A 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 both the fruit and the tree. The objectives of this study were to develop a real-time fruit detection system using machine vision and laser ranging sensor and to develop an end effector capable of detaching the fruit similar to the human picker. The Fuji apple variety was used in this study. In the detection of the fruit, machine vision was combined with laser ranging sensor. The machine vision recognized the fruit and the laser ranging sensor determined the distance of the fruit. The system detected single fruit with 100 % accuracy in both front and back lighted scenes and the distance measurement accuracy was ±3 mm. In detaching 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 an average time of 7.1 seconds.

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

1. INTRODUCTION

The two main tasks of a fruit harvesting robot are to detect the fruit and to pick the fruit without damaging it and the tree. These two tasks are the challenges faced by researchers today and this is also the reason why robotic fruit harvesting is not yet commercially applied. The development of a fruit harvesting robot is a viable solution to the decreasing number of farm workers and the increasing cost of agricultural operations such as harvesting.

To detect the fruit, several authors e.g. (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. Most of the works 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 a specific shape of the fruit (Ling *et al*., 2004). Although promising results have been obtained, problems were also encountered. One of these was uneven lighting condition (Bulanon *et al*., 2002b). This condition could affect the reflectance of objects which could result in not detecting the fruit or detecting a non-fruit object. This leads to the second problem, which is false detection. In some shape-based approach, leaves were detected as fruit. The third problem is occlusion where fruits are partially hidden by other fruits and leaves. Some researchers have reported methods to detect occluded objects. One of the popular methods is the circular Hough Transform, which is effective for circular 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, however the distance of the fruit is unknown. The use of stereo vision, ultrasonic sensor, and laser ranging sensor 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 end effector development. Another challenge is the manner of removing the fruit from the tree. Different fruits have different ways of harvesting. In case of the Fuji apple (Fig. 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 less storage life and a low market value especially in Japan.

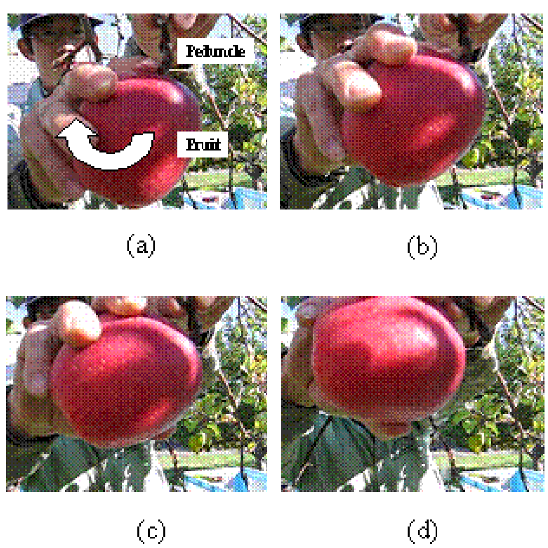


Figure 1. Manual harvesting of Fuji apples; (a) initial position; (b) start of rotation; (c) fruit rotation; (d) fruit detached.

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

2. MATERIALS AND METHODS

2.1 Tested Fruit

The fruit tested in this study is the red Fuji apple. This is one of the popular apple varieties in Japan. 50 % of the apple production in Japan is of this variety. Fuji apples are harvested in the beginning of November.

2.2 Development of Fruit Detection System

2.1.1 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 (Fig.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.

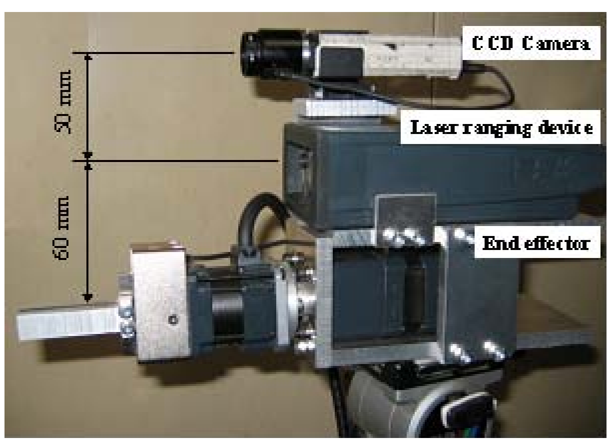


Figure 2. End-effector with fruit detection system.

2.2.2 Software Development

The fruit detection algorithm (Fig.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 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 the leaf and the branch 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

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

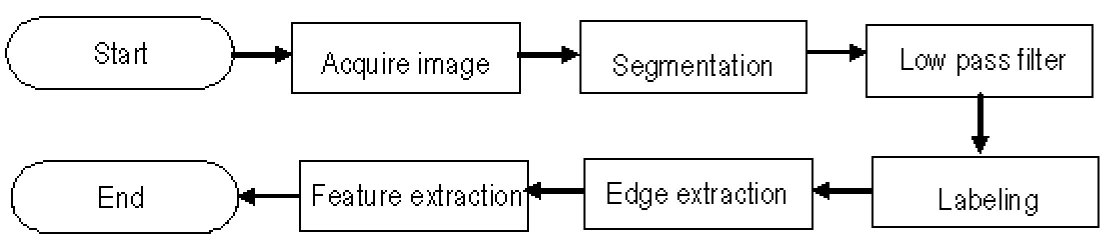


Figure 3. Image processing algorithm for fruit detection.

After segmentation, a low pass filter was passed over the segmented image 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, segment center were determined in feature extraction. These features were used to classify the segments as single fruit and occluded fruit. In this study, single fruit was considered as harvestable while occluded fruit was not. A single fruit is a fruit that has 25% occlusion or less. Occlusion here is defined as leaf/branch occlusion and fruit occlusion. Although apples don't grow in clusters, an apple which is located behind a certain apple could be viewed as a single multiple fruit cluster and it is considered here as fruit occlusion. However, they could also be viewed as single fruits in another view. 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 area of the segment to the area of the circle with the diameter of the major axis of the segment. The shape area factor of a single fruit was found to be more than 0.75.

For the distance measurement, 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 positions 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 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, it was tested in the field in the first week of November 2004. One hundred images were acquired; fifty images were under front lighting and fifty images were 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 manner the human picker removes the fruit from the tree and the apple harvesting force analysis made by Kataoka *et al*. (1999). The end effector has two components: the peduncle holder and the wrist (Fig.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. This 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 and it rotates the peduncle holder after it pinches the peduncle. It has a torque of 1.5 Nm, which, based on force analysis, is sufficient for harvesting.

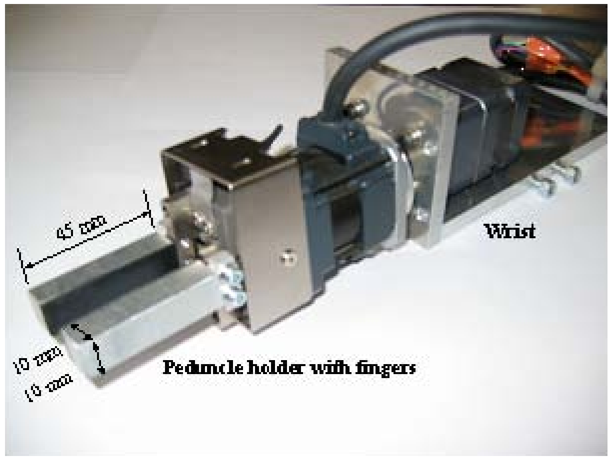


Figure 4. End effector prototype.

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

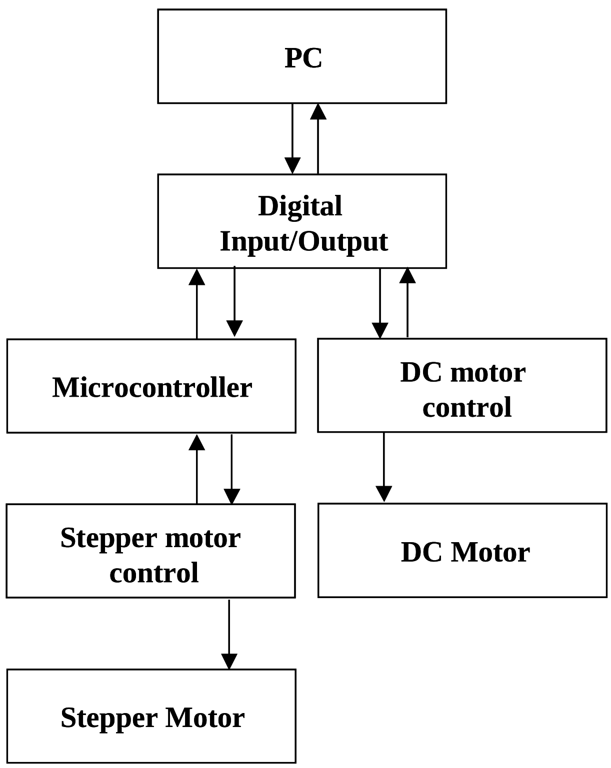


Figure 5. Control of End effector.

2.3.2 Performance of End Effector

To evaluate the performance of the end effector, it was also tested in the field during the harvesting season of the Fuji apples in Hokkaido University. The harvested fruits were from three Fuji trees. Twenty two apples were harvested. In the end effector performance test, the fruit was positioned with the peduncle inside the fingers of the peduncle holder. This was the initial position with the fingers parallel to the ground. Performance evaluation started with the closing of the fingers and then the fingers were rotated 120 degrees.

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 and it also increases the work area of the robot. Harvesting test of the robot was made in the first week of November 2005, which was the harvesting period for the Fuji apples. The tests were done both in the Yoichi experimental orchard and the apple orchard inside Hokkaido University in Sapporo. Seventy five (75) apples were tested.

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 result of the image processing algorithm. Two sets are shown here; Fig.7(a) is when the fruits are subjected to uneven lighting and Fig.7(b) is when there is an occlusion.

Although Fig.7(a-1) was taken under front lighting condition, the presence of other objects in the scene such as a branch could cause uneven lighting. The two fruits had different illumination; the larger fruit is brighter as compared to the other fruit, which is shaded. Although the fruits had different illumination, the segmented image shows that both fruits were recognized in the image. Fruits in both frontlighted and backlighted images were successfully detected. This shows that the segmentation method was able to adjust to the different lighting conditions of the fruit. The *r* and *g* feature space transformation decouples intensity from the original RGB image and this facilitated the segmentation to adjust to different lighting condition. An effective segmentation method should be utilized because it affects the subsequent processes.

Figure 7(b-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 false detection, which would affect the accuracy of the harvesting system. Therefore in this study, the main focus is to determine if the segmented portion is a single fruit or an occluded fruit and 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.

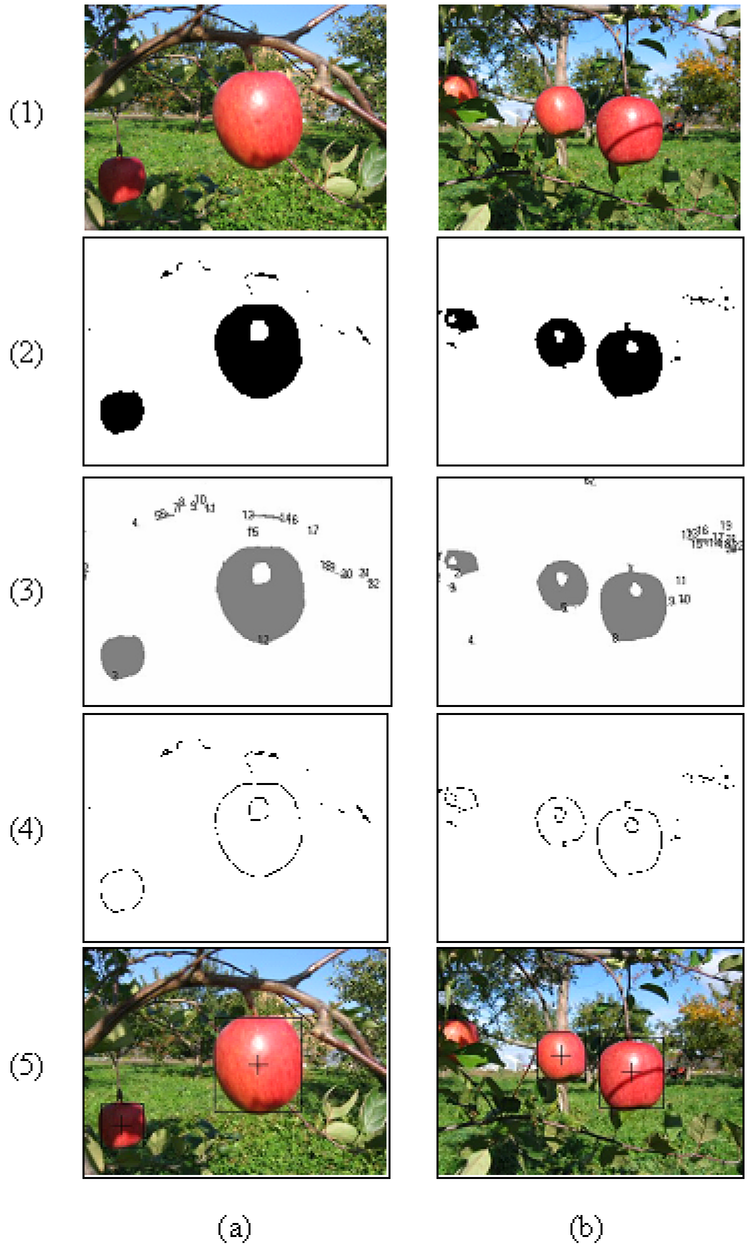


Figure 7. Image processing results; (a) sample of uneven lighting; (b) sample of occlusion; (1) acquired image;(2) segmentation; (3) labeling; (4) edge extraction; (5) feature extraction.

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 fruit and they were detected as an occluded fruit. Although they were detected as occluded fruits, they were not considered as harvestable fruit. This shows that the shape area factor was effective in dealing with non-fruit objects, which were falsely segmented. It is also noted here 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 it's 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 2 frames per second. Labeling took much 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

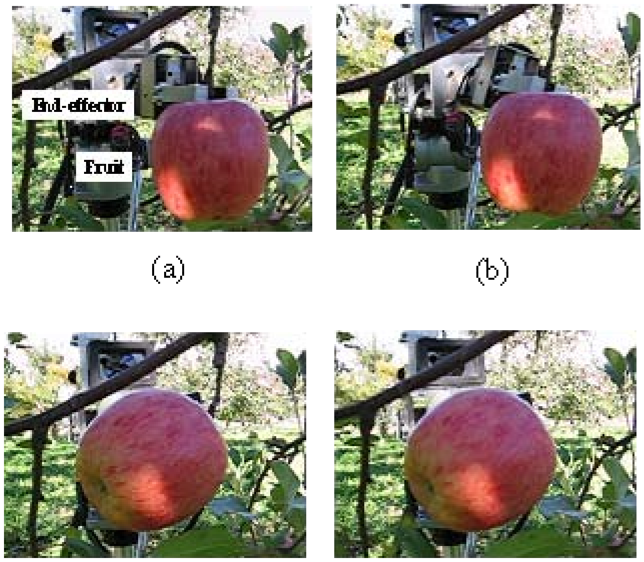
	Processing time, ms	Relative percentage, %
Segmentation	15	4.8
Filtering	46	14.9
Labeling	187	60.6
Edge extraction	46	14.9
Feature extraction	15	4.8
Total	309	100

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 1 frame per second. This 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 of the detected single fruit was measured with a ±3 mm accuracy.

3.2 Performance of end effector

Figure 8 shows the robotic harvesting of Fuji apples. Figure 8(a) shows the starting position. From here the operation was controlled by the PC. Then the fingers closed and held the peduncle (Fig. 8(b)). Once the close signal was received by the PC, the wrist rotated the peduncle holder from the initial position to 120 degrees (Fig.8(c)-(d)). Comparing this with Fig.1, the twisting motion of the stem at the abscission layer in robotic harvesting is similar with manual harvesting. Results (Table 3) showed that the end-effector had more than 90% success rate. In case of the fruits that were not successfully removed, one had a short peduncle and when it was removed, the fruit had no peduncle. The other fruit fell down when the holder pinched the 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 was enough to show that it could remove the fruit similar to the way human picks the fruit. 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 pulse signal to the wrist stepper motor. Decreasing this time would mean increasing the frequency of the pulse signal.



(a) (b) (c) (d)

Figure 8. Robotic harvesting of Fuji apples; (a) initial position; (b) fingers closed; (c) fruit rotation; (d) fruit detached.

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 makes contact with the peduncle only and not the fruit. It is possible 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 probability of causing damage to the fruit. In designing an end effector for fruit harvesting, contact area should be one of the considerations. Lesser contact area is better for the fruit but without sacrificing grasping capability of the end effector.

The limitation of this end effector is the way it approaches the fruit. The end effector should approach the fruit horizontally. When attaching this end effector to a manipulator, this 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 the branch or leaf. Because of this, 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 when it picked the fruit, 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, there were other fruits behind the target fruit which would make the fruit looked overlapped in the image. So we had to move the robot to another position where it would be recognized as a single fruit. Although, the success rate is considerably high, the response time of the robot was still slow. The main reason for this one as stated above is the machine vision image processing rate. If the image processing could be improved and its speed be increased, then the robot could be used for apple harvesting. Another improvement that will be looked into is the design of its fruit picker. It is thought that the current length of its peduncle holder is short and its width is large. If the length would be increased and its width decreased, the chance of holding the fruit with shorter peduncle is high. Further development in the manipulator area should also be looked into specifically the determination of the configuration of the manipulator that is 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 showed a bright future in this research area.

4. Conclusion

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 laser ranging sensor for the fruit's distance information. Results showed that it could detect single apples with a 100% accuracy and no false detection of single fruit. It could measure the fruit's range with ±3mm accuracy. Image processing took less than one second and it can be concluded that real-time application is possible. The developed end effector prototype 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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