Master's Thesis of Engineering

On-the-go Embedded System for Spatial Mapping of Lettuce Fresh Weight in Plant Factory

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Abstract

Real-time monitoring of crop growth parameters in plant factory can provide useful information about accurate assessment of their growth status for precision crop management. Plant weight is one of the most important biophysical properties used to determine the optimum time for harvesting. Conventional plant weight measurements are destructive and laborious. An on-the-go image processing system consisting of image acquisition and weight estimation was developed to generate a fresh weight map of lettuces grown in hydroponic solutions. Key technologies developed in this study include a robust image preprocessing technique that separates individual lettuce images in the presence of overlapping leaves and a real-time image processing method that estimates their fresh weights. Images were captured with a low cost web camera and processed using a myRIO-based embedded controller. The camera and embedded system moved along an XY axis frame above a plant growing bed (0.94 x 1.8m) using two stepping motors and linear actuators. The image preprocessing algorithm consisted of three main subroutines, i.e., image segmentation, target plant recognition and overlapping leaf separation. For the image segmentation, the S channel of the HSV color space and Otsu's threshold were used to separate the plants from the background. The target plant was identified based on the mass center of the region of interest. The overlapping leaves were removed using an iterative erosion method. The plant weight was calculated by counting the number of pixels automatically. The accuracy of the fresh weight estimation by the system showed a highly linear regression with a slope of 1 and a determination coefficient (R^2) of 0.9. The results showed that it was possible to measure the plant fresh weight of each lettuce in real time. And the overlapping leaf problem can be solved until the harvesting of lettuces. It was expected the developed system would be a useful tool for mapping fresh weights of lettuces grown in a plant factory.

Keyword: Plant factory, Image processing, Real-time, Overlapping leaf, Plant growth, Biomass.
Student Number: 2015-22347

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Chapter 1. Introduction

1.1. Study Background

Plant factory is a closed growing system for agricultural production, which can allow crop quality to be controlled and constantly monitored while providing optimized conditions for plant growth. Plants grown in the plant factory are easier to manage in an efficient manner as compared to traditional growing methods that are dependent on growing seasons [1]. In addition, recently, with the loss of agriculture areas due to global warming, great attention on plant factory has been increased.

The observation of plant growth is important in the plant factory agricultural production. The optimum conditions for plant growth can be determined based observed results. Plant fresh weight is one of the most important biophysical properties used to determine the optimum time for harvesting. However conventional plant weight measurements, picking plants up and measuring weight using a scale, are destructive and laborious. In particular, since the purpose of the plant factory is to provide the optimal environment for plant growth and to maximize the harvesting efficiency, destructive fresh weight measurement method is not suitable and it is necessary to fast and accurately acquire

information on the growth the crops. Therefore, it is necessary to propose a solution for estimating the plant fresh weight information nondestructively and easily in plant factory. Load cell based plant weight measuring device is an effective solution for acquire fresh weight information nondestructively. However, this is costly and difficult to use for a wide plant factory.

A lot of machine vision-based methods have been proposed for plant growth monitoring. The results of these researches showed that it is possible to estimate plant fresh weight by using image processing method. However, there were three limitations in existing related studies: (1) the manual image acquisition is a waste of time and labor, it is difficult to perform in a wide plant factory; (2) the application of the image post-processing technology is time-consuming and may lead to that information of plant growth cannot be received in time. (3) When the problem of leaf overlapping occurred, the performance of lettuce fresh weight estimation will be reduced. In the late stage of plant growth, the developed system is difficult to estimate the fresh weight of plant. Therefore, in this study, developed an automatic real-time machine vision system for measurement of plant fresh weight. Moreover, in

order to improve the performance of this system, an overlapping leaf separation algorithm was developed.

Embedded system have advantages such as small size, low price, and good safety. Nowadays, embedded system are becoming more important in various academic sector because the developing technologies for embedded systems such as microcontrollers and memories. In particular, wide attention in precision agricultural. In this study, to solving the limitation of cable length, an embedded system was used for image processing.

1.2. Review of Literature

Biomass and harvest

Jens et al. (2016)[2] developed color information based image processing algorithm for strawberry harvesting. The algorithm was applied to the fruit harvest machine and successful applied to patent. In light of the case, the study of selectively harvesting crops is significant.

OKAMURA et al. (2014)[3] in order to determine the optimal harvesting time of transgenic lettuces in a closed plant factory, examined the amount of growth and the vaccine productivity of vaccine-producing lettuce with different cultivation periods. The results showed that 30 days after implantation is the optimal harvest time and that the lettuce weight continues to increase until 50 days after transplantation. This study provided the theoretical basis for monitoring lettuce yields by lettuce weight monitoring.

Cho et al. (2007)[4] developed a models using leaf length, leaf width, SPAD value, and different combinations of these variables for predicting individual leaf area, fresh weight, and dry weight of a cucumber. The results of this study were as follows: the leaves of the plant are related to the weight of the plant and the weight of plant can be predict by the leaf area of the plant.

Image processing algorithm

Jung et al. (2015)[5] developed a regression equation using the pixel value analysis methods for measure the fresh weight of lettuce grown in closed hydroponic system. It is reported that this regression equation can be used to accurately predict the fresh weight of a lettuce. However, the performance of this technology need to be improved in plant grown environment because that there were several plants in an image include target plant and non-target plants. Therefore, it is necessary to develop a new algorithm for measuring the fresh weight of lettuce.

L Hu et al. (2013)[6] developed an automatic plant position recognition algorithm for intra-row mechanical weeding. The RGB imaged plants were distinguished from soil by analyzing the excessive green (2G-R-B) vegetation index image. The Ostu's algorithm method was employed to transform a gray image to a binary image. And then the binary image was dilated and eroded three times repeatedly to remove isolated pixels in binary images or to remove noise for subsequent analysis. The standard deviation of longitudinal histogram was used as the scanning line to get the crop row area information in a binary image. Test results showed that, the method was sufficient in plants recognition and localization for intra-row mechanical weeding under different weather

and field conditions. The accurate identification rate was 95.8% with the absolute error of 4.2 pixels for cotton seedlings. An identification rate of 100% with the absolute error of 6.8 pixels was achieved for lettuce seedlings. This algorithm can identify target crops among weeds because their leaf area is different. However, it is difficult to use in plant factory that grown plants with the same leaf area.

D. M. Bulanon et al. (2010)[7] develop a real-time fruit detection system using machine vision and a laser ranging sensor and developed an end effector capable of detaching the fruit in a way similar to manual pick. The system detected a single fruit with 100% accuracy in both front and back lighted scenes with ±3 mm accuracy in distance measurement. Since the algorithm has good performance in orchard where background is very complex, including sky, trees, ground, and leaves. Therefore, it is possible to real time image process in a relatively simple place, plant factory.

Plant growth monitoring system in plant factory

Load cell based plant weight measuring device is effective and has been studied by many researchers, including Takaichi et al. (1996)[8], M Kacora et al. (2001)[9], Baas et al. (2003)[10], Helmer et al. (2005)[11]

Ji-soo Kim et al. (2016)[12]. Bass et al. (2003)[10] used multiple load cells for measured the total weight of gerbera. Helmer et al. (2005)[11] used two load cells for measured the vine weight and evaporation rate of water in plants.

David Story et al. (2010)[1] developed a machine vision-guided plant sensing and monitoring system for detecting calcium deficiency in lettuce crops grown in greenhouse conditions using temporal, color and morphological changes of the plant. The machine vision system consisted of two main components: a robotic camera positioning system and an image processing module. The machine vision system extracted plant features to determine overall plant growth and health status. The machine vision-guided system was capable of extracting plant morphological, textural and temporal features autonomously. Through this study, we know that the combination of camera positioning system and image processing algorithm can be applied well in plant factory.

Wen-Tai Chen et al. (2016)[13] developed an individual plant measurement device using a load cell. The results show that plant weights measured by the weight measurement device are accurate. In the study, a device similar to Wen-Tai Chen et al. (2016)[13] was developed for validate the plant fresh weight measured by image

processing.

Overlapping leaf problem

Solving the problem of leaf overlapping is important for agricultural image processing system, but few studies have focused on this aspect. The methods for separating overlapping objects such as touching grains [14], touching kernels [15] and overlapping plant fruits [16] have been widely researched. However, these methods are difficult to use to separate the lettuces overlapping leaves due to the shape of research objects in these studies is simple. The watershed segmentation algorithm is a useful method for solving the overlapping problem. This method has been used to separate a breast tumour in two-dimensional sonography [17], the left ventricle in echocardiographic image[18]. However, over separation is an inherent problem of watersheds [19]. Hernández et al (2017) developed a novel application for mobile devices that integrates several computer vision techniques for plant segmentation and analysis in crop pictures [20]. In this study, to separating overlapping or touching objects, a morphological operator *erode* based separating method has been developed. However, this method reduces the area of the object and is difficult to correctly calculate the area of each object.

1.3. Research Purpose

This study aims to develop a real time image processing system that could measure the fresh weights of individual lettuces in real-time. This system includes two main parts: an XY camera-guided system use for positioning the camera and an embedded system use as image processor.

The specific sub-objectives of this study are as follows:

1. To implement a plant image collection and processing system consisting of a RGB camera and an embedded board, which could collect and process the images simultaneously to estimate the fresh weight of lettuces in real-time,
2. To develop a method to convert for differences in fresh weight between the measured and actual values occurring due to variability in canopy among crop species as well as different camera parameters, i.e., resolution and object distance.
3. To develop an algorithm for solving the overlapping leaf problem, keeping performance of the developed system in the late of plant growth.

Chapter 2. Materials and Methods

2.1. Plants growing system

In this study, lettuce was grown using a recirculating hydroponic syste m based on ebb and flow, which is commonly known as the flood drai n method, as shown in Fig.1. Schematic diagram of an ebb-and-flow-based hydroponic growing system, as shown in Fig.2. The recirculatin g system temporarily flooded the growing bed with a nutrient solution, and subsequently drained the solution back into a mixing tank. The n utrient solution in our system was provided every 2 hour. An array of white fluorescent tube lamps was installed on the plant bed as a light s ource for daytime lighting from 9:00 AM to 11:00 PM. The average p hotosynthetic photon flux density of the light source at the growing be d was 133.45μmol $S^{-1}m^{-2}$. Temperature in the plant factory was mai ntained at 18 to 22 degree Celsius and the relative humidity of about 5 0%. A plant growing bed (0.94×1.8 m) is fixed inside, 45 plants (5×9) can be grown. Images were captured with a low cost web camera and processed using an embedded controller. The camera and embedded system moved along an XY axis frame above a plant growing bed (0.9 4 x 1.8m).

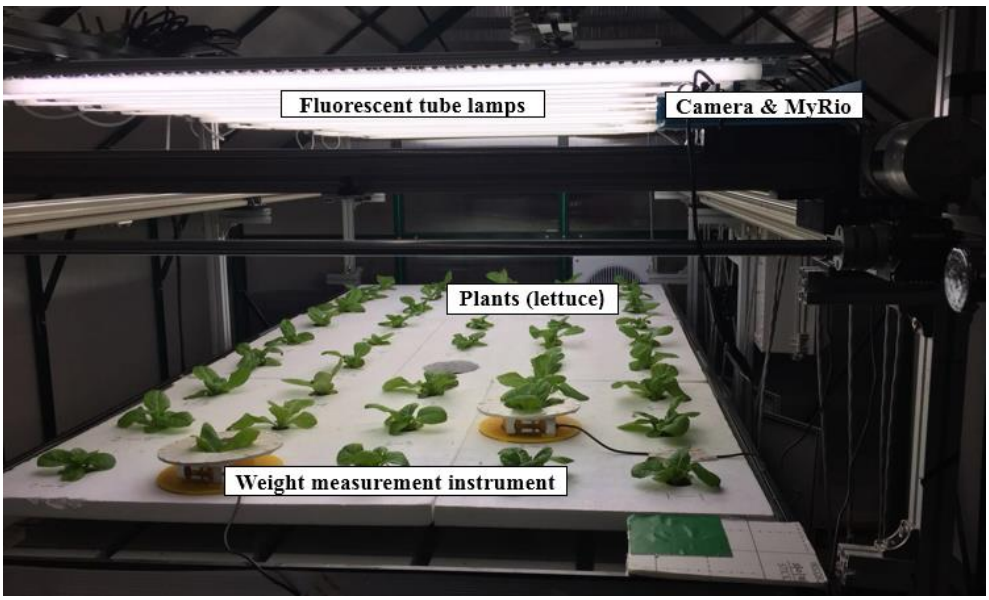


Figure 1. Photo view of the hydroponic system

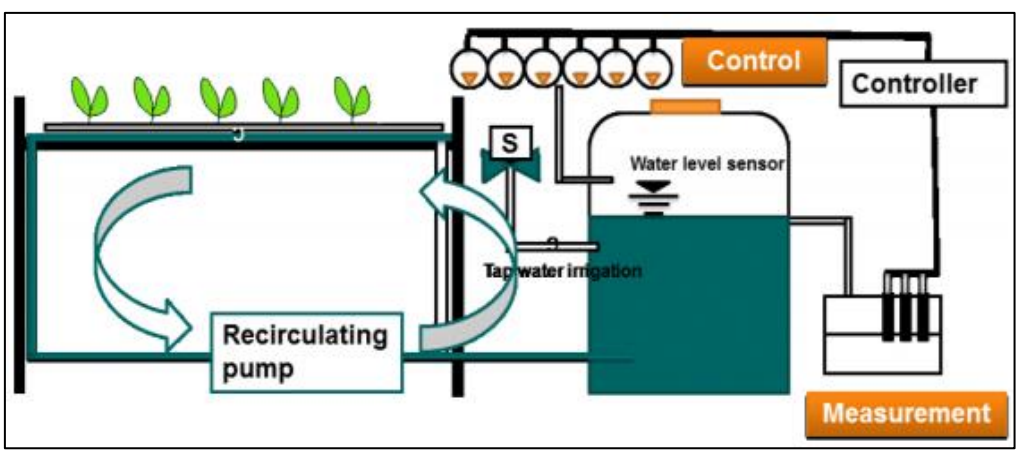


Figure 2. Schematic diagram of an ebb-and-flow-based hydroponic growing system

2.2. The XY camera-guided system

An automated fresh weight measurement system was developed to collect images of lettuces, which was installed 0.45m above the planting bed in the plant factory, as shown in Fig. 3. This measurement system included two main parts: (1) XY axis frame using stepping motors and linear actuators and (2) a RGB camera-based imaging system which was moved along the XY axis above the plant growing bed to capture images in designated locations. The developed system consisted of a motion controller, two motor servo drivers (MoonWalker i-serve SBL-24200U-B, NTREX, Korea), two step motors (BLM57090-1000, leadshine, China), three belt linear actuators (MoonWalker MW-EQB40, NTREX, Korea), a MyRio (National Instruments, USA) based embedded system and a low cost web camera (C270, Logitech, Switz erland). The actuators were controlled using a PC via RS232 serial communication. Fig. 4 shows the connection diagram of the hardware of the proposed system.

Figure 3. Installation of automated fresh weight measurement system in plant factory

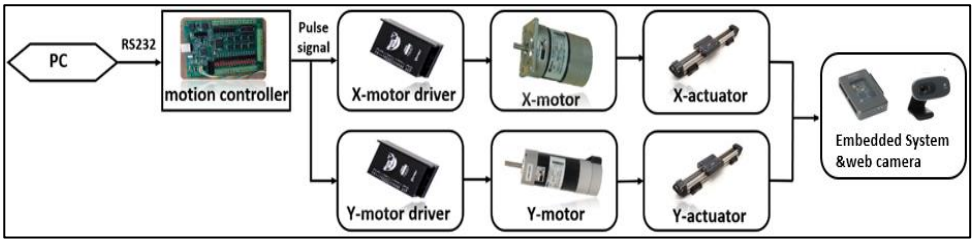


Figure 4. Connection of main hardware circuit.

The motion controller converted the control signals to pulse signals, which were received from PC, and sent it to the motor servo derivers for controlling motors. Motors were driven by pulse signals and moved the camera to a pre-determined position which was determined by plants growing bed and the image size. In this system, the camera moved 0.0075 millimeter for each pulse signal input. Figure 5 is the diagram of specific control logic, 10033 pulses were applied 5 times to control the motion in the x-axis direction and 26800 pulses were applied 9 times to control the motion in the y-axis direction. The running route of the image sensor are shown in Fig. 6. The camera moved in the S-shape and back to the starting point finally. The control logic program of the developed system was written in LabView.

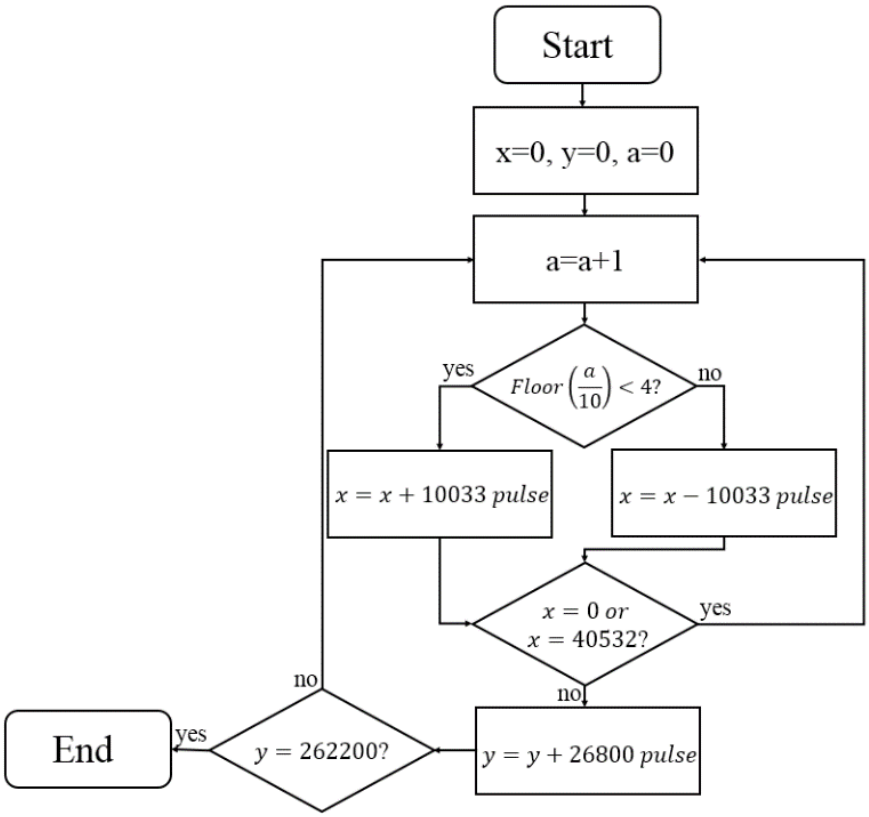


Figure 5. The diagram of specific control logic

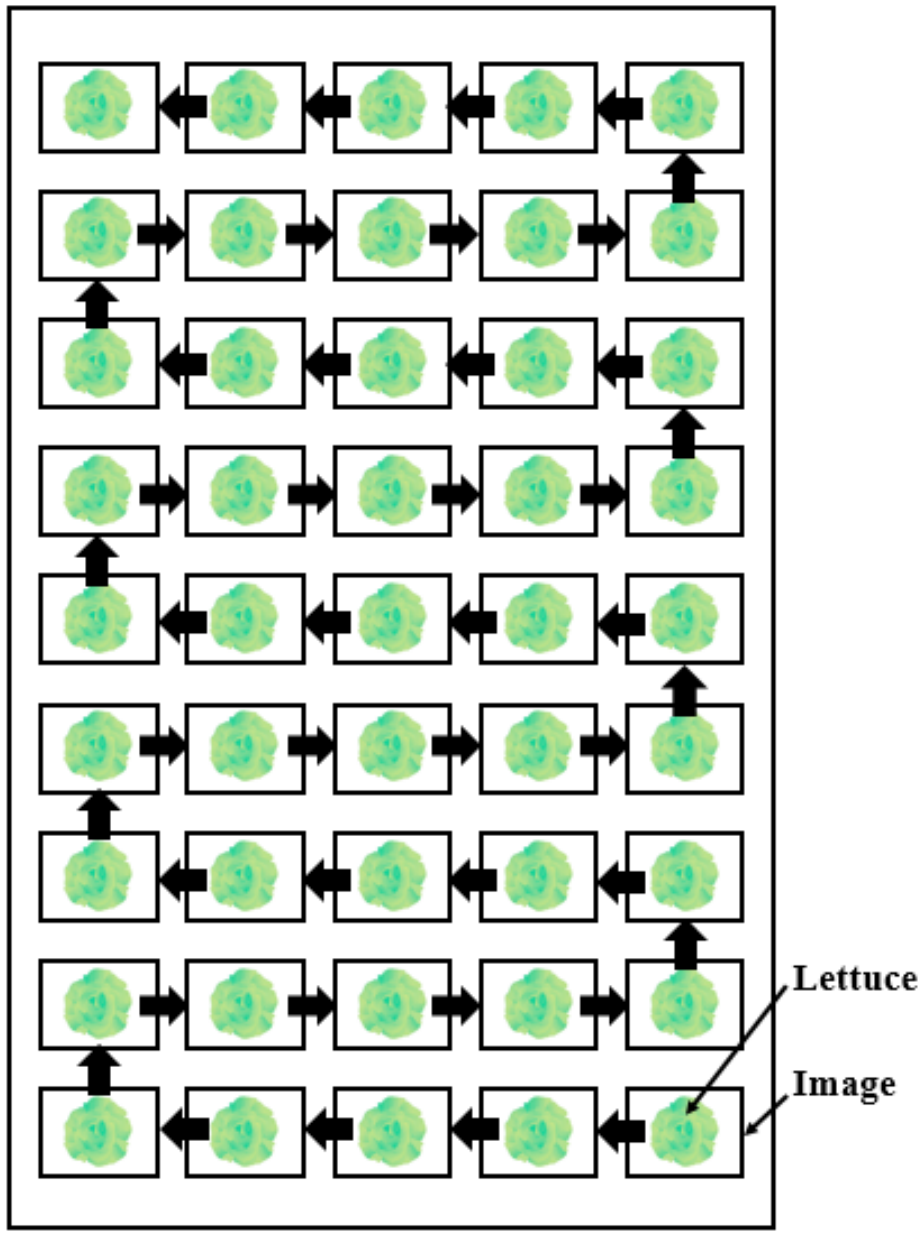


Figure 6. The running route of the image sensor

2.3. Description of image processing system

The overall image processing system consisted of a camera position module, an embedded system based image acquisition/ processing module and a data storage module. A low cost web camera (C270, Logitech, Switzerland) (Fig.7) and NI MYRIO (Fig.8) based embedded system was used as image acquisition/ processing module. Processing results can be store on a mobile hard disk and a host computer. The functional flow of the image processing system is as follows. First, a host computer retrieves a list of target locations which was determined by the locations of each plant. Host computer send a signal to the XY camera-guided system to position the camera at a determined location. After the camera is positioned above on the center of the plant, a RGB image is taken and processed. Finally, the image and processing results are stored on a mobile hard disk and real time transferred to a host computer. The captured image dimension was 800 × 600 pixels and was analyzed as a JPG image. The program for the image processing system was written in the Labview (NI, USA). The schematics of this image processing system shown in Fig. 9.

Figure 7. Web-camera and the technical specifications

Figure 8. NI MyRio

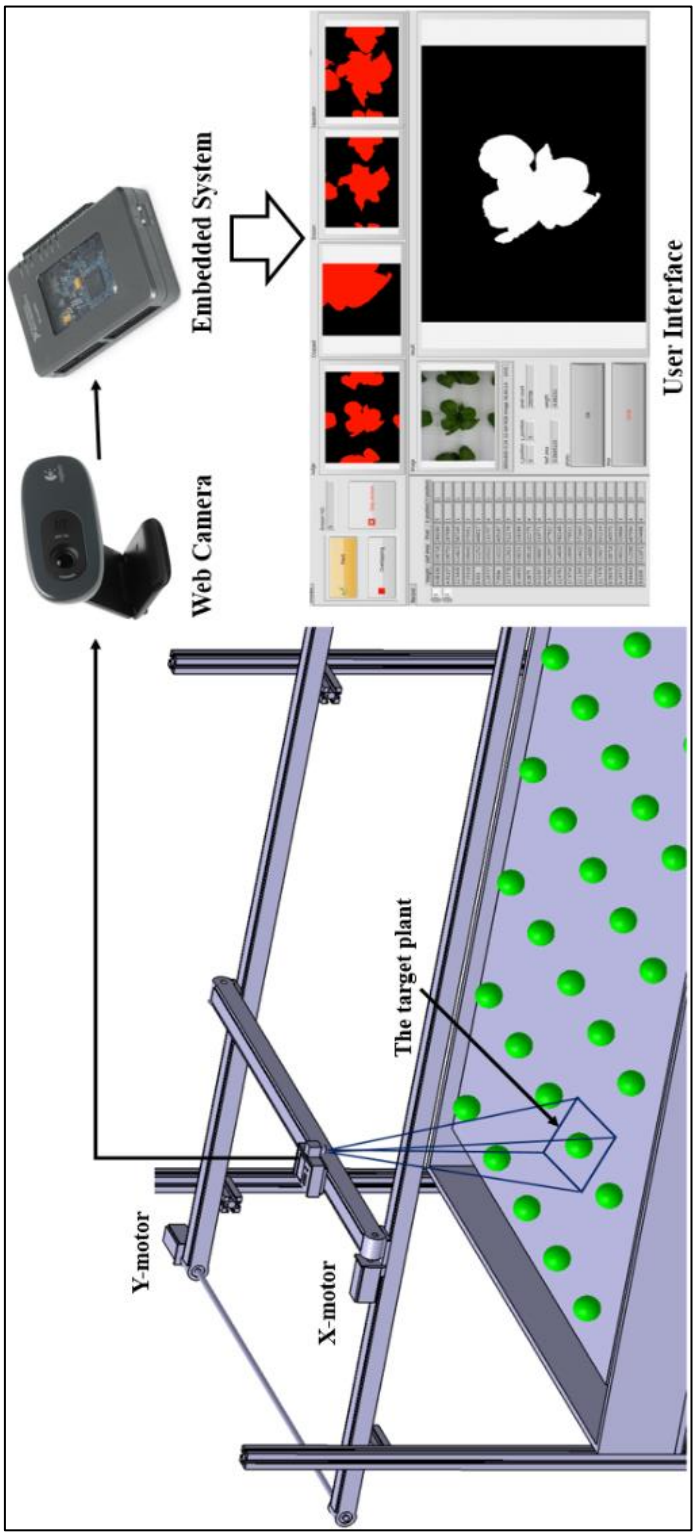


Figure 9. The schematics of this image processing system.

2.4. Plant weight measurement device

In order to validate the estimated fresh weight of lettuces by the developed system, the actual fresh weight of lettuce need to compared with the estimated fresh weight of lettuces continuously in the plant growth period. However the actual fresh weight of lettuce continuous measurement in the plant growth period is difficult because the destructive. The research of Chen, Wei-Tai, et al. (2016) proposed a solution, developed a plant weight measurement device for measuring the individual lettuce non-destructively and continuously during the lettuce growth period. The results showed that the device was effective and accurate. In order to test the performance of the developed system in this study, two weight measurement devices was developed with reference to the research of Chen, Wei-Tai, et al. (2016), as shown in Fig.10. The load cell (BCL, CAS, Korea) was used, with a measuring resolution of 0.1g, and capability to measure weight from 0 to 300 g. The bottom disk was placed on the plant growing bed. The load cell was fixed between the Top disk and Bottom disk, plant holder fixed on the top disk and passing through the bottom disk. Plant planted on the top disk with a sponge, the plant weight on the top disk creates a downward force onto the load cell. The load cell connected to an

amplifier (RWS-T01A, SMOWO, China) and transfer a voltage signal to host computer by the CDAQ (NI, USA). The average value of 1000 voltage signals were used to convert to weight value. The hardware connection of plant weight measurement device, as shown in the Fig.11. The different weight's paper cups and water were used for calibration, calculate the voltage corresponding to each weight, as shown in the Figure 12. Since the ebb and flow irrigation system were used in the developed system, the nutrient solution affects the measurement of weight. In order to eliminate the effects of water, the plant fresh weight was measured when the nutrient solution was drained back into the mixing tank. To test the performance of the plant fresh weight measurement device the validation experiment was performed November 6 to 24, 2018 (18 days).

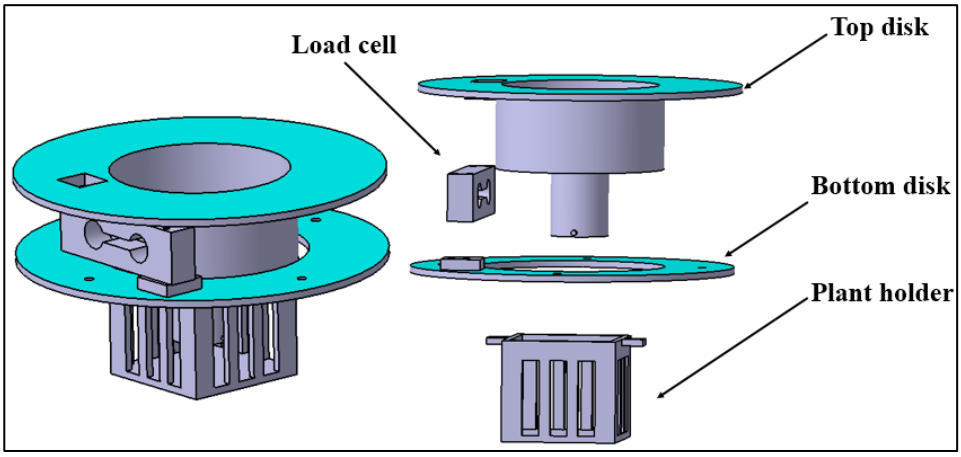


Figure 10. The structure of plant weight measurement device.

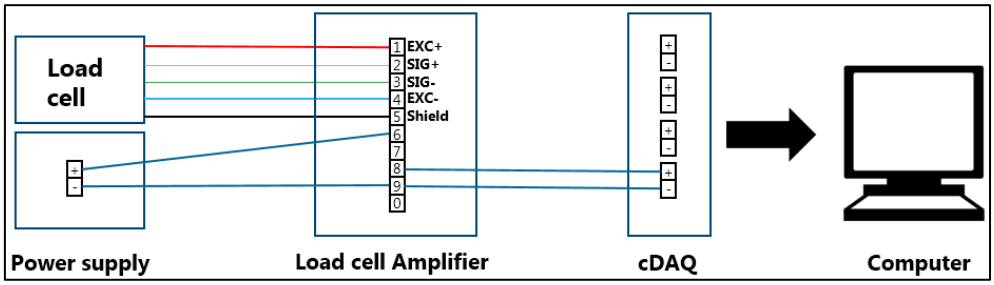


Figure 11. The hardware connection of plangt weight measurement system

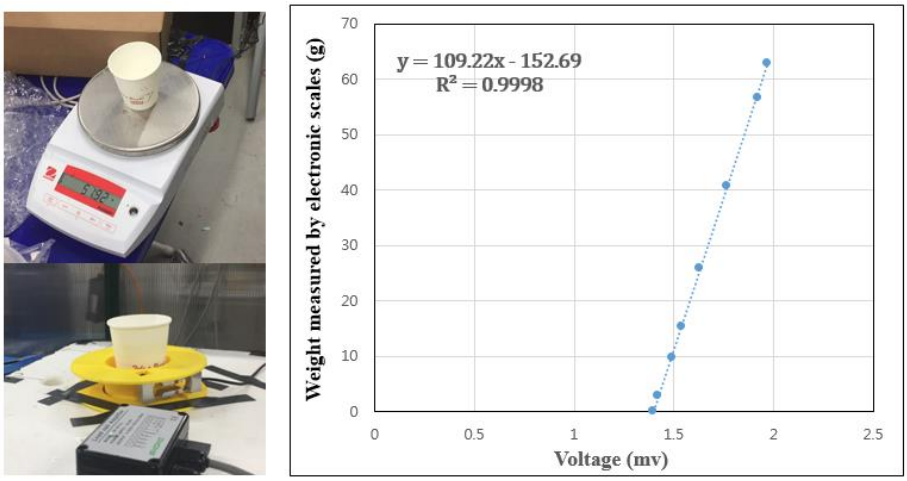


Figure 12. The calibration method of the plant weight measurement device

2.5. Image processing and feature detection

The image processing was performed in real time after the image acquisition. The acquired image mainly consisted of three different parts, i.e., target plant, non-target plants and background. To calculating the fresh weight of target plant, segmenting plants from the background and extracting target plant from plants were implemented. When the problem of overlapping leaf occurred, the overlapped leaves would be appeared as a plant, the leaf area of plant could not obtained correctly. To get a correct result of the target plant leaf area, the overlapping leaves were separated before extracting target plant. Final, the fresh weight of target plant was calculated using number of pixels. Figure 13 shows the image processing procedures for fresh weight measurement. Figure 14 shows the examples of image processing procedures.

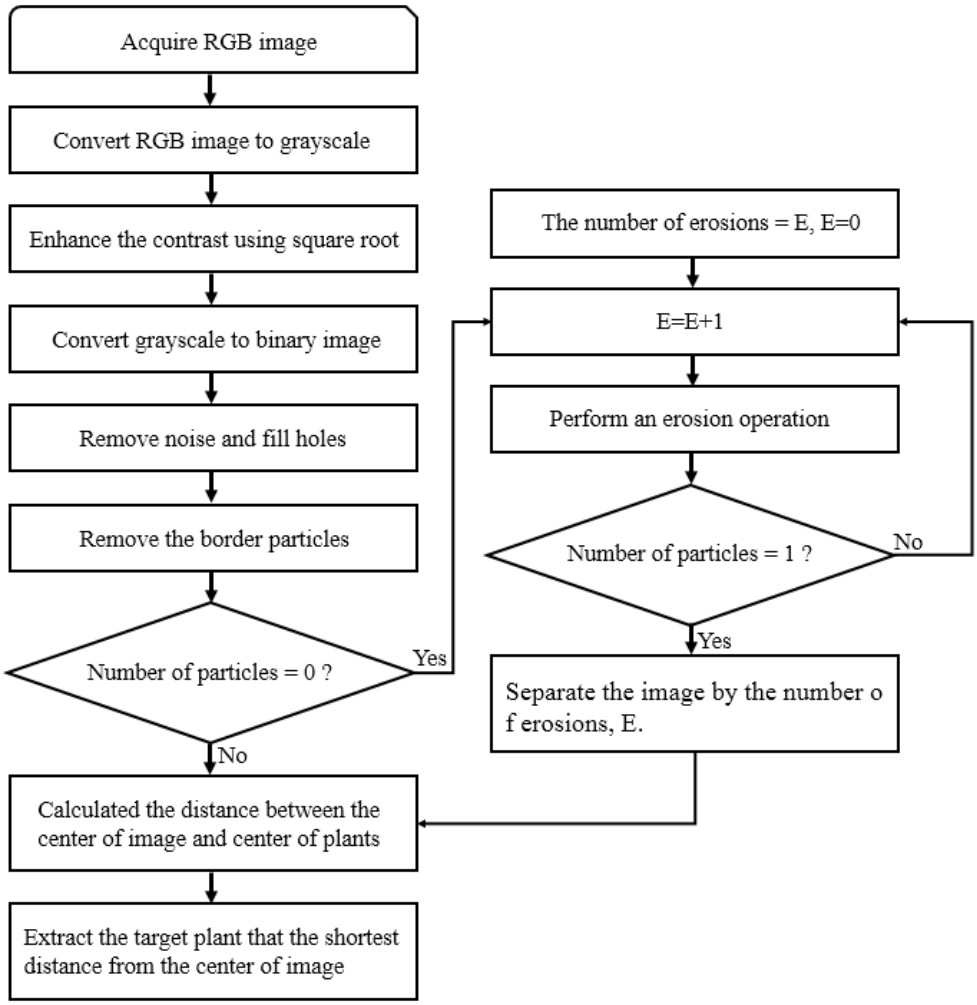


Figure 13. Image processing procedures for fresh weight measurement

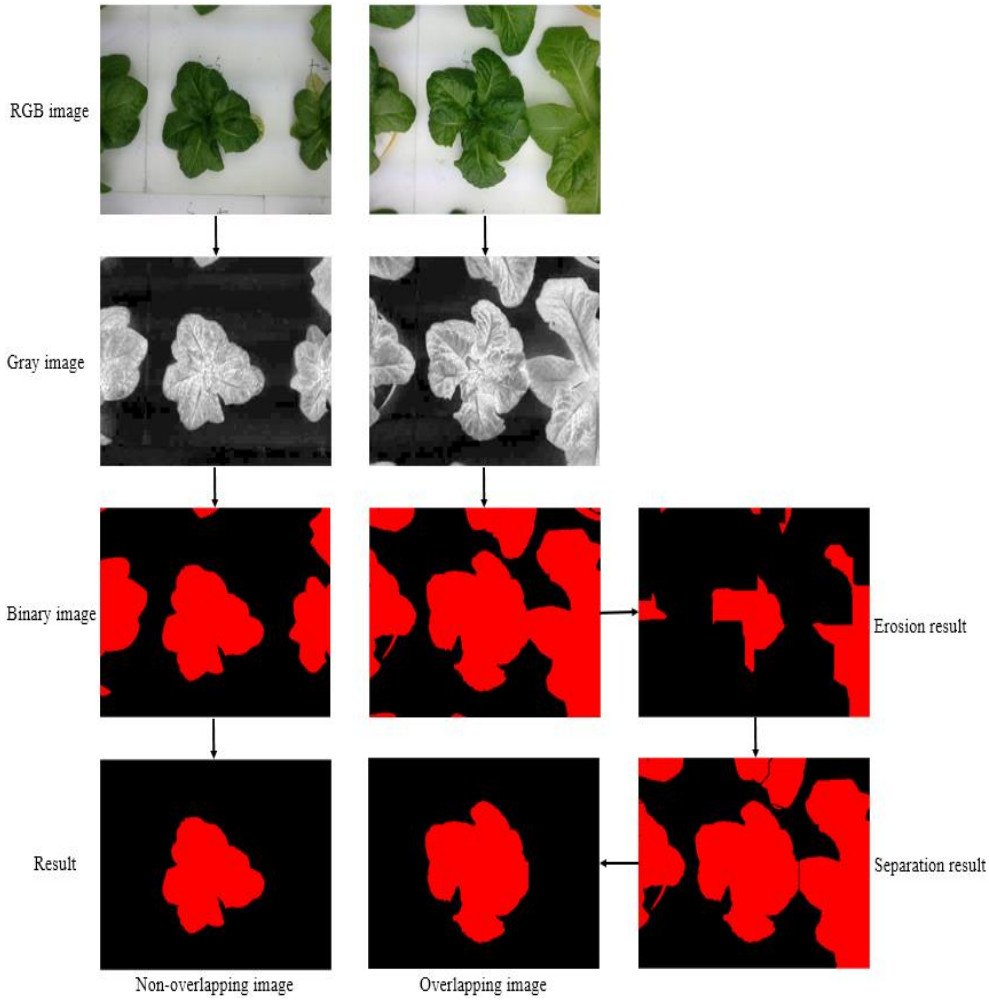


Figure 14. Image view of image processing procedures.

2.5.1. Image segmentation

In order to extract the plant from the background in each image, the S channel of the HSV color space was used to convert RGB image to grayscale image. A square root function[21] was use to enhance the contrast of grayscale image. As shown in Figure 15, in a histogram analysis of RGB images in terms of S color channel, it was possible to effectively separate the images of the lettuce plants from the background using the Otsu method, which automatically calculates optimal threshold values, thereby minimizing inter-class variance and maximizing intra-class variance.

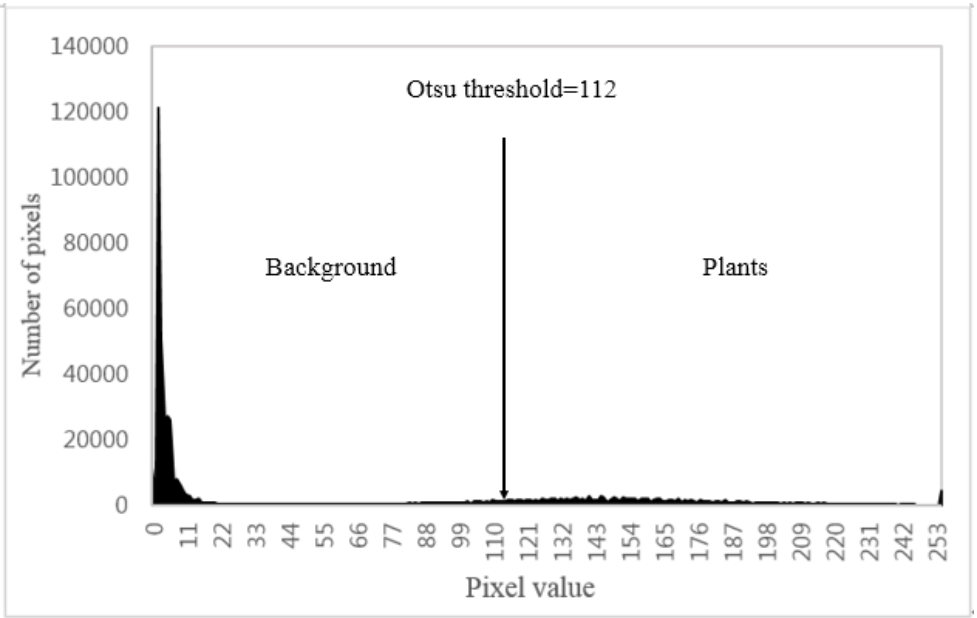


Figure 15. S histograms of pixels of image segmentation with the Otsu threshold value.

Residual noise existed in the binary image were obtained through threshold segmentation. This noise could affect the subsequent processes and quality judgement. Residual noise elimination through blob analysis was the next step in segmentation. In the binary image, the morphological operation could be used for noise elimination. However, the shape of the seedlings could easily be affected by noise removal because the morphological operation method acts on the entire image, including the aimed objects. Therefore, the result is not ideal. For this reason, the blob analysis method was used to remove noise here. Many blobs were formed from the white pixels in the binary image, which belonged to either the seedling shape or to noise. The number of noise blob pixels was smaller than that of seedling blobs. Accordingly, the numbers of blob pixels were compared to establish the noise blobs. Supposing n blobs exist in the image, and $1 \leq i \leq n$. Assuming that the element M_i represents the blob i, B represents the set of noise blobs, O represents the set of aim objects (Plants), A_i represents the pixels number of blob i and T represents the value of the pixel number threshold. The relationship is as follows:

$$\begin{cases} A_i \leq T, \ if M_i \subset B \\ A_i \leq T, \ if M_i \subset O \end{cases} \tag{1}$$

By manually selecting an appropriate value of the pixel number threshold, residual noise could be eliminated. (Jun H,Tong 2012) [19] The process of filling holes also carried out to decrease the error of segmented image by the function *IMAQ FillHole* and *IMAQ RemoveParticle*. Figure 16 shows the example of the image segmentation.

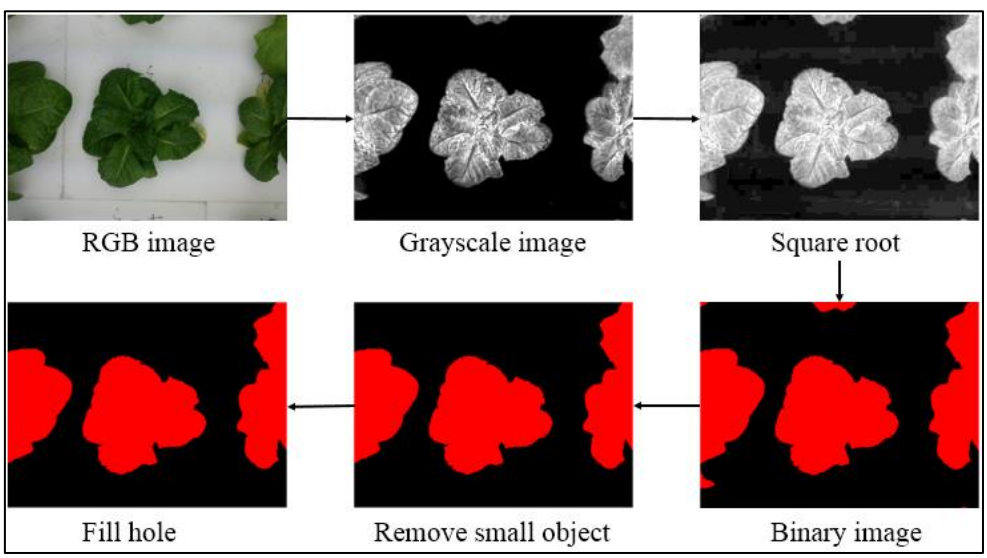


Figure 16. Example of image segmentation.

2.5.2. Target plant extraction

As shown in Figure 17, in the images captured in plant factory, in addition to a target plant, there were several non-target plants that were planted around the target plant.

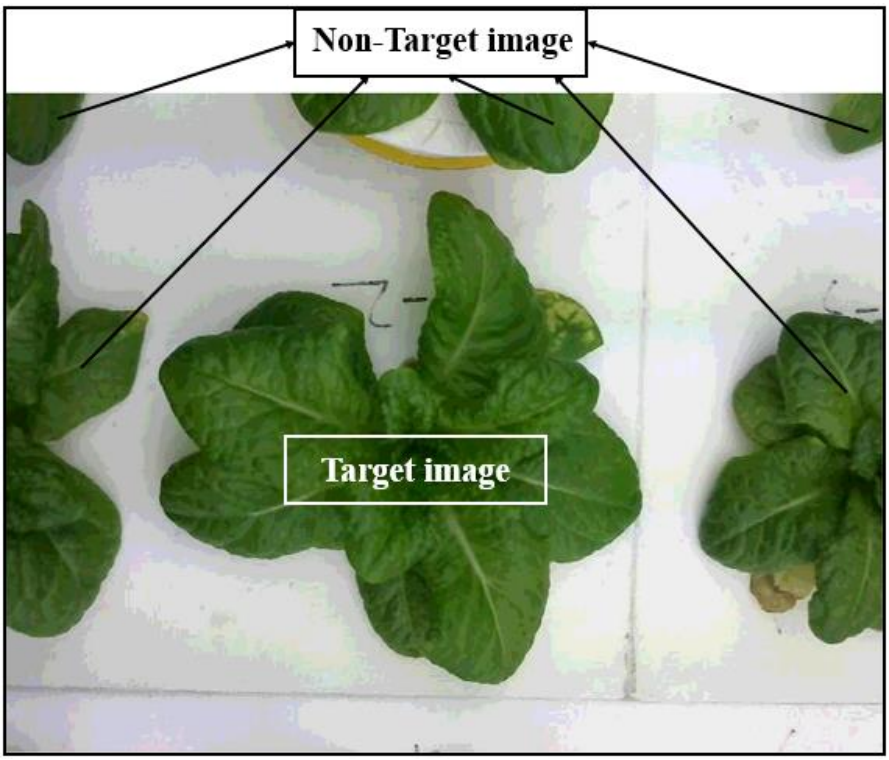


Figure 17. An example of image captured in plant factory.

Because the positions of photograph were above on each hole of plant growing bed and the plants were planted on the holes of plant growing bed. Therefore the target plant was closer to the center point of the image than other plants in the image. To calculate the target plant information correctly, a method based on position was used for extract

the target plant from an image. First, the center point position of each plant image was calculated and defined as coordinates, (x_a, y_b). The distance between the center point positions of each plant and the image using the following formula:

$$\text{Distance} = \sqrt{(x_a - x)^2 + (y_b - y)^2} \quad (2)$$

where:

x = x-coordinate of the image center

y = y-coordinate of the image center

x_a *= x-coordinate of the plant center*

y_b *= y-coordinate of the plant center*

When the shortest distance was obtained, the plant was identified as the target plant. Finally, the function *IMAQ Particle filter* in Labview was used for Target plant extraction

2.5.3. Overlapping leaves separation

Before separating the overlapping leaves, it is necessary to determine if there is an overlapping leaf problem in the image. In an acquired image, in addition to the target plant, all other non-target plants were in contact with the border of the image. The function *IMAQ RejectBorder* in Labview was used for remove the particles that touches the border of the image. Then if the overlapping leaf problem in the image, no particles leaf in the image after remove the particles that touches the border of the image because the target plant overlapped with other plants and were filtered out together, as shown in the figure 18 (b). If there was no overlapping leaf problem in the image, one particles left in the image, as shown in the figure 18 (a).

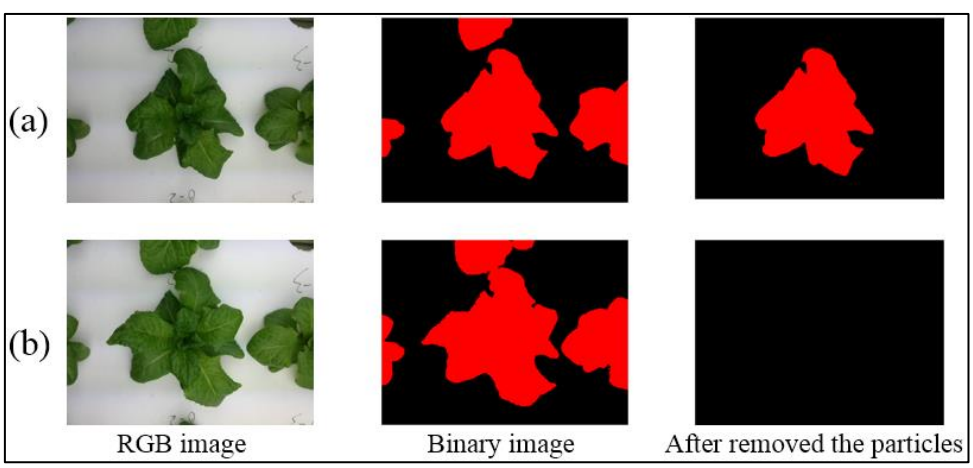


Figure 18. Example of remove the particles that touches the border of the image, (a) no overlapping leaf problem in the image (b) overlapping leaf problem in the image

Therefore, the number of leaf particles after remove the particles that touches the border of the image was used for determining if there is an overlapping leaf problem in the image. When there was no particles remained, there was an overlapping leaf problem in the image, otherwise, there was no overlapping leaf problem in the image.

In a binary image, if two leaves overlapping one another might appear as a single particle, a narrowing can be observed on the original leaves intersected each other. The function *IMAQ Separation* in Labview was used for breaking narrowing and separates overlapping leaves with respect to a user-specified filter size. The specific location of the narrowing can be determined by the image erosion iteratively. Erosion is the morphological transformation which combines two sets using the vector subtraction of set elements. If A and B are sets in Euclidean N-space, then the erosion of A by B is the set of all elements x for which $x + b \in A$ for every $b \in B$. The erosion of A by B is denoted by $A \ominus B$ and is defined by *(ROBERT et al., 1987)*

$$A \ominus B = \{x \in E^A | x + b \in A \; for \; every \; b \in B\} \qquad (3)$$

The number of the erosion operations was determined by the situation of the overlapping. The more serious the overlapping situation is, the more numbers of erosion operations needed. In this study, the number

of the erosion operations was calculated automatically by erode the image iteratively until the overlapping leaves separated that the number of particles is one after removed the particles of touch the border of the image. The process of overlapping leaves separation as shown in Fig 19.

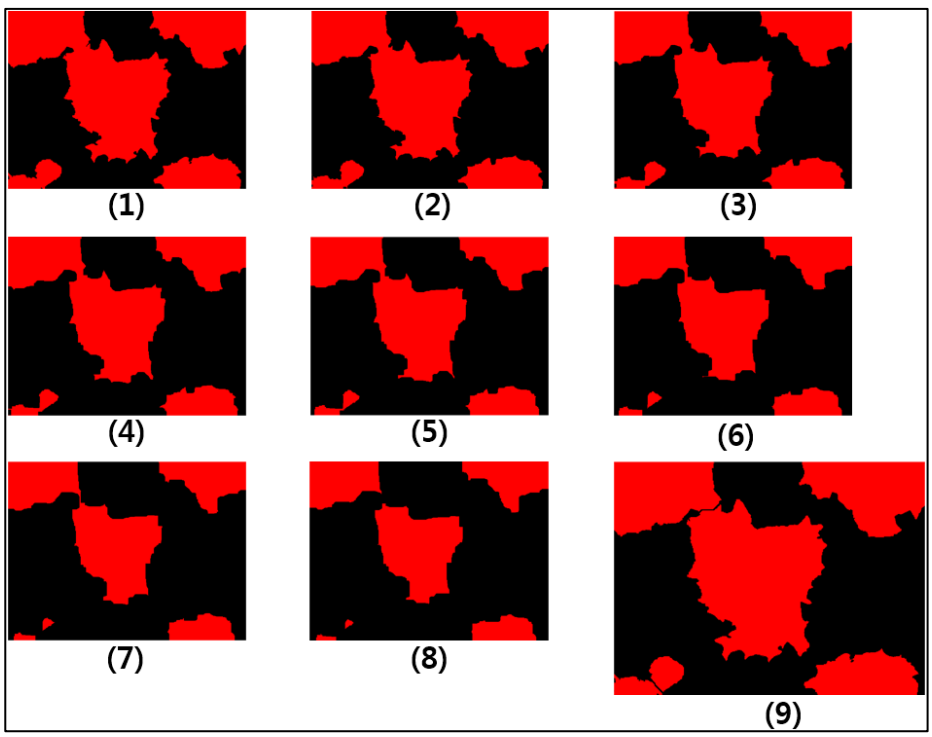


Figure 19. The process of overlapping leaves separation. (1) Overlapping binary image (2) ~ (8) Erosion process iterativy (9) Reconstructed image that without the isthmus between target plant and other plants

Structuring element is a matrix that identifies the pixel in the image

being processed and defines the neighborhood used in the processing of each pixel. The erosion operates on a small structuring element is a time-consuming process, but if the structuring element is too large, the accuracy of the overlapping leaves separation were reduced. In this study, the structuring element of size 7×7 was used in the erosion operation. The structuring element is defined as

$$B = \begin{matrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \end{matrix} \tag{4}$$

If the narrowing has a width of M pixels, a separation using a filter size of (M+1) breaks it and restores the two original leaves. The erosion size (N) of separation can be calculated by following equation:

$$N = \begin{cases} k - 1\,, & M = 2k - 1 \\ k\,, & M = 2k \end{cases} \tag{5}$$

where

M = The width of the narrowing;

k = a constant.

If M is an even number, the particles are divided into two parts after k erosions. If M is an odd number, it uses k erosions.

2.5.4. Image cropping

In late stage of plant growth, it was very difficult to overlapped leaves due to the leaves of target plants become too large. Therefore, the accuracy of the overlapping leaf separation was not high enough to separate the overlapped leaves in the late stage of plant growth. In order to increase the accuracy of the separation performance, the images were cropped by target plant's size and shape after separated the overlapped leaves. The image cropping is extracts a part of an image with adjustment of the horizontal and vertical resolution. The Figure 20 illustrates an extraction of an image where X step size equals 2 and Y step size equals 3.

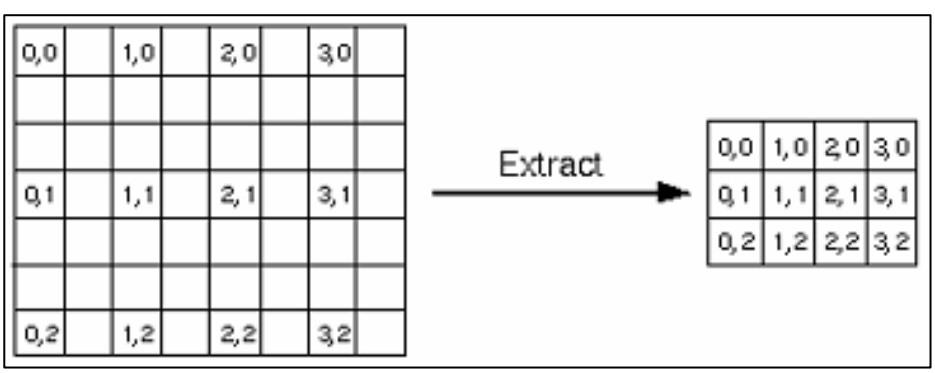


Figure 20. The principle of image cropping

In this study, the image cropping method was used for increasing the performance of overlapping leaf separation. In particular, when the under-separation was occurred. As shown in Figure 21, a binary image

of separation failed due to under-separation, using the image cropping method the separated image was cropped for increasing the accuracy of result.

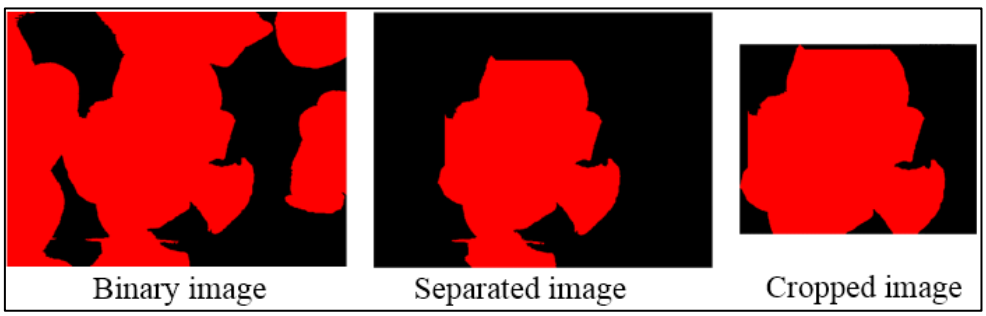


Figure 21. Example of image cropping.

In order to crop the image by the shape and size of target plant, the technique of extracting plant was applied using Minimum Bounding box (MMB) algorithm. Minimum Bounding box (MMB) algorithm was to draw a dynamic box for separating each lettuce, which was determined by two-dimension Axis Aligned MBB algorithm (Bergen, 1997)[22]. The bounding box area for a set of objects was a closed region that contains the union of the entire objects in the set. We used one of the simplest MBB algorithms, a two-dimension axis aligned MBB for separating the lettuces. The equations of minimum rectangle calculation are shown in the following formula (6) ~ (9):

$$\mathrm{B} = (C_x, C_y, b_1, b_2) \tag{6}$$

$$\mathrm{Grid}(\mathrm{B}) = \{i_1 b_1 + i_2 b_2 \mid i_1, i_2 \in Z\} \tag{7}$$

$$B^{g}_{(\mathrm{i,j})} = \left\{ x_1 b_1 + x_2 b_2 \middle| \begin{matrix} i \le x_1 \le i+1, \\ j \le x_2 \le j+1, \end{matrix} \quad i,j \in Z \right\} \qquad (8)$$

$$(b_1, b_2) \ = [(\max X_{B_{(i,j)}} - \min X_{B_{(i,j)}}), (\max Y_{B_{(i,j)}} - \min Y_{B_{(i,j)}})\ ] \quad (9)$$

where

B=The minimum rectangle;

b_1 & b_2=The lengths of the rectangle;

C_x & C_y=The centroid of the box in the x-axis and y-axis.

Then the distance between the sides of rectangle and the sides of image could be calculated and indicated as Top, Right, Bottom, Left, as shown in Fig. 22. The image cropping method in this study was performed by the distance between the sides of rectangle and the sides of image. When the one of the Top and Bottom equal to zero, the top position of image cropping and Bottom position of image cropping were all equals a value that was not equal to zero. Neither the Top position of image cropping and Bottom position of image cropping were zero, the longer distance value of them was used to image cropping. The same method was used to determine the Left position of image cropping and Right positon of image cropping, as shown in Fig. 23.

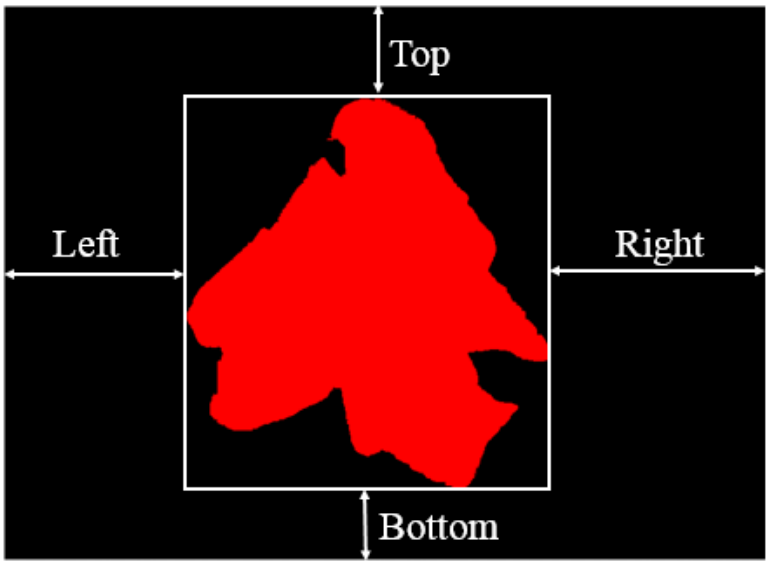


Figure 22. Example of MMB algorithm.

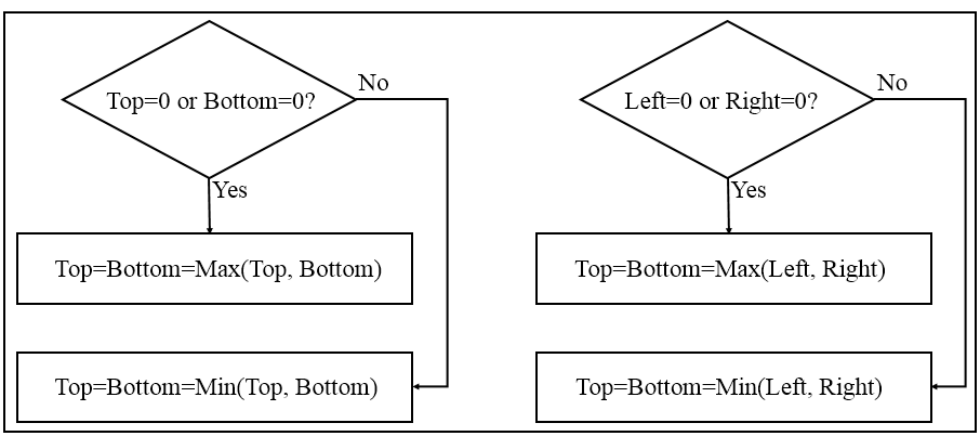


Figure 23. Flow chart of determined the position of image cropping.

2.6. Plant weight calculation and pixel conversion

In a previous study[5], a polynomial calibration models were developed to related the number of pixels in images of leaf areas determined by the image processing methods to actual fresh weights of lettuce measured with a digital scale. The study analyzes the ability of the machine vision based calibration models to predict the fresh weights of lettuce. The coefficients of determination (> 0.93) and standard error of prediction (SEP) values ($< 5g$) generated by the developed models imply that the image processing could accurately estimate the fresh weight of each lettuce plant during growing stage. The results demonstrate that the growing status of a lettuce plant can be estimated using leaf images and regression equations. This shows that a machine vision system installed on a plant growing bed can potentially be used to determine optimal harvest timings for efficient plant growth management. Figure 24 shows the polynomial regression equations with pixel counts based on the morphological analysis and pixel-value analysis. In the figure, the predictor variable x represents the number of pixel counts, and the outcome variable y represents the fresh weight of lettuce.

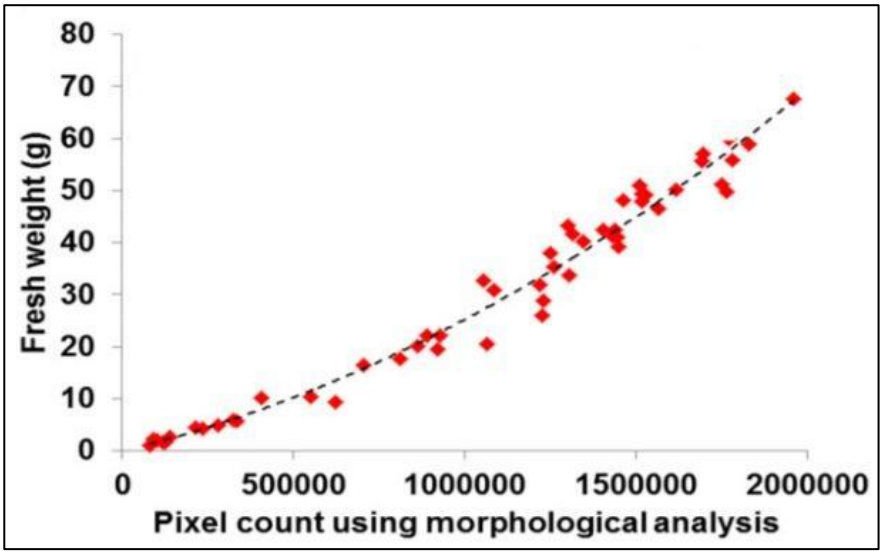


Figure 24. Calibration curves for morphological images. (Jung et al., 2015)

The lettuce fresh weight can be calculated by following equation:

$$\text{Fresh weight(g)} = 9.4332 \times 10^{-12}X^2 + 1.5821 \times 10^{-5}X \qquad (10)$$

where

X = the number of pixels in plant.

In this study, the camera model (C270, Logitech, Switzerland) and the height of photography (450 mm) were different from Jung et al, so the true size of a pixel are different. In order to predicted fresh weight correctly, a preprocess method was used for modified the number of pixels. A green square with 0.1 m sides was placed on the plant growing bed, calculated the number of pixels of the green square by camera

before collecting plants images. The true size of a pixel can be calculated using following equation:

$$\text{The true size of a pixel} = \frac{\text{Actual area}}{\text{Number of pixels}} \tag{11}$$

where

Actual area = 0.01 m^2 *;*

The pixel count = 48543.69.

Therefore, the true size of a pixel was calculated as 2.06×10^{-7} in this study. The pixel count could be pre-processed using the ratio of the true size to a pixel of this study defined as:

$$\mathrm{X} = X_0 \times \frac{2.06\times10^{-7}}{5.176\times10^{-8}} \tag{12}$$

where

X = the preprocessed number of pixels value;

X_0 *= the number of pixels before preprocess.*

2.7. Result compensation (Two point calibration)

The results obtained were different from the actual results due to the variability in canopy among crop species. Therefore, the calculated plant fresh weight value also need to convert. There were 2 samples (a big sample and a small sample) taken in the middle of plant growth period for fresh weight conversion. Estimated the fresh weight of these two samples using the developed system and pick up these two samples and measured the actual weight using an electronic scale. The final result of the plant fresh weight estimated can be calculated using following equation:

$$W_R = \frac{y_2 - y_1}{x_2 - x_1} W_0 + (y_1 - \frac{y_2 - y_1}{x_2 - x_1} x_1) \qquad (13)$$

where

W_R *=The final result;*

W_0 *= The plant fresh weight before calibration;*

x_1 *= The estimated fresh weight of sample 1 by image;*

x_2 *= The estimated fresh weight of sample 2 by image;*

y_1 *= The measured fresh weight of sample 1 by electronic scale;*

y_1 *= The measured fresh weight of sample 2 by electronic scale.*

Chapter 3. Results and Discussion

3.1. Plant weight measurement device validation

Figure 25 is the result of plant weight measurement device valid ation. The horizontal axis is the fresh weight of lettuce which w as pick up and measured by the electronic scales. The vertical a xis is the fresh weight of lettuce measured by the developed pla nt weight measurement device. 14 lettuces were used to test the performance of this device. Figure 26 shows the weight growth curves of lettuce measured by two plant fresh weight measureme nt device from November 6th to 24th, 2017 (18 days). Each poi nt on the figure is the plant fresh weight value measured in eve ry day. It can be seen that the plant weight measurement device measures individual plant's weight non-destructive and continuous ly in the plant factory. The high-precision results were obtained. Therefore, the growth of individual plants during the growth peri od can be monitored and recorded using this plant fresh weight measurement device. The high-precision results were obtained. T he plant weight measurement device could be used to validate th e result of the developed image processing system.

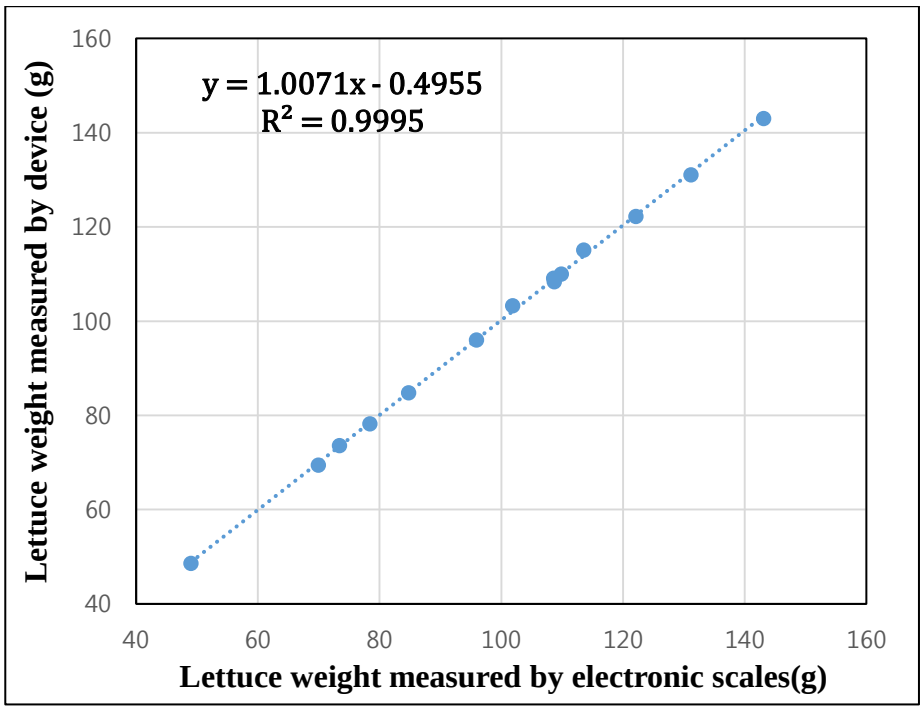


Figure 25. The validation of plant weight measurement device

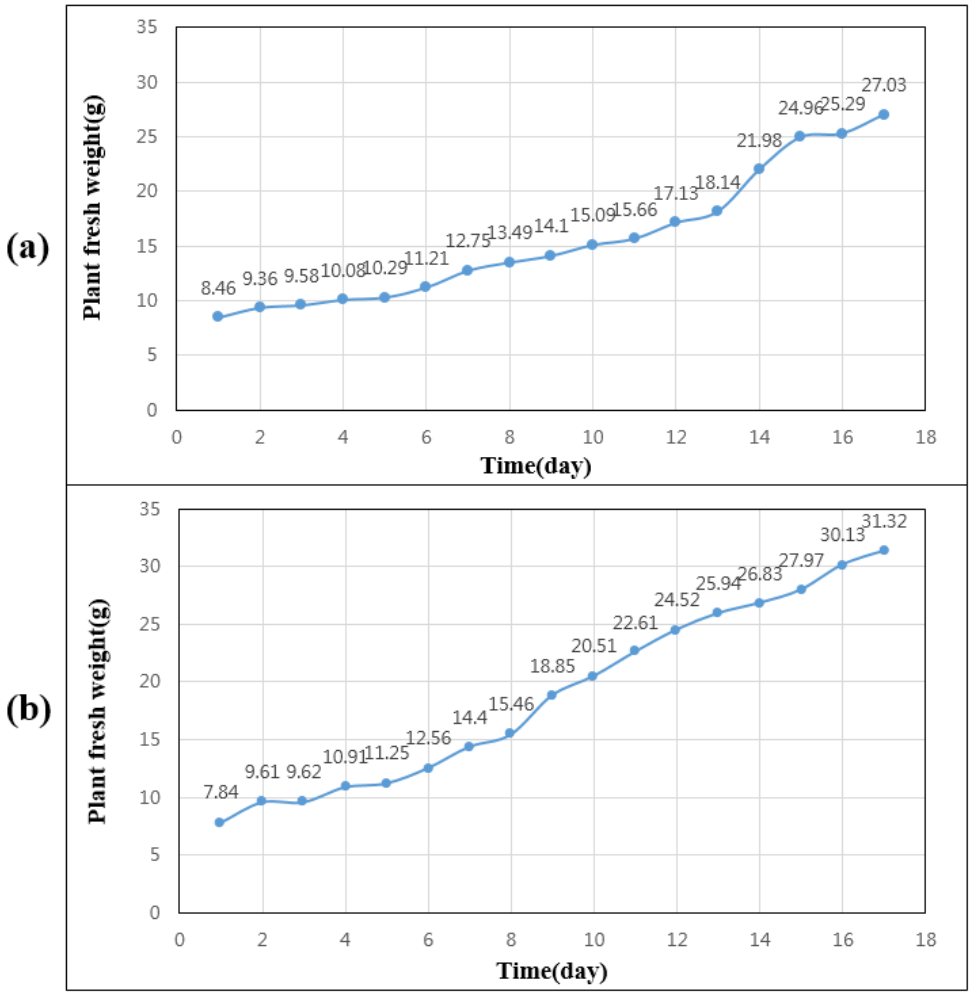


Figure 26. The plant fresh weight growth curves measured by two device

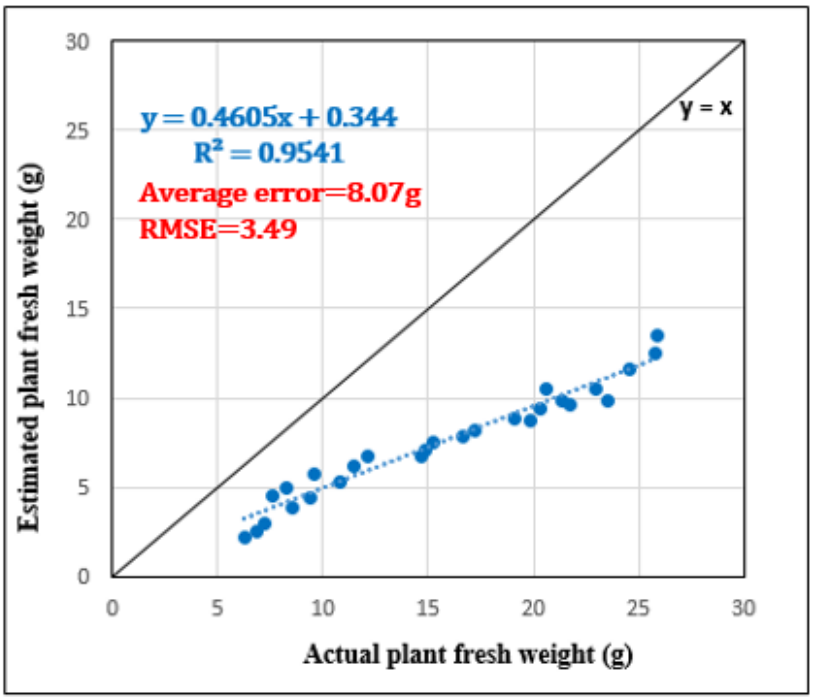
3.2. Fresh weight prediction validation

In order to measure the fresh weight of individual lettuce correctly, tw o samples were taken and measured using an electronic scale in 8th da y after transplantation. The measured results were used for compensati ng the fresh weight measured by image processing. Two plants were pl anted in the plant weight measurement device from February 10th to 2 6th, 2018 (16 days) measured the fresh weight by the device and imag e every day. Figure 27 shows the results of plant weight measurement validation of the plants. The vertical axis represents the fresh weight o f lettuce determined by the image processing system. The horizontal a xis is the fresh weight of the plants measured by the weight measurem ent device. The upper graph is the before compensation, the slope is 0.4605, the lowwer graph is the result after compensation, th e slope goes up to 0.9547. In order to compare the results of b efore compensation with the result of the after compensation, the average errors were analyzed and used. The average error of th e results of before compensation was calculated as 8.07g (RMSE =3.49) and the average error of the results of after compensation was calculated as 3.93g (RMSE=1.36). The average error and s tandard deviation were greatly reduced. The cause of the error st

ill existed is the different degrees of the leaves drooping and the slight error of the plant fresh weight measurement device. The cali bration operation can be used to further improve the accuracy of the pl ant fresh weight measurement. The calibration operation is pick a lettu ce and measured the difference value of the estimated weight (image) and the actual weight (electronic scale), then minus the value in the ne xt results. For example, a lettuce was picked in the 9th day (random) a fter transplantation, the estimated weight was calculated as 18.05g and the actual weight was measured as 14.6g, the difference value can be calculated as 3.45g. Figure 28 is the final result of the results minus th e difference value (3.45g), the average error was reduced to 1.08g (RMSE=0.95). In the actual application, this calibration method w ill be carried out, so the plant fresh weight will be measurement more accurately. The results showed that the compensation meth od is effective and can be used for improving the acuurcy of th e plant fresh weight estimation. A plant weight estimating time was on average 3.5s, and the specific processing time is shown in Table 1. The processing time of image acquisition and camera movement was about 79 percent of the total processing time. T hus, if the hardware performance is improved, the time required

for estimating the fresh weight of the plants on the growing bed might be greatly reduced.

(a)



(b)

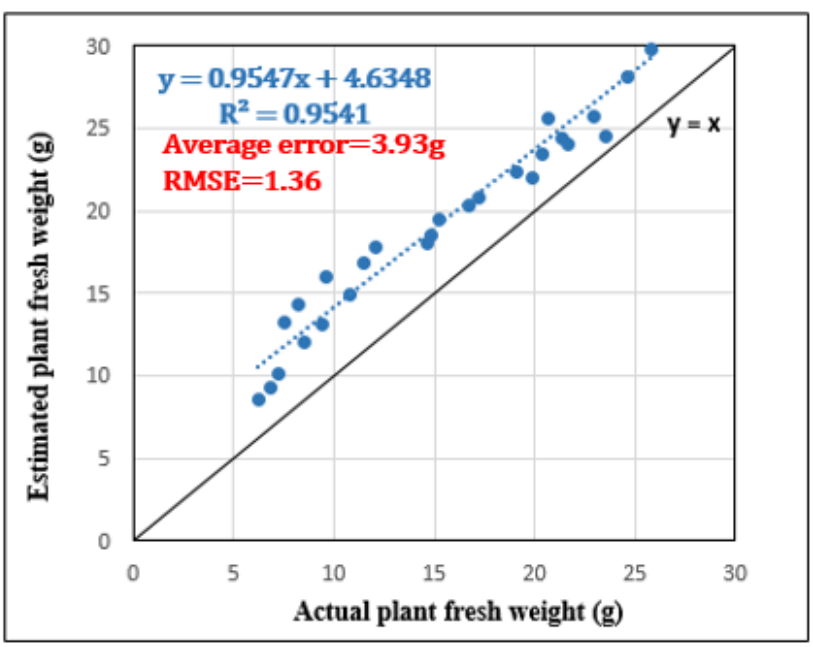


Figure 27. The results of plant weight measurement validation of plants:

(a) the result before conversion; (b) the result after conversion.

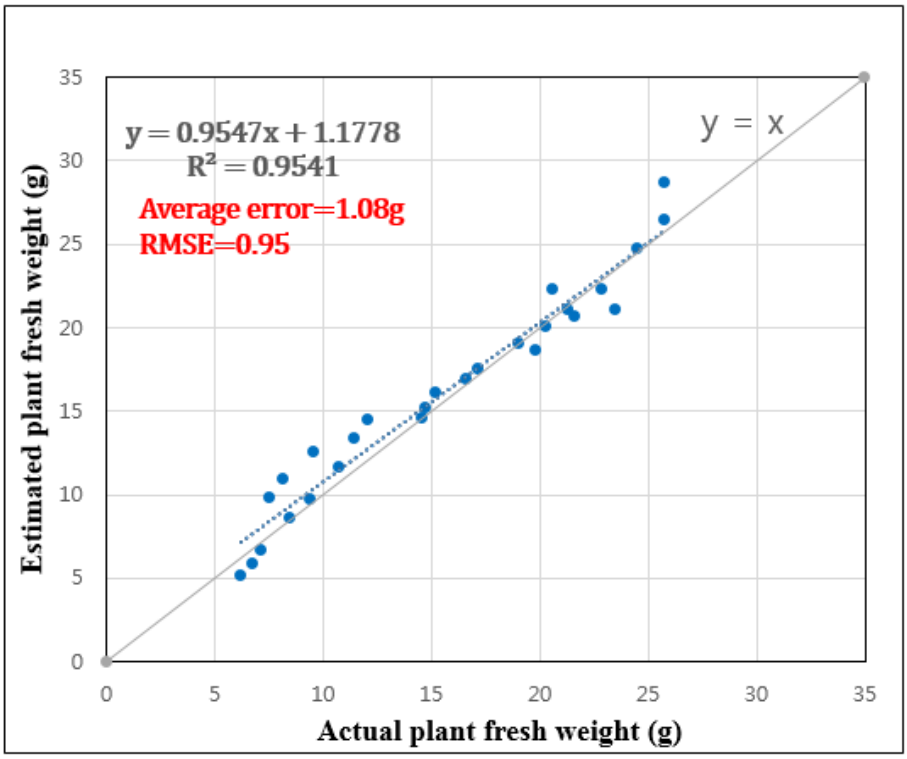


Figure 28. The calibrated result of the plant fresh weight measurement

Table 1. The processing time of a plant. (RMSE (ms) = 110.3)

	Processing time (ms)	*Percentage (%)*
Image acquisition	1500	41.8
Image segmentation	645	18.3
Target plant extraction	63	1.76
Fresh weight calculation	35	0.98
Camera location	1333	37.16
Total	3585	100

3.3. Spatial Mapping of Lettuce Fresh Weight

Using the developed image processing system, the locations of each plant could be calculated and expressed as XY coordinates. The location of the first plant taken was regarded as the origin. The spatial map of lettuce fresh weight was generated using a mapping software (Surfer®13, Golden Software, USA) to display spatial variability in fresh weight. Figure 29 was the generated spatial maps of lettuce fresh weight, the changes in the plant fresh weight distribution and plant fresh weight from the date after transplant 1 to the date after transplant 11 could be observed clearly. Use of such a mapping software was effective in investigating spatial variability in the fresh weight of lettuces grown in a bed installed in a plant factory. Especially in a relatively large plant factory, the use of the system would be useful in helping farmers to determine the harvesting time as well as to monitor the growth status of individual plants.

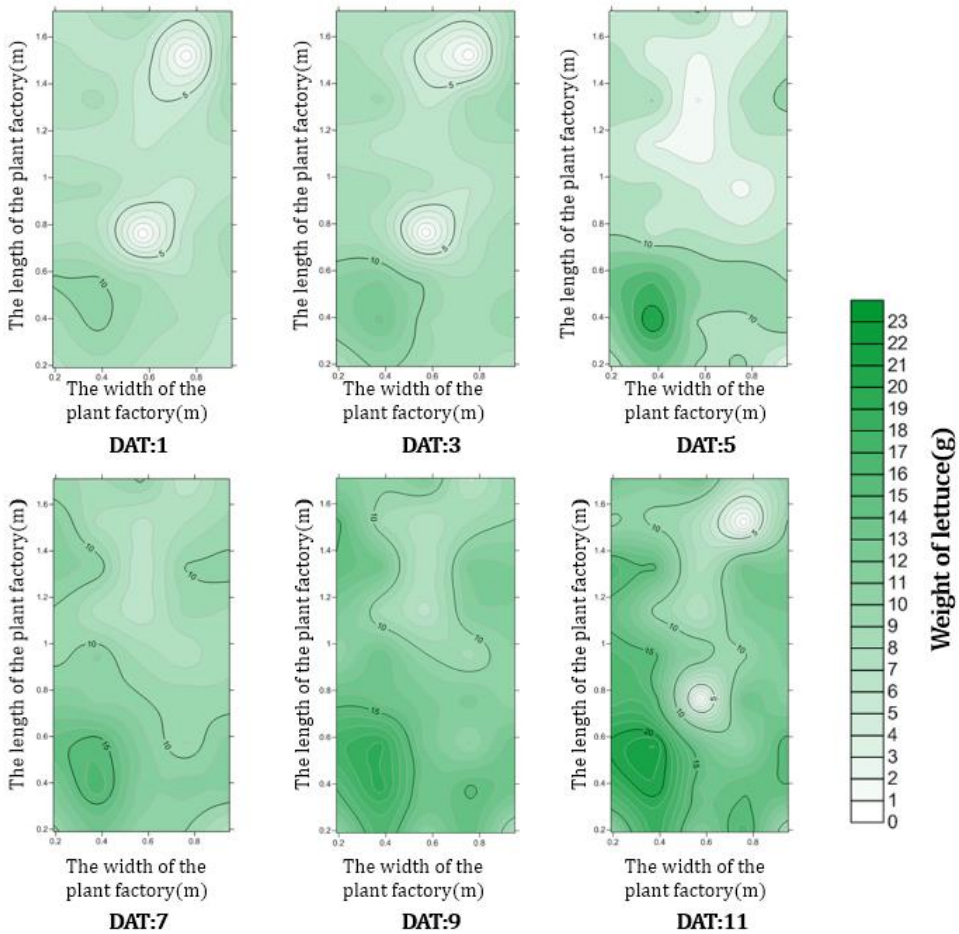


Figure 29. The example of lettuce fresh weight spatial map

.

3.4. Overlapping leaves separation

The overlapping leaf problem was occurred on the 8th day after transplantation. With the passage of time, the number of overlapped samples was increased and the level of overlapping becomes serious. The performance of the overlapping leaves separation algorithm was evaluated through comparing pixel count in the target plant canopy region calculated by image processing and the pixel count in the target plant leaf region calculated manually using the software, ENVI (Exelis Visual Information Solutions, USA) as shown in Fig. 30.

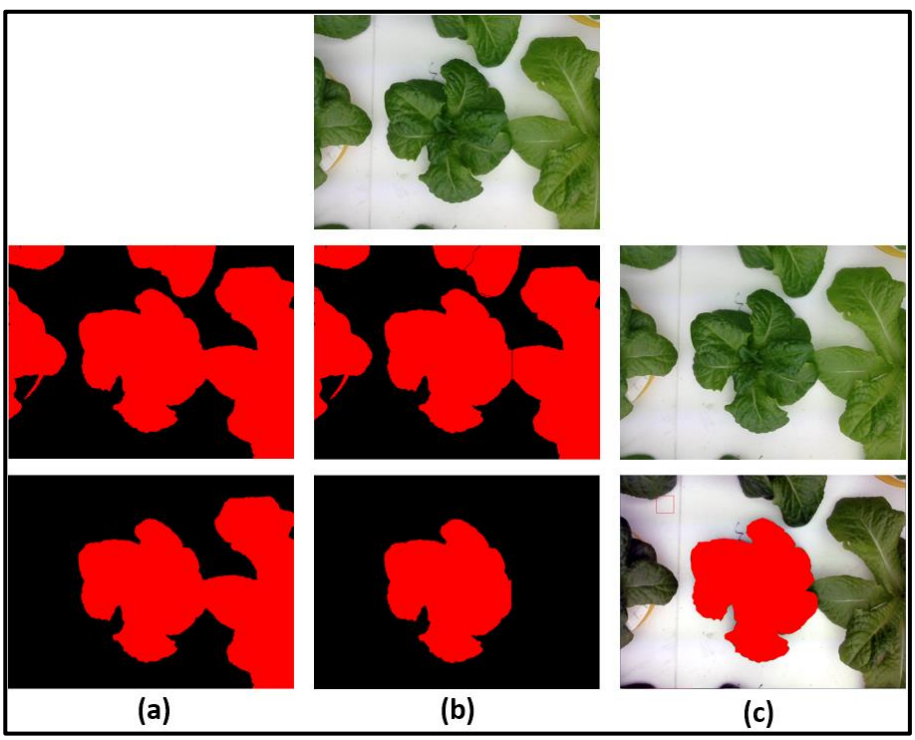


Figure 30. Results of overlapping leaves separation. (a) The result without proposed method. (b) The result by using proposed method. (c)

Manually separated using ENVI.

Figure 31 shows the performance of the developed overlapping leaf separation algorithm. The vertical axis represents the canopy area of lettuces calculated by the developed overlapping leaf separation algorithm. The horizontal axis is the actual canopy area of lettuce calculated by the pixel count which was obtained in the software, ENVI by hand. This result shows that when the canopy area of plants was less than $0.042m^2$, the developed overlapping leaf separation algorithm has an acceptable performance. When the canopy area of plants was over $0.042\ m^2$, the accuracy of overlapping leaf separation begins to gradually decline. This means that $0.042\ m^2$ of the lettuce is the maximum limit for this separation of the algorithm. Table 2 is the image processing result of a lettuce in each canopy area, this verified the conclusion of the Figure 31. When the canopy area of plants was over $0.042m^2$, the degree of overlap was too serious to separate using the proposed overlapping leaf separation algorithm.

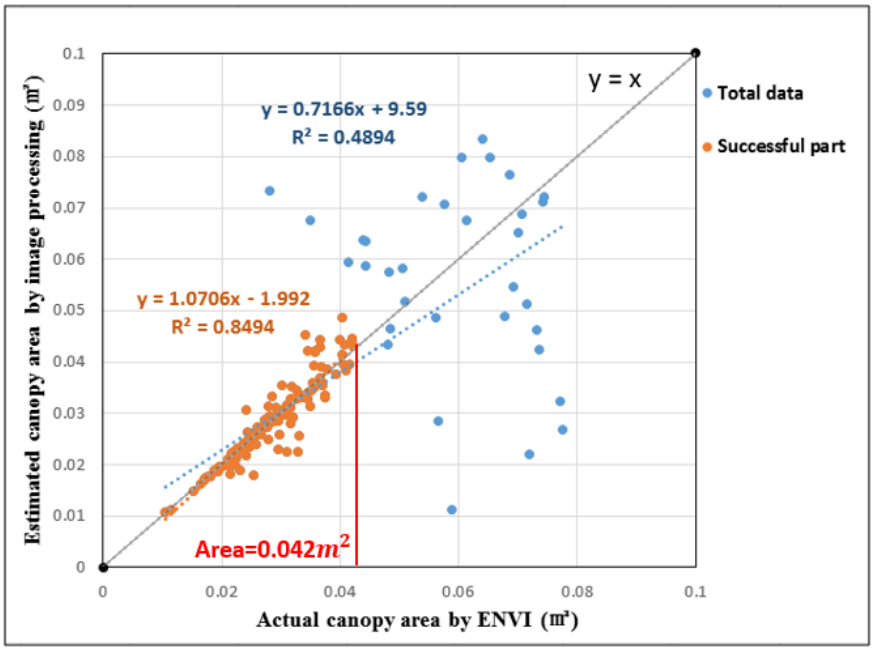
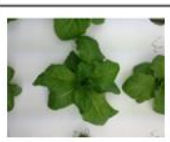
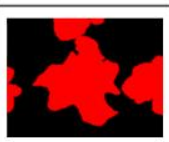
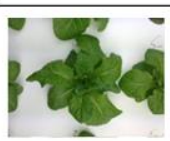
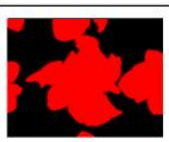
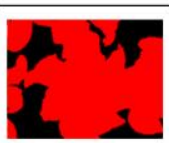
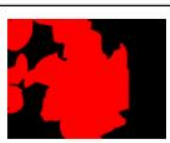


Figure 31. The total result of overlapping leaf separation

Table 2. The result of a lettuce in each canopy area.

Canopy Area (m^2)	RGB Image	Binary Image	Separated Image	Cropped Image
0.026				
0.030				
0.035				
0.042				
0.048				

The largest lettuce (canopy area = $0.042\,m^2$) in the successfully separated plant was selected to analyze the length of the leaves, as shown in Fig. 32. The average length of the leaves in this lettuce was calculated as 12.7cm. Actually the actual length of the lettuce leaves were longer than the calculated length due to the leaves drooped. If the measured length of leaves in image were assumed to be 80% of the actual length of leaves, the actual average length of leaves is about 15cm. This size is close to the length of a hand of adult. According to our findings in a commercial plant factory, the best harvest time for lettuce is when the size of the leaves of lettuce is approximately equal to the size of the hand. Therefore, the performance of the developed overlapping leaf separation algorithm is sufficient before the harvesting of lettuce.

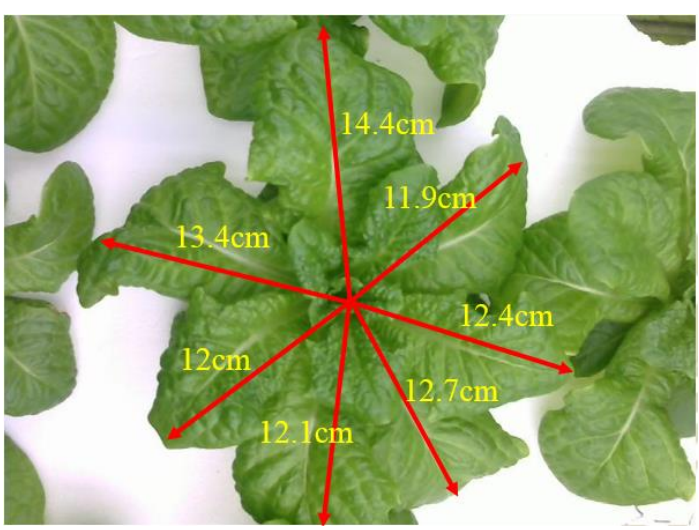


Figure 32. The canopy area of the $0.042m^2$ lettuce.

Table 3 shows the total results of the overlapping leaf separation in different date of transplant (DAT). The results showed that the results using the proposed overlapping leaves separation algorithm has a high accuracy from 8th to 11th of date of transplant. However, the performance of the proposed algorithm was reduced in the later stage of plant growth. In the 12th and 13th of date transplant, there were some successful separation of overlapping leaves as well as failures due to some plant canopy too large. Therefore, the overall results was not very good in the 12th and 13th of date transplant. However, most lettuces were large enough to harvest in the 11th of date of transplant.

Table 3. The overlapping leaf separation result in different date of transplant (DAT)

DAT	**8th**	**9th**	**10th**	**11th**
NO. of samples	4	9	15	22
Slope	0.97	0.99	0.96	0.95
R square	0.99	0.99	0.91	0.95
DAT	**12th**	**13th**	**14th**	
NO. of samples	27	34	40	
Slope	0.78	0.73	0.36	
R square	0.84	0.86	0.16	

The watershed segmentation algorithm is a useful method for solving the overlapping problem in an image. In order to prove the performance of the proposed algorithm, the watershed segmentation algorithm was used for comparing with the proposed algorithm. The same image data as above were used in the watershed segmentation algorithm. Figure 33 is the result of watershed segmentation algorithm was used. Because the canopy shape of lettuce is complex and irregular, the probability of the over separation problem was high in watershed segmentation algorithm. Therefore, compared to the watershed segmentation algorithm the proposed algorithm in this study has better performance.

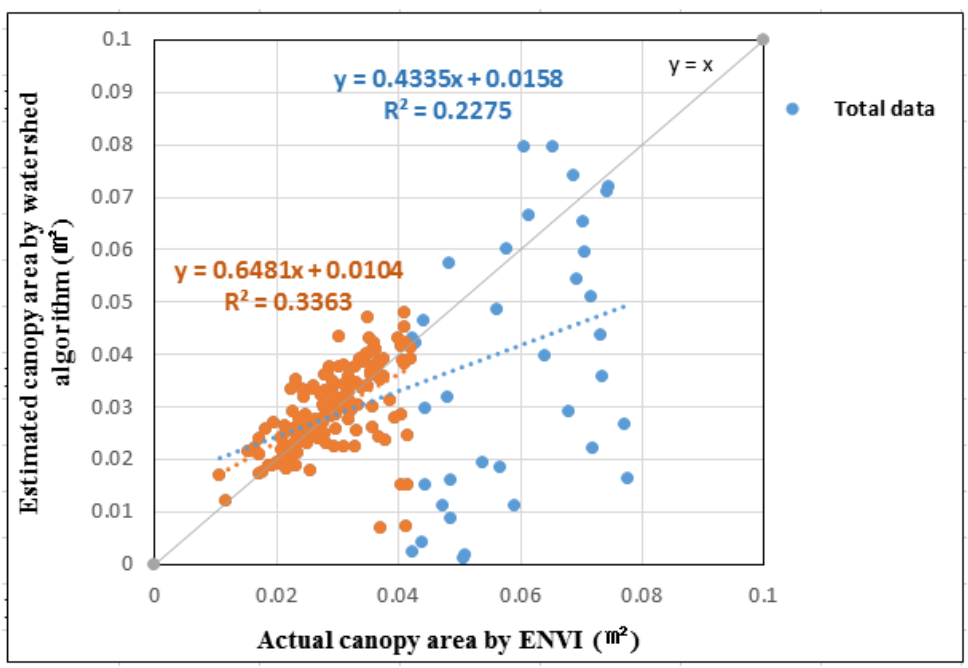


Figure 33. The result of watershed segmentation algorithm was used

Chapter 4. Conclusions

In this research, an on-the-go image processing system was developed that could monitor the growth status of plants grown in a plant factory. The system showed the ability to measure the plant fresh weight with an acceptable level of accuracy in real-time. In the late stage of plant growth the plant weight fresh weight measurement in an image became difficult due to overlapping leaf. The overlapping leaf problem has been solved to some extent by using proposed overlapping leaf separation algorithm and has a better performance than traditional method, watershed segmentation algorithm. By using the developed separation algorithm, the plant fresh weight could be measured until the harvesting of lettuce. Using the measured fresh weight and the location of each plant, the spatial map of lettuce fresh weight could be generated. With such a spatial map, the fresh weight distribution in plant factory could be monitored more clearly.

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식물공장 내 상추의 생체중 공간 매핑을 위한 이동형 임베디드 시스템 개발

강 길 송

국문 초록

식물공장에서 작물생장 변수에 대한 모니터링은 작물의 상태를 평가할 수 있으며, 작물을 정밀관리 할 수 있는 정보가 된다. 작물의 생체중은 수확을 위한 최적의 시간을 결정하는 데 사용되는 가장 중요한 생물 물리학적 인자 중 하나이다. 기존의 재래식 작물 무게 측정 방법은 파괴적이고 힘들다는 단점이 있다. 따라서 본 연구에서는 식물공장 내 실시간 작물 생체중 예측을 위한 이동식 영상처리 시스템을 개발하였다. 본 연구에서 개발된 주요 기술은 목표작물 추출 및 생체중을 실시간 예측하는 기술이며, 작물 잎의 겹침이 있는 사진에서 개별 상추를 분리하는 기술을 포함하다. 개발된 시스템에서 사진은 저비용 웹 카메라로 획득하였으며, NI MYRIO기반 임베디드 컨트롤러를 사용하여 영상처리를 진행하였다. 카메라와 임베디드 시스템은 스테핑 모터와 선형 액추에이터를 사용하여 작물 성장 베드 위의 XY 축 프레임을 따라서 이동한다. 본 연구에서 사용된 영상처리의 주요 알고리즘은 영상 분할, 목표작물 추출, 겹친 잎의 분리 3부분으로 구성된다. 영상 분할 단계에서는 HSV 색 공간의 S 채널과 Otsu's threshold 방법을 이용하여 작물 분할을 진행한다. 목표 작물 추출은 분할된 영상에서 영상 중심점과 가장 가까운 작물을 목표 작물로 인식하여 추출하

였다. 목표 작물 겹치면 영상에서 반복적인 침식 (erosion) 방법을 사용하여 겹친 잎을 분리하였다. 이후, 작물 생체중은 최종 단계 영상에서 자동으로 픽셀 수를 계산하여 예측하였다. 개발된 임베디드 시스템에 의한 생체중 예측과 실제 측정한 상추의 무게를 이용해 선형 회귀식을 구한 결과, 기울기가 0.95이고 결정 계수(R2)가 0.95 의 정확도를 나타내었다. 따라서, 개발 된 시스템을 이용한 실험결과는 실시간으로 각 상추의 생체중을 측정 할 수 있음을 보여 주었으며, 상추 수확한 시기까지 잎이 겹친 문제를 해결할 수 있다. 따라서 식물 공장에서 상추의 생체중을 예측하고 매핑하는데 유용한 도구가 될 것으로 기대된다.

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- 찬우 열심히 살고 있는 대단한 사람이다. 너에게 많은 것을 배웠어, 도움이 많이 해줘서 감사하고, 잘난 사람이 되는 게 기대할게
- 정환이 차한 사람이다. 같이 출장하는 것이 재미있고 많이 배워서 감사하고, 다음학기 교수님 없는데도 연구을 열심히하고 졸업을 무사히 할 수 있으면 좋겠다.
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