Research Paper

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# Accurate Position Detecting during Asparagus Spear Harvesting using a Laser Sensor

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**Abstract**

A serious problem in Japanese agriculture is the aging and shortage of farm laborers. Agricultural robots are expected to solve or alleviate this problem, as well as provide additional information about agricultural products. In this research, we focus on machine vision for an asparagus harvesting robot. Although TV cameras are often used for machine vision in harvesting robots, it is difficult to use them in direct sunlight, due to fluctuations in illumination intensity and color temperature effects of sunlight. So a laser sensor was used. This sensor detected asparagus spears based on their distance from sensor and their length. Total success rate of detection was 75 % of asparagus spears and 71 % of parent asparagus.

[Keywords] harvesting robot, machine vision, laser sensor, asparagus

## I Introduction

Agricultural issues in Japan include operators' aging and shortage, low food self-sufficiency, insufficient food security and safety. Agricultural robots are expected as a method to solve those problems. Many robots have been developed so far such as for harvesting strawberry, eggplant, tomato, cucumber and other fruits (Kondo *et al*., 2004).

Nagasaki prefecture has a brand extension strategy for asparagus. Since asparagus is a high profit item, spreading of the growing area is expected. The amount of production of asparagus in Nagasaki was the third rank in 2006 in Japan. Asparagus harvesting operation is, however, laborious and painful because of bending at the waist for a long time. In addition, it is necessary to harvest asparagus spears everyday, because they grow up to 10 cm per day. Moreover temperature in greenhouses often becomes nearly 40 °C in summer, so harvesting operation is harsh conditions and is limited only to the morning (Taguchi *et al*., 2008). The number of asparagus spears harvested by hand is limited to about 2000 per day and development of a harvesting robot is desirable.

The most important sensor of the harvesting robot is machine vision. Most machine vision harvesting robots use color TV cameras, because fruits were different colors from leaves and stems. However, the color TV cameras are not effective to detect asparagus spears, because the target spears have green color which is similar with parent plants, while the parent plant sizes are much different from the other small spears. Another problem to use the color TV camera is to adjust the camera settings following the change of sunlight such as brightness and color temperature. In addition, corresponding problem when many targets were in a camera field should be solved when the target position was detected by the stereo vision method. From these reasons, a laser sensor was used as a machine vision of the harvesting robot in this research and three dimensional images were obtained. Monta reported a harvesting robot with a laser sensor for tomato (Monta *et al*., 2003). Although precise size, shape and location are detected by laser sensor, it was difficult to identify the color change from green to pink or red. However asparagus harvest is based on their length, so in this research we don't have to take color into consideration.

One of the reasons why no harvesting robot has been commercialized is that robots' operation speed is slower than human's. For example, speed of a developed strawberry harvesting robot was 13 s for picking a fruit in night time (Hayashi, *et al*., 2010). In asparagus harvesting operation, three times higher harvesting speed than human are 6000 spears in a day. This means the machine should harvest asparagus in less in than 10.8 s if it works 18 hours in a day. To shorten this time two laser sensors were used.

Another difficulty is plant training system. A lot of asparagus spears are usually overlapped with parent plants and some of them were obstacles for robot operation. The plant training system should be adaptable so that the robot

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can harvest spears easily as they tried to do for tomatoes, cucumber, and strawberry in other harvesting robot projects (Monta *et al*., 2004, Kondo *et al*., 1998). It is not easy to change plant training system in asparagus, because asparagus grows with rhizome and many spears unexpectedly come out from ground surface (Shiigi *et al*., 2009). In this research, a laser system was used for the asparagus whose parent plants were grown in center while spears were in both edges in ridge.

## II Materials

### 1. Cultivation training

The date of this experiment was from August 31th to September 2nd in 2009. The target asparagus was grown at Nagasaki prefecture. Cultivation training allows half-term forcing that is able to harvest asparagus constantly. Each ridge is 25 m long and 0.80 m wide. In order to make it easier to harvest for robot, parent asparagus was put in the center of ridge and harvest target could grow at the edge of ridge, and the height of top surface was 30 cm by plastic board (Fig. 1). The variety of the asparagus was ”welcome”, which is disease-resistant, thick and green.

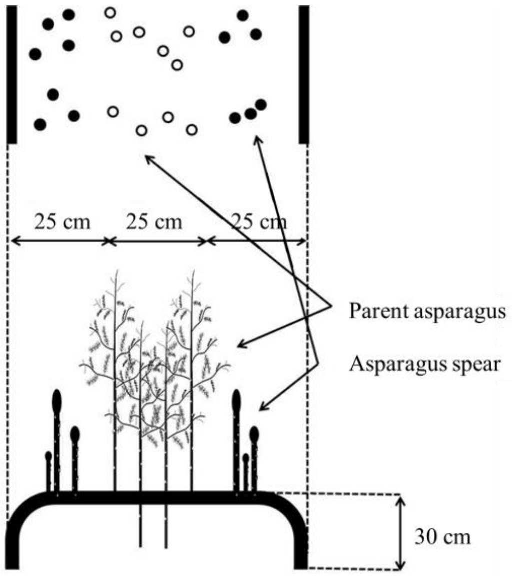



Fig. 1 Cultivation training of asparagus

### 2. Classification of asparagus based on their position

45 scenes were acquired by the laser sensor at day time and same scenes were done at night time. Measured asparagus spears were 102 and parent asparagus spears were 168. Before applying data, the three dimensional position of each asparagus, to detection algorithm, data were classified into three types of patterns like (Fig. 2). Harvesting target asparagus is recognized based on its length, but some of them were overlapped with steel poles in agricultural field, parent asparagus or asparagus leaves. These overlapping often made it difficult to recognize target asparagus. Class 1 means harvesting target grew independently, Class 2 shows some obstacle were behind harvesting target, and Class 3 includes an obstacle in front of harvesting target.

Class 1 Class 2 Class 3

Fig. 2 Class of asparagus based on overlap

## III Materials and Method

### 1. Experimental equipment

#### (1) Laser sensor

Laser sensor was made by Hokuyo Automatic Co., Ltd. The specification of this sensor is shown in Table 1. The light source of this sensor is infrared laser, which is low light interference. The advantages of using laser sensor are to be able to work at all day. The best distance from the sensor to the target can be regulated in 350 mm, because most of asparagus grow this range. Two identical laser sensors were used for measuring asparagus locations and lengths in greenhouse.

Table 1 Specification of laser sensor

| | |
|---|---|
| Name of Product | URG-04LX |
| Light Source | Infrared laser |
| Wave length | 785 nm |
| Angular resolution | 0.36° |
| Measurement range (Angle) | -120° ~ 120° |
| Measurement range (Distance) | 20 ~ 4000 mm |
| Accuracy | ±10 mm(white paper) |
| Response time | 100 ms |

#### (2) Motorized stage

The two laser sensors were set with a space of 160 mm and were moved vertically at the speed of 40 mm/s for 4 s by a motorized stage (SGSP46-500(Z), Sigma Koki Co., LTD). Maximum travel of this stage is 500 mm and position accuracy is 0.025mm. The stage is controlled by controller (SHOT-202, Sigma Koki Co., LTD). The motorized stage was set on a hydraulic carrying task wagon (BX 15, Sugiyasu Co). The field is adjusted for robot as plastic plate or iron rail like Fig. 3, so measurement error from field would be decreased. Asparagus data was obtained from three ridges. Fig. 4 shows how we detected positioning data of asparagus.

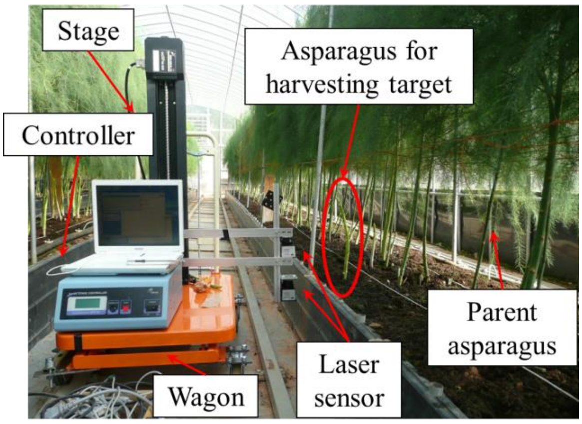



Fig. 3 Equipment for detecting asparagus

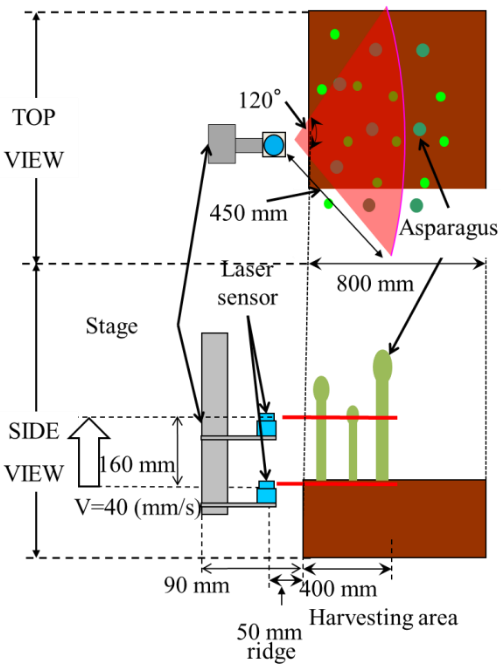



Fig. 4 Frame format of Fig. 3

## 2. Data acquisition

The number of data was 15 at each three ridges (total amount of data is 45). Harvesting target asparagus spears were 102 and parent spears asparagus were 168. Position of robot was decided based on growth area of asparagus spears classified three patterns (Fig. 2). Illumination condition was more than 60 klx in daytime.

## 3. Detection algorithm

Since asparagus spears in Class 1 were independent of obstacles, it is easy to recognize from its length, but Class 2 and Class 3 asparagus has an overlapping problem. We decided that the direction parallel to ridge is X, depth direction is Y and perpendicular to ground is Z and origin coordinate is the point the laser irradiated. Original data acquired from laser sensor consists of length and angle. Angle measurement range is adjusted from -60° to +60° and angular resolution is 0.36°, so there are 333 (= 120 / 0.36) points of data. Vertical scanning interval was 10 mm and the vertical scanning range was until 320 mm, and there are 33 points of data. Therefore we can get length value of polar coordinate in the image which range was 33 in vertical and 333 in lateral direction. Using two laser sensors, at first, the two data need to be connected. Because of misconnection between 15 mm and 16 mm, the data coming from upper sensor was corrected 0.36° in a clockwise direction. In order to detect length image, clustering of phase discrimination is usual, and usually general method is Gauss curvature (Wakizako *et al*., 1995). But in this experiment, Gauss curvature was not used to separate harvesting target asparagus from other objects, because most of asparagus comes out horizontally. So, first order partial differential and threshold processing was applied to length image, after that we extracted flat surface and separated harvesting target from parent asparagus. Threshold processing used binarization of the image differentiating to X direction by some threshold value. Threshold value was between -10 pixel and +10 pixel. This processing can discriminate harvesting target and overlapped obstacle in terms of X direction.

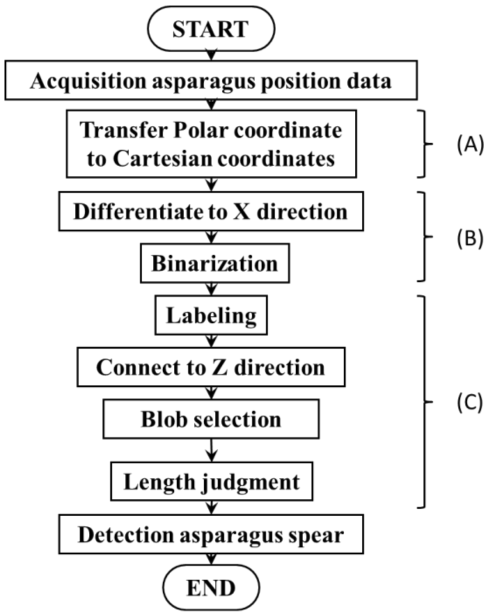
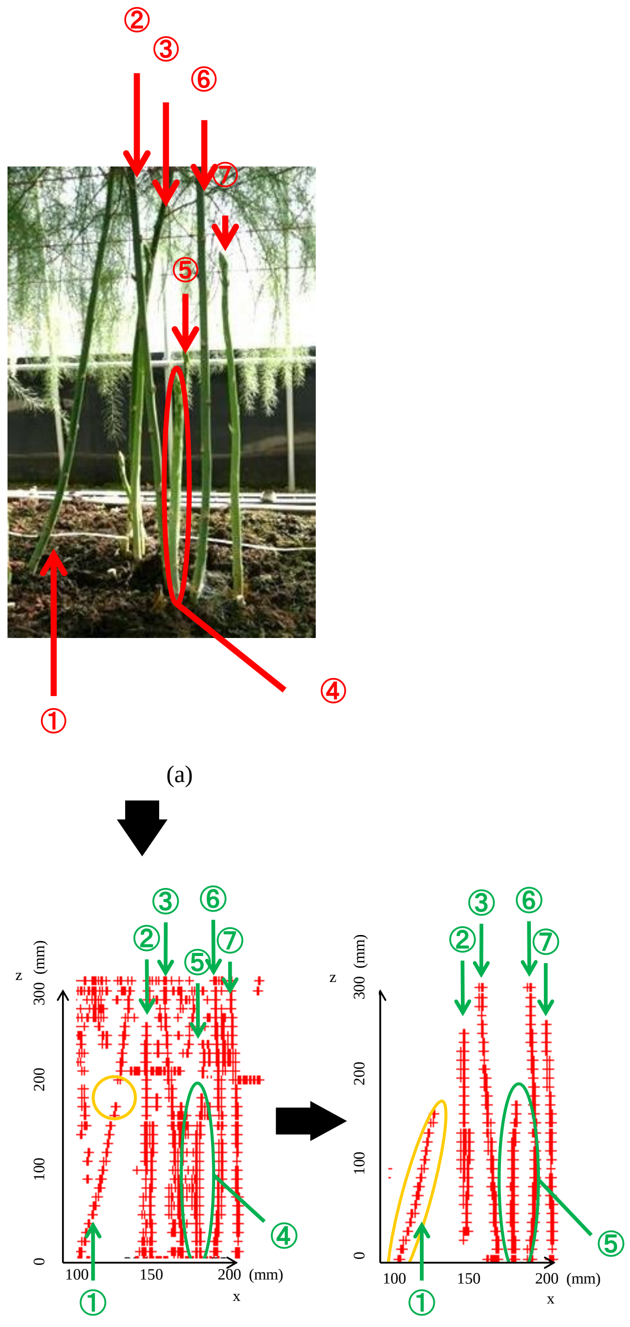



Fig. 5 Flow chart for detection algorithm

Labeling operation was based on actual data of two-dimensional location information and connected to Z direction. We then eliminated noise based on area, and detected harvesting target from its length. The ideal harvest length is up to about 25 cm and asparagus higher than 30 cm cannot be recognized as harvesting target. Fig. 5 is the flow chart for processing. Programming language of detection system was Visual Studio 2003 made by Microsoft.




(a)

(b) (c)

Fig. 6 Flow of processing

## IV Results and Discussion

Fig. 6 shows asparagus photograph and processed images in which four parent asparagus ((1); circled in the Fig.6, (2), (3) and (6)) and three spears ((4), (5) and (7)). Table 2 shows their diameters, lengths X and Y positions. These asparagus in Fig. 6 is the example of the operation how is the target detected. Yellow and green circles indicated the same asparagus in processed images. Fig. 6 (b) is the result of operation of (A) and (B) in Fig. 5 and Fig. 6 (c) is that of (C) in Fig. 5. In the photo of Fig. 6 (a), the number of asparagus from (1) to (7) corresponds to those of number in Fig. 6 (b). Here, parent asparagus length was over 30 cm, but yellow circled one ((1)) was separated into two parts after differentiation to X direction and connection to Z direction as shown in Fig. 6 (c).

Table 2 Asparagus in Fig .6

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Diameter (mm) | 12 | 14 | 15 | 11 | 12 | 14 | 12 |
| Lengths (mm) | * | * | * | 230 | 261 | * | 449 |
| X Coordinate | -205 | -20 | 115 | 0 | 20 | 55 | 120 |
| Y Coordinate | 350 | 405 | 455 | 215 | 460 | 230 | 235 |

* means more than 500 mm

(2) is a parent asparagus but its top and bottom were deleted in Fig. 6 (c), because it was far away from the sensor and the leaves overlapped at its head.

Only (4) was detected as a target spear for harvesting. (5) just behind (4) was also harvesting target, but its distance was more than 450 mm from the laser sensor, so that it could not be recognized from this side but from the opposite side of ridge. (6) and (7) are recognized as parent asparagus successfully. In this experiment, average diameter of asparagus is 12 mm and at least more than 10 mm asparagus could be recognized regardless parent asparagus or spear.

Y direction (depth) can be scanned from 0 mm to 4000 mm but in this processing, objects that are more than 450 mm from laser sensor are deleted. That's because the sensor is adjusted that the range of 350 mm is the best accuracy.

Table 3 Success rate for asparagus detection
(Each value in parentheses shows ratio in %)

(a) Asparagus spear

| | Class 1 | Class 2 | Class 3 |
|---|---|---|---|
| Day time | 19/21 (90) | 22/29 (76) | 4/10 (40) |
| Night time | 12/14 (85) | 15/20 (75) | 4/8 (50) |

(b) Parent asparagus

| | Class 1 | Class 2 | Class 3 |
|---|---|---|---|
| Day time | 26/28 (92) | 14/16 (87) | 15/33 (45) |
| Night time | 32/35 (91) | 18/20 (90) | 15/36 (41) |

Table 3 shows the success rate for asparagus detection.

Although Class 1 asparagus growing independently are detected more than 85 % of the time, it is difficult to separate Class 3 asparagus. Distance error between actual position and scanned data is an average of 6.5 cm in X direction and 3.2 cm in Y direction (depth). Actual position was measured by hand with caliper square. Since asparagus spears grow at the edge of ridge, Y direction error is less than that of X.

Total success rate was 75 % at asparagus spears and 71 % at parent asparagus. Main reason for misdetection was over lapping asparagus and leaf, insufficient resolution and misconnection. Overlapping caused image division, and it affected later processing. Moreover, one of the failure reasons is the resolution of laser sensor. For example, if an object sit 400 mm from laser sensor, resolution is 2.51 mm/dot (400 mm × sin(0.36°)) and this resolution can be decreased considering to flat surface. Although this situation is theoretical value, the more scanning angle spread the lower resolution is. In this experiment, data acquisition was only one direction, so it needs to get various kinds of direction. Some noises came from asparagus leaves which overlapped spear head. Therefore, in order to remove noise and avoid overlapping, cultivation training should be changed such as uplifting asparagus leaves so they do not come in scanning area or forwarding growing position of asparagus spear to parent asparagus. Since scanning interval is 10 mm, in separating spear from parent asparagus, individual variability is considerable at Z direction. Although it would be better to decrease scanning interval, the laser sensors should be moved slower. So measurement method also should be improved, for example using many laser sensors or scanning finely important part like asparagus head. Furthermore connection algorithm needs to be improved in differential and labeling operation. Yellow circle in Fig. 6 (c) shows a failure of connection and results in parent asparagus being regarded as harvest target. In order to decrease this type of failure, connection processing should be changed. In labeling operation, data connection at Z direction is based on only a one upper data. This method could not deal with the case that asparagus grows at an angle or data line up uncontinuously extremely. In a general way, machine vision systems use color cameras and lighting devices. And also requires consideration of sunlight or halation. So these types of system can work at night.

## V Conclusions

In this experiment, laser sensors not color camera were used. Laser can be used any time avoiding direct sunlight. To upgrade success rate for detection and decrease false recognition, we need to improve the measurement method, image processing and cultivation method. The machine is able to work all day, but the air builds up condensation in the early morning in a greenhouse and this makes sensors unable to work. Using this type of sensor, it requires attention to temperature or degree of humidity. It takes 100 ms in one scanning. To detect asparagus spears, considering the scanning interval (10 mm) and space of two sensors (160 mm), 16 times measurements every 10 mm are required. Therefore the shortest time is 1.6 s and this time will increase with image processing. In addition, motorized stage moves vertically for 4 s, the shortest scanning time is 1.6 s, end effector needs at least 5.5 s to harvest and time for traveling is 3 s (Taguchi, *et al*,. 2009). So it takes 10.1 s totally. If harvesting machine works 18 hours per day, 6415 asparagus spears can be harvested. From this, harvesting speed should be considered for practical utilization of this harvesting robot.

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