Evaluation of Tomato Fruit Harvestability for Robotic Harvesting

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Evaluation of Tomato Fruit Harvestability for Robotic Harvesting

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Abstract—**Harvestability is a quantitative index of how easy tomato fruits are to harvest using a robot. Previous studies on tomato harvesting robots have focused on tomato fruit detection methods, harvesting mechanisms, harvesting success rates, and harvesting times. However, tomato fruit harvestability using robots has not been quantitatively assessed. In this paper, we propose a method for evaluating the tomato fruit harvestability using a tomato harvesting robot. We first evaluated the harvestability qualitatively, based on the results of harvesting experiments conducted in a tomato greenhouse. Harvestability was then quantitatively evaluated using a camera (hereinafter referred to as a hand camera) attached to an end-effector of the tomato harvesting robot developed. The hand camera consists of an RGB camera and a depth camera. The occlusion ratio of obstacles (stems, peduncles, and other fruits) to a target fruit is calculated using the RGB image and depth image acquired by the hand camera. The larger the occlusion ratio was, i.e., the more obstacles there were in front of the target fruit, the more difficult the target fruit was to harvest. Conversely, if the occlusion ratio is low, the harvestability is high. This study shows that the occlusion ratio is effective as a quantitative indicator of the tomato fruit harvestability.**

I. Introduction

In the production and distribution of agricultural crops, the use of plant factories is an efficient cultivation method for addressing issues such as quality preservation and stable shipping. Plant factories enable the planned production of agricultural crops by equipping a field with infrastructure and controlling the cultivation environment (temperature, humidity, irrigation). For example, Hibikinada Green Farm Co., Ltd. (hereinafter referred to as Hibikinada Green Farm) in Japan, which adopted Dutch cultivation methods, has implemented long-term multi-stage cultivation of tomato plants.

Plant factories differ from outdoor cultivation in that they have infrastructure equipment. They are used as experimental fields for studies aimed at development of smart agriculture because it is easy to introduce robot technology, information communication technology, and Internet of Things in plant factories. Wakamori et al. have clarified the relationship between leaf wilting and stem diameter variation in a study conducted in a commercial greenhouse [1]. Yoshida et al. have studied automatic harvesting of cherry tomato clusters cultivated in a plant factory and proposed a cutting point detection method for use with harvesting robots [2].

We seek to automate monitoring tomato plants and harvesting tomato fruits using robots, with the cooperation of the Hibikinada Green Farm [3, 4]. This paper focuses on the automatic harvesting of tomato fruits. Monta et al. have studied a tomato harvesting robot from 1980s and developed an end-effector which consists of two parallel plate fingers and a suction pad [5]. Kondo et al. have developed a tomato harvesting robot that has a four-degree-of-freedom (4-DOF) horizontal articulated type of manipulator and a cutting mechanism that enables harvesting of a tomato cluster [6]. Yaguchi et al. have developed a tomato harvesting robot that has a six-degree-of-freedom (6-DOF) vertical articulated type of manipulator and a harvesting mechanism that grips one fruit with grippers and plucks it from the separation layer in the peduncle [7]. Additionally, regarding harvesting robots that target vegetables or fruits other than tomato fruits, Zhao et al. have developed an apple harvesting robot having the spoon-shaped end-effector with the pneumatic actuated gripper [8]. Feng et al. have developed a strawberry harvesting robot having a nondestructive end-effector, used to suck the fruit, hold and cut the fruit-stem [9]. Arad et al. have developed a sweet pepper harvesting robot [10]. Studies on fruit detection methods and harvesting mechanisms for harvesting robots have been carried out, and the detection rate, harvesting success rate, and harvesting time have been examined in these studies.

On the other hand, harvestability, which pertains to how easy or difficult fruits are to harvest using a harvesting robot, has not been examined in previous studies. To improve the intelligence of harvesting robots, we propose a method for evaluating harvestability and describe the results of verification experiments carried out in plant factories. The remainder of this paper is organized as follows. The design and harvesting behavior of the tomato harvesting robot used in the verification experiments are described in Section II, the method for evaluating harvestability is detailed in Section III, the verification experiments are presented in Section IV, the results are discussed in Section V, and the conclusions are presented in Section VI.

II. Developed Tomato Harvesting Robot

We have developed tomato harvesting robots based on a modular design [4]. The robots consist of four elements: a moving mechanism for moving on a rail in a tomato greenhouse, a vision sensor for detecting tomato fruits, an end-effector for harvesting tomato fruits, and a manipulator for approaching a target fruit with the end-effector and carrying the harvested fruit to a harvest box. In a previous

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study [4], we described three different tomato harvesting robots with different components. In this section, the design and harvesting behavior of a rail movement-type tomato harvesting robot with a three-axis orthogonal manipulator used to evaluate the harvestability are described.

A. *Robot Design*

Figure 1 shows an image of the tomato harvesting robot. The movement mechanism is designed such that the robot can move on a rail 600 mm wide in a tomato greenhouse. We adopted a suction cutting device as the end-effector. This end-effector sucks a target fruit, holds the sucked fruit inside the device, and then cuts the peduncle of the target fruit. While the end-effector proposed by Yaguchi et al. plucks the fruit, the suction cutting device cuts the peduncle, so it is possible to harvest the fruit with calyx. Therefore, it is possible to ship the fruit to market while maintaining freshness. In addition, this end-effector is attached to a camera to evaluate the tomato fruit harvestability. The camera is described in detail in Section III. The manipulator is of a three-axis orthogonal type, and the stroke lengths along the x, y, and z axes are 200, 200, and 500 mm, respectively. The payload of the manipulator at the hand position is 4 kg. A Microsoft Kinect is used as a vision sensor.

B. *Harvesting Behavior*

Figure 2 shows a flowchart of the harvesting behavior of the tomato harvesting robot. This robot searches for tomato fruits using the vision sensor while moving on the rail (process (i) in Fig. 2). When mature fruits are detected (process (ii) in Fig. 2), the mature fruits in the workspace of the robot are counted (process (iii) in Fig. 2). Regarding the detection method, in order to recognize mature and immature tomato fruits, we referenced k-means++ method which is one of the unsupervised classification methods [11]. The RGB images acquired by the vision sensor mounted on the robot are used to detect mature and immature fruits, and the positions of the detected fruit are calculated using the detection results and the depth value in the Depth image. Next, a harvest priority value is calculated for each detected fruit, and the fruit with the highest harvest priority value is selected as the target fruit (process (iv) in Fig. 2). The harvest priority value is determined based on the distance from the vision sensor to the detected fruit and whether there are other fruits around the detected fruit. The harvest priority value is highest when the distance is the smallest and there are no other fruits around the detected fruit. If there are other fruits around the detected fruit, they may be damaged during the harvesting motion, so the harvest priority value is lowered. The target fruit is determined, the end-effector approaches the target fruit (processes (v)-1 to (v)-3 in Fig. 2), and the harvesting motion is performed (processes (v)-4 to (v)-6 in Fig. 2). If the target fruit is sucked and it is judged that cutting is possible, the cutting motion is carried out. If the cutting is successful (process (vi) in Fig. 2), the harvested fruit is carried to a harvest box (process (viii) in Fig. 2). If the harvesting is successful and there are other harvestable fruits at this position, processes (iii) to (ix) in Fig. 2 are repeated. When it is judged that the target fruit cannot be cut and the harvesting motion fails but that there are other fruits at this position (process (ix) in Fig. 2), the fruit with the second highest harvest priority value is selected as the next target fruit, and the harvesting motion is performed again. However, if the harvesting motion fails twice at the position at which the robot is stopped (process (vii) in Fig. 2) or if there is no fruit in the robot workspace (process (ix) in Fig. 2), the robot moves along the rail, and searches for tomato fruits again (process (i) in Fig. 2). If there is only one fruit at the position and the harvesting motion fails once, the harvesting behavior shifts to process (i) in Fig. 2.

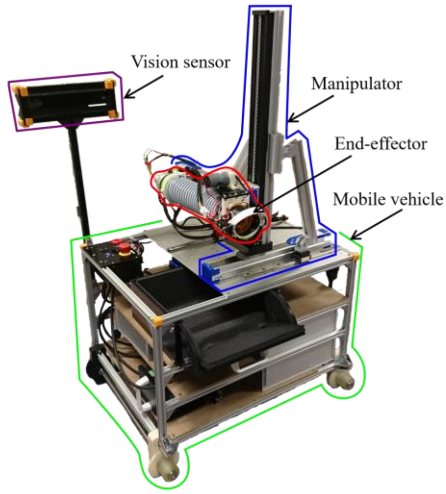

Fig. 1. Tomato harvesting robot. This robot consists of four elements: a mobile vehicle, vision sensor, end-effector, and manipulator.

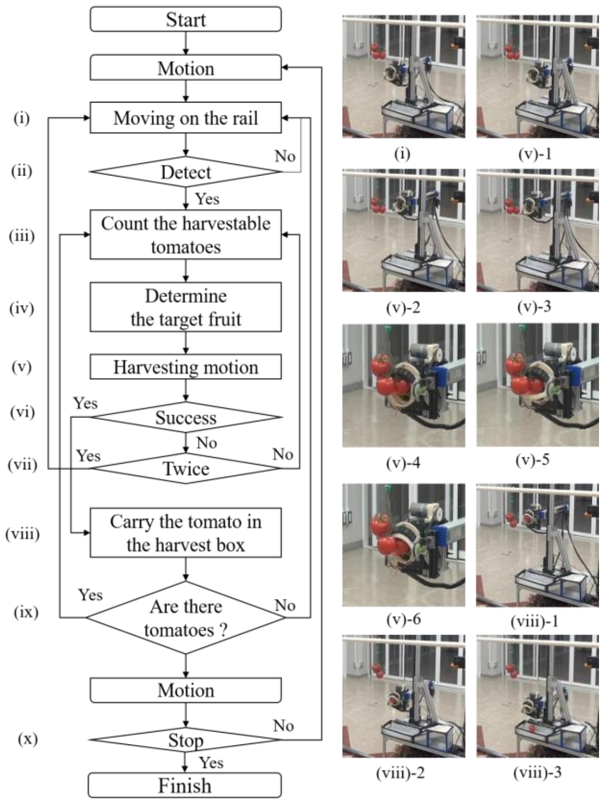

Fig. 2. Flowchart of the harvesting behavior. The robot searches for tomato fruits while moving along the rail (process (i)). When the robot detects tomato fruits, the harvesting motion is started (processes (ii) to (v)). The end-effector approaches the target fruit (processes (v)-1 to (v)-3), the target fruit is harvested

by the suction cutting device (processes (v)-4 to (v)-6)), and the harvested fruit is carried to the harvest box (processes (viii)-1 to (viii)-3).

III. EVALUATION OF HARVESTABILITY

To evaluate the harvestability, the end-effector has a camera (hereinafter referred to as a hand camera). In this section, the design of the hand camera and the method for evaluating harvestability are described.

A. Hand camera mounted on end-effector

Before deciding on the specifications of the hand camera, we carried out harvesting experiments and qualitatively evaluated the characteristics of fruits that were easy or difficult to harvest using the developed robot. Figure 3 shows an example of images of the tomato clusters before and after the harvesting experiments. These images were taken from the front of the tomato clusters, using a commercial camera. The fruits with numbers 1, 2, 4, 5, 6, and 8 in Fig. 3 were successfully harvested, but the fruits with numbers 3, 7, 9, and 10 were not. It was confirmed that there were stems and peduncles in front of most of the fruits that were not successfully harvested. Therefore, it was concluded that it is possible to quantify harvestability by detecting obstacles in front of the target fruit.

To evaluate harvestability, it is desirable to be able to recognize stems, peduncles, and fruits and to remove the background objects from the image. In this study, we used a hand camera, which is a combination of an RGB camera and a depth camera. Figure 4 shows the position at which the hand camera is attached to the end-effector and the appearance of the hand camera. The hand camera is attached to the upper part of the cutting part of the end-effector. A C920 camera manufactured by Logitech was used as the RGB camera, and a CamBoard pico flexx camera manufactured by PMD Technologies was used as the depth camera. We calibrated the alignment of the images using a checkerboard to overlap regions of the images acquired by the RGB camera with those acquired by the depth camera. Corners were detected by applying the algorithm proposed by Harris et al. [12] to the images of the checkerboard acquired by each camera. The original point for alignment was determined from the detected points, and alignment was performed. This calibration and the evaluation method described below were implemented using MATLAB/Simulink.

B. Evaluation method

Figure 5 shows the processing flow of the method for evaluating harvestability. The RGB image and depth image acquired by the hand camera are input images (process (i) in Fig. 5). To recognize mature fruits and obstacles, RGB color space is converted to HSV color space, and binarization is performed based on each threshold to extract each candidate region (process (ii) in Fig. 5). In this study, the thresholds for extracting mature fruits and obstacles were empirically determined. Next, an image with the background region removed is generated using the binarized image of each candidate region of mature fruits and obstacles, and the depth image (process (iii) in Fig. 5). The local minimum value of the candidate region of the mature fruits in the depth image is used as the center position of the target fruit, and a region of radius r is recognized as one tomato fruit (process (iv) in Fig. 5). When there are two or more mature fruits in the image, other fruits are recognized from the candidate region, excluding the first recognized fruit region. The radius r is empirically determined based on the distance from the vision sensor to the target fruit. To recognize stems, peduncles, and immature fruits that may become obstacles, the binarized image, which is the candidate region for obstacles, is labeled for each connected pixel (process (v) in Fig. 5). In the recognized candidate region for labeled obstacles within the recognized mature fruit region, if the depth value of the candidate region for the obstacles is smaller than that of the center coordinates of the target fruit, the region is defined as the obstacle region (process (vi) in Fig. 5)). In the image in the fourth column of Fig. 5, the black region is the background region, the red circle is the recognized target fruit region, the green region is the obstacle candidate region, and the white region is the obstacle region. The harvestability is evaluated using the occlusion ratio of the obstacle region to the target fruit region (process (vii) in Fig. 5)).

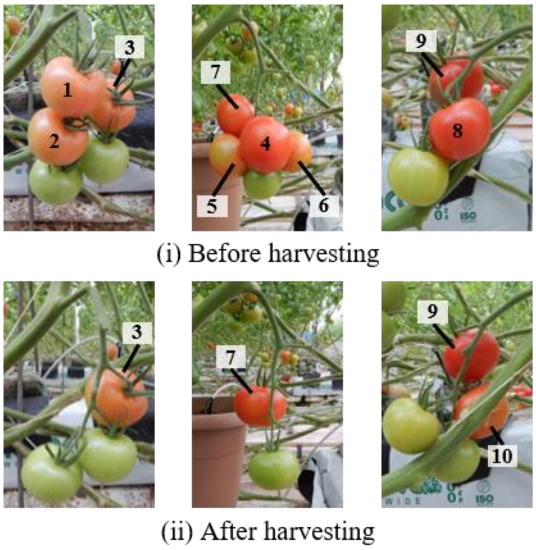

Fig. 3. Tomato clusters before and after harvesting experiment. Fruits numbered 1, 2, 4, 5, 6, and 8 were able to be harvested, and fruits numbered 3, 7, 9, and 10 were not able to be harvested.

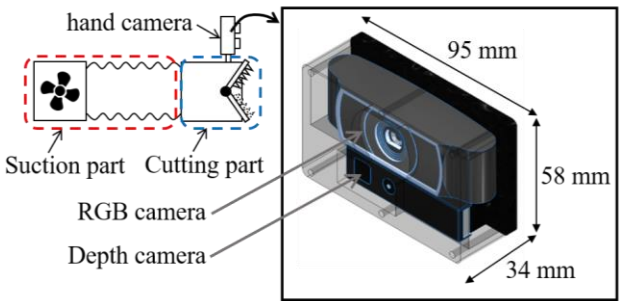

Fig. 4. Hand camera for evaluating harvestability. This camera is fixed to the cutting part and consists of two cameras: an RGB camera (Logitech, C920) and a depth camera (PMD Technologies, CamBoard pico flexx).

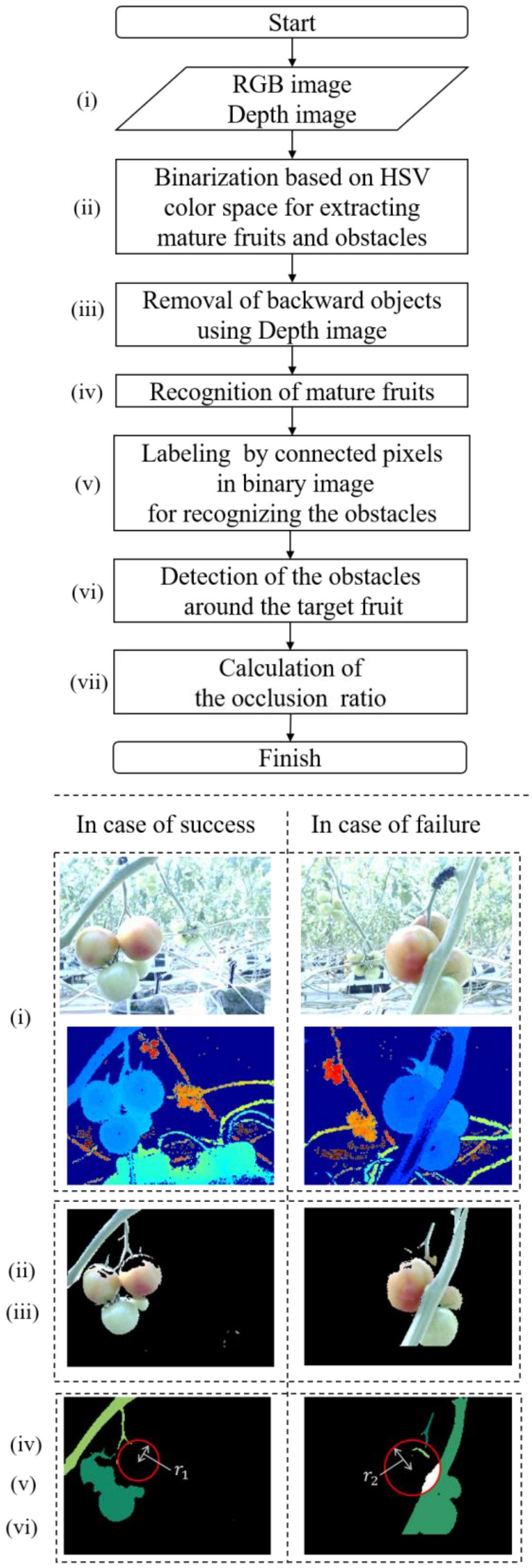

Fig. 5. Processing flow for evaluating harvestability. RGB and depth images acquired by the hand camera are input images (process (i)). Candidate regions of mature fruits and obstacles are extracted using the RGB image (process (ii)), and the background region is removed using the depth image (process (iii)). The target fruit and obstacle region are recognized from among candidate regions of mature fruits and obstacles (processes (iii) to (vi)). Harvestability is evaluated using the occlusion ratio of the obstacle region to the target fruit region (process (vii)).

IV. Verification of Proposed Method

We carried out experiments in Hibikinada Green Farm on February 24, 2020, using ten tomato fruits to verify the evaluation method. In the experiments, the developed tomato harvesting robot was set up on the rail in the Hibikinada Green Farm. The robot automatically performed the harvesting behavior described in II-B. While the robot was harvesting, the images were acquired by the hand camera at 10fps. In order to evaluate the proposed method, we used the images based on the harvesting results. Regarding the images used to evaluate the proposed method, in the harvesting behavior shown in Fig. 2, the images acquired when the robot detects the fruit and approaches the end-effector to the target fruit position with the manipulator was used. The images shown in Fig. 5 are examples of images acquired by a hand camera during the above-mentioned harvesting behavior.

The tomato harvesting robot successfully harvested six of the ten fruits. Table 1 shows the harvesting time results, from selecting the target fruits to carrying the harvested fruits to a harvest box when the harvesting is successful. The time until the fruit is detected while the robot is moving along the rail is not mentioned in this paper because it depends on the position of the fruit grown in the tomato greenhouse. "*Average*" in Table 1 is the average time required for harvesting a target fruit when the harvest is successful, that is, the average of six successful harvests. "*S.D.*" is the standard deviation of the harvesting time. Table 2 shows the verification results for the evaluation method for the ten tomato fruits. "Occlusion ratio" is the ratio of the fruit region to the obstacle region, "O" indicates when the harvesting motion succeeds, and "X" indicates when the harvesting motion fails.

TABLE 1: Harvesting time per fruit. "*Average*" is the average of six harvesting times. "*S.D.*" is the standard deviation of the harvesting times.

Motion	*Time [s]*	
	Average	*S.D.*
Select a target tomato	1.0	0.2
Approach and suction	8.2	2.6
Cut	8.8	1.1
Drop	4.9	1.6
Total	22.9	3.4

TABLE 2: Verification results. "Occlusion ratio" is the ratio of the fruit region to the obstacle region. "O" indicates when the harvesting motion succeeds, and "X" indicates when the harvesting motion fails.

Fruit number	Occlusion ratio	O or X
1	0.00	O
2	0.02	O
3	0.04	O
4	0.06	O
5	0.09	O
6	0.16	O
7	0.29	X
8	0.33	X
9	0.35	X
10	0.49	X

V. Discussion

A. Harvesting time

In the results shown in Table 1 for the harvesting time per fruit, the standard deviation of the "Select a target tomato" process is smaller than that of other processes, and this time depends on the specifications of the control computer. The "Approach and Suction" and "Drop" processes depend on the position of the target fruit, and the "Cut" process depends on the speed and torque of the driving part in the cutting part of the end-effector. It is possible to eliminate the "Drop" time by adding a mechanism to guide the harvested fruits to the harvesting box rather than sequentially carrying the harvested fruits to the harvesting box. This would reduce the overall harvesting time.

B. Evaluation of harvestability

The results of the evaluation of harvestability are shown in Table 2. The occlusion ratio in the cases of successful harvests were smaller than those in the cases of unsuccessful harvests. When there were obstacles in front of the target fruit, the occlusion ratio was higher, and the target fruit was more difficult to harvest. It is possible to improve tomato harvesting efficiency by implementing this harvestability evaluation method in modifying the harvesting behavior of the tomato harvesting robot and selecting a harvesting strategy that is based on maximizing the harvestability determined by the evaluation method.

VI. Conclusions

We have proposed a method for evaluating the harvestability of tomato fruits using harvesting robot. We have shown quantitatively that the occlusion ratio of obstacles to the target fruit is effective as an evaluation indicator of harvestability. If the occlusion ratio is low, the harvestability is high, and if it is large, the harvestability is low. In future work, not only the occlusion ratio but also the position relationship between the target fruit and the obstacles will be added as an evaluation indicator of tomato fruit harvestability. It is necessary to consider a harvesting strategy based on the harvestability for a tomato harvesting robot. The manipulator of the harvesting robot used in this study was a three-axis orthogonal type of manipulator. Another subject of future research will be evaluation of tomato harvestability when using a manipulator with a higher number of degrees of freedom.

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