A Machine Vision System for the Apple Harvesting Robot

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Abstract. *One of the requirements of a fruit harvesting robot is the ability to recognize and locate fruit from the leaf and branch portions; machine vision system is one of the methods used to detect the location of the fruit. This paper showed the development of a machine vision algorithm that would guide an apple harvesting hand prototype. The objectives of this study were to differentiate the fruit from the other portions of the tree, such as the leaf and the branch, and to locate the fruit center and the abscission layer of the fruit's peduncle. The study was divided into two stages, the recognition stage and the location stage of the apple fruit.*

In the recognition of the apple, Fuji *variety was tested. Apple images were collected using a color CCD camera under natural lighting condition. Color models of* Fuji *were examined to determine the color properties used to differentiate the fruit from the other portions of the tree, such as the leaf and branch portions. The LCD (Luminance and Color Difference of red) model and the chromaticity model were used for the analysis. The color properties: luminance, color difference of red and chromaticity were tested to determine the thresholds for segmentation using the decision theoretic approach. This approach derived decision functions that could classify the apple fruit, leaf, and branch. The decision functions for the LCD model were dependent on luminance and color difference of red while the decision functions for the chromaticity model were dependent on the trichromatic coefficients,* r *and* g*. Segmentation was implemented using multivariable thresholding and the decision functions were the thresholds. Results showed that both models could segment at least 80% of the apple fruits.*

The location of the fruit center and the abscission layer were determined using a geometrical approach and basic image processing procedures. A geometrical relation between the apple fruit center and the abscission layer was established and combined with standard image processing procedures. The experimental results showed that the method of locating the fruit center and the abscission layer of the fruit peduncle was effective with a success rate above 80%.

Keywords. *Apples, color, image processing, machine vision, robots*

INTRODUCTION

One of the popular fruits in Japan is the apple. The annual production of apple reaches about one million tons. However, the intensive labor associated with the harvesting of apples causes a potential problem in recent years. As the farm labor is aging and fewer people are entering the agricultural industry, there is a decreasing trend of farm labor availability. Therefore, there is a need to evaluate alternative methods to the manual harvesting of apples.

One of these alternative methods is the automation of apple harvesting using a robot that could emulate manual harvesting. With the increasing costs of labor and the decreasing costs of computers, vision systems, and robotic equipment, robots will replace laborers in the orchard in the near future. The automated harvesting system should perform the following operations: (1) recognize and locate the fruit; (2) reach for the fruit; (3) detach the fruit without causing damage both to the fruit and the tree; and (4) move easily in the orchard (Sarig (1990)).

Recently, a number of researches on the automatic harvesting of different fruits has been reported. A study by Kataoka *et al*.(1999) showed the development of an apple robotic harvesting hand. The method of detaching the fruit was similar to the manual method. In the manual method, the fruit should be detached together with the peduncle. A fruit without a peduncle has a lower market value. However, the robotic hand should be guided towards the apple fruit. Thus machine vision is required to guide the developed hand. The developed robotic hand required the location of the fruit center and the abscission layer.

Studies on the application of machine vision to guide a robot have been reported. Parrish *et al*.(1977) tried a monochrome camera, to acquire images, and pattern recognition technique for image processing to guide his robot. On the other hand, Slaughter *et al*.(1987, 1989) used a color camera to capture the images and color image processing to recognize the oranges. The basic approach that has been used by these researchers was to obtain a digital image of the fruits and develop an image processing algorithm capable of recognizing and locating the fruits. In the location of the fruit, most of the reports have focused on the fruit center only. However, the developed harvesting hand needs the location of the fruit center and the abscission layer.

The objective of this study was to develop a machine vision system to guide the developed robotic hand. In this paper, the objectives were to develop an image processing algorithm to recognize the apple fruit from the other portions of the tree, such as the leaf and the branch, and to determine the locations of the fruit center and the abscission layer.

METHODOLOGY

IMAGE ACQUISITION SYSTEM

The apple tested in this study was the *Fuji* variety. This is the most popular variety in Japan. The *Fuji* apple is a red colored fruit. Color images of *Fuji* apple trees were collected using a color CCD camera with 640 × 480 pixels (Sony, DCR-VX1000). The fruits were randomly selected from the apple orchard in the experimental farm of Iwate University. The images were taken under natural daylight lighting condition. Both fine and cloudy conditions were considered. The images were digitized into a 240 × 320 × 24-bit bitmap image using the IEEE 1394 based video capture board and they were processed on a Windows based system. Figure 1 shows the image acquisition set-up.

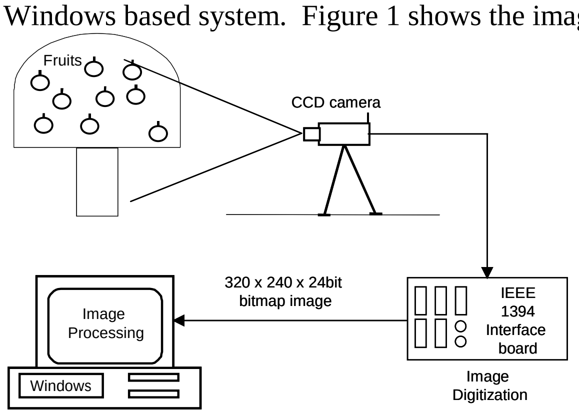


Figure 1 Image Acquisition Set-up.

IMAGE ANALYSIS METHODS

Fifty pixels from each portion of the tree: fruit, leaf, and branch, were manually recognized and sampled from the acquired apple images. Three sets of apple images were used for sampling. Two color models were used to analyze the sampled pixels. The first color model is used in the transmission of television video signals (Awcock, (1996)). The color properties used in this model are: luminance, Y, color difference of red, C_R, color difference of green, C_G, and color difference of blue, C_B. Since the image acquisition system deals with RGB values, the next equation converted the RGB values to luminance and color difference signals.

$$Y = 0.299 \times R + 0.587 \times G + 0.114 \times B \quad (1)$$
$$C_R = R - Y \quad (2)$$
$$C_G = G - Y \quad (3)$$
$$C_B = B - Y \quad (4)$$

where R, G, and B are the color intensity values ranging from 0 to 255, respectively. Since the dominant color of the apple fruit is red, only the color difference of red was considered in this study. Luminance was compared with the color difference of red and this was named the LCD(Luminance and Color Difference) model.

The second color model was the chromaticity model. This model is based on the HSI (Hue, Saturation, Intensity) color model. Hue and saturation taken together is called chromaticity (Gonzalez (1992)). The chromaticity diagram was used to represent the color properties of the three tree portions. This diagram showed color composition as a function of trichromatic coefficients, r and g. Basically, a color can be specified by three trichromatic coefficients defined as,

$$r = R / (R + G + B) \quad (5)$$
$$g = G / (R + G + B) \quad (6)$$
$$b = B / (R + G + B) \quad (7)$$

It is obvious from the above equations that,

$$r + g + b = 1 \quad (8)$$

SEGMENTATION OF FRUIT

In the segmentation of the images to recognize the fruit, thresholding was used. Thresholding can be implemented using a single threshold or several thresholds. In this study, thresholding using several variables was used. The variables were derived from the two color models of the image using the decision theoretic approach (Sonka, (1993)). Figure 2 shows the concept of the decision theoretic approach. Two groups of objects, object A and object B, were used as an example. Two patterns, M and N, described the two groups. A pattern may be a color, shape, size, or any properties of the objects. The patterns derived from each group were plotted as points in a two-dimensional graph. A decision function could be defined that would separate the two-pattern clusters and classify the objects. A linear decision function, $D(M, N)$, could be defined such that:

$$D(M, N) = a\,M + b\,N + c \quad (9)$$

where a, b, *and* c are arbitrary constants. All points on this line satisfy the condition, $D(M, N) = 0$, and any point above the line satisfies, $D(M, N) > 0$ which is the Object A cluster of points while any point below belongs to Object B cluster and satisfies the condition, $D(M, N) < 0$. The minimum distance classifier was used to determine the decision theoretic functions. The minimum distance classifier works well when the distance between the means is large compared to the spread of each class with respect to its mean. Although the simultaneous occurrence of large mean separations and small class spread occurs seldomly, Han (1990) showed that proper selection of class patterns would result in the desired classification. Han developed an image processing algorithm to differentiate crop canopy from the soil. The classification algorithm used also the decision theoretic approach with the linear discrimination method and the nearest neighbor method to calculate the decision functions. The two methods accurately differentiated the canopy from the soil. Furthermore, the minimum distance classifier (Gonzalez (1992)) is optimum in the Bayes sense if the pattern classes are Gaussian and all classes are equally likely to occur.

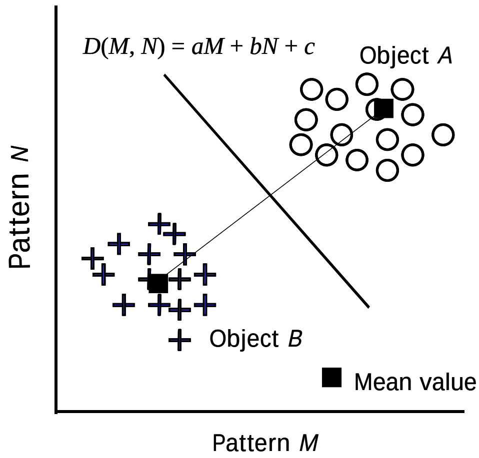


Figure 2 Decision Theoretic Approach Method.

Three decision functions were calculated in this study: the first function, D_1, separated the fruit portion and the leaf portion, the second function, D_2, separated the fruit portion from the branch portion, and the third function D_3, separated the leaf portion from the branch portion. Then the apple image was segmented into fruit portion and background portion; the leaf and branch portions were considered as background thus D_3 was not used in the segmentation process.

LOCATIONS OF FRUIT CENTER AND ABSCISSION LAYER

A model of an apple with a peduncle is shown in Figure 3. Three points in Figure 3 were identified, point O as the center of the fruit, point C as the intersection of a horizontal line passing through the fruit center as the leftmost outline of the fruit, and point P as the abscission layer. L_1 was defined, as length PC, while L_2 was defined, as length CO. L_3 was defined as length PO. The angle PCO was defined as angle α. L_2, L_3, and angle α were measured. The values of angle α and the coordinates of point O and point P were evaluated if the values had a statistical trend. Inset in Figure 3 is a sample picture of *Fuji* apple showing how the proposed model was applied.

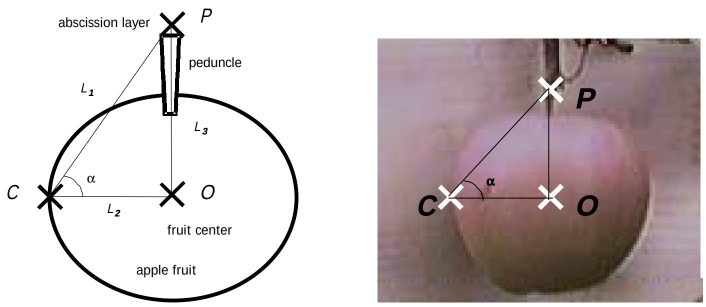


Figure 3 Apple and Peduncle Geometrical Model.

Results from the geometrical analysis of the sample apple images were used to develop a technique that could calculate the position of the abscission layer given the fruit center location and L_2. The fruit center location and L_2 could easily be estimated by the established image processing techniques. Based on the technique to estimate the abscission layer location and established image processing techniques, an algorithm to locate the fruit and the abscission layer was developed. The algorithm was programmed using Visual Basic programming language.

RESULTS AND DISCUSSION

PHYSICAL PROPERTIES OF FUJI APPLE FRUIT

The physical properties of harvested *Fuji* apples were measured manually; diameter, height, and mass. 30 samples were tested. The diameter and height, which were measured by a vernier caliper, were defined as the horizontal and vertical width of the fruit, respectively. Table 1 shows the physical properties of the *Fuji* apple. The *Fuji* apple had an average diameter of 82.2 mm and an average height of 70.4 mm.

Table 1 Physical Properties of Fuji Apple.

	Diameter (mm)	Height (mm)	Aspect ratio (-)	Mass(g)
Maximum	92.2	85.0	1.08	348.0
Minimum	63.2	51.8	1.22	170.0
Average	82.2	70.4	1.17	261.2
S.D.	4.7	5.3	0.07	39.5

The shape factor or complexity, which can be expressed as the ratio (perimeter^2/area), was calculated (Kondo, (1998)). This is a dimensionless quantity that measures the elongation of shape. In case of a circle, the shape factor can be calculated using the next equations.

$$P_C = 2 \times \pi \times r_c \qquad (10)$$

$$A_C = \pi \times r_c^{\,2} \qquad (11)$$

where P_C is the perimeter of the circle, A_C is the area of the circle and r_c is the radius of the circle. Thus, the shape factor, S_C, of the circle is;

$$S_C = 4 \times \pi = 12.6 \qquad (12)$$

In case of the Fuji apple, the perimeter and area was calculated using the formula of the ellipse using the diameter as the major axis and the height as the minor axis. The next equations show the calculation of the shape factor of the *Fuji* apple.

$$P_F = 2 \times \pi \times \sqrt{(d^2 + h^2)/2} \qquad (13)$$

$$A_F = \pi \times d \times h \qquad (14)$$

where P_F is the perimeter of the fruit, A_F is the area of the fruit, d is half the average diameter, and h is half the average height of the fruit.. Thus, the shape factor, S_F, of the *Fuji* apple is;

$$S_F = 2 \times \pi \times (d^2 + h^2) / d \times h = 12.7 \qquad (15)$$

From the results above, the Fuji apple seems to have a shape of the circle because its shape factor is almost equal to a circle.

COLOR MODELS OF THE APPLE TREE

The LCD model and the chromaticity model were used to analyze the apple image. Figure 4 shows the Visual Basic form of the LCD model of the apple image. It was clear that the fruit, leaf, and branch portions had different luminance and color difference of red. The fruit portion had the highest color difference of red value, followed by the branch portion and the leaf portion with the lowest color difference of red value. Relative to the color difference of red, the distance of the mean of the fruit from the means of the leaf and the branch was larger as compared to the randomness of the class. This was showed by $D_{1,}$ which seemed to be horizontal. The equations of the three decision functions were listed in equation 16. These were derived by the minimum distance classifier. Since the study was focused on differentiating the fruit portion, only decision functions D_1 and D_2 were used in the segmentation process. A pixel was regarded as a fruit portion if D_1 and D_2 were greater than zero, otherwise the pixel was a background. Although, D_1 and D_2 were required, it was obvious from the figure that D_1 alone could segment the image

$$\begin{bmatrix} D_1 \\ D_2 \\ D_3 \end{bmatrix} = \begin{bmatrix} 19.64 & 74.55 & -4326.56 \\ 41.47 & 41.55 & -7527.85 \\ 21.83 & -35.00 & -3133.80 \end{bmatrix} \begin{bmatrix} Y \\ C_R \\ 1 \end{bmatrix} \quad (16)$$

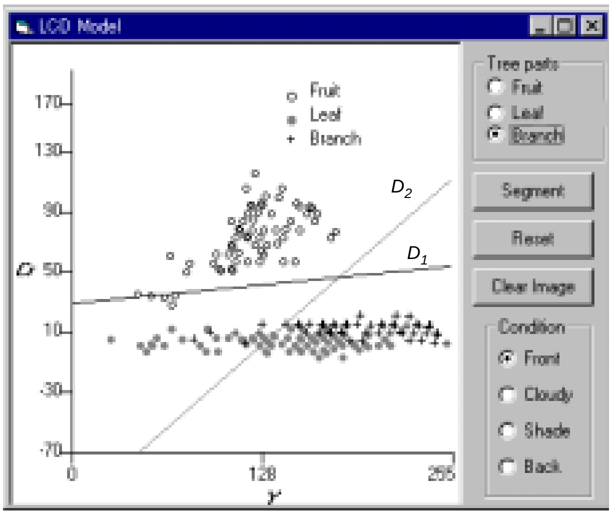


Figure 4 LCD Model of Apple Tree.

The Visual Basic form of the chromaticity model of the apple image is shown in Figure 5. The fruit, leaf, and branch portions had different values of *r* and *g*; which means that the three tree portions had different chrominance. The fruit portion had the highest *r* value and the lowest *g* value. The leaf portion had the highest *g* value and the lowest *r* value. The branch portion was in between the fruit and the leaf. The equations of the decision functions are listed in equation 17. It was observed from Figure 5 that the minimum distance classifier was effective in differentiating the fruit from the two portions because the portions had a large mean difference and a low randomness among each portion. Compared to the LCD model, both decision functions were required for the segmentation of the image. It was clear from both models that the minimum distance classifier would not be successful in separating the leaf and the branch because the mean values of the two portions were small compared to its randomness. However, this did not affect the segmentation of the fruit from the two portions.

$$\begin{bmatrix} D_1 \\ D_2 \\ D_3 \end{bmatrix} = \begin{bmatrix} 0.13 & -0.13 & 0.00 \\ 0.07 & -0.05 & -0.01 \\ -0.06 & 0.08 & -0.01 \end{bmatrix} \begin{bmatrix} r \\ g \\ 1 \end{bmatrix} \quad (17)$$

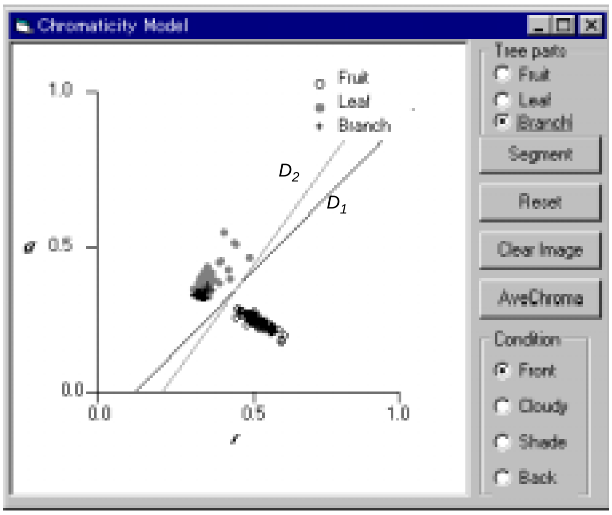


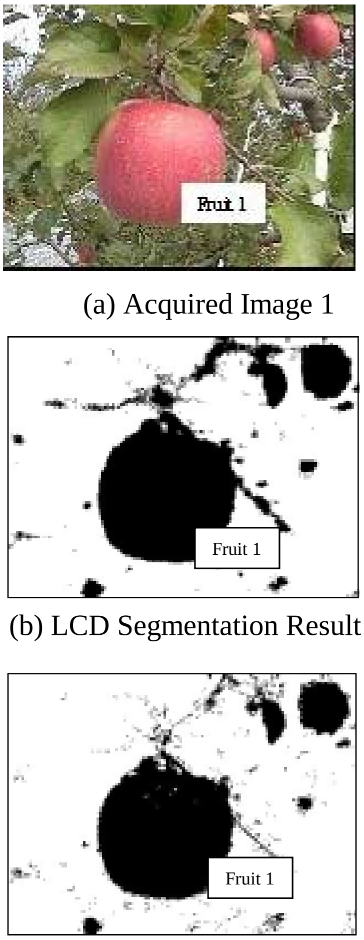
Figure 5 Chromaticity Model of Apple Tree.

RECOGNITION OF THE APPLE FRUIT

Two sample images are shown in this paper. The first sample image is shown in Figure 6(a). This image was taken under natural daylight condition during a fair weather at midday. In this paper, this was considered as a bright image. Figure 6(b) shows the result of the segmentation using the decision functions derived from the LCD models while Figure 6(c) shows the result of the segmentation using the decision functions from the chromaticity model. Figure 7(a) shows the second sample image, which was considered as a dark image because the fruit was in the shade. Figure 7(b) and Figure 7(c) show the result of the segmentation using the decision functions from the LCD and the chromaticity models respectively.

The segmentation using the decision functions from the LCD and chromaticity models had effective results as shown in Figures 6 and 7. Equation 16 was used for segmentation by the LCD model and equation 17 was used for segmentation by the chromaticity model. Results from both the LCD and chromaticity segmentation had a success rate above 90% with a noise rate below 5%. A good machine vision system should have a high recognition rate so that the succeeding processes such as feature extraction and fruit location would also have a high success rate. If the system fails to recognize the object, the succeeding procedures would also fail. Furthermore, a machine vision system with a low noise rate would also improve the system because it would reduce the processing time. Noise filtering process would take less time if there is less noise.

Twelve apple images were tested to evaluate the performance of both models. The correct area segmented and the misclassified area were measured. The misclassified area was considered as noise. Both LCD and chromaticity models had a success rate of above 80% while the noise rate for both models was below 10%. The high success rate and the low noise rate showed that the decision theoretic approach was effective in calculating the thresholds for segmentation.

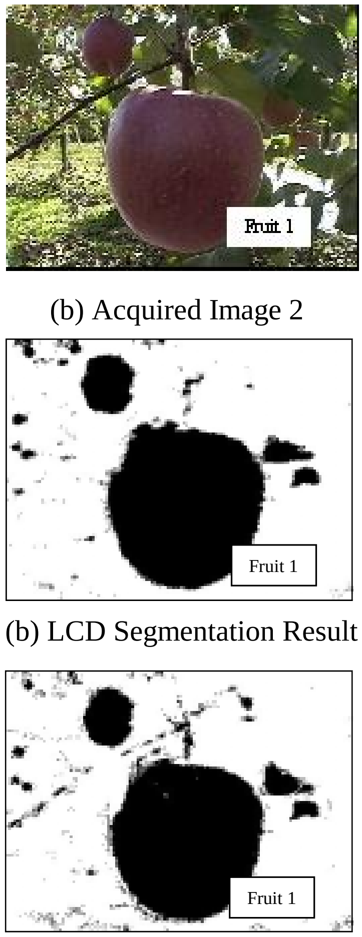


(a) Acquired Image 1

(b) LCD Segmentation Result

(c) Chromaticity Segmentation Result

Figure 6 Acquired and Segmented Images (1).



(b) Acquired Image 2

(b) LCD Segmentation Result

(c) Chromaticity Segmentation Result

Figure 7 Acquired and Segmented Images (2).

ESTIMATION OF FRUIT CENTER AND ABSCISSION LAYER LOCATIONS

From the apple and peduncle geometrical model, it was found that the average value of angle α is 46.8° with a standard deviation of 3.1. It was also found that the *x* coordinates of the apple center and the abscission layer of the peduncle had similar values. It means; if a vertical line is drawn on the apple center, the peduncle center lies on the same vertical line. Based from these results, the following steps were proposed to locate the abscission layer (Figure 8):

(Step 1) Capture and digitize an image.

(Step 2) Segment the image using thresholding with decision functions from the LCD or chromaticity models.

(Step 3) Filter the segmented image from noise.

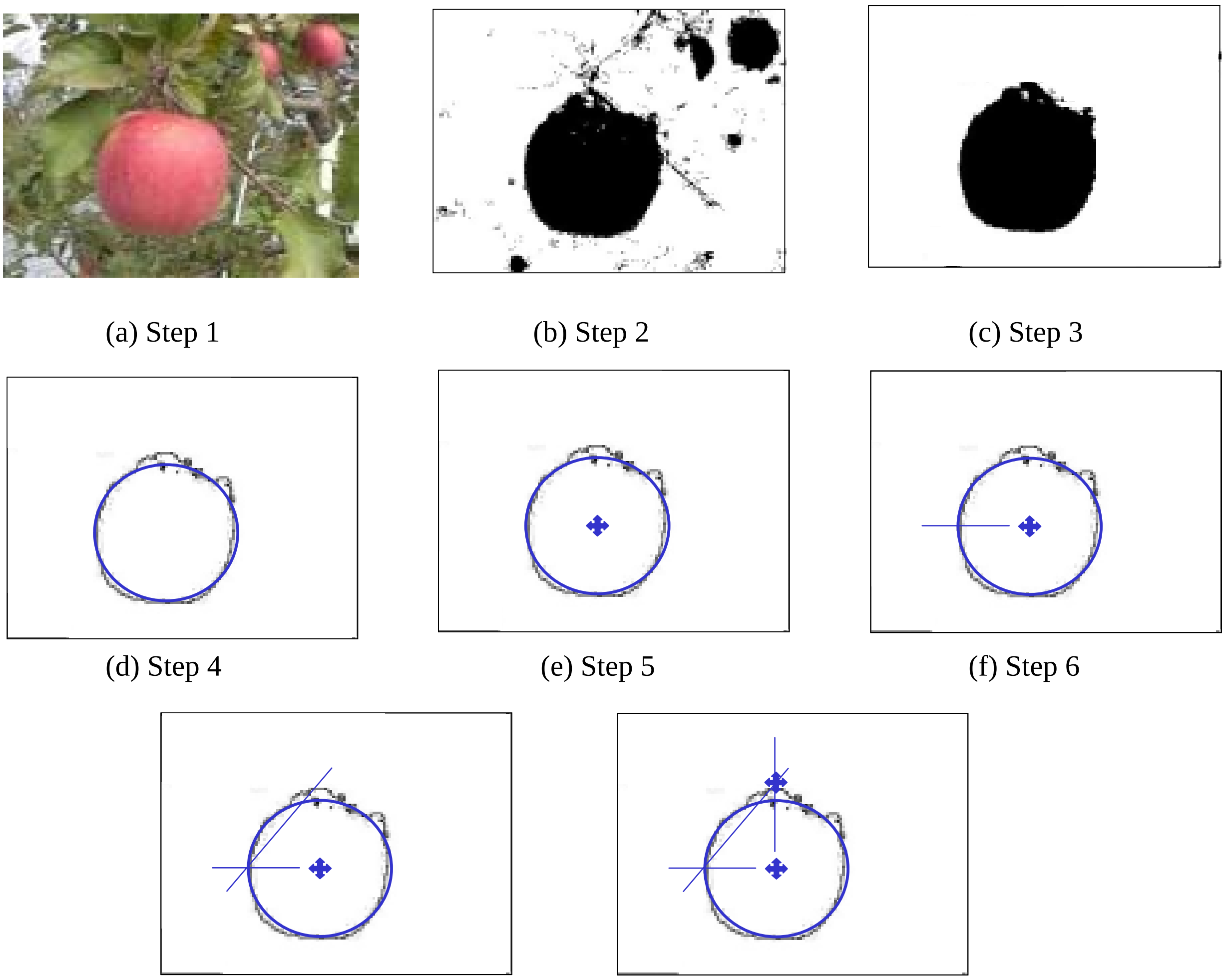
(Step 4) Find the edge of the fruit and estimate a circle that best fits the fruit because the shape factor of the fruit is nearly equal to 12.6.

(Step 5) Locate the center of the circle.

(Step 6) Project a horizontal line passing through the center and intersecting the leftmost perimeter of the apple.

(Step 7) Draw a line passing through the intersection of the horizontal line and the leftmost perimeter using the angle α as the slope.

(Step 8) From the center of the apple, project a vertical line until it intersects the line in (Step 7). The intersection is the location of the abscission layer.



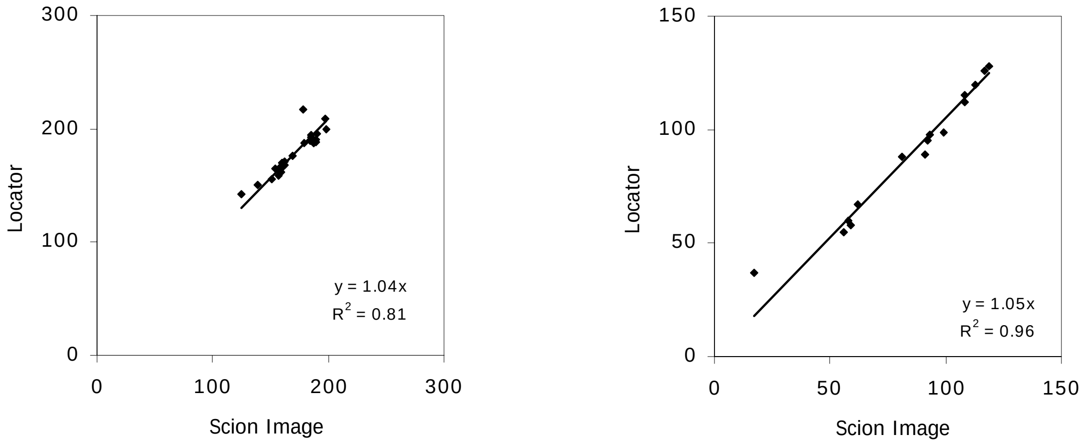
(a) Step 1 (b) Step 2 (c) Step 3

(d) Step 4 (e) Step 5 (f) Step 6

(g) Step 7 (h) Step 8

Figure 8 Image Processing Procedures to Locate Fruit Center and Abscission Layer

Since the steps mentioned above could be implemented with established image processing procedures, a program that would locate the apple fruit center and the abscission layer was developed. The program was named the Locator. The Locator was evaluated using 15 sample images and was compared with the measurements made using Scion Image. This software is an image processing and analysis program that can be used to measure area, centroid, perimeter, etc. of user defined regions of interest. Measurements could be performed manually or automatically using macros. Locator was compared with Scion Image because spatial calibration is supported to provide real world area and length measurements. The sample images tested were single fruits. Figure 9(a) shows the comparison of the *x* coordinate of the abscission layer measured by the Locator and Scion Image. The coordinates were in pixels. The regression line of Figure 9(a) shows that the Locator and Scion Image had similar results. The correlation coefficient was also high at 0.81. Likewise, Figure 9(b) shows the comparison of the *y* coordinate of the abscission layer measured by the Locator and Scion Image. The regression line of Figure 9(b) shows a slope almost equal to one and a correlation coefficient of 0.96. These results showed that the Locator was able to detect the coordinates of the abscission layer.



(a) *x*-coordinate of Abscission Layer (b) *y*-coordinate of Abscission Layer

Figure 9 Comparison of the Performance of Locator and Scion Image Software

While three coordinates are required by the robot to approach the fruit, studies have shown that a two-dimensional image is sufficient to determine the third coordinate or the distance from the camera to the fruit. The proposed machine vision system would be mounted on the manipulator; it will use the differential object size method to determine the distance. In this method the relation between image size and distance from camera to object are used. As the camera moves toward the object, the image size of the object increases. However, further field experiments will be conducted to evaluate this method and its accuracy.

CONCLUSION

A machine vision system to recognize the location of the fruit center and abscission layer of the peduncle was developed. The machine vision system consisted of a color CCD camera for image acquisition and a personal computer for image processing. In recognizing the apple, two color models were used: the LCD model and the chromaticity model. Decision functions were derived from the color models and these were used as the thresholds in the segmentation procedure using multivariable thresholding. Experimental results showed that the thresholds derived from both models could segment at least 80% of the apples.

On the other hand, the location of the fruit center was estimated by the standard image processing techniques while the location of the abscission layer of the apple fruit was determined using the geometrical property of the three points of the apple fruit namely, the apple center, the intersection point of the horizontal line passing through the fruit center and the left perimeter of the fruit, and the abscission layer. However, the location that is given is two-dimensional. The third dimension or the depth can be determined using the differential object size method. Field experiments will be made to evaluate the developed recognition and locator algorithm. The experiments will also evaluate the accuracy of the differential object size method.

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