Fruit detection system and an end effector for robotic harvesting of Fuji apples

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Abstract: The challenges in developing a fruit harvesting robot are recognizing the fruit in the foliage and detaching the fruit from the tree without damaging either the fruit or the tree. The objectives of this study were to develop a real-time fruit detection system using machine vision and a laser ranging sensor and to develop an end effector capable of detaching the fruit in a way similar to manual pick. The Fuji apple variety was used in this study. In the detection of the fruit, machine vision was combined with a laser ranging sensor. The machine vision recognized the fruit and the laser ranging sensor determined the distance. The system detected a single fruit with 100% accuracy in both front and back lighted scenes with ±3 mm accuracy in distance measurement. To detach the fruit from the tree, an end effector was developed with a peduncle holder and a wrist; the peduncle holder pinches the peduncle of the fruit and the wrist rotates the peduncle holder to detach the fruit. Field test results of the end effector showed more than 90% success rate in detaching the fruit with average time use of 7.1 seconds.

Keywords: apple, end effector, image processing, machine vision, robotic harvesting, Japan

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1 Introduction

The development of a fruit harvesting robot is a viable solution to the decreasing number of farm workers and the increasing cost of fruit harvesting. The two main tasks of a fruit harvesting robot are to detect the fruit and to pick the fruit without damaging it or the tree. Accuracy and efficiency has been the problem that keeps robotic fruit harvesting from being commercially applied, and the challenge faced by researchers.

Researchers (Jiminez et al., 2001; Bulanon et al., 2001; Hannan & Burks, 2004; Ling et al., 2004; Monta et al., 1998) have reported the development of fruit detection systems on image capture and processing. Most of the studies on fruit detection used machine vision wherein a CCD (charge coupled device) camera was used to capture the scene and a PC (personal computer) to do the image processing. The techniques in image processing could be divided into spectral-based or shape-based analysis. Spectral-based analysis was effective for fruits with reflectance different from the background (Bulanon et al., 2002a) while shape-based analysis was used to look for fruits of a specific shape (Ling et al., 2004). Although promising results have been obtained, problems were also encountered. One problem was uneven lighting condition (Bulanon et al., 2002b) that could affect the reflectance of objects, and result in failure in detecting the fruit or mistake of picking a non-fruit object. False detection was another problem when objects of similar shapes such as leaves were detected in some shape-based approach. The third problem is occlusion where fruits are partially shadowed by other fruits and leaves. Some researchers have reported methods to detect occluded objects. One of the

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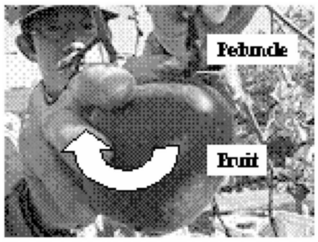
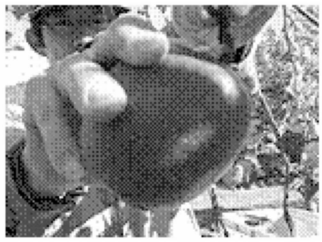
popular methods is the Circular Hough Transform, which is effective for round objects such as oranges, apples and tomatoes (Plebe & Grasso, 2001). However, results showed that this method was computationally intensive which would pose a challenge for real-time application and they also reported that the contour of other objects such as the leaves generated false detection. Another research reported the use of air blowing device to avoid leaf occlusion (Dobrusin et al., 1992), however this may not be applicable to the apple trees. Finally, the lack of distance or range information is a challenge for researchers. The acquired image gives only two-dimensional information when the distance of the fruit remains unknown. The stereo vision, ultrasonic sensors, and laser ranging sensors have been used to supplement the distance information (Hannan & Burks, 2004). A robust fruit detection system is required to work in a complex environment such as an orchard.

Picking of the fruit is the task wherein the robot makes contact with the fruit. It should be pointed out that fruits for the fresh market should be free of damage. This is one of the challenges of the end effector development. Another challenge is the manner of removing the fruit from the tree. Different ways of harvesting are used for different fruits. In the case of the Fuji apple (Figure 1), the fruit should be lightly cradled between the palm and the finger, the thumb or the forefinger against the base of the peduncle. The apple should be removed with a twisting and lifting motion. Figure 1 shows that the center of rotation is the topmost portion of the peduncle. This topmost portion is called the abscission layer, located between the peduncle and the fruit spur. This procedure is strictly followed because it is important that the peduncle remain on the apple, as an apple without a peduncle has a shorter storage life and a lower market value especially in Japan.

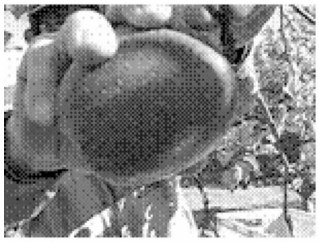
The objectives of this paper were: 1) To develop a fruit detection system that could detect a single fruit and measure its distance from the camera, 2) to develop an end effector prototype that mimics the human harvesting method, 3) to evaluate the performance of both the fruit detection system and the end effector.



a. Initial position



b. Start of rotation



c. Fruit rotation

d. Fruit detached

Figure 1 Manual harvesting of Fuji apples

2 Materials and methods

2.1 Tested fruit

The fruit tested in this study is the red Fuji apple which is one of the most popular apple varieties in Japan, accounting for 50% of its apple production. Fuji apples are harvested in early November.

2.2 Development of fruit detection system

2.2.1 Hardware development

The fruit detection system is composed of a machine vision system to recognize the fruit and a laser ranging sensor to determine the distance to the fruit. The machine vision system consists of a compact color CCD video camera to capture images of the apples, a USB frame capture device to digitize the acquired images, and a PC (Pentium 1 GHz) for image processing. The acquired image was a 320×240 bitmap image.

The tested laser ranging sensor can measure distance from 30 cm to over 100 cm. The camera was mounted on the laser ranging sensor (Figure 2). This position was configured to align the optical axis of the camera with the laser. The goal here is once the desired object, in this case the apple is positioned at the center of the image through visual servoing, the laser ranging sensor could easily measure the distance to the fruit. The laser ranging sensor was connected to the computer through the RS-232.

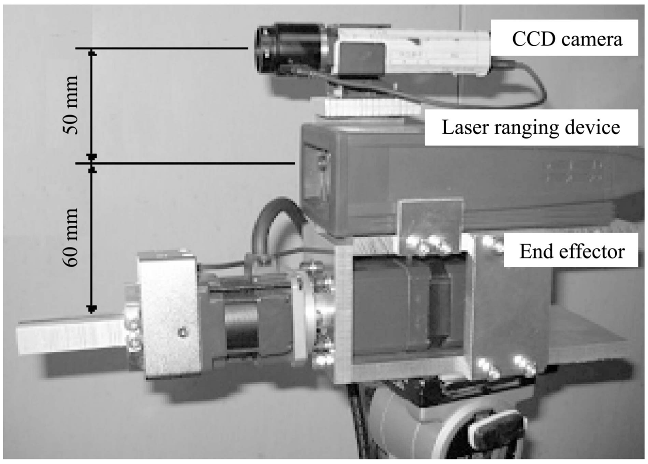


Figure 2 End-effector with fruit detection system

2.2.2 Software development

The fruit detection algorithm (Figure 3) for the machine vision has six steps: acquisition, segmentation, filtering, labeling, edge extraction, and feature extraction. Segmentation is the first step of object recognition. Van Henten et al. (2003) reported segmentation as one of the sources of failure during harvest. The segmentation method used was a color based method developed by Bulanon et al. (2002a). In this approach the chromaticity coefficients *r* and *g* were used as the feature space. Two decision functions, d_1 and d_2, that separated the fruit from the other classes in the feature space were derived using the decision theoretic approach (Gonzalez & Woods, 1992). This method could be applied under different lighting conditions. The chromaticity coefficients and the decision functions, d_1 and d_2, are expressed by the following equations:

$$r = \frac{R}{R+G+B} \tag{1}$$

$$g = \frac{G}{R+G+B} \tag{2}$$

$$\begin{bmatrix} d_1 \\ d_2 \end{bmatrix} = \begin{bmatrix} 0.09 & -0.11 \\ 0.12 & -0.06 \end{bmatrix} \begin{bmatrix} r \\ g \end{bmatrix} \tag{3}$$

Where d_1 and d_2 are the decision functions that separate the fruit from leaves and branches respectively. Although the other parts of the background such as the ground and the sky were not included in the derivation of the decision functions, results showed that the two functions were sufficient to separate the fruit from the background.

Using the decision functions, a segmented image $g(x, y)$ is defined as

$$g(x,y) = \begin{cases} 1 & \text{if } d_1 > 0 \text{ and } d_2 > 0 \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

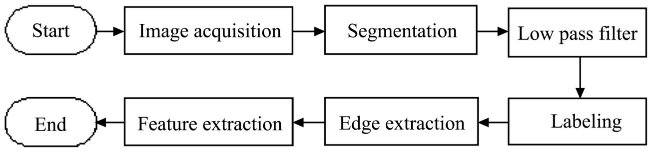


Figure 3 Image processing algorithm for fruit detection

The segmented image passed a low pass filter to remove noise. Connected pixels were classified as one segment or blob (Davies, 1997). A Laplacian edge detector was used to extract the edges of the segments. At this point, the segments were not yet considered as fruit. The morphological properties such as area, major axis, length, width, aspect ratio, and segment center were determined in feature extraction. These features were used to classify the segments as a single fruit and an occluded fruit. In this study, a single fruit was considered as harvestable while an occluded fruit was not. A single fruit is a fruit that was 25% or less occluded. Occlusion here is defined as leaf/branch occlusion and fruit occlusion. Although apples do not grow in clusters, an apple located behind another apple could be viewed as a multi-fruit cluster and it is considered here as fruit occlusion. However, they could also be viewed as single fruits from another perspective. The goal here is to harvest the apples with high accuracy.

To determine if the segment was a single fruit or an occluded fruit, a “shape area factor” was defined. The shape area factor is the ratio of the segment area to the area of the circle of which the diameter is the major axis of the segment. The shape area factor of a single fruit was defined to be more than 0.75.

To measure the distance, the camera and the laser ranging sensor were mounted on a cylindrical manipulator and the motion of the manipulator was controlled by visual servoing (Bulanon et al., 2005). Visual servoing positioned the target fruit (apple) in the center of the image. Once the fruit center was aligned with the image center, the distance to the fruit was measured automatically using the laser ranging sensor.

The program for the image processing, laser control, interface of machine vision and the laser ranging sensor was developed using the Visual C# programming language.

2.2.3 Performance evaluation

To evaluate the performance of the fruit recognition system, tests were conducted in the field in the first week of November 2004. A hundred images were acquired with fifty images under front lighting and the other fifty under back lighting condition.

2.3 Development of end effector

2.3.1 End effector design

The design of the end effector was based on the apple harvesting force analysis made by Kataoka et al. (1999), simulating the manner the human picker removes the fruit from the tree. The end effector has two components: the peduncle holder and the wrist (Figure 4). The peduncle holder is a DC motor equipped with two fingers with an opening width of 15 mm and a gripping force of 11 N which is enough to hold the fruit by its peduncle, as the average weight of Fuji apples is estimated to be less than 400 g. The wrist is a stepper motor that rotates the peduncle holder after pinching the peduncle. It has a torque of 1.5 Nm, which, based on the force analysis, is sufficient for harvesting.

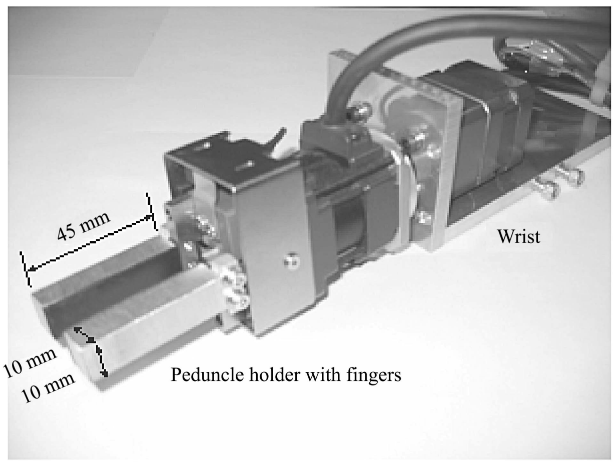


Figure 4 End effector prototype

The control of the prototype is shown in Figure 5. The peduncle holder receives open/close signal from the PC through the digital I/O and sends feedback of its status to the PC. The wrist is controlled by a 500 Hz pulse signal produced by a microcontroller connected to the PC through the digital I/O. The control interface in the PC was developed using Visual C#.

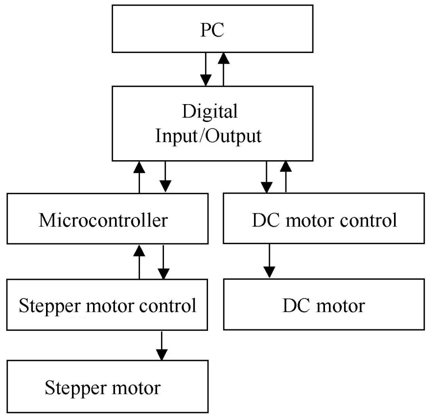


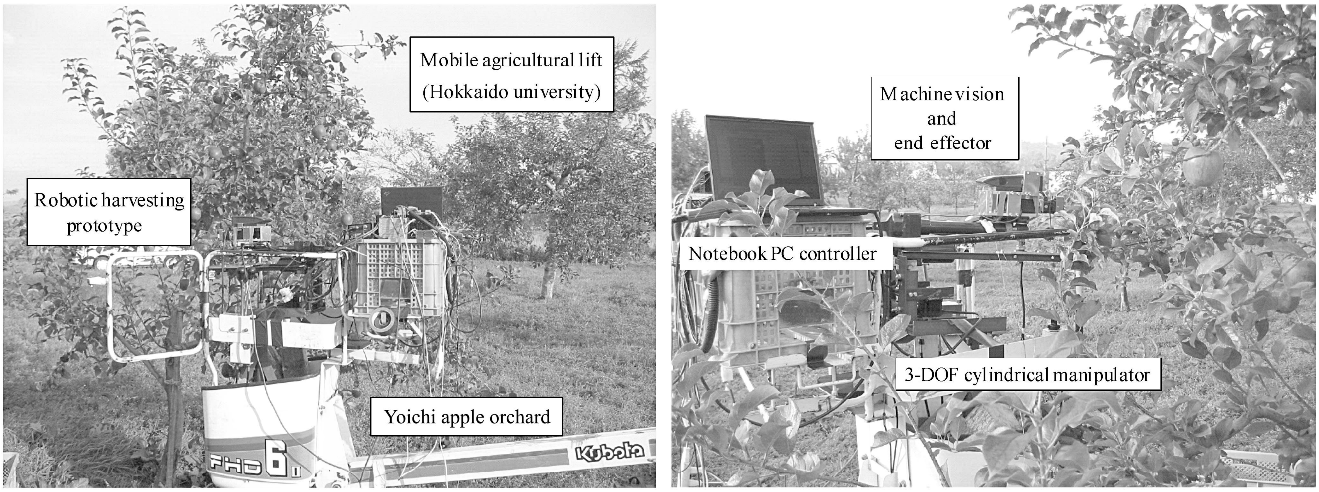
Figure 5 Control of end effector

2.3.2 Performance of end effector

The performance of the end effector was evaluated in the field test during the harvesting season of the Fuji apples in Hokkaido University. Twenty two apples were harvested from three Fuji trees. Each of the fruits was initially positioned with the peduncle inside the peduncle holder's fingers that were horizontally laid. Performance evaluation started with the closing of the fingers followed by a 120° rotation.

2.4 Field test of the apple harvesting robot prototype

The apple harvesting robot prototype is composed of the developed machine vision (eyes), the fruit picker (hand) and the developed cylindrical manipulator (arm). The apple harvesting robot was mounted on a vehicle lift so that it could easily move in the orchard in a broad work area. Harvesting test of the robot was conducted in the first week of November 2005, which was the harvesting season for the Fuji apples. The tests were done in the Yoichi experimental orchard and the apple orchard inside Hokkaido University in Sapporo. Seventy five apples were tested.



a. Robotic harvesting prototype b. Robotic components

Figure 6 Field test of robotic harvesting prototype

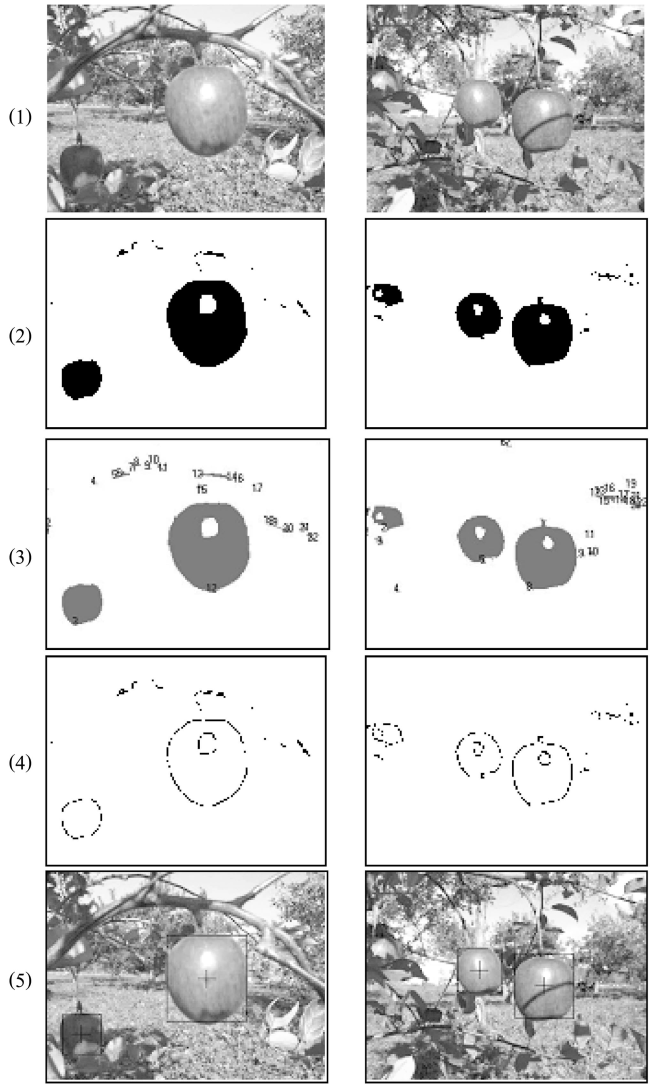
3 Results and discussion

3.1 Fruit recognition system

The fruit recognition system was tested in the field. Figure 7 shows the results of the image processing algorithm. Two sets of images are shown here; Figure 7a is when the fruits were subjected to uneven lighting and Figure 7b is when there was an occlusion.

Although Figure 7a-1 was taken under front lighting condition, the presence of other objects in the scene such as a branch could cause uneven lighting. The segmented image shows that both fruits were recognized although the two fruits had different illumination conditions: the larger fruit was brighter than the smaller one which was shaded. Fruits in both frontlighted and backlighted images were successfully detected, showing that the segmentation method was able to adapt to the different lighting conditions. The *r* and *g* feature space transformation decouples intensity from the original RGB image, which facilitated the segmentation to adjust to different lighting condition. An effective segmentation method should be utilized considering its influence on the subsequent processes.

Figure 7b-1 shows the performance of the algorithm when a fruit is occluded (extreme left fruit is occluded by leaves). The final image shows that only the two single fruits were detected. The algorithm identified the occluded fruit and so it was not considered as a harvestable fruit. The biggest challenge of occlusion is



a. Sample of uneven lighting b. Sample of occlusion

Zone: (1) acquired image; (2) segmentation; (3) labeling; (4) edge extraction; (5) feature extraction

Figure 7 Image processing results

false detection, which would affect the accuracy of the harvesting system. Therefore, the main focus is to determine if the segmented portion is a single fruit or an occluded fruit and to treat the single fruit as the fruit to be harvested. In this way, false detection could be avoided and the probability of harvesting the fruit successfully is increased. Furthermore, in the case of Fuji apples, flower thinning operation lessens the probability of fruits occluded by other fruits in the image.

Table 1 shows the result of the performance of fruit recognition system. There were a total of 190 single fruits and 73 occluded fruits. All the single fruits were detected while there were false detections in the detection of occluded fruits. Some parts of the image such as the branch were segmented as fruits and detected as occluded but non-harvestable, which indicates that the shape area factor was effective in dealing with falsely segmented non-fruit objects. It is also noted that this image processing step could be considered a spectral-based approach plus a shape-based approach because of the addition of the shape area factor to classify the objects in the image. Table 2 shows the execution time for each image processing step and its relative percentage. The total time is less than 500 ms, which means that real-time application of this algorithm is possible and this could be implemented using a maximum frame capture rate of two frames per second. Labeling took most of the total execution time. Improving the labeling algorithm could decrease the total time and increase the frame capture rate.

Table 1 Performance of fruit detection algorithm

	Total	Detected	False positives	Selected harvesting
Single Fruit	190	190	0	190
Occluded Fruit	73	84	11	0

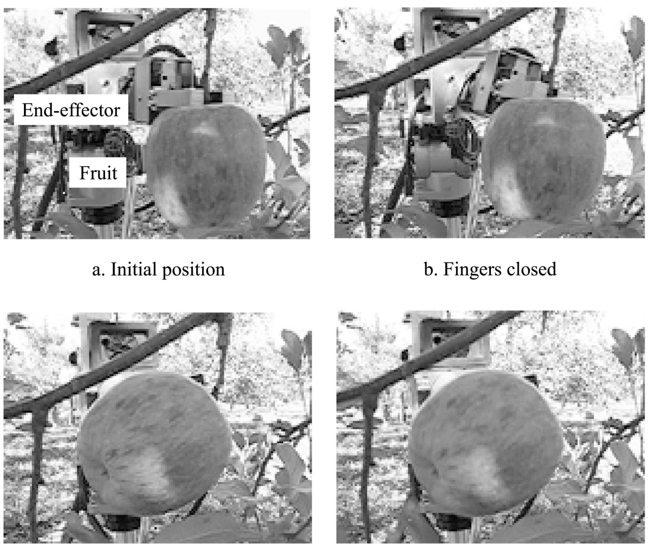
Table 2 Processing time for fruit detection

	Processing time/ms	Relative percentage/%
Segmentation	15	4.8
Filtering	46	14.9
Labeling	187	60.6
Edge extraction	46	14.9
Feature extraction	15	4.8
Total	309	100

To evaluate the performance of the laser and the machine vision system, the image processing algorithm was implemented in real time with frame capture rate of one frame per second, which was used in the visual servoing of the manipulator. When a single fruit was detected, the camera was moved to position the center of the detected single fruit to the center of the image. Once the fruit center coincided with the image center, the camera was moved 50 mm upward and the laser measured the fruit center. The distance to the detected single fruit was measured with ±3 mm accuracy.

3.2 Performance of end effector

Figure 8 shows the robotic harvesting of Fuji apples. Figure 8a shows the starting position. The operation was controlled by the PC. Then the fingers closed and held the peduncle (Figure 8b). Once the close signal was received by the PC, the wrist rotated the peduncle holder for 120 degrees (Figure 8c-d). Compared to Figure 1, the twisting motion of the stem at the abscission layer in robotic harvesting is similar to manual harvesting. Results (Table 3) showed that the end effector had a more than 90% success rate. Among the cases that the fruits were not successfully harvested, some apples had a short peduncle and became peduncle-less after picked. Some other fruits dropped when the holder pinched their peduncle. Table 4 shows the physical properties of the harvested apples. Although, the number of trials was not sufficient to warrant the reliability of this prototype, it



a. Initial position b. Fingers closed

c. Fruit rotation d. Fruit detached

Figure 8 Robotic harvesting of Fuji apples was enough to show that it could remove the fruit similarly to the way human pickers do. Removal of the fruit took an average of 7.1 seconds with a minimum of 3 seconds and a maximum of 14 seconds. Removal time depends on the frequency of the pulse signal to the wrist stepper motor. To decrease the time use would mean increasing the frequency of the pulse signal.

Table 3 Performance of end effector

	Number of fruits	Percentage/%
Successful removal	20	90.9
Unsuccessful removal	2	9.1
Total	22	100

Table 4 Physical properties of harvested apples

	Diameter/mm	Height/mm	Peduncle length/mm	Weight/g
Maximum	89	82	19.5	300
Minimum	66	67	12.5	150
Average	77.8	78.7	16.5	238.5

The main advantage of this end effector is its contact with the fruit. It touches the peduncle only instead of the fruit. It is feasible to hold the fruit with the peduncle only because of the high tensile strength between the peduncle and the fruit. Other developed end effectors (Monta et al. (1998); Cho et al. (2002)) had direct contact with the fruit while controlling the gripping force. Although the gripping force is controlled, there is still a high risk of causing damage to the fruit. In designing an end effector for fruit harvesting, contact area should be one of the considerations. Less contact area without sacrificing grasping capability of the end effector is a better choice.

The limitation of the end effector in this study is the horizontal way it approaches the fruit. Attaching the end effector to a manipulator is one of the constraints that should be considered in the trajectory planning. In addition, the fruit recognition system should also take into consideration that this end effector requires the position of the peduncle with high accuracy. Bulanon et al. (2001) had reported an image processing technique to determine the peduncle position. In this method, the fruit center and the fruit outline are required. These two features are easily determined in the present fruit recognition system.

3.3 Field test of harvesting robot prototype

Results of the field test showed that the robot successfully harvested about 89% of the apples. Eleven percent (11%) of the apples was not successfully picked. There were several factors that were considered for the failure: (1) the position of the peduncle, (2) size of the peduncle and (3) difficulty in the fruit recognition. In reason (1), some fruits did not have a position where the position of the peduncle is straight because of blockage by branches or leaves, because of which, the machine vision was not able to correctly calculate the position of the peduncle. In reason (2), some fruits have very short peduncle and the picker held the branch instead of the peduncle and thus the branch was taken together with the fruit. In case of reason (3), there were instances where the machine vision failed to recognize the fruit because of the background where other fruits behind the target fruit make the targeted fruit looked overlapped in the image. In this case we had to move the robot to another position where it would distinguish the single fruit. Although, the success rate is considerably high, the response time of the robot is still long. The main reason for this as stated above is the machine vision image processing rate. If the image processing could be improved and its speed be increased, the robot could be commercially applied for apple harvesting. Another improvement that will be further looked into is the design of its fruit picker. The current length of its peduncle holder is considered short and its width considered large. If the length can be increased and its width decreased, the chance of holding the fruit with shorter peduncle will be higher. Further development in the manipulator area should also be looked into, especially the determination of the manipulator configuration suitable for the apple tree plant training system. The current manipulator was not developed based on the plant training system of the apple. Although there are still a lot of improvements needed for the current apple harvesting robot, the results suggested a bright future in this research area.

4 Conclusions

A fruit detection system and an end effector that can be attached to a commercial manipulator were developed for robotic apple harvesting. The fruit detection system used machine vision to recognize the fruit and a laser ranging sensor to measure the fruit's distance. Results showed that it detected single apples with a 100% accuracy without any false detection of single fruits. It measured the fruit's range with ±3 mm accuracy. The image processing took less than one second which suggests that real-time application is possible. The end effector prototype developed was based on the way human picks the apple. It makes contact with the peduncle of the fruit only. Performance test of the end effector showed that it has a success rate of over 90%. The machine vision system and the end effector were attached to a cylindrical manipulator. Field tests showed that the robotic harvesting prototype successfully picked 89% of the apples. Future studies would involve improving frame rates of machine vision system, handling system of the end effector, and development of a manipulator suitable for the apple trees.

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