Machine Vision Algorithm of Eggplant Recognition for Robotic Harvesting

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Abstract

A machine vision algorithm to recognize eggplant fruit and estimate its size for selective robotic harvesting was developed and tested. Images acquired in both outdoor and indoor conditions were examined. The algorithm was designed for a two-step operation. The first step was a simple color segmentation to distinguish low intensity for speeding and the second step was a vertical-dividing operation using two templates to eliminate noise such as stems and leaves. The vertical-dividing operation could exclude 60-pixels-length object and cope with the fruit angle up to approximately 20°. The algorithm could recognize eggplant fruits accurately at a high ratio from 80.0 to 97.5% with the operating time of approximately 1 sec. The fruit length and the fruit maximal diameter, which would be indices of selective harvesting, were estimated from geometric features of the fruit binary image. Estimation accuracy of the fruit maximal diameter was varying from 16.0 to 21.5% and higher than the one of the fruit length.

Keywords : machine vision, eggplant, image recognition, selective harvesting, size estimation

Introduction

Eggplants are one of the most valuable vegetables widely cultivated in Japan. In 1997, about 475,000 tons of eggplants were produced in an area of 14,000 ha¹⁾. A survey in 1997 revealed that the labor employed in harvesting eggplants was 7,197.1 hrs/ha out of total working hours of 18,866.8 hrs/ha in a greenhouse production²⁾. Eggplant harvesting is a labor-intensive and complex work, therefore, it is usually done manually by cutting peduncle in a traditional production. This work hinders vegetable growers from expanding the production scale. Moreover, with the aging of the vegetable growers and the increasing ratio of female laborers, mechanization of the harvesting work using a robotic system has been more desirable. For the development of eggplant

harvesting system, selective harvesting is indispensable, since the eggplants are harvested in the process of thickening, in addition, grading after harvest is severe due to the market demand for high quality. Out of fundamental techniques of robotic harvesting system, a visual sensor seems to be a key technology because of complexity of biological product. In other words, the peculiarity, such as random location of fruit bearing, variable fruit shape and wide range picking size, makes the development of a visual sensor difficult.

Image processing technique is a vital tool for recognizing an object and the general approach is to segment a target from background using chromatic information such as spectral reflectance. Slaughter and Harrell demonstrated that the natural contrast in color between fruit and other objects in a color image could be used to differentiate citrus fruits from background leaves, soils and the sky³⁾. Kawamura *et al.*

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detected tomato by the difference between R signal and brightness⁴⁾. Tillett and Batchelor developed an algorithm, which uses knowledge of the shape of a mushroom, to track around the outline in the gray-level image⁵⁾. Other studies using morphological features have also been reported. Batchelor and Searcy determined a location of stem/root joint of carrots as an indicator for proper cutting location⁶⁾. Simonton measured position and orientation of geranium cutting⁷⁾. Tian *et al.* identified tomato seedlings from the soil and weed in outdoor fields⁸⁾. For targets, such as cucumber and eggplant fruit, which have a similar color with leaves and stems, it is necessary to exploit an advance algorithm. Kondo *et al.* developed an algorithm to facilitate cucumber recognition by connecting the centerline of binary objects, even though leaves occluded the fruits⁹⁾. With regard to eggplant recognition, less work has been done. Kondo *et al.* reported chromatic characteristics of eggplants using R, G and B filters¹⁰⁾. Moreover, Kondo measured spectral reflectance of eggplants and concluded that 800–900 nm wavelength was efficient for fruit detection and the reflectance of the fruit and stem was low in the visible spectrum¹¹⁾. The studies, however, were confined to show the feasibility of machine vision recognition.

The prior criterion for the development of a machine vision algorithm to be installed to a robotic harvesting system is computational cost. A high-speed machine vision algorithm enables a manipulator to implement a real-time control for harvesting potentially swaying fruits. A pattern matching technique could have been considerable but it was not employed in this study because it generally takes a long operation time in the case of random target sizes and random target locations. Moreover, the machine vision algorithm is required to measure fruit size and to be used under outdoor natural conditions. On the other hand, the eggplant fruit can be exposed by the trimming the leaves and stems so as to facilitate fruit recognition. In this study, eggplant morphological data was corrected to identify indices for selective harvesting and a two-step algorithm, with a combined color segmentation operation and an operation, which divides objects vertically (vertical-dividing opera-

tion), was developed. The objectives of the study were as follows:

- (1) To discuss morphological features of eggplant required for the development of the machine vision algorithm.
- (2) To describe the algorithm of eggplant recognition combined with a color segmentation operation and a vertical-dividing operation.
- (3) To evaluate the algorithm performance by applying it to eggplant images acquired in outdoor and indoor conditions.

Materials and methods

Eggplant dimensions and fruit angle

Eggplants generally vary significantly in size and shape with variety, so a variety with the shape of long-eggs known as 'Senryo 2' and widely cultivated in Japan was selected and used in this study. Fruit weight is the most important index for selective harvesting. To identify indices for selective harvesting, the relationship between fruit weight and dimensions of several parts of eggplant crop were investigated on 40 samples. The measured dimensions were length of fruit, length of calyx, maximal diameter of fruit, minimum diameter of fruit, length of peduncle, diameter of peduncle, diameter of fruit bearing stem. Fig. 1 shows the relationship between the fruit weight and the dimensions measured and Table 1 indicates the correlation coefficient. The graph shows that the

Fig. 1 Relationship between fruit weight and eggplant dimensions

Table 1 Correlation coefficient between fruit weight and eggplant dimensions

Variety	Length fruit	Length calyx	Max. diam. fruit	Min. diam. fruit	Length peduncle	Diam. peduncle	Diam. fruit bearing stem
'Senryo 2'	0.95	-0.07	0.97	0.91	0.68	0.56	0.33

length, the maximal diameter and the minimum diameter were increased as the fruit grows, and the correlation coefficients were also high. However, it would be difficult for a visual sensor to measure the minimum diameter because its rate of increase was low, so the fruit length and the maximal diameter could be considered more appropriate indices for selective harvesting.

In addition, fruit angle was investigated as fruit inclination to the vertical. Photos of fruits were taken from the direction perpendicular to the row and the inclinations of the fruit to the vertical were measured. Accordingly, the average angle of 'Senryo 2' was 7.8° and the standard deviation was 5.0°. It is thus valid that the fruit could set almost in a vertical way.

Machine vision system

The machine vision system was composed of an AT compatible computer (DEC Japan, Lpx 560), an image processing board (Sharp Semiconductor, GPB-1) and a CCD camera (Sony, XC-003) with a 6 mm automatic iris lens. The image processing board had 12 frames with 512(H) × 480(V) pixels with 255 gray levels, and an optional board with three AD converters was attached on the image processing board. Accordingly, the three images (R, G and B) could be captured simultaneously without a gap, although a target potentially sways by wind or other forces. An average image acquisition time was 33 ms.

Image processing technique

Color segmentation has proven to be one of the most important ways to distinguish biological targets. Using a color information of eggplants, which falls within the low spectral reflectance in the visible spectrum¹¹⁾, a two-step machine vision algorithm to recognize eggplants was developed. The first step was a color segmentation operation to detect possible fruit portion, and the second step was a vertical-dividing operation to extract long and vertical object. The machine vision program was developed on the AT compatible computer using C language. Fig. 2 shows the flowchart and the process was as follows.

Fig. 2 Flowchart of the machine vision algorithm

First, the two templates, Template A and Template B, were prepared in the frames for the vertical-dividing operation. They were cross stripe patterns shown with white color against black background as described in Fig. 3. The pattern consisted of 3-pixels-width vertical lines with 3-pixels interval and 20-pixels-width horizontal lines with 60-pixels interval. Template B was the one that the horizontal lines in Template A were got down 40 pixels.

Second, the fruit image captured in the manner described in the following section was loaded in the frames.

Third, the color segmentation operation was applied. A gray image was derived by adding three RGB images. The low intensity pixels in the gray image were segmented using a threshold value determined by a discriminant analysis. Then, red background pixels were segmented from gray image de-

Fig. 3 Construction of Template A and Template B

Fig. 4 Vertical-dividing operation by the two templates

rived by subtracting G image from R image, and binary image of the red background was eliminated from the fruit binary image. Moreover, green leaf pixels were segmented and eliminated from the fruit binary image in the same manner as the red background, so that some noises would disappear. This operation might, however, classify stems and leaves as fruit, since they have a similar color with the fruit.

Forth, the vertical-dividing operation was applied. A long and vertical portion in the fruit binary image would be considered as most possible fruit portion, because the eggplant fruits set almost vertically. Fig. 4 illustrates the vertical-dividing operation. After color segmentation, the fruit binary image including

stems and leaves (Fig. 4-a) could be divided vertically by calculating logical product between the fruit binary image and the two templates (Fig. 4-b, 4-c). Here, the portions less than 60 pixels in length would be divided into 3-pixels-width lines. Only the maximal area objects from the Template A and B remained (Fig. 4-d, 4-e). By calculating logical product of both maximal area objects, several long lines with 3-pixels-width could be obtained. These several long lines could be joined after applying the swelling operation, so that the final object could be recognized as a fruit (Fig. 4-f).

Finally, the program computed five geometric features of the fruit binary image, namely area, centroid,

filet diameters, maximal axis length and maximal width defining the maximal distance between two lines that are parallel to the direction of the maximal axis and contact with the object.

Evaluation test of the vertical-dividing operation

The vertical-dividing operation could eliminate the objects less than 60 pixels in length theoretically, so a test to evaluate the vertical-dividing operation was conducted. A fruit binary image including the stem was created manually, and it was composed of a fruit binary image and a diagonal line inclined by 45° from the top-left to the bottom-right (Fig. 5-a, Fig. 5-b). The vertical length of the diagonal line defining as the L_v in Fig. 5-a was changed from 0 pixel to 75 pixels by 15 pixels, on the other hand, the fruit binary image was rotated counterclockwise from -20° to $+20^\circ$ by 5° . Then, the area of fruit binary image after the vertical-dividing operation was counted. Here, the area of the fruit binary image before the operation was 43,310 pixels.

Image sample acquisition

Image samples were recorded under three different lighting conditions, namely '400 mm Outdoor', '400 mm Indoor' and '200 mm Indoor'. For example, '400 mm Outdoor' means that the camera was placed at 400 mm away from the target in the outdoor condition. '400 mm Indoor' and '200 mm Indoor' were defined in the same way. 40 images were captured in each acquisition condition using the machine vision system. An illumination around a fruit varied from 14,000 to 110,000 lux in the outdoor condition and from 450 to 550 lux in the indoor condition, respectively. In addition,

a red curtain was used to control background color in all indoor acquisitions. Focus was adjusted manually according to the distance and exposure was adjusted using automatic iris function of the lens.

Transformation coefficients of pixel to size are required to evaluate the accuracy of the algorithm. Euclidean distances of diagonal line in the frame at 400 mm away and in the frame at 200 mm away were measured. Results of 0.474 mm/pixel at '400 mm' and 0.226 mm/pixel at '200 mm', respectively, were obtained as the transformation coefficients. The estimated fruit size was computed from the binary image size by multiplying the coefficient. Thus, the length of 60 pixels, which could be eliminated by the two templates, became 28.4 mm at '400 mm' and 16.6 mm at '200 mm'.

Results and discussion

Evaluation results of the vertical-dividing operation

The results of the experiment of the vertical-dividing operation are shown in Table 2. The sample images of the vertical-dividing operation are shown in Fig. 5-b and 5-c. As the L_v of the diagonal line increased, the operation could not eliminate noise, then the recognition area increased. The error of area extraction was approximately 15% at the L_v of 60 pixels, and the diagonal line with the L_v of 75 pixels was not excluded. Although it was reasonable that the error of area extraction increases as the fruit inclines, there was no obvious difference in the range from -20° to $+20^\circ$. Therefore it is valid that fruit angle could be neglected on fruit recognition by the

Fig. 5 Result of vertical-dividing operation: The area of the fruit binary image was 43,310 pixels and the rotation angle was 0° . The L_v and the A_i of the diagonal line were 45 pixels and 45° respectively.

Table 2 Effect of the rotational angle of the fruit binary image and the L_v of the diagonal line on fruit extraction(%)

L_v of the diagonal line	Rotational angle of the fruit binary image								
	-20°	-15°	-10°	-5°	0°	+5°	+10°	+15°	+20°
0 pixel	99.50	99.11	99.49	99.82	99.82	100.40	100.45	100.49	100.37
15 pixels	99.78	99.18	99.84	99.87	100.06	100.43	100.48	100.63	100.56
30 pixels	101.32	100.63	100.54	100.42	100.30	100.63	100.86	101.05	101.91
45 pixels	103.46	102.66	102.44	102.12	101.88	102.22	103.85	103.02	105.07
60 pixels	117.45	116.52	116.19	115.67	114.56	114.09	112.93	111.15	109.09
75 pixels	153.69	152.69	152.30	151.59	150.30	149.67	148.30	146.32	144.02

Fig. 6 Recognition results by the machine vision algorithm

machine vision algorithm.

Recognition of eggplant fruit

The algorithm was tested on 40 samples in each acquisition and the final fruit binary images were evaluated by classifying into 5 detection groups, namely 1) whole/part fruit detection, 2) fruit and shadow detection, 3) shadow detection, 4) other fruit detection, and 5) no detection. The recognition results are shown in Fig. 6. The algorithm recognized the whole/part of the fruit at a rather high ratio, so the number of successful recognition were 36 images(90.0%) at '400 mm Outdoor', 32 images(80.0%) at '400 mm Indoor' and 39 images(97.5%) at '200 mm Indoor'. Typical operation samples in outdoor condition are shown in Fig. 7 and 8. The part detection was caused by halation on upper portion of the fruit, in other words, the color information of this

portion was lost because of its glossy nature (Fig. 7). Since a similar phenomenon have been observed in the previous study¹⁰⁾, a further study to overcome this problem would be necessary. On the other hand, recognition failures were observed in several images. For example, a fruit and a shadow were detected simultaneously because of overlapping of the fruit and the leaves more than 60 pixels in length, and a shadow only was detected under direct natural sunlight. Then, other fruit at the back of the target was detected because the image area was larger than that of the target. There were also instances where the algorithm detected no object on three images at '400 mm Outdoor' under direct natural sunlight and two images at '400 mm Indoor', respectively. This is because the Template A and B remained individual maximal objects in the vertical-dividing operation.

Compared '400 mm Outdoor' and '400 mm Indoor', the recognition performance of the algorithm was quite satisfactory, although there were instances that the algorithm detected erroneously the shadows at '400 mm Indoor'. It was found that the algorithm would be robust on wide variation of lighting level.

Regarding the effect on the distance, the ratio at '200 mm Indoor' was higher than the one at '400 mm Indoor'. It was reasonable to suppose that the closer acquisition distance, the higher the ratio of recognition. That is to say, noise was eliminated efficiently by the color segmentation operation and the vertical-dividing operation, because the target became larger in the frame at the close camera position.

Processing time

Processing time of the algorithm was measured in each acquisition condition. Average processing times were 0.83 sec at 'Outdoor 400 mm', 0.89 sec at

Fig. 7 Image samples in direct sunlight natural condition

Fig. 8 Image samples in indirect sunlight natural condition

'400 mm Indoor' and 1.02 sec at 'Indoor 200 mm' respectively. The algorithm seemed possible to be used for visual feedback control from these results. In addition, the algorithm could recognize at a rather high speed at 400 away as compared with the one at 200 mm away. It was assumed that the binary area before the vertical-dividing operation affected processing time, since a labeling process in the vertical-dividing operation took a long time in the case of the large target.

Accuracy for eggplant size estimation

The accuracy for fruit size estimation was evaluated on the samples of successful recognition. The

fruit length and the fruit maximal diameter were estimated from the maximal axis length and the maximal width in the fruit binary image, respectively. The results of the size estimation are shown in Table 3. The diameter estimation was better than the length estimation in all acquisitions. The algorithm underestimated the fruit length because of the halation at the upper part (sample shown in Fig. 7).

Comparing '400 mm Indoor' and '200 mm Indoor', the accuracy for the diameter improved as the camera got closer, because the algorithm could eliminate the noise efficiently at '200 mm Indoor'. The accuracy for the length, however, dropped resulting in an underestima-

Table 3 Results of fruit size estimation by the machine vision algorithm

	400 mm Outdoor (36) *		400 mm Indoor (32) *		200 mm Indoor (39) *	
	Length	Diameter	Length	Diameter	Length	Diameter
Ave. error(%)	33.5±20.3	19.9±16.0	25.6±20.0	21.5±21.5	33.6±12.7	16.0±12.5
Correlation coefficient	0.25	0.55	0.51	0.47	0.60	0.70

* : Number of samples succesful recognition

a. Original Image

b. Fruit binary image

Fig. 9 Image samples at '200 mm Indoor' **Fig. 10** Relationship between the actual diameter and the estimated diameter at '200 mm Indoor'

tion at '200 mm Indoor'. This was because that the fruit binary image could not fit into the frame for several samples as shown in Fig. 9. The relationship between the actual diameter and the estimated diameter at '200 mm Indoor' is shown in Fig. 10. It was noted

that the algorithm could be used to estimate the diameter but still has an estimation error, so further research needs to be conducted to improve the accuracy and to counter with a halation.

Conclusions

This study has led to the feasibility that eggplants could be discriminated by the machine vision. The algorithm was robust to light level because simple color segmentation was used to obtain the eggplant fruit binary image. Moreover, the vertical-dividing operation eliminated noise such as leaves and stems based on the morphological characteristic that the fruit bears almost vertically, and it could be valid that there was no effect of fruit angle on fruit recognition. The algorithm could recognize potentially at a high ratio, although it is observed that the algorithm detected erroneously both the fruit and leaves because of overlapping. The machine vision algorithm could accurately estimate the fruit maximal diameter, which would be one of the indices for selective harvesting. Underestimation of the fruit length, however, was

observed when the halation on the fruit surface occurred in the direct sunlight condition. The other cause of the underestimation was that the fruit could not fit into the frame when the camera was at close range. Further, the processing speed showed the possibility of the algorithm to be used for visual feedback control of the harvesting system. Consequently, the machine vision using the developed algorithm would provide a fundamental function of the robotic eggplant harvesting.

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ロボット収穫のためのナス認識マシンビジョンアルゴリズム

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