An Automatic Vision-Based Plant Growth Measurement System for Leafy Vegetables

Ta-Te Lin*, Tsung-Cheng Lai, Ting-Yu Liu,
Yu-Hui Yeh, Chang-Chih Liu, Wei-Chang Chung

Department of Bio-Industrial Mechatronics Engineering,
National Taiwan University, Taiwan, R.O.C
**Corresponding author. E-mail: m456@ntu.edu.tw*

Abstract

The measurement of plant features is a fundamental element of plant science research and related applications. The information related to plant features is especially useful for its applications in plant growth modelling and climate control in greenhouses or plant factory. Many methods have been applied in plant growth measurement. Traditional direct measurement methods are generally simple and reliable, but they are also time consuming and laborious. In contrast, vision-based methods are non-destructive and efficient methods to describe exterior plant features and plant growth. In this research, a stereo vision system which is composed of two off-the-shelf cameras with parallel optical axes was integrated with an image processing algorithm developed to monitor plant growth of Boston lettuce in a plant factory. The stereo vision system was mounted on a sliding rail to extend the field of view of the planting beds. Images were continuously recorded by the system to be used to determine plant features and construct panoramic images. The image processing algorithms calculating geometric features such as projected leaf area, plant height, plant volume, and equivalent diameters were developed and incorporated with the automatic measurement platform. Subsequently, the plant growth curves were deduced from plant feature data calculated. Results showed a promising performance of this automatic vision-based system in practice.

Key words: Feature, Image Processing, Non-destructive Measurement.

1. Introduction

As a fundamental question to be answered in plant science researches, the plant feature measurement has different applications in greenhouses and plant factory, especially in plant growth modeling and climate control. Norman et al. (1989) classified plant feature measurement techniques into three general categories: direct measurement, indirect measurement, and allometric determination. Generally, traditional direct measurement methods are simpler but time-consuming and destructive to plants. Many non-destructive measurement methods have been developed including vision-based measurement methods aiming to provide alternative and more efficient solutions. Vision-based measurement methods are non-destructive and effective ways to extract exterior plant features and estimate plant growth. Since advanced environmental control techniques have the need of an informative and quick method to measure the plant physiological responses, vision-based measurement methods have drawn a lot of research interests. Brenner et al. (1995) compared three non-destructive measurement methods on leaf area index: DEMON, Sunfleck Ceptometer, and LAI-2000. The feasibility of non-destructive measurement methods in practice was suggested as the results showed no significant measurement difference between non-destructive and direct methods. Afterward, He et al. (2003) successfully constructed a 3D modeling of plant population from 2D images and estimated the growth variables, including leaf area and average height, by incorporating information extracted from digital camera images with pixel stereological algorithm. This not only set a milestone in plant feature measurement research and also made stereo vision techniques as a representative method in non-destructive measurement methods. Chien and Lin (2005) utilized orthogonal images to improve the estimation accuracy on leaf number and leaf area of vegetable seedlings. Later, Lin et al. (2006) showed the possibility to use plant silhouette images to do more precise plant feature extraction on total leaf area, plant height and weight without predetermined calibration.

In this research, an automatic vision-based plant growth measurement system was developed to extract plant features from images acquired during plant growth on planting beds in a plant factory. The advanced image processing algorithms of SIFT, SURF (Bay, 2008), and RANSAC (Fishchler, 1981) were applied to identify overlapping areas and plant borderlines, thus to create panoramic images encompassing the whole planting bed. Furthermore, image processing techniques were applied to calculated 2D and 3D geometric features of plants in the panoramic images to assess the plant growth under different conditions. This paper demonstrates this automatic system's practical use in a plant factory.

2. Automatic vision-based plant growth measurement system

2.1 System setup and operations

The automatic vision-based measurement system was developed and put in practice in a plant factory from 8/3/2012 to 24/3/2012. The Boston lettuce was the selected leafy plant whose growth was observed. In order to monitor the plant growth continuously, the entire planting bed was pictured repeatedly every 30 minutes. The system operation flowchart is outlined in Fig. 1.

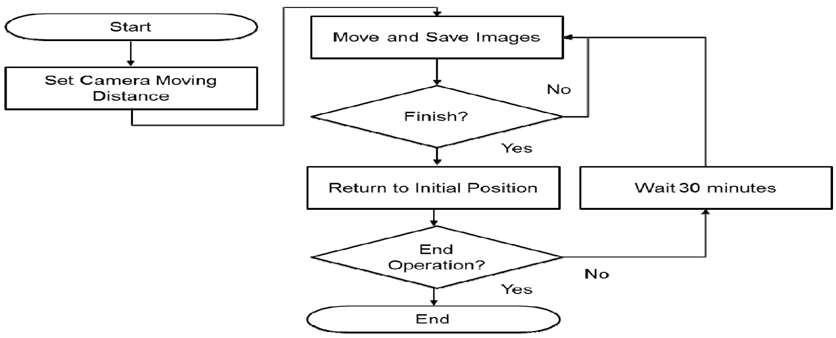


FIGURE 1: System operation flowchart

Fig. 2 illustrates the hardware design of the system and its working environment in the plant factory. As plants were cultivated on the planting bed using a hydroponic recirculating system, the cameras needed to move across the planting shelve to the precise locations and then take images. The camera moving distance was set to be 1 cm for each step in this research. In order to move the camera to its locations, a belt driven by a linear actuator was set up on the top of the planting shelve with a brushless DC electric motor and a brushless servo driver. An upside-down English “F” letter shaped arm was fixed on the slider of the belt. The aluminum arm was extended into the planting bed with two cameras mounted on its PE plastic board attached. The cameras were located 23 cm above the planting bed to ensure the whole plant was in the field of view. In each image acquisition and recording process, the cameras were moved from left to right across the whole planting bed. A series of repetitive movements including camera moving, stopping at specified location and image acquiring, was carrying out until the end of the planting bed before returning to the starting position. This iterative process continuously recorded image data and fed them back to the computer connected every 30 minutes until the experiment was terminated.

There were two planting rows with four planting holes in each row for each planting bed. The whole system monitored plant growths in two planting shelves (16 Boston lettuces in total) with one shelve having 16-hour lighting and the other with 24-hour lighting per day. 28 watts T5 tube lights were used in the experiments to provide two different groups of illumination control. One temperature and humidity sensor was attached on each axial arm to record these spatial environmental factors concurrently.

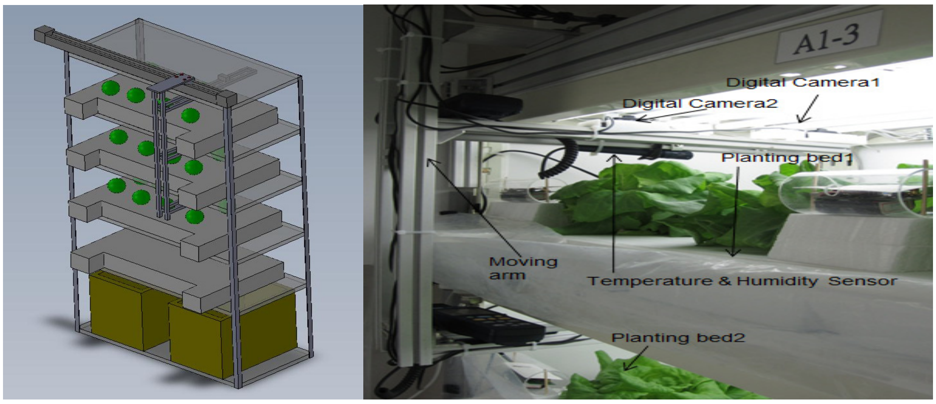


FIGURE 2: System hardware design and working environment

2.2 Image processing methodology

There were a number of image processing techniques and stages implemented in this research. Fig. 3 shows all image processing steps required for the growth data to be extracted from the raw image data. In particular, the OpenCV library functions were utilized in the image processing algorithm developed (Carsten et al., 2004).

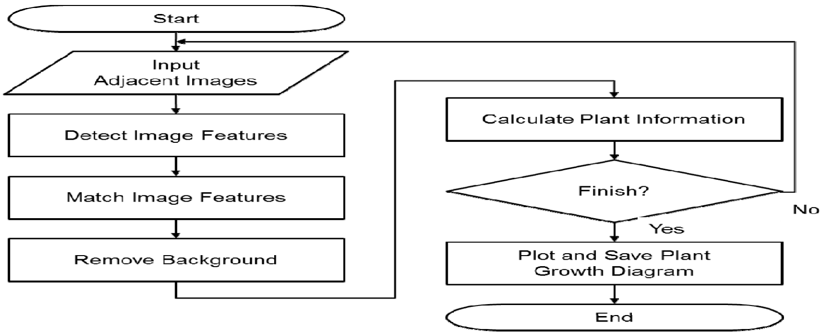
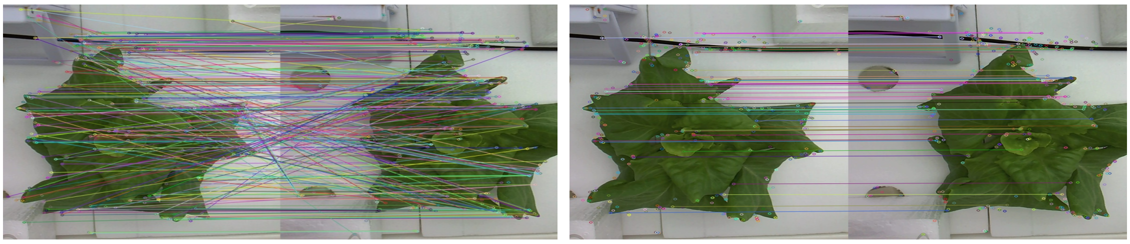


FIGURE 3: System image processing and data extraction stages

The performance of stereo vision techniques relies heavily on the correct determination of corresponding points in two images. Before calculating plant features, raw images were first processed to find and match corresponding points between two adjacent images in position. Lines shown in Fig. 4a represent the relative movements of the “corresponding points” found by the SURF algorithm (Bay, 2008). However, as the camera was moving in a horizontal direction from left to right, the corresponding points in adjacent images should only display approximate parallel horizontal movement lines.

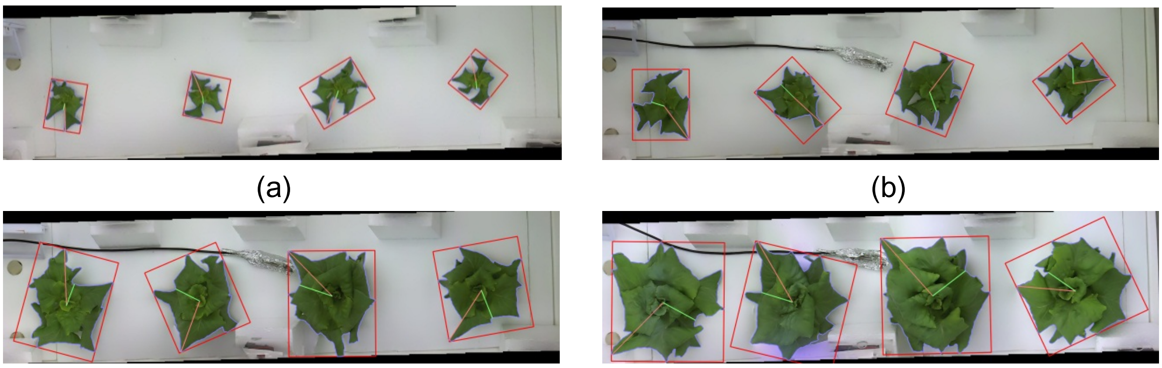
In order to remove the mistaken points matched by the SURF function, another algorithm, RANSAC (Fischler, 1981), was utilized to filter out these errors. The RANSAC function takes and compares random pairs of corresponding points between two raw images to find similarities in their relative relationships. Corresponding points that share a similar relative relationship are viewed as inliers while others are outliers. An inaccurate description of the true relative relationship between two images can be alerted by a large number of outliers. Hence, the true relationship for the corresponding points should be the relationship with the highest average number of inliers. In this research, the relative relationship was the approximate 4 cm relative movement from left to right. Fig. 4b shows corresponding points matched in two adjacent images after outliers being eliminated by RANSAC algorithm.



(a) (b)

FIGURE 4: Corresponding point detection and matching: (a) corresponding points found by SURF function; (b) corresponding points matched after outlier elimination

A panoramic image cannot be created by simply pasting adjacent images over one another with corresponding points found. In this research, in order to eliminate the errors caused by light angle differences in two images, the minimum Cut algorithm (Davis, 1998) was employed to match up borders with minimal errors found. The matched up image was then passed to a brightness control process which removes any unnatural changes in brightness. In order to minimize the time required to match up images, the relative relationship found in the preprocessing image calculation is applied onto the next set of raw images. Then the images were calibrated for any unforeseen errors. These processes were repeated until all adjacent raw images were stitched into one elongated image, the panoramic image, as shown in Fig. 5.



(a) (b)

(c) (d)

FIGURE 5: Stitched images of Boston lettuces in the planting bed at various growth stages. (a) ~ (d) are images of the 24-hour lighting group at day 5, 8, 11 and 14, respectively

2.3 Plant feature calculation

As this research is an extension project of Lin et al. (2011), we incorporated the plant feature calculation method from the paper with the automatic system developed in this research. In Lin et al. (2011), semi-global block matching (SGBM) function in OpenCV library was applied to calculate the disparity from an image pair. After calibrating with the disparity map, known focal lengths and distance between two camera sensor centers, the plant heights were calculated. In this research, the foreground of the panoramic image (the plant area in Fig. 5) must be separated from the background to calculate different 2D plant features. The GrabCut algorithm from the OpenCV library was used to cut the plant area out from the background and find the center of the image. Then, both 2D and 3D plant features including plant volume, plant height, width, length and diameters were extracted from the panoramic images constructed. Fig. 6 showed a typical example of plant images from camera went through different stages of image processing in order to extract plant features.

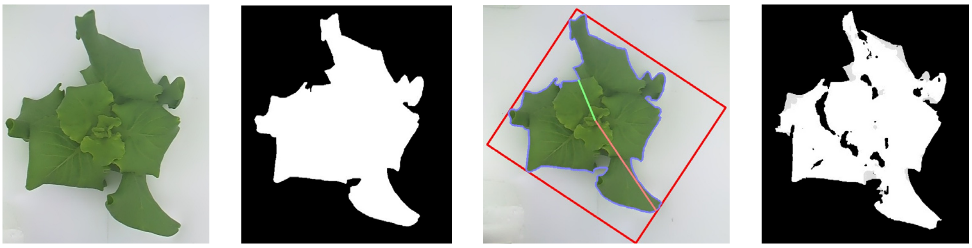


FIGURE 6: Image processing steps (left to right): raw image; background segmentation; maximum and minimum radii in plant feature calculation; disparity map in grey scale

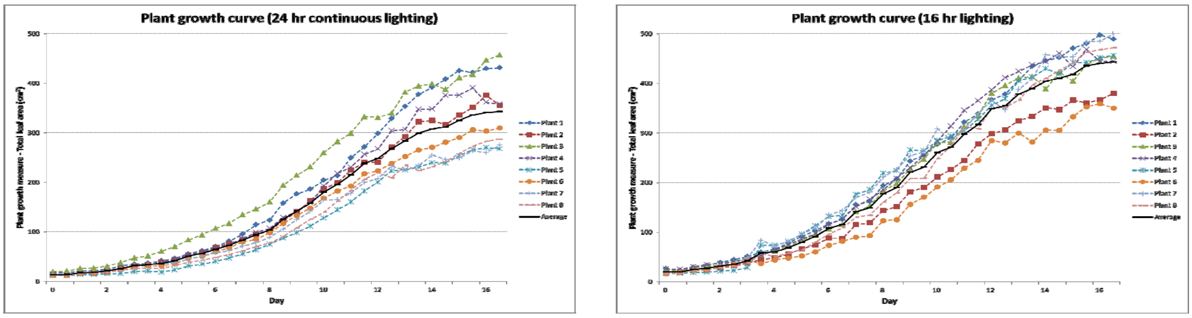
3. Result and discussion

The automatic vision-based measurement system developed in this research made the non-destructive plant growth monitoring possible. Although both 2D and 3D plant features were extracted, only total leaf area growth curves are presented here owing to page limit. The total leaf area was calculated by summing the product of each pixel and the pixel to centimeter ratio for all the pixels which were considered as the plant area. Fig. 7 plotted the growth curves of Boston lettuces examined starting from 9 days after seeding (March 8th). The black solid lines depict the average growth curve. In general, all growth curves show smooth leaf area increases. However, we see variations in them. The average total leaf area at March 24th in the 24-hour lighting group is around 340 cm^2 (267 cm^2 to 457 cm^2) while the other one is approximately 440 cm^2 (350 cm^2 to 500 cm^2). The 16-hour lighting group has shown not only a better but also a more steady growth performance in total leaf area than the 24-hour lighting group. The other plant features like minimum and maximum diameters also suggest similar growing pattern.

The system also provides spatial-temporal temperature and humidity information of the planting beds. For 24-hour lighting group, the average temperature at each sampled location ranged from 19.9 to 21.3°C comparing to the large 4.6°C average temperature difference between light on and off period in the 16-hour lighting group. Temperatures varied more considerably at both the second and third columns than both sides of the planting bed. Humidity level seemed to have obvious variation across days in the light on period but stable in the light off period. No particular pattern can be found in the humidity level across different time in a day and across planting position. Hence, we expect the humidity level has close correlation with the lighting.

From the 24-hour lighting group growth curves, it is clear that the plants in first row of the planting bed (plant 1 to 4), which is closer to the temperature control fan, all had better growths than the ones in the second row (plant 5 to 8). Incorporating the experimental results with the environmental observations, we suggest that with sufficient lighting Boston lettuce grow bigger and more consistent in a cooler and more humid environment.

Although the plant growth can be measured and visualized by this automatic system, we believe there are more can be done in future works. For example, there are unexpected minor drops shown in growth curves. These drops were induced by curly and overlapped leaves. Also, calibration of the plant features to the real fresh weight and dry weight will be the next step for a more realistic estimation of plant growth.



(a) (b)

FIGURE 7: Growth curves of Boston lettuce under (a) 24-hour lighting; (b) 16-hour lighting

4. Conclusion

This research demonstrates the functionality and feasibility of an automatic plant growth measurement system. The experimental results of the selected leafy vegetable, Boston lettuce, grown in a plant factory are presented here. The proposed vision-based measurement system combined with plant growth models has shown successful plant measurement and growth monitoring. The concurrent spatial-temporal temperature and humidity observations recorded are also available for detailed environmental analysis. It is believed that this integrated system can provide useful information and application in many areas such as horticultural research and practical plant production processes.

Reference list

Bay, H., Ess, A., Tuytelaars, T. & Gool, L. V., (2008). SURF: Speeded-Up Robust Features. Computer Vision and Image Understanding. 110, 346-359.

Brenner, A. J., Romero, M. C., Haro, J. G., Gilabert, M.A., Incoll, L.D., Fernandez, J. M., Porter E., Pugnaire, F.I., & Younis, M.T. (1995). A comparison of direct and indirect methods for measuring leaf and surface areas of individual bushes. Plant, Cell & Environment, 18: 1332-1340.

Carsten, R., Vladimir, K., & Andrew, B. (2004). GrabCut: Interactive Foreground Extraction Using Iterated Graph Cuts. ACM Transactions on Graphics, 23, Issue 3.

Chien, C. F., & Lin, T. T. (2005). Non-destructive growth measurement of selected vegetable seedlings using orthogonal images. Transactions of the ASAE. 48(5), 1953–1961.

Davis, J., (1998). Mosaics of scenes with moving objects. Computer Vision and Pattern Recognition. 354-360.

Fishchler, M. A., (1981). Random sample consensus: a paradigm for model fitting with application to image analysis and automated cartography. Communication Association Machine. 24(6), 381-395.

He, D., Matsuura, Y., Kozai, T. & Ting, K. (2003). A binocular stereovision system for transplant growth variables analysis. Applied Engineering in Agriculture 19(5), 611-617.

Lin, T. T., Chien, C. F., Liao, W. C., Chung, K. C., Chang J. M. (2006). Machine vision systems for plant growth measurement and modelling. Environ Control Biol, 44(3), 181-187.

Lin, T. T., Lai T. C., Liu, C. C. & Cheng, Y. C. (2011). A three-dimensional imaging approach for plant feature measurement using stereo vision. Journal of Agricultural Machinery Science. 7(2), 153-158.

Norman, J., Campbell, G., Pearcy, R., Ehleringer, J., Mooney, H. & Rundel, P. (1989). Plant physiological ecology: field methods and instrumentation. Chapman and Hall London.