to constitute the 3D position and orientation of the gripper for the harvesting task. The inverse kinematics problem is then resolved to obtain six required joint angles. The gripper is controlled to move along the tube and close to the tube's surface when approaching the lettuce. Flow chart of the proposed system is shown in Fig. 10.

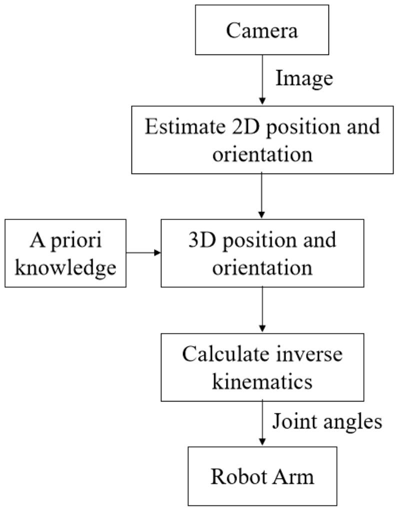

Figure 10. Flow chart of the proposed system.

IV. EXPERIMENT RESULTS

The vision system consists of a Logitec webcam C270 connected to a laptop running computer vision algorithms. The camera is fixed with respect to the robot coordinate system and parallel to the tubes' (and the floor) surface. The system was calibrated to obtain camera intrinsic, extrinsic and lens distortion parameters. The calibration procedure can be found elsewhere, for example [19]. The centers of holes are estimated by computer vision algorithms running on a laptop then inverse kinematics are calculated and joint variables are sent to the robot controller. When the gripper approach its destination, the laptop issues a closing command to the gripper through a serial connection. The gripper then closes its arms and the manipulator picks the lettuce to the container. The vision system then checks whether the lettuce is successfully picked up simply by checking the color of the object inside the gripper arms.

A. Hole Detection

The hole detection function was evaluated using 520 images taken under varying lighting conditions. The detection accuracy is defined as the ratio of the number of detected holes to the total number of holes. The hole detection results are given in Table IV. As can be seen in the table, the system can correctly detect all uncovered holes on tubes without false positives.

TABLE IV. HOLE DETECTION RESULTS

Number of images	*Number of holes per image*	Accuracy (%)
130	0	100
130	1	100
130	2	100
130	3	100

B. Location Error and Harvesting Performance

Location error and harvesting performance were evaluated using images captured with different poses of the robot with respect to the tube. At each pose, four images were taken with the number of uncovered hole(s) ranging from zero to three. The image with three uncovered holes was used to find hole centers which were considered as ground truth for comparison. Totally 200 images were taken under varying lighting conditions.

Location error is defined as the distance between the estimated center (presented in section II) and the hole center estimated from the circular Hough transform (called ground truth in Figs. 3-6). Figs. 3-6 shows results for cases presented in Section II. The mean, max and standard deviation of location error are given in Table V.

The system yields the smallest mean location error for case A_2. This can be explained by the fact that in this case the direction vector estimated by using the tube's long edges is more accurate than using the two hole centers as in case A_1. The error in case B is very similar to those of case A_2 due to the use of the same method. Case C results in the largest error as expected because the tubes' edges are more challenging to precisely detect. The maximum error for all cases is less than 1 cm, which indicates that the system is suitable for real-world applications. For the grasping task, the system obtain a 100% success rate.

TABLE V. MEAN, MAX AND STANDARD DEVIATION OF LOCATION ERROR

Case		**Error (mm)**		
		Mean	**Standard deviation**	**Max**
A_1 (Eq. (1))	2 uncovered holes	1.271	0.621	2.933
A_2 (Eq. (2))		0.831	0.567	2.261
B	1 uncovered holes	0.883	0.481	2.114
C	0 uncovered holes	5.276	2.444	9.615

V. CONCLUSIONS

The paper propose a computer vision based robotic harvesting system for lettuces employing a prior knowledge of the lettuces growing pattern to simplify the problem of estimating locations of lettuces' stems. Experiment results show that the system, with mean location error of 0.83 mm (typical cases) and maximum error of 9.62 mm, can efficiently perform the task in real word environments. Further investigations are in progress implementing a mobile system to obtain a truly autonomous and optimal operation.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Viet-Cuong Pham implemented the proposed method and was in charge of the overall project. Hoang-Giap Nguyen conducted the experiment and analyzed the data; Thanh-Khang Doan and Gia-Bao Huynh contributed to the robot harvesting task and data collection; The paper was written and approved by all authors.

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