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Machine Vision Algorithm for Robots to Harvest Strawberries in Tabletop Culture Greenhouses

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Abstract

A strawberry harvesting robot consisting of a four DOF manipulator, an end-effector with suction pad, a three camera vision system and a rail type traveling device was developed as a trial to conduct experiments in a tabletop culture greenhouse. In order to harvest the strawberries with curved or inclined peduncles, a wrist joint which can rotate 15 degrees to the left or right from its base position was added. On the algorithm side, peduncle inclination angle was measured by the center camera. Harvesting experiments show that it was possible to precisely harvest more than 75% of fruits which were not occluded by other fruits with the developed robot. Experimental data also show that peduncle length, color and inclination pattern change with the seasons. Complex situations often exist in the real field conditions such as limited visibility of back end strawberries, occluded fruits, obstructions and complex peduncle patterns. Further studies are desirable to automate the harvesting task using a robot.

[Keywords] strawberry, tabletop cultivation, harvesting robot, stereo vision, rail type traveling device, wrist joint.

I Introduction

Recently, the working hours in strawberry greenhouses are getting longer. During harvesting, human operators have to sit in a half-sitting posture from early morning. Harvesting work continues for about six months every year, and improper posture of the working condition causes load and fatigue on workers. It has been found that working posture not only reduces the harvesting efficiency but also adds fatigue to workers. Therefore, the tabletop cultivation method is becoming popular because it improves the comfort of workers. In this cultivation method, fruits hang down and workers can harvest the fruit while standing with better efficiency. In the tabletop cultivation method, strawberries can be detached with the stems and leaves still connected, and thus robots can be used for harvesting the strawberries. (Kondo et al., 1998). Harvesting robots for tabletop cultivation which can travel with the help of a prismatic joint have been reported (Arima et al., 2004). This study by Arima also showed that a suction head could compensate the errors caused by the visual sensors.

For a robotic system to be highly efficient and cost effective, it is essential to be able to detect a high percentage of mature fruits. To achieve this goal, it is important to overcome basic existing difficulties such as occlusion and illumination variation (Liming et al., 2007). Furthermore, it is important to perform the harvesting at a reasonably high speed, which depends on the movement capability of the robotic arm. The vision system plays a critical role in the development of a robot with high performance (Tarrio et al., 2006). The use of visual sensors in previous robots could provide two-dimensional information and depth of the fruit, based on previously harvested fruit (Arima et al., 2001). In this study, a harvesting robot was developed that can obtain three-dimensional information by the captured image, and as a result accurate depth is known for each fruit. The size of the suction head and the suction power were optimized to harvest the single fruit. This robot has the capability to detect the inclined peduncle and harvest fruit based on this information.

II Materials and Experimental Devices

1. Strawberry Green House

The harvesting experiment was conducted in Ehime prefecture. A green house named Watanabe Farm House of

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Matsuyama City was selected to conduct the experiment in the night time. At this farm the tabletop culture method was followed to cultivate Benihoppe strawberries. The length of the strawberry bed was 45 m, the width of the bed was 39 cm and the height of the bed from the ground was 90 cm.

Fig. 1 Green house and robot

2. Light Source and Camera Layout

In this study, white LED was chosen for the light source because of its long life, durability and low maintenance cost. Five light sources were prepared using 120 LED lamps for each source. A polarization filter was used to remove the halation from the image. Three color CCD cameras were aligned to capture the images. The left and right cameras utilized distortion free CCTV. The lens had a focal length of 4.5 mm. For the center camera, a CCTV lens with focal length of 6.0 mm was used.

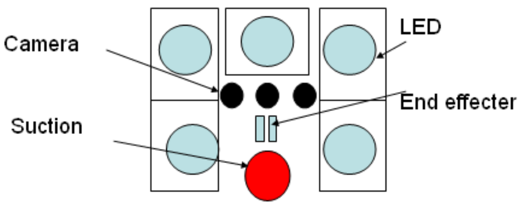

Fig. 2 Light source and camera layout

3. Mechanical System of the Robot

In this study, a robot with a 4-degree of freedom manipulator was utilized to conduct the experiment. It can move upward or downward to reach the vertical position of the strawberry, rotate left or right side based on the calculated angle, move towards strawberry based on the stereo depth and also rotate the wrist joint in the direction of the inclined peduncle. This wrist joint can rotate 15 degrees to left or right from its base position. Two sensors were fixed to detect the presence of the strawberry in the suction pad.

III Machine Vision and Experimental Method

1. Classification of Strawberries

In this study, strawberries are classified according to their surface visibility. We have classified the strawberries as A, B, C, D and E types. Type A is the simple single strawberry. If a green strawberry is nearby a red strawberry but it is not connected to it, then it is called a B type strawberry. If two red strawberries are connected and almost make a cluster of strawberries, then it is considered to be a C type strawberry. If a green portion is hiding less than 50% of the red part then we classify it as a D type strawberry. Otherwise it is classified as an E type strawberry (Kondo et al., 2005). The classification of strawberries is shown in Table 1.

Table 1 Classification of strawberries

A	Whole fruit is visible and separated from others.
B	Whole fruit is visible, but other adjacent fruit might be behind.
C	Ripe fruits are occluded (Cluster formation).
D	Fruit exposure is more than 50% and occluded.
E	Fruit exposure is less than 50% and occluded.

2. General Flow of Harvesting

(1) Harvesting Flow

In this study, three cameras (left, right and center) were used. The right and left cameras were used to calculate the stereo depth of the object from the camera. The left camera was used to detect the maturity of the fruit, cluster existence and also to detect obstruction in front of the strawberry. The center camera was used to detect the target strawberry, correct the position and detect the peduncle and the angle of peduncle. The general flow chart for harvesting is shown below.

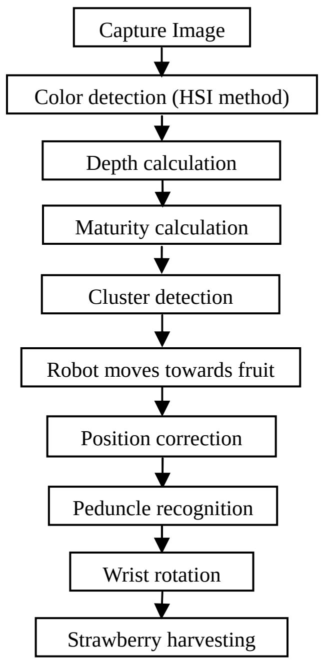

Fig. 3 General flow of the harvesting process

The harvesting procedure is as follows. First, the robot searches for the red strawberry, and in this study, the HSI method was used for color conversion. Second, the depth of the fruit is calculated. Third, maturity of the fruit is calculated, and if maturity is greater than 80%, then the robot moves towards the fruit. Fourth, the robot captures the center camera image, correcting deviations between the fruit and the robot and calculating peduncle angle inclination. Fifth, the wrist joint is rotated in the direction of peduncle and the fruit is harvested. If fruit is not present in the vacuum pad in such case, the robot will come back to its base position. If fruit is harvested successfully, then the fruit will be kept in the tray sequentially, and the robot comes back to its base position to harvest other strawberries.

(2) Color Conversion by the HSI Method

A cylindrical model was used for color conversion. To detect peduncles for the month of March the following values were used

20 < Hue < 45, 63 < Saturation < 250, 80 < Intensity<200.

These values for the color detection change with season. For example, in May-June, the color of peduncles will be brownish green. In such case the values need to be adjusted to detect the color of peduncles.

(3) Depth Calculation

In this study, two methods were used to calculate the depth of the object without using stereo calibration. We assume that the depth can be calculated using Equation (1) for the non-calibrated cases. Equation (1) is slightly different than the actual stereo depth calculation equation for the calibrated cases.

$$f(d) = \frac{\mu \times F}{(Disparity) \times \varepsilon} \tag{1}$$

Here μ is the distance between the cameras, and F is the focal length of the lens, and ε is the disparity correction factor.

In Equation (1) we have disparity and ε as the variable parameters, which are inversely proportional to the depth. To obtain the optimized depth, first disparity will be calculated and later it will be multiplied with the optimized ε factor to obtain the corrected disparity. The ε factor was optimized by the golden section method. We assumed that the optimum value of ε factor lies between 0.0-0.5 (line search width). The calculated disparity value was used in Equation (1) to calculate the theoretical depth. Deviation of the experimental as well as theoretical depth was calculated. If deviation was greater than the tolerance value then the value of ε factor was optimized by the next iteration.

$$f(\Delta d_i) = \sqrt{\{f(d_i) - f(D_i)\}^2}$$

Here, $f(d_i)$ is the calculated theoretical depth, $f(D_i)$ is the experimental depth and $f(\Delta d_i)$ is the deviation of the experimental and theoretical depths. The specific disparity tolerance value of the function is $f(\Delta d_i) < 0.001$.

Finally, the average of ε factor is used to calculate the global correction factor.

$$\eta = \frac{\sum_{i=1}^{i=p} f(\Delta d_i)}{p}$$

Here, η is the global disparity correction factor.

$$Depth = \frac{\mu \times F}{(Disparity) \times \eta} \tag{2}$$

In order to improve the depth calculation, we devised second method shown in Equation (3), which is simply a second order equation. In this method, we obtain the least square data fitting equation which is used to calculate the depth of the fruit from the camera.

$$D = \alpha \times (X)^2 + \beta \times (X) + \delta \tag{3}$$

Here, $\alpha = 0.0112, \beta = -5.5225, \delta = 934.28$. D is depth of the object from the camera and X is the disparity.

(4) Maturity Calculation

First, one hundred Type "A" fruits of different maturity levels were selected. Second, the maturity levels of strawberries were decided by humans. Third, the same strawberry was kept in front of the machine to calculate the maturity. In this study, maturity of the fruit is calculated using the left camera. The equation used for maturity calculation is shown below,

where $A = \sum_{i=1}^{i=p} R_i$ and $B = \sum_{i=1}^{i=p} R_i + \sum_{i=1}^{i=q} U_i$

R is the Red Pixels, U is the non-red pixels, p represents the total red pixels and q represents the total non-red pixels.

$$M = \left(\frac{A}{B}\right) \times 100 \tag{4}$$

Here, M is maturity in percentage, A is the area of the red pixels in the fruit and B is the total pixels of the fruit

(5) Cluster Detection

Most of the strawberries during the experiment were found to be cluster type. Type C, D and E strawberries are known to the machine as single fruits. In this study, one method based on the gradient of the vectors was applied to detect the C type strawberries. For non-linear functions, the gradient vector at points $\left(\tilde{x}_1, \tilde{x}_2\right)$ and $\left(\dot{x}_1, \dot{x}_2\right)$ were calculated as follows:

$$\nabla f\left(\tilde{x}_1, \tilde{x}_2\right) = \begin{pmatrix} \dfrac{\partial f\left(\tilde{x}_1, \tilde{x}_2\right)}{\partial x_1} \\ \dfrac{\partial f\left(\tilde{x}_1, \tilde{x}_2\right)}{\partial x_2} \end{pmatrix} \tag{5}$$

$$\nabla f\left(\dot{x}_1, \dot{x}_2\right) = \begin{pmatrix} \dfrac{\partial f\left(\dot{x}_1, \dot{x}_2\right)}{\partial x_1} \\ \dfrac{\partial f\left(\dot{x}_1, \dot{x}_2\right)}{\partial x_2} \end{pmatrix} \quad (6)$$

Equation (7) was used to check the convexity breakout of the external boundary at point (x_1, x_2).

$$f(x_1, x_2) = \nabla f\left(\dot{x}_1, \dot{x}_2\right) \bullet \nabla f\left(\tilde{x}_1, \tilde{x}_2\right) \quad (7)$$

where, $\dot{x}_1 = (x_1 - \tau)$, $\dot{x}_2 = (x_2 - \varsigma)$, $\tilde{x}_1 = x_1 + \tau$ and $\tilde{x}_2 = x_2 + \varsigma$, τ and ς are the arbitrary constants with small values.

If $f(x_1, x_2) < 0$, then in that particular case, the convexity breakout is present in the detected region of interest.

(6) Position Correction

After improving the depth calculation method through stereo imaging, it was observed that, even if we could move to the proper depth, we could not improve the harvesting rate. Targets were missed because of the magnified error in the pixel size calculation. To reduce the error in the position of the robot, we corrected the position of the robot with respect to the target strawberry. This was accomplished by improving the deviation by capturing the center camera image at 100 mm from the target fruit. We processed the image and determined the strawberry which was nearest to the center of the image. After implementing this method, we observed that the robot could harvest fruits with a precision of ±5mm deviational error.

(7) Peduncle Recognition

Previously it was assumed that peduncle is in the center of the strawberry, and the algorithm was developed based on this assumption. However, it was observed that this assumption was not providing better results and therefore more considerations were needed to handle the peduncle detection. In this study, first, the region of strawberry is detected, then, in the upper portion of the region, we impose the restriction of the fret diameter to the object. If the fret diameter is less than 0.6 then only we consider it as the peduncle; otherwise we assume that the existing object is a leaf, immature fruits, stems of the strawberry or stems of the leaf. However, the proposed method fails for certain conditions. For example, if the two peduncles are attached, the calyx is highly curved, or if a small green strawberry is attached with the peduncle (which means this strawberry may be on the other side of the tray, or it may be in front of the peduncle).

IV Results

1. Depth Calculation

In this section, the obtained results based on the implemented methods will be discussed. A method to calculate the approximated depth which is shown in Equation (3) was found to provide satisfactory results. Fig. 4 shows the comparison of the theoretical depth with experimental depth. The results show that the depth obtained for the object by using Equation (2) matches with the experimental depth values up to a certain degree, but later it starts deviating from the experimental values. Actually, Equation (2) is the linear approximation of the non-linear function. Therefore, the error was amplified with increasing depth. These approximations were not sufficient to harvest the strawberries because the end effecter could not reach up to the target fruits, or the angular rotation of the robot was not calculated properly. Equation (3) is a second order approximation of the experimented results. In this study, this equation was used to conduct the experiment. Fig. 5 shows the variation of disparity with respect to the depth.

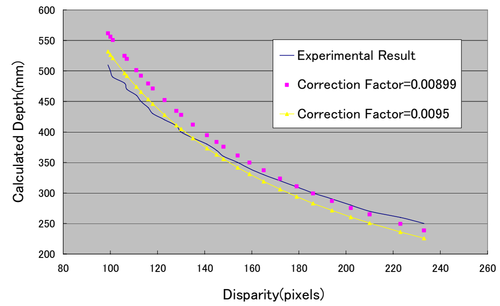

Fig.4 Results based on first order approximation

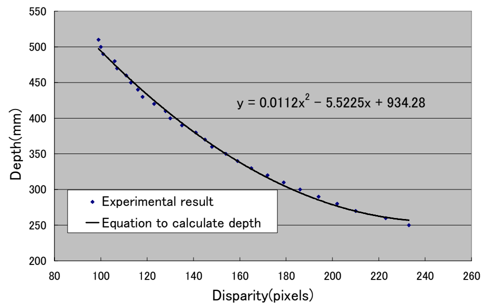

Fig. 5 Results based on second order approximation

2. Maturity Calculation

In this study, 100 strawberries were chosen randomly to understand the maturity detection of the machine. First, the maturity was decided by humans, and then the same strawberry was shown to the machine to get the maturity by the machine. Fig. 6 shows the relationship between the maturity detected by humans and the machine. It was observed that maturity calculation depends on two major factors. The first is the distribution of light source and the second is the visibility of different surfaces of the same fruit. Because we used LED light, the color information is very limited, which reduced the potential to discern the pink color in the unripe zone. It was observed that the width of the red color band should be increased to capture the pinkish portion and green color band for the unripe portion of the strawberry. To improve the maturity detection of the fruit, a better light source should be considered in the future such as the combination of the colored LED (RGB) light and the ratio in which it should be mixed. It was observed that the visibility of the fruit surface changes with the position of the camera and thus the maturity of the fruit. Future studies are needed to implement the above mentioned changes in the machine.

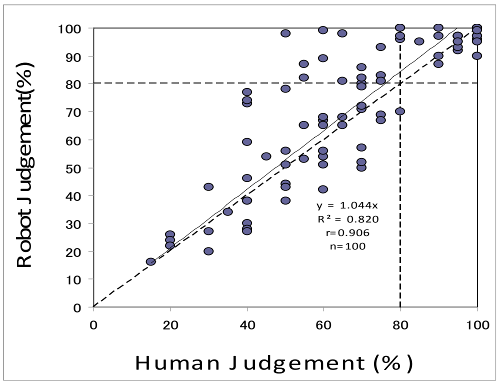

Fig. 6 Comparison of maturity by humans and the machine

3. Cluster Detection

The proposed model for clusters was tested during the 2007 experiment. It was observed that this method helps to detect the convexity break out for the simple clusters. In actual situations, the strawberry curve is not smooth. If we pick the points (grid interval) very close in that case, the calculated gradient vector will not be stable and we will end up with the non-convex curved. Based on the experiment, the optimum grid interval was selected to complete the simulation. The cluster detection model worked well but it was found to be sensitive to the strawberries which have abnormal shapes. Table 2 shows the result of detected clusters during the experiment. Total numbers of detected clusters were higher because obstructed strawberries were also detected as clustered strawberries. Further studies are needed to understand the C, D and E type strawberries based on their surroundings and the shape.

Table 2 Cluster detection results

Month	Humans	Robot
March	41	92
April	26	40
May	42	85

4. Peduncles Recognition

First, we selected the region of interest of the strawberry, and then we separated the calyx region just above the calyx region number of peduncles that were detected. If more than one peduncle is detected, we assume that the peduncle nearest to center of strawberry would be the target peduncle. Peduncle inclination was calculated and robot was moved accordingly. To enhance the performance of the machine, a wrist joint was added, so that robot could harvest the curved peduncle. The results show that curved peduncles were harvested successfully.

At present the end-effecter is wide enough to hold more than two or three peduncles together, and it also had enough force to cut the two or three peduncles together. In this study, an algorithm was implemented to avoid harvesting the strawberry which has two or three peduncles together. If the peduncles are very close, the peduncles will be held by the end effecter and more than one strawberry will be harvested. If it is green strawberry or a leaf is near the peduncles, the fret diameter criteria will not meet the given condition and the machine will not harvest the strawberry. In Fig. 7, the small boxes show the peduncles and big boxes show the strawberries. A successful case is shown in the first image. In the second and third image, the peduncle is not visible because of the leaf and green strawberry. Probably, in such cases, the robot would have failed to harvest the strawberries. In such cases, the robot was not allowed to harvest because, if allowed, it would have harvested green strawberries along with the mature fruits. Further improvements are needed to increase the harvesting rate without harvesting the green strawberries.

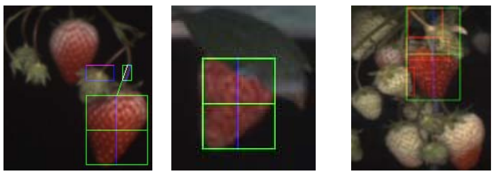

Fig. 7 Peduncle detection

Table 3 Success rate of peduncle recognition

Month	Type of fruits				
	A	B	C	D	E
March	91%	72%	57%	48%	0%
April	95%	77%	56%	69%	0%
June	71%	73%	60%	60%	0%

5. Harvesting Rate Calculation

The results show that, by applying the position correction method, the robot could approach to the target fruits with fair precision based on center camera. Table 3 shows the results of the experiment conducted from 2007/03/9–2007/05/31. In this period, experiments were conducted during each month at different intervals. The actual situation in the field is complicated and in such situation many parameters should be considered to understand the real performance of the robot.

$$H\_R = \left(\frac{Harvested}{Trials} \right) \times 100 \qquad (8)$$

Here, H_R is harvesting rate of the robot, $Trials$ means the total number of attempts to harvest the strawberries, $Harvested$ is total successful attempts for the non-occluded fruits, during experiment. The results show that the robot could achieve an average harvesting rate of 76.55%. More experiments should be conducted in the future to determine the overall performance of the robot including harvesting of the unripe fruits, picking of peduncles other than the target one, picking of the hidden peduncles behind the ripe fruits and the harvesting of the green fruit which was attached with the ripe fruits.

Table 4 Average harvesting rate for each month

Month	Total Trials	Fruits Harvested
March	386	292
April	222	192
May	271	183

V Discussion

In this section, we discuss about the problems, their probable solutions and the future studies which should be conducted in order to improve the performance of the machine.

1. Target Detection Failure

The center camera detects the target strawberry as mentioned earlier. However, in exceptional cases the robot could not harvest the target fruit. In exceptional cases, fruits are usually clustered or hidden by a leaf when observed from the center camera at capturing time. In such situation, the robot detects the non-target fruit as a target fruit. Fig. 8 below shows the images of exceptional cases. In such case, fruits in the rectangle were selected, but the robot went to harvest the strawberry which was in the elliptical region. Further studies are needed to develop an algorithm which can detect the obstructions in front of the strawberry such as a leaf, peduncles and small green strawberries.

Fig. 8 Target detection failure

2. Obstructed Strawberries

Usually C, D and E type strawberries can be classified as clustered strawberries. In this study, a simple approach was applied to avoid the harvesting of the obstructed type strawberries. A simple algorithm was developed to detect the obstruction in the region of the target strawberries. The present method could not differentiate whether the strawberry is behind or in front of the red strawberry. The model should be improved in future to calculate the three dimensional information in the vicinity of the red strawberries as well as unripe strawberries.

3. Strawberries at the Back End of the Tray

During stereo calculation, it was observed that the fruits hanging at the back side of the tray were visible. As a result, many targets were detected to be processed, which reduced the harvesting performance of the robot. Further studies are needed to develop an algorithm which eliminates the strawberries at the back end of the table to increase the speed in stereo processing.

VI Conclusion

A robot was successfully tested for harvesting the strawberries having inclined peduncles in tabletop culture. A machine vision system was developed to increase the performance of the robot in the real field situation. Two equations were proposed and tested to calculate the proper depth of the object from the robot, it was observed that a second order approximated equation gave better results. One model to detect the cluster of the strawberries based on the gradient was also developed. The proposed model was found to be able to sense for the existing obstructions (peduncles, green fruits or leaves) in front of the target fruit. The robot developed based on the above mentioned method could harvest 76.55 % of the strawberries in the real situation. However, this harvesting rate was based on a simplified model. Further studies are needed to develop a harvesting rate model which represents the actual complexity of the field, such as harvesting of green strawberries along with red ones. Future studies are needed to develop an algorithm which can detect strawberry types based on their shape. Furthermore, a better light source should be developed to improve the maturity calculation of the fruit.

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