Available at www.sciencedirect.com

ScienceDirect

journal homepage: www.elsevier.com/locate/issn/15375110

Research Paper

Evaluation of a strawberry-harvesting robot in a field test

Shigehiko Hayashi [a,*], Kenta Shigematsu [a], Satoshi Yamamoto [a], Ken Kobayashi [a], Yasushi Kohno [b], Junzo Kamata [c], Mitsutaka Kurita [c]

[a] Institute of Agricultural Machinery, BRAIN, NARO, 1-40-2 Nisshin, Kita, Saitama 331-8537, Japan
[b] Ehime Research Institute of Agriculture, Forestry and Fisheries, Kou 331, Kaminanba, Matsuyama 799-2405, Japan
[c] SI Seiko Co. Ltd., 66 Takaoka, Matsuyama 791-8036, Japan

ARTICLE INFO

Article history:
Received 17 December 2008
Received in revised form
17 May 2009
Accepted 16 September 2009
Published online 22 December 2009

We developed a strawberry-harvesting robot, consisting of a cylindrical manipulator, end-effector, machine vision unit, storage unit and travelling unit, for application to an elevated substrate culture. The robot was based on the development concepts of night operation, peduncle handling and task sharing with workers, to overcome the robotic harvesting problems identified by previous studies, such as low work efficiency, low success rate, fruit damage, difficulty of detection in unstable illumination and high cost. In functional tests, the machine vision assessments of fruit maturity agreed with human assessments for the Amaotome and Beni-hoppe cultivars, but the performance for Amaotome was significantly better. Moreover, the machine vision unit correctly detected a peduncle of the target fruit at a rate of 60%. In harvesting tests conducted throughout the harvest season on target fruits with a maturity of 80% or more, the successful harvesting rate of the system was 41.3% when fruits were picked using a suction device before cutting the peduncle, while the rate was 34.9% when fruits were picked without suction. There were no significant differences between the two picking methods in terms of unsuccessful picking rates. The execution time for the successful harvest of a single fruit, including the time taken to transfer the harvested fruit to a tray, was 11.5 s.

1. Introduction

The pericarp of a strawberry (*Fragaria* × *ananassa* Duch.) is so soft that workers must harvest the fruits carefully to avoid damage. The fruits are harvested early in the morning, before the temperature of the fruits rises and they become soft; in some regions of Japan, workers sometimes need to work by headlights or electric torches early in the morning. Moreover, workers need to select mature red fruits from among the many fruits that have set. These factors result in long working hours during the harvest period. Statistical data indicate that the total amount of time spent working on strawberry crops in Japan is slightly less than 20 000 h ha^{-1}; harvesting accounts for one-quarter of this total (MAFF, 2007). Therefore, there is a strong desire to mechanize harvesting. Mechanical harvesting trials have been performed on the assumption of once-over harvesting, but exploitation of this strategy is not yet widespread (Hancock, 1999). Selective harvesting, which is commonly used, requires high-tech and sophisticated robot technology. In short, it is necessary to design an intelligent robot with human-like perceptive capabilities; for instance, the machine would need to calculate fruit position, assess maturity level and pick the fruit without damaging the pericarp.

* *Corresponding author.*
E-mail address: shigey@affrc.go.jp (S. Hayashi).
1537-5110/$ – see front matter
doi:10.1016/j.biosystemseng.2009.09.011

Fundamental studies on robotic harvesting started with orchard fruits (Schertz and Brown, 1968; Parrish and Goksel, 1977); since then, such studies have been ongoing in several countries (Sarig, 1993). This technology has then been used for vegetable fruits. Tillett (1993) reviewed several prototype robots and clarified the significance of the manipulator design and its application to practical use. Several studies have applied robotic technology to fields in greenhouses; for instance, for cucumber harvesting (Van Henten *et al.*, 2003), tomato harvesting (Monta *et al.*, 1998), aubergine harvesting (Hayashi *et al.*, 2003) and de-leafing (Van Henten *et al.*, 2006). However, the performance and cost have not met commercial requirements. In relation to strawberry harvesting, previous studies have proposed several types of robot for soil culture and elevated substrate culture. While a picking mechanism that used a suction device was a valid way to compensate for the error in the visual sensor (Kondo *et al.*, 2001), the utilization of such a system led to errors in picking, whereby immature fruits were picked together with the target fruits and the pericarp was damaged during tube conveyance (Arima *et al.*, 2003). A scissor-type end-effector that simultaneously grasped and cut a peduncle (Cui *et al.*, 2007) showed a success rate of 80% in a laboratory test on simulated soil culture, but the accuracy of the machine vision unit with regard to peduncle detection decreased when the fruit orientation changed. A demonstration of the scissor-mechanism in an actual field will be the subject of a future study.

In 2003, the Institute of Agricultural Machinery, Bio-oriented Technology Research Advancement Institution (IAM-BRAIN) launched a project to develop a strawberry-harvesting robot for an elevated substrate culture, which provides potential advantages for robotic harvesting because the fruits are separated from the leaves. By 2005, elevated substrate culture had been applied over an area of 399 ha in Japan (JGHA, 2008). In a forcing culture, the harvest season continues for about 6 months (Hancock, 1999), and the number and size of the fruits and leaves vary widely. Therefore, the manner in which the fruits set and overlap might vary significantly. Considering these actual cultivation conditions and the problems indicated in previous studies on robotic harvesting—low work efficiency, low success rate, damage of fruit, difficulty of detection in unstable illumination and high cost—we devised the following development concept. First, the robot operated only at night to overcome the problem of low work efficiency, and artificial lights were used to ensure constant illumination for image capture. Second, we adapted the method of detecting, cutting and handling the peduncle to minimise fruit damage. In addition, nighttime operation would help to minimise fruit damage, since the fruit temperature is lower than during the day. Third, the target success rate was set at more than 60% (and not 100%, which would correspond to an ideal operation). Therefore, the remaining fruits needed to be picked by workers in a task sharing operation in order to reduce costs associated with using the robot. Thus, the robot works slowly during the night and harvests only certain fruits, which are easily picked. Then, in the morning, the workers commence picking the remaining fruits.

Based on this concept, we developed a functional model of a strawberry-harvesting robot that moved in a straight line and picked fruits with open–close gripper (Hayashi *et al.*, 2005). A newly manufactured strawberry-harvesting robot could then move back and forth and harvest fruits from benches on both sides of an aisle. A fruit storage function was also installed for the field test. Moreover, the functions of maturity assessment and peduncle detection were incorporated in the machine vision algorithm. The end-effector was mainly composed of an open–close gripper and a suction device, and it could perform two picking actions: suction picking and no-suction picking.

The objectives of this study were: (1) to describe the developed harvesting robot; (2) to examine individual functions, especially maturity assessment and peduncle detection; and (3) to conduct a harvesting test in a field and analyse the results from the standpoint of practicality. The tests were conducted during the harvest season from December 2007 to May 2008. Long-term operation of the strawberry-harvesting robot would be an important and necessary factor in evaluating the performance, reliability and viability of the system.

2. Materials and methods

2.1. System components

The robot was composed of a cylindrical manipulator with three degrees of freedom (DOF), end-effector, machine vision unit, storage unit and travelling unit (Figs. 1 and 2a). The main components are shown in Fig. 2b. The robot was 1872 mm in length, 545 mm in width and 1545 mm in height. Two 12 V-batteries were used as the power source for all the components.

2.1.1. Manipulator

The robot moved in a straight line and employed a picking method that allowed it to pick on both sides of a passage. The manipulator rotated at a speed of $360^\circ\ s^{-1}$ by means of a rotary actuator, allowing it to face both sides, and was capable of moving through a distance of 400 mm vertically and 300 mm horizontally at a speed of $500\ mm\ s^{-1}$ using linear actuators. The rotary actuator was installed in a hanging arrangement to give space under the end-effector and to avoid collisions between the tray and the end-effector when the end-effector placed the fruit into the tray, particularly into the furthermost pockets of the tray.

2.1.2. End-effector

During harvesting, fruits should remain untouched as much as possible so as to avoid damage; hence, the end-effector mostly handled the fruit by the peduncle. The end-effector was composed of a gripper for simultaneously grasping and cutting the peduncle, a suction device for holding the fruit and a photoelectric sensor for checking the presence of the picked fruit (Fig. 3). An urethane layer 1 mm thick was attached inside the gripper to hold the peduncle, and one of the fingers of the gripper was shaped like a cutter. The gripper and suction device could slide independently by 40 mm with pneumatic sliders; moreover, depending on the peduncle orientation, they could rotate 15° to the left or right from the base position using two pneumatic cylinders. The end-

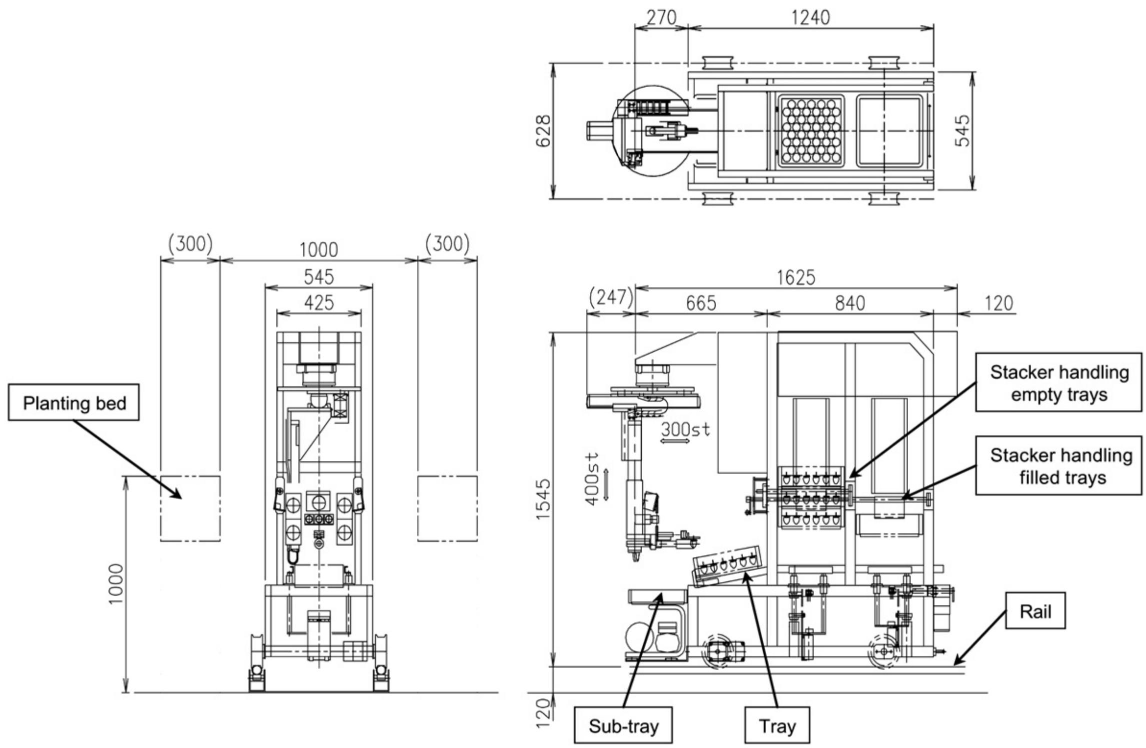

Fig. 1 – Schematic drawing of the strawberry-harvesting robot; all dimensions in millimetres.

effector could perform two picking operations, suction picking and no-suction picking, as shown in Fig. 4. In suction picking, the suction device was used to hold the fruit before cutting to compensate for the three-dimensional (3D) position error caused by the variations in the size and shape of the fruit and the conditions around the fruit.

2.1.3. Machine vision unit

The machine vision unit was composed of five light sources with 120 light-emitting diode (LED) chips for each source, and three aligned colour charge coupled device (CCD) cameras (see Fig. 2b). The centre camera was used to calculate the inclination of the peduncle, whereas the two cameras mounted on both sides of the centre camera were used in a stereovision system to determine the 3D position of the fruit. These two cameras were spaced 160 mm apart. The lenses used in the two side cameras and the centre camera had a focal length of 5 mm and 6 mm, respectively. Polarization filters were attached to the cameras and the light sources. The machine vision algorithm was implemented on a PC.

2.1.4. Storage unit

The storage unit was composed of trays, stackers and a conveyor. The tray was 330 mm in length and width, and

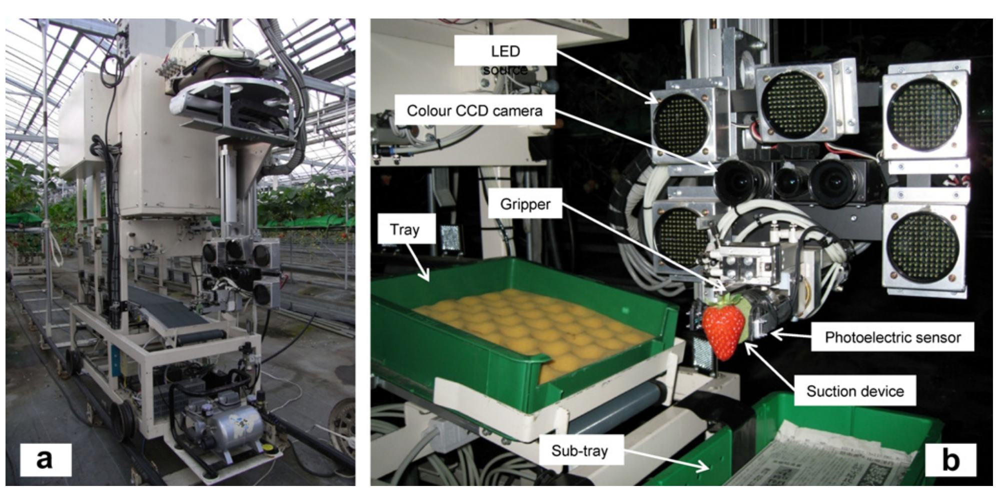

Fig. 2 – Photos of the strawberry-harvesting robot. (a) General view; (b) detailed view of the main components.

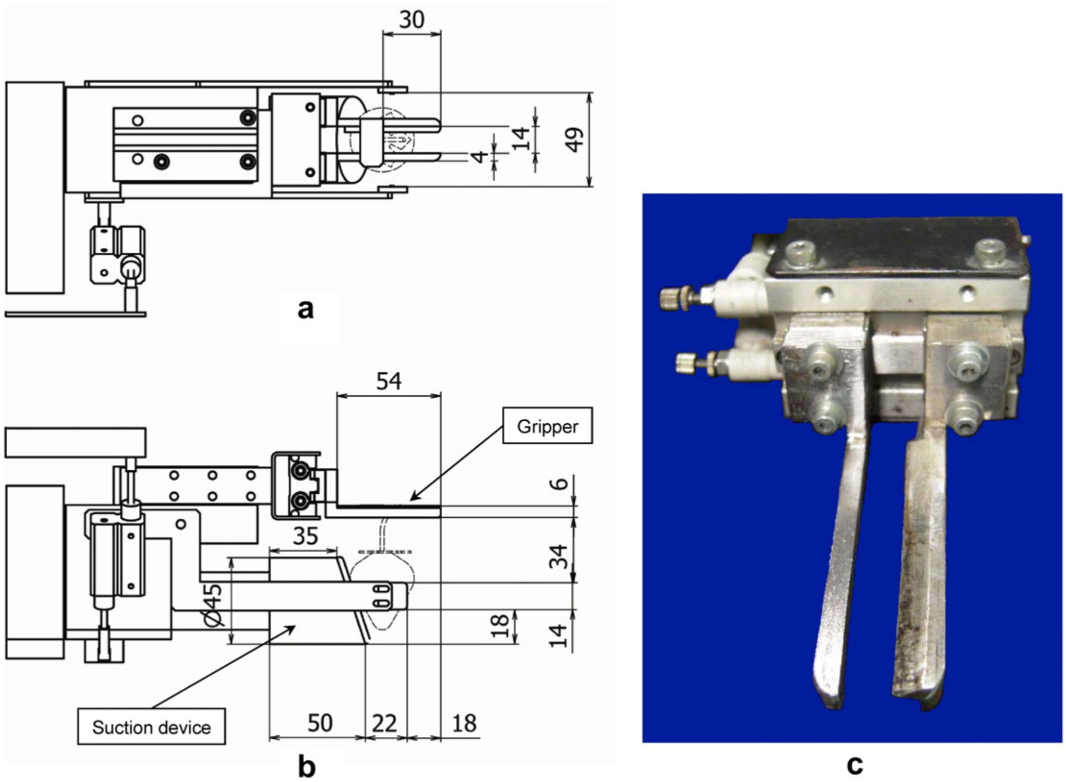

Fig. 3 – Schematic drawing and photo of the end-effector; all dimensions in millimetres. (a) Top view, (b) front view, (c) close-up image of the gripper.

Fig. 4 – Motion of the end-effector during the picking operation. (a) Suction picking; (b) no-suction picking.

was covered with urethane foam containing 44 pockets to hold the harvested fruits. An empty tray was conveyed from a stacker that handled empty trays to a position under the end-effector, as shown in Fig. 1. When the tray became full, it was returned to a stacker that handled filled trays, and the next empty tray was conveyed.

2.1.5. Travelling unit

A DC motor allowed the travelling unit to move in 200 mm steps on 628 mm wide rails. The travelling speed was 0.19 m s^{-1}, so one step took approximately 1 s.

2.2. Operational flow of harvesting

The robot harvested the left-side fruits during forward travel, rotated its main components through 180° at the end of the row, and then harvested the other side of the aisle (see flowchart, Fig. 5). One empty tray was discharged from the stacker handling empty trays and placed under the end-effector, and the machine vision unit then captured an image while the robot was stationary.

Red regions, where the pixel data satisfied the colour condition (1), were recognized as fruits, and their 3D positions were calculated using binocular stereoscopic measurement:

$$0.47 \le r' \le 1 \tag{1}$$

where r' is the chromaticity value obtained from the following Eq. (2):

$$r' = R/(R+G+B) \tag{2}$$

Next, the maturity level of fruits whose 3D positions could be calculated was assessed on the basis of the ratio of the ripe area fraction (the area fraction of the fruit that satisfies the ripeness condition) to the unripe area fraction (the area fraction of the fruit that does not satisfy the ripeness condition). The RGB images of the left camera were chosen for maturity assessment and were transformed into Hue-Saturation-Intensity (HSI) images by the following Eq. (3) to sense a subtle change in colour:

$$\begin{aligned}
I_{max} &= \max(R,G,B)\\
I_{min} &= \min(R,G,B)\\
I &= (I_{max}+I_{min})/2\\
S &= \begin{cases}(I_{max}-I_{min})/(I_{max}-I_{min})\times 255: & I<128\\ (I_{max}-I_{min})/(510-(I_{max}+I_{min}))\times 255: & I\ge 128\end{cases}\\
H &= \begin{cases}(G-B)/(I_{max}-I_{min})\times 60: & I_{max}=R\\ (B-R)/(I_{max}-I_{min})\times 60+120: & I_{max}=G\\ (R-G)/(I_{max}-I_{min})\times 60+240: & I_{max}=B\end{cases}
\end{aligned} \tag{3}$$

The ripe area friction (Rr) was the region satisfying the colour conditions (4):

$$\begin{cases}0\le H\le 14\\ 120\le S\le 250\\ 20\le I\le 80\end{cases} \tag{4}$$

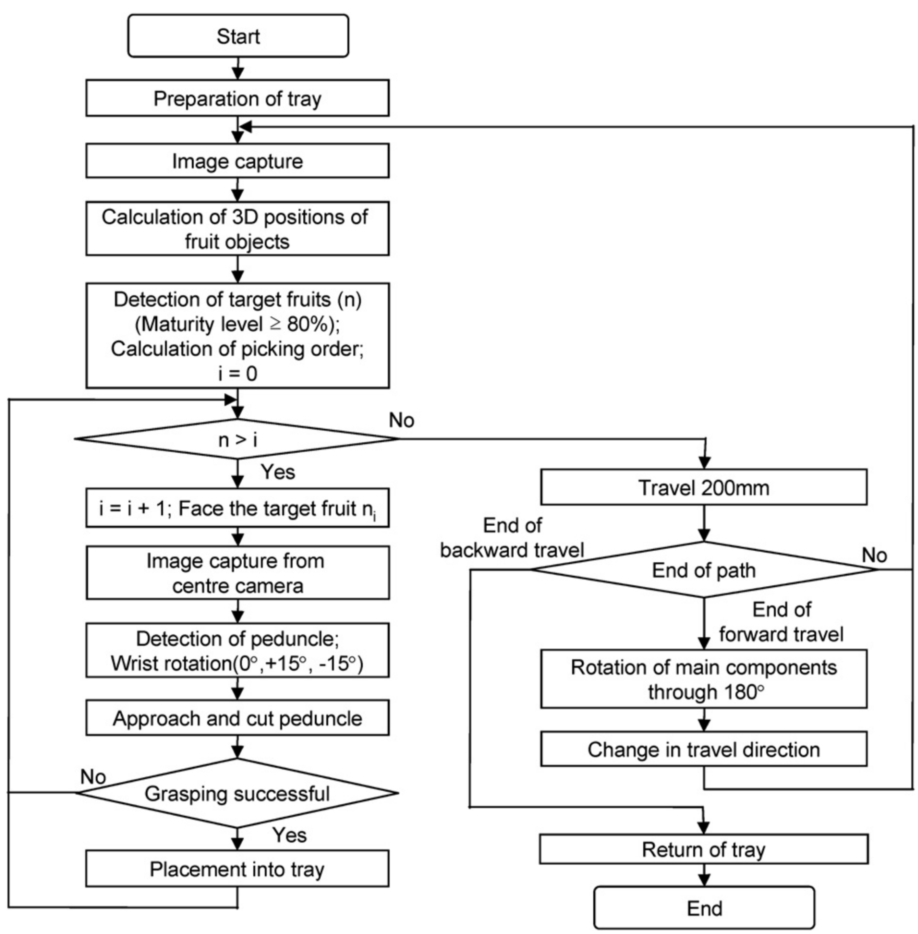

Fig. 5 – Operational flowchart for the harvesting robot.

The colour of the unripe portion (Ur) ranged widely, from light green to light pink to dark pink. Therefore, the area connecting the regions satisfying the colour conditions shown in (5)–(7) was considered to be the unripe area fraction (Ur).

$$\begin{cases} 41 \le H \le 80 \\ 50 \le S \le 250 \\ 100 \le I \le 250 \end{cases} \tag{5}$$

$$\begin{cases} 0 \le H \le 40 \\ 20 \le S \le 250 \\ 81 \le I \le 250 \end{cases} \tag{6}$$

$$\begin{cases} 328 \le H \le 359 \\ 30 \le S \le 250 \\ 51 \le I \le 250 \end{cases} \tag{7}$$

Then, the maturity level (Mv) was computed using the following Eq. (8):

$$Mv = Rr/(Rr + Ur) \times 100 \tag{8}$$

Sufficiently mature fruits (Mv = 80% or more) were recognized as target fruits and an attempt was made to pick them in the order of distance.

After the machine vision unit and the end-effector faced the target fruit, the end-effector approached the fruit when the distance between the target fruit and the centre camera was about 280 mm. Here, the centre camera captured an image, and the area of the target fruit was detected as the region satisfying the colour conditions (9):

$$\begin{cases} 1 \le H \le 30 \\ 150 \le S \le 255 \\ 0 \le I \le 255 \end{cases} \tag{9}$$

The region of interest (ROI) for searching for the peduncle was set at 20 pixel above the region of the target fruit to avoid the calyx region, as shown in Fig. 6. The ROI was 15 pixels in height, and the pixel width was equal to the breadth of the fruit. Candidate objects were detected as the regions satisfying the colour conditions (10):

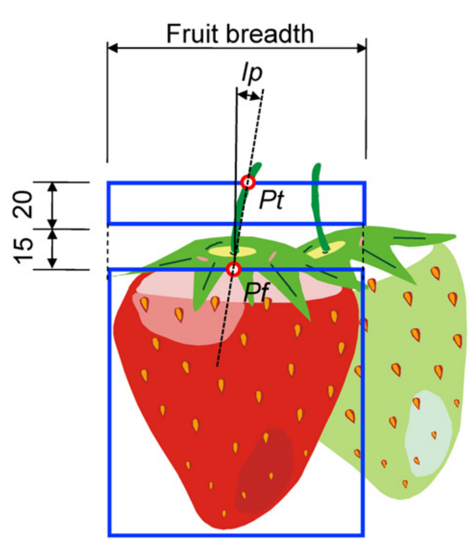

Fig. 6 – Detection of peduncle and definition of peduncle inclination (Ip).

$$\begin{cases} 5 \le H \le 100 \\ 15 \le S \le 120 \\ 35 \le I \le 100 \end{cases} \tag{10}$$

Then, small, wide or round particles were eliminated; the candidate object closest to the fruit point (Pf) was selected as the peduncle; and the peduncle point (Pt) was determined. The angle between the line Pt–Pf and a vertical line was then defined as the inclination of the peduncle (Ip), as shown in Fig. 6. After this image processing, the end-effector wrist rotated to one of three positions, 0°, +15° or −15°, corresponding to Ip. The rotational angle was determined by the following equation:

$$Wr = \begin{cases} +15: & 13 \le Ip \le 80 \\ 0: & -13 < Ip < 13 \\ -15: & -80 \le Ip \le -13 \end{cases} \tag{11}$$

where Wr is the rotational angle of the wrist (°) and Ip is the inclination of the peduncle (°), as calculated by the image processing. When the machine vision unit did not detect a peduncle, the gripper did not rotate.

As mentioned above, the end-effector could perform two picking operations. In suction picking, the end-effector approached the target fruit with the suction device in a forward position to suck the fruit. When picking the fruit, the gripper slid forward on either side of the peduncle, grasping and cutting the peduncle simultaneously (Fig. 7a). In no-suction picking, the suction device stayed in the retracted position, and suction was not used to hold the target while the peduncle was being cut. After grasping and cutting the peduncle, the manipulator returned to its original position and checked whether the fruit had been grasped. If the end-effector failed to cut the peduncle or if the fruit was not held between the emitter and receiver of the photoelectric sensor, the gripper opened to release the fruit to the sub-tray. If the end-effector held the fruit correctly, the manipulator faced the tray (after rotating through 90°) and placed the fruit into the tray (Fig. 7b).

This picking task was attempted for all of the target fruits detected by stereovision, after which the harvesting robot advanced by a 200-mm step, and the harvesting operation was repeated starting from the image capture step. When the robot reached the end of the harvest path, it travelled in the backward direction. In addition, when the tray became full during harvesting, it went back to the stacker handling filled trays and the next empty tray was prepared. Once the whole area was harvested, the tray was returned to the stacker handling filled trays.

2.3. *Functional test*

The functions of the individual components of a robot influence the total system performance, so we examined the machine vision algorithm developed in this study, especially from the standpoints of maturity assessment and peduncle detection. Moreover, the execution times for each motion in the harvesting procedure were measured.

2.3.1. *Maturity assessment*

The performance of the machine vision unit during maturity assessment influences the error rate during harvesting: the

Fig. 7 – Operational scenes of the harvesting robot. (a) Grippers cutting peduncle during sucking operation; (b) placing fruit into the tray.

error rate will increase if the unit mistakenly identifies an immature fruit as being a mature one. In general, the maturity level is manually assessed on the basis of the proportion or uniformity of the ripe area of a fruit or the colour intensity (or gloss). However, the machine vision in this study assesses this maturity level on the basis of the ripe area fraction of the fruit. To evaluate the machine vision performance, we investigated the correlation between the maturity level assessed by human observation and that assessed by the machine vision unit. Moreover, we compared the machine vision performance when assessing the maturity of two cultivars, Beni-hoppe and Amaotome, to determine the effect of cultivar differences on performance.

A fruit sample was assessed by human observation (0–100%) and placed 400 mm in front of the centre camera in the greenhouse. Subsequently, an image of the fruit was captured and processed to calculate the maturity level using Eq. (8). One hundred samples of each cultivar were used.

2.3.2. *Peduncle detection*

Although the fruits hang down in an elevated culture, they are not exactly vertical. Therefore, the orientation of the peduncle varies widely. In addition, the peduncles of other fruits are located near the target fruit. Therefore, the performance of the machine vision unit with regard to peduncle detection greatly influences the success of the picking operation. To examine the peduncle detection performance, the machine vision algorithm was applied to the centre camera images obtained for the fruit, which the stereovision recognized in a field, and the resultant images were recorded. These resultant images were then analysed and divided into three categories: target peduncle detection, wrong peduncle detection and no peduncle detection. Next, the inclination of the peduncle (Ip) was calculated for the images where the target peduncle was detected, and was compared with the actual inclination measured by human observation. One hundred samples of the cultivar Beni-hoppe were used.

2.3.3. *Execution time for each motion*

The execution times for each motion of the harvesting operation were measured to examine the performance of the robot. A fruit sample was placed 400 mm in front of the centre camera, and the harvesting procedure was performed. During the operation, the execution times for fruit picking and placement in the tray were measured. Here, when considering the motion for fruit picking, we took into account the following steps: image capture, image processing, approach, cut and check for grasping. In addition to the harvesting operation, we measured the execution times for preparing the tray, changing the tray and travelling over a distance of 200 mm.

2.4. *Harvesting test in a field*

Strawberries were planted in an elevated substrate bed in a greenhouse on 17 September 2007. Harvesting tests for the robot were conducted at night (illumination less than 10 lx) throughout the harvest season from December 2007 to May 2008. Harvesting tests were conducted 19 times with suction picking and 10 times with no-suction picking at intervals of about 2–3 weeks. The test area was 36 m in length along one side of the bed and included 192 plants. The target fruits for picking were mature fruits ($Mv = 80\%$ or more), which were judged by human observation before the tests were conducted. We used the cultivar Beni-hoppe, which is popular and cultivated widely in Japan (Takeuchi *et al.*, 1999).

2.4.1. *Classification of fruit position*

In preliminary trials, the performance of the robot seemed to be influenced by the position of the fruit, which varies during the harvest season. The robot clearly fails if the target fruit is occluded by other fruits, because the manipulator approaches straight from the aisle side. Therefore, the ways in which the target fruits could be positioned were classified into five categories (Fig. 8) to analyse the relationship between the position and the harvesting performance.

2.4.2. *Successful harvest*

Among the target fruits, the successfully harvested fruits were counted during harvesting tests. Successfully harvested fruits were defined as those that were grasped and cut correctly by the gripper, so they included fruits in the tray and in the sub-tray. The fruits that were released into the sub-tray were recognized as successfully harvested fruits because they were uninjured and of saleable quality, even though they were not detected by the photoelectric sensor in the grasping check

Fig. 8 – Classification of fruit positions. (A) Whole fruit is visible and separated from others; (B) whole fruit is visible, but other immature fruit might be behind target fruit; (C) whole fruit is visible, but other mature fruit might be behind target fruit; (D) exposure of fruit is 50% or more, but less than 100%; (E) exposure of fruit is less than 50%.

step. Therefore, the successful harvesting rate (*SHR*, %) was defined as follows:

$$SHR = Ns/Nt \times 100 \quad (12)$$

where *Ns* is the number of successfully harvested fruits among the target fruits, and *Nt* is the number of target fruits at 80% or more maturity.

2.4.3. *Unsuccessful harvest*

We defined incidences where the robot could not harvest the target fruit as unsuccessful harvests. The reason for unsuccessful harvest was analysed and divided into two groups: (1) unsuccessful fruit detection (*UD*) whereby the stereovision failed to detect the target fruit and (2) unsuccessful fruit picking (*UP*) whereby the gripper failed to cut the peduncle.

Moreover, since the robot was programmed not to attempt to pick the fruits in the *UD* group, the unsuccessful picking rate (*UPR*) among the attempted fruits was defined by Eq. (13) to examine the performance of the end-effector:

$$UPR = Nup/(Nt - Nud) \times 100 \quad (13)$$

where *Nup* and *Nud* are the number of fruits in the *UP* and *UD* groups, respectively.

2.4.4. *Mistaken harvest*

We also defined incidences where the robot mistakenly picked immature fruits as mistaken harvests. The mistaken harvests of immature fruits were divided into two groups: (1) fruit picked along with the target fruit (*PT*) and (2) fruit picked alone (*PA*).

2.4.5. *Execution time*

The substantial execution time for each 36 m long field test was measured from the capture of an image to the end of the harvest; the time required for the preparation of the tray and the return of the tray was excluded from the measurement (see Fig. 5). However, the time required for changing the tray was included in the execution time when it was performed during the test.

3. Results and discussion

3.1. *Functional test*

3.1.1. *Maturity assessment*

The performance of the machine vision unit was compared to that of human observation from the viewpoint of maturity assessment of Amaotome and Beni-hoppe (Fig. 9). Both machine vision assessments agreed closely with the human assessment (Fig. 10). The coefficient of determination was 0.956 for Amaotome and 0.821 for Beni-hoppe. The number of immature fruits (maturity level less than 80%) mistaken to be mature by the machine vision unit were 0 out of 68 immature fruits for Amaotome and 13 out of 74 immature fruits for Beni-hoppe; thus, there was a significant difference in the rate of misjudgement, as calculated by the chi-square test at the 5% level.

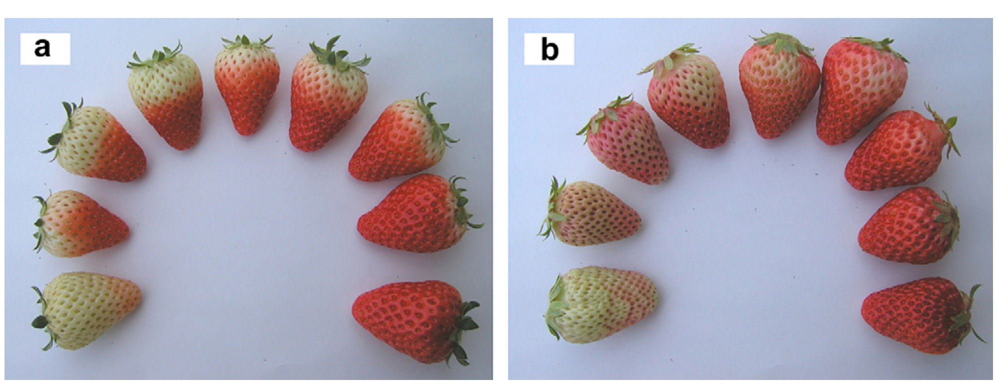

Fig. 9 – Sample images of strawberry cultivars. (a) Amaotome; (b) Beni-hoppe. Manually assessed maturity levels of the fruit samples in the image (from left to right) are 5%, 30%, 40%, …, 100%.

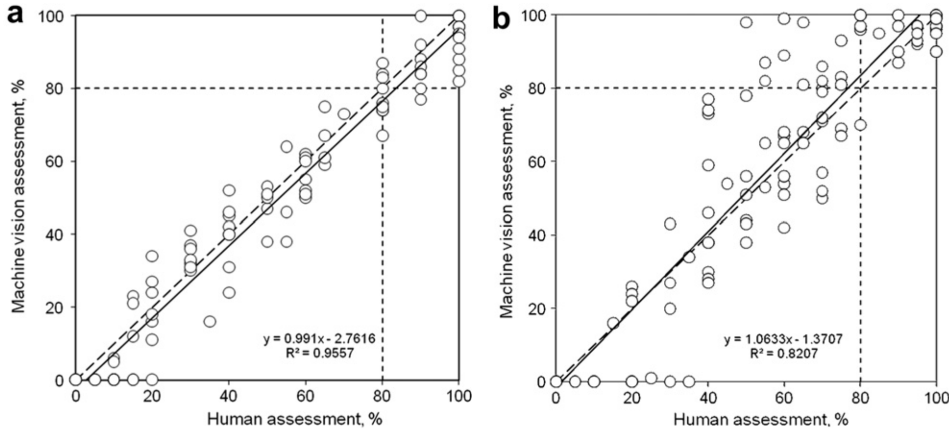

Fig. 10 – Comparison of maturity assessments for Amaotome and Beni-hoppe. (a) Amaotome; (b) Beni-hoppe.

It is well known that red colouration develops through the production of anthocyanins and that the process of colouring varies among cultivars (Maegawa, 1992). We observed that some of the Beni-hoppe fruits became entirely pink during colouring (Fig. 9b). In contrast, the Amaotome fruits tended to turn red from the bottom upward, with a clear border between the red and light green portions (Fig. 9a), thus enabling the proposed machine vision algorithm to yield a highly accurate maturity assessment. This clearly shows that cultivars such as Amaotome in which the red and light green portions are easily distinguished during maturation, seem to be more suited to robotic harvesting.

3.1.2. *Peduncle detection*

The machine vision algorithm correctly detected the target peduncle at a rate of 60% with an absolute error of inclination of $7.4 \pm 5.9^{\circ}$. However, the rates of wrong peduncle detection and no peduncle detection were 10% and 30%, respectively. The rate of target peduncle detection was found to be lower than the rate reported by Cui *et al.* (2007) for soil culture experiments (80%). This was because immature fruits in the foreground tend to occlude the target in an elevated substrate culture, while the fruits tend to spread out on the ground in a soil culture. Moreover, it was observed that the machine vision algorithm did not binarise a reddish peduncle or a dark peduncle shaded by adjacent fruits as candidates, resulting in wrong peduncle or no peduncle detection.

3.1.3. *Execution time for each motion*

The measured execution time for each motion is shown in Table 1. The average execution times for picking and placement were 7.7 s and 3.8 s, respectively. Therefore, it took 11.5 s to properly harvest a fruit. The time required by the robot seems to be about 2.5–3 times the time required for manual harvesting, which is estimated to be roughly 3.5–5.0 s per fruit. However, the results indicate that the execution time of our system is less than the times reported in previous robotic studies, e.g., 65.2 s for cucumber harvesting (Van Henten *et al.*, 2003) and 43.2 s for aubergine harvesting (Hayashi *et al.*, 2003).

3.2. *Harvesting test in a field*

3.2.1. *Performance of successful harvest*

The results of the field tests for suction picking and no-suction picking are shown in Tables 2 and 3, respectively. Moreover, Fig. 11 shows the harvesting performance for the target fruits in each classification of the fruit position. It was found that the robot made multiple attempts to pick a single fruit and rarely picked two target fruits simultaneously.

In suction picking, out of 1130 target fruits, the robot successfully placed 450 harvested fruits in the tray and 17 harvested fruits in the sub-tray. Therefore, during the harvest season, the *SHR* was in the range 7.7–75.8%, and the overall *SHR* was 41.3%. On the other hand, in no-suction picking, the robot successfully placed 132 harvested fruits in the tray and 17 harvested fruits in the sub-tray out of 427 target fruits, thereby providing an overall *SHR* of 34.9%. Comparing the number of fruits placed in the sub-tray to the number of target fruits, it is obvious that the rate of placement was higher in no-suction picking than in suction picking. This result can be attributed to the fact that the fruit was often positioned out of line with the optical axis of the photoelectric sensor, since the suction device was not holding it.

On the basis of the number of attempts made for picking the fruit, it was found that in suction picking, 467 out of the 590 attempts made by the robot were successful, and thus, the success rate was 79.2%. On the other hand, in no-suction

Table 1 – Execution time of each motion.

	Average execution time, s
Picking fruit[a]	7.7
Placement into the tray	3.8
Preparation of the tray	16.0
Changing the tray	15.0
Travelling for 200 mm	1.0

a Motion of picking fruit included the following steps: image capture, image processing, approach, cut and grasping check.

Table 2 – Results of harvesting test in greenhouse: suction picking operation.

No.	Date[a]	Target fruit[b]	Number of fruit picking attempts		Successful harvest		Unsuccessful harvest		Mistaken harvest		Execution time, s
			Target and immature fruits	Target fruit	In the tray	In the sub-tray	UD[c]	UP[d]	PT[e]	PA[f]	
1	2007/12/27	47	23	19	13	2	30	2	0	3	1037
2	2007/12/28	63	46	31	22	0	41	0	21	9	1399
3	2008/1/11	42	25	18	16	0	24	2	5	6	1030
4	2008/1/11	59	30	20	18	0	39	2	11	10	1124
5	2008/1/24	41	33	21	19	0	21	1	10	10	1108
6	2008/2/7	24	13	7	6	0	18	0	1	4	849
7	2008/2/22	77	42	26	16	1	54	6	2	9	1495
8	2008/3/3	85	66	51	37	1	36	11	5	8	1615[g]
9	2008/3/3	80	55	32	30	0	46	4	3	17	1522[g]
10	2008/3/17	47	41	35	25	1	15	6	5	5	1201
11	2008/3/17	49	35	30	23	3	20	3	2	2	1155
12	2008/4/1	13	18	8	4	0	7	2	0	8	944
13	2008/4/1	13	7	3	1	0	10	2	0	3	780
14	2008/4/22	120	76	61	40	3	64	13	12	9	1677[g]
15	2008/4/22	138	57	44	36	0	96	6	7	9	1564[g]
16	2008/5/7	15	10	9	6	2	7	0	4	1	688
17	2008/5/7	38	23	20	13	2	19	4	6	2	879
18	2008/5/27	95	91	84	70	2	15	8	7	7	1665[g]
19	2008/5/27	84	83	71	55	0	19	10	14	11	1354[g]
Total		1130	774	590	450	17	581	82	115	133	23086

a Planting date was 17 September 2007.
b Fruit with maturity level of 80% or more.
c UD: unsuccessful fruit detection.
d UP: unsuccessful fruit picking.
e PT: immature fruit picked together with target.
f PA: immature fruit picked alone.
g Tray was changed once.

picking, 149 out of the 187 attempts made by the robot were successful, and the success rate was 79.7%. Consequently, there was no significant difference between the success rates achieved in the two picking methods, as estimated by a chi-square test at the 5% level.

3.2.2. *Performance of unsuccessful harvest*

The main cause of unsuccessful harvesting was that the machine vision unit did not detect the fruit (see Tables 2 and 3). The fruit detection results were greatly influenced by the way the fruit was positioned, so *UD* occurred in classification D and

Table 3 – Results of harvesting test in greenhouse: no-suction picking operation.

No.	Date[a]	Target fruit[b]	Number of fruit picking attempts		Successful harvest		Unsuccessful harvest		Mistaken harvest		Execution time, s
			Target and immature fruits	Target fruit	In the tray	In the sub-tray	UD[c]	UP[d]	PT[e]	PA[f]	
1	2008/3/4	39	35	20	14	1	19	5	3	6	1219
2	2008/3/4	48	14	12	10	0	35	3	2	2	986
3	2008/3/18	29	32	20	16	0	12	1	4	6	1095
4	2008/3/18	23	20	11	6	2	12	3	1	5	902
5	2008/4/24	88	51	31	24	1	59	4	10	12	1385
6	2008/4/24	81	52	24	16	4	59	2	25	23	1431
7	2008/5/8	22	11	6	1	3	16	2	1	2	810
8	2008/5/8	37	19	15	13	2	22	0	2	3	876
9	2008/5/28	26	30	25	14	2	7	3	0	1	854
10	2008/5/28	34	35	23	18	2	12	2	1	8	1049
Total		427	299	187	132	17	253	25	49	68	10607

a Planting date was 17 September 2007.
b Fruit with maturity level of 80% or more.
c UD: unsuccessful fruit detection.
d UP: unsuccessful fruit picking.
e PT: immature fruit picked together with target.
f PA: immature fruit picked alone.

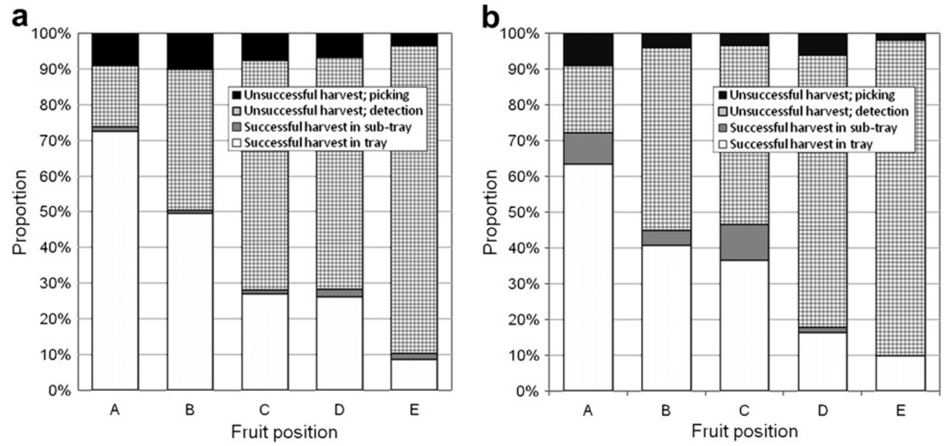

Fig. 11 – Comparison of the harvesting performance of suction picking and no-suction picking operations. (a) Suction picking; (b) no-suction picking.

E (Fig. 11). On the other hand, *UP* seemed to be caused by 3D position errors or the low peduncle detection performance at the target peduncle detection rate of 60%. In addition to these causes, it was observed that the tip of the gripper sometimes pushed adjacent fruits, causing the target fruits to move.

The incidences of *UP* were 82 out of 549 fruits in suction picking and 25 out of 174 fruits in no-suction picking. Therefore, the overall *UPR*s were 15.4% in suction picking and 14.4% in no-suction picking, i.e., suction picking and no-suction picking did not exhibit a significant difference, as calculated by a chi-square test at the 5% level. These findings indicate that the suction device of the end-effector did not greatly contribute to the picking performance, although suction was effective at reducing the swinging of the fruit during the grasping check.

Furthermore, wrong peduncle detection and no peduncle detection accounted for 40% in total in the functional test, but the *UPR*s were approximately 15% in the harvesting test. This result implies that the robot successfully picked target fruits whose peduncles were not detected. In other words, the three position wrist control used in this study was effective, especially for the case where wrist rotation was stopped when the peduncle was not detected.

3.2.3. *Mistaken harvest*

We found mistaken harvests of immature fruits in both *PT* and *PA* cases (see Tables 2 and 3). *PT* occurred mainly when the peduncles of the target fruit and immature fruit were close and positioned together between the fingers of the gripper. Although adjusting the clearance between the fingers of the gripper could help to minimise *PT*, we must bear in mind that using a narrow clearance resulted in an increase in the *UPR* in preliminary trials. On the other hand, the main cause of *PA* was misjudgement of the maturity level of the target fruit by the machine vision unit. Therefore, an improvement in the maturity assessment for the machine vision unit would be required for further studies.

3.2.4. *Execution time*

In the 36 m long test areas, the execution times varied widely from 688 s (suction picking Test no. 16) to 1655 s (suction picking Test no. 18), due to the number of target fruits (*Nt*). The average execution time per unit length was 32.3 s, which included a travelling time of approximately 5 s. Such a level of performance in terms of work efficiency indicated great potential for using the designed robot in practical applications, particularly considering the fact that the robot was designed to operate continuously throughout the night. We selected a travelling speed of 0.19 m s^{-1} from the standpoint of mechanical vibration. Therefore, there is great potential to increase the speed by securing the rigidity of the rails or the stability of the robot's body. In addition, the speed of the system could possibly be increased by optimising the control program or adopting multi-arm operation.

In this study, the strawberry-harvesting robot moved back and forth along a set of rails. To expand the harvesting area into a two-dimensional space, it is essential to use a traverse device that enables the robot to move to the next aisle; a specially designed greenhouse structure would be required to accommodate such a transverse device. Areas for future study include the improvement of individual performances, modification of the design of a greenhouse structure, including its layout, and further development of the control software for the robot and traverse device.

4. Conclusions

In light of the strong need to develop new production systems for greenhouse horticulture that make use of robots for various harvesting processes, we developed a strawberry-harvesting robot for use in an elevated substrate culture; the robot was designed in accordance with the concepts of nighttime operation, peduncle handling and task sharing with human workers. The robot was composed of a 3-DOF cylindrical manipulator, end-effector, machine vision unit, storage unit and travelling unit. A method in which the robot approached the target fruit in a straight line was employed, and the machine vision unit calculated the 3D position of the target fruit and detected the peduncle. The end-effector then simultaneously grasped and cut the peduncle to avoid damaging the pericarp.

In functional tests, the machine vision assessment of fruit maturity was found to agree with human assessment for the Amaotome and Beni-hoppe cultivars, but the coefficient of determination was 0.956 for Amaotome and 0.821 for Beni-hoppe. The rate at which the machine vision unit assessed immature fruits as mature was significantly lower for Amaotome than for Beni-hoppe. Therefore, it was obvious that differences in the fruit colouring process—i.e., in the size of the light pink portion of the fruit—influenced the difference in maturity assessment performance between the two cultivars. Moreover, the machine vision unit correctly detected the target peduncle at a rate of 60%. The proposed algorithm could not cope sufficiently well with complicated conditions for a peduncle or a reddish or dark peduncle. Besides modification of the algorithm, the use of high-luminance LEDs and a high-resolution camera could be considered to improve the peduncle detection performance.

In harvesting tests in the field, the overall *SHR*s were 41.3% for suction picking and 34.9% for no-suction picking, but they were still far from the numerical target of 60%, because the stereovision system experienced detection failures, i.e., failures in matching the left and right camera images. The use of an additional camera would help to improve the accuracy of detection. In a comparison of the picking motions, the success rates in both suction picking and no-suction picking based on the number of attempts were approximately 80%; additionally, the *UPR*s for suction picking and no-suction picking were similar, i.e., approximately 15%. Thus, for practical applications, the possible method for miniaturization of the end-effector unit would involve complete removal of the suction device so that collisions between the tray and the end-effector are certainly avoided and the harvested fruits are placed into the pockets from a closer position. In such a case, it would be necessary to develop a method to reduce the swinging of the fruit during the transfer to the tray and to check that grasping was successful. Furthermore, mistaken harvesting of immature fruits was observed, resulting in a decrease in yield.

The execution time for harvesting a fruit, including its placement in a tray, was 11.5 s; the obtained execution time was estimated to be 2.5–3 times longer than the time required during human harvesting. The work efficiency per unit length was 32.3 s. The speed of the system could possibly be increased by optimising the control program, increasing the travelling speed or adopting multi-arm operation.

Acknowledgements

The authors gratefully acknowledge Mr. Shigeru Watanabe for maintaining the strawberry crop and for providing useful guidance on the development of the strawberry-harvesting robot.

REFERENCES

Arima S; Monta M; Namba K; Yoshida Y; Kondo N (2003). Harvesting robot for strawberry grown on table top culture (Part 2). Journal of Society of High Technology in Agriculture, **15**(3), 162–168.

Cui Y; Nagata M; Guo F; Hiyoshi K; Kinoshita O; Mitarai M (2007). Study on strawberry harvesting robot using machine vision for strawberry grown on annual hill top (Part 2). Journal of Japanese Society of Agricultural Machinery, **69**(2), 60–68.

Hancock J (1999). Cultural Systems, Strawberries. CABI Publishing, NY, USA. pp 111–130.

Hayashi S; Ganno K; Kurosaki H; Arima S; Monta M (2003). Robotic harvesting system for eggplants trained in V-shape (Part 2). Journal of Society of High Technology in Agriculture, **15**(4), 211–216.

Hayashi S; Ota T; Kubota K; Ganno K; Kondo N (2005). Robotic harvesting technology for fruit vegetables in protected horticultural production. In: Proceedings of the 7th Fruit, Nut and Vegetable Production Engineering Symposium, Montpellier, France. pp 227–236

JGHA. (2008). Planting Area by Division of Hydroponic Methods and Crops. Survey of Installation of Glass and Plastic House. Japanese Greenhouse Horticulture Association, Tokyo. p 23 [in Japanese].

Kondo N; Monta M; Hisaeda K (2001). Harvesting robot for strawberry grown on annual hill top (Part 2). Journal of Society of High Technology in Agriculture, **13**(4), 231–236.

Maegawa H (1992). Studies on fruit colouring in strawberry cv. 'Toyonoka' (Part 1). Bulletin of the Nara Agricultural Experiment Station, **23**, 13–20.

MAFF. (2007). Strawberry. Statistical Survey on Farm Management and Economy—Statistics on Farm Management by Crop Division in 2005. Ministry of Agriculture, Forestry and Fisheries, Tokyo, Japan. pp 226–231 [in Japanese].

Monta M; Kondo N; Ting K C; Giacomelli G A; Mears D R; Kim Y; Ling P P (1998). Harvesting end-effector for inverted single truss tomato production systems. Journal of the Japanese Society of Agricultural Machinery, **60**(6), 97–104.

Parrish E; Goksel A (1977). Pictorial pattern recognition applied to fruit harvesting. Transactions of the ASAE, **20**(5), 822–827.

Sarig Y (1993). Robotics of fruit harvesting: a state-of-the-art review. Journal of Agricultural Engineering Research, **54**, 265–280.

Schertz C; Brown G (1968). Basic considerations in mechanizing citrus harvest. Transactions of the ASAE, **11**(2), 343–348.

Takeuchi T; Fujinami H; Kawata T; Matsumura M (1999). Pedigree and characteristics of a new strawberry cultivar 'Beni hoppe'. Bulletin of the Shizuoka Agricultural Experiment Station, **44**, 13–24.

Tillett N D (1993). Robotic manipulators in horticulture: a review. Journal of Agricultural Engineering Research, **55**, 89–105.

Van Henten E J; Van Tuijl B A J; Hoogakker G J; Van Der Weerd M J; Hemming J; Kornet J G; Bontsema J (2006). An autonomous robot for de-leafing cucumber plants grown in a high-wire cultivation system. Biosystems Engineering, **94**(3), 317–323.

Van Henten E J; Van Tuijl B A J; Hemming J; Kornet J G; Bontsema J; Van Os E A (2003). Field test of an autonomous cucumber picking robot. Biosystems Engineering, **86**(3), 305–313.