Development of A Multi-Angle Imaging System for Automatic Strawberry Flower Counting

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Abstract

Timely harvesting of strawberry is critical because the strawberry fruit do not last long in the field once they are ripe. Therefore, farm managers need to estimate the required labor and to recruit workers in advance. Strawberry plants produce fruit continuously. However, it is difficult to predict the yield at a specific time period. High-yield periods, also called "major fruit waves", may appear at any time during strawberry growing seasons depending on many environmental and management-related factors. One of the effective methods for predicting fruit yield is to count number of strawberry flowers. Therefore, the objective of this study was to develop an automatic system for counting the number of strawberry flowers using computer vision and artificial intelligence. The system consisted of four digital color cameras, two light emitting diode lights, a desktop computer, and a GPS receiver, all installed on a ground platform made of metal square tubes. To acquire images of flowers hidden under leaves, the cameras were mounted at different angles with respect to the ground to form a multi-angle imaging system. A uniform artificial illumination was provided for the imaging system using the light emitting diode lights. Acquired images were processed using the onboard desktop computer. Algorithms were developed to synchronize the images from different cameras and to combine them together. GPS coordinates were also synchronized with each image. A trained Faster R-CNN model was applied to detecting flowers from the images. In addition, the model was also trained to detect immature and mature fruit. The system was attached to the end of a small tractor that is doing regular operations in the fields and driven along the rows in strawberry fields. Eventually, yield maps were created by associating the counted number of flowers and the acquired GPS coordinates.

Introduction

In Florida, strawberry production occurs during the dry winter months from October to March (Salamé-Donoso, Santos, Chandler, and Sargent, 2010). Open-field production is the main system used in Florida strawberry production. The strawberry transplants are planted in raised beds and covered with plastic mulch (Himelrick, et al. 1993). The plants are drip irrigated and protected from frost using sprinkler irrigation. The plants produce fruit continuously and the yields fluctuate greatly over the harvest season. Under favorable environmental conditions, high yields, which is also called "major fruit waves", can be achieved. It is almost certain that there will be several major waves throughout a harvest season but when they will occur is difficult to predict. On the other hand, growers and distributors have to make yield forecasts to make hiring and marketing decisions (Brown, 2003). Therefore, MacKenzie and Chandler (2009) developed an equation which used weekly flower count data and temperature data to predict weekly fruit yields. Based on their study, to achieve a reasonably accurate yield prediction, flowers from a subset of plants in a field must be counted on predetermined dates. Counting strawberry flowers is a very labor intensive work. To be able to apply the developed equation to Florida strawberry industry, automated flower counting methods should be created.

Vision-based methods are among the most effective approaches for object detection and counting. In agriculture, computer vision has been applied to yield estimation of various fruits, e.g. orange (Gan, et al., 2018), blueberry (Tan, et al., 2018), and apple (Linker, Cohen, and Naor, 2012). Our previous study on strawberry flower detection and yield estimation was conducted recently using aerial-based images acquired from a small unmanned aircraft system (Yang et al., 2019). The study achieved accuracies of between 80% and 88% on three different days and an accuracy of 84% in average. To further improve the accuracy, a ground-based multi-angle imaging system was developed in this study.

The objective was to develop a system to create a distribution map of strawberry flowers to predict major fruit waves.

Methods

A strawberry field was prepared at the Plant Science Research and Education Unit (PSREU) at the University of Florida in Citra, Florida during the 2017-18 and 2018-19 growing seasons. Ten rows of strawberry plants each 67-meter long were prepared in each year, among which two rows that had sprinkler irrigation equipment were not used for image acquisition. The strawberry cultivars were a combination of 'Florida Radiance' and Sensation® in the 2017-18 season and only 'Florida Radiance' in the 2018-19 season.

Hardware Description.

A prototype of ground-based strawberry flower counting system was designed and assembled, which consisted of four digital color cameras (Point Grey Grasshopper, 4.1 Megapixel, FLIR, Wilsonville, OR), a desktop computer (Alienware Aurora R7, Dell, Round Rock, TX), a differential GPS receiver (Ag GPS 132, Trimble, Sunnyvale, CA), LED lights, power supplies and a medal frame. Heavy-duty wheels were attached to the bottom of the platform. The overall hardware arrangement used for image acquisition in the field is shown in Figure 1.

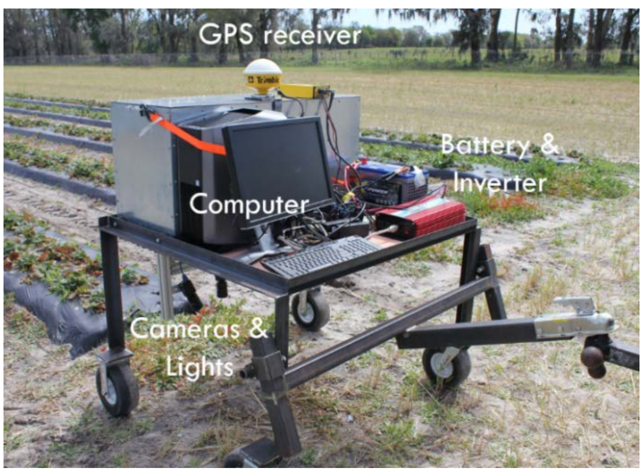

Figure 1. Hardware arrangement: computer, cameras and lights, GPS receiver and power supply.

The hardware design evolved to improve the quality of image acquisition from 2017-18 season to 2018-19 season. A major improvement was made by adjusting the positions and angles of the cameras. Figure 2(a) shows the arrangement of the four cameras in the 2018-19 season. The cameras on the left and right sides were positioned with their center 710 mm above ground and approximately 500 mm above the surface of the strawberry beds. They had a 60° angle relative to the horizontal line. The two cameras in the middle were mounted at the same height with a 90° angle relative to the horizontal line. Based on the observation of image data acquired in 2017-18 season, the middle cameras missed flowers located under leaves directly below the cameras. Although, the exact number of missed flowers were not quantified, the observation exposed the drawbacks of the design. Therefore, the cameras were rearranged during the 2018-19 season as shown in Figure 2(b). All four cameras were located at the same height at 700 mm above ground and had a 60° relative to the horizontal line. Lenses with a focal length of 12 mm were used to cover a field of view of approximately 305 x 305 mm close to the bed. This area was illuminated using LED lights mounted above cameras.

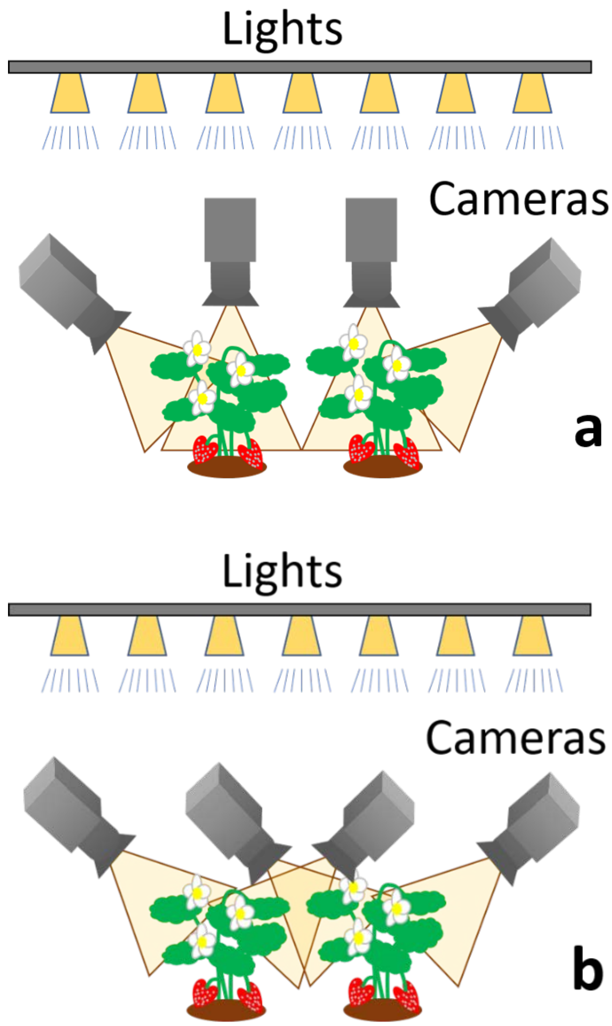

Figure 2. A comparison of two camera configurations. (a) The positions and angles of the four cameras in the 2017-18 season. (b) The positions and angles of the four cameras in the 2018-19 season.

Due to the close distance between cameras and plants, high acquisition speed, 90 frame per second (fps), was used to reduce motion blur in images. However, to reduce redundant images, only 5 images per second were stored in the hard drive. A solid state drive (SSD) was used for reading and writing image data to prevent the computer from dropping image frames.

The GPS antenna and receiver were mounted on the top of the medal frame. GPS coordinates were acquired through the NMEA GGA sentence along with the images. They were used to create distribution maps of flowers.

Experimental Setup.

Field experiments were conducted once a week from late January to early April. The setup was covered using a custom-made waterproof and lightproof canvas and towed by a tractor for field experiments as shown in Figure 3. The tractor traveled at 0.5 m/s over the beds. Each image acquisition started at the beginning of each row and stopped at the end.

Figure 3. Field experiment using the imaging cart towed by a tractor.

Algorithm Description.

A C++ program was written to automate the image acquisition process. Firstly, the four cameras were synchronized for image acquisitions so that they had the same frame rate. The synchronization made it possible to combine images from multiple cameras. Secondly, parameters of the cameras were set automatically by a program to save time in field experiments. Thirdly, the GPS and the four cameras were synchronized so that distribution maps can be created. Finally, the images and GPS data were stored in separated files with the same frequency.

A Python algorithm was written to do the post-processing. Deep learning models based on Faster R-CNN were trained using part of the image data from 2018-19 season. The models were trained to detect not only flowers, but also immature and mature fruit. Five hundred images were manually labeled in three classes, flower, immature fruit, and mature fruit, and the training took approximately 30 hours. Then, a Python program was written to utilize the trained models for detecting flowers in images. Two tracking methods, optical flow and feature-matching based method, were implemented to avoid counting the same flower multiple times in overlapped images. The total number of flowers in each row was determined by combining the detection results and the tracking results. In addition, GPS data and the numbers of flowers were matched to show variabilities of the number of flowers in each row. The training of the deep learning model was only required once in the post-processing. All other steps were integrated into one program which generates distribution map data automatically.

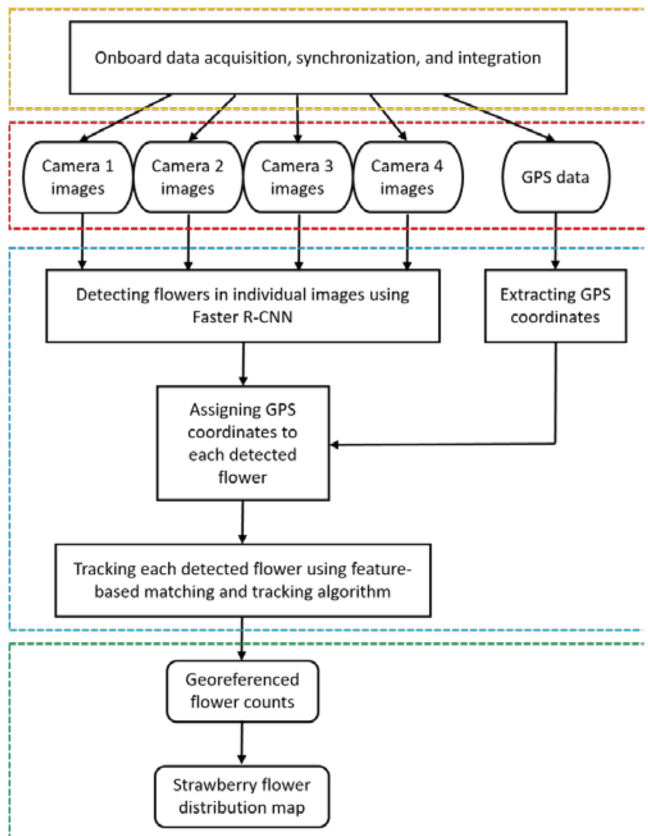

Figure 4. Data acquisition and processing pipeline. Orange box: onboard data acquisition using C++ program; Red box: the input data for post-processing; blue box: flower detection and counting algorithm; green box: output data and distribution map of strawberry flowers.

Results and Discussions

Multi-angle Image Acquisition.

Images were randomly sampled and evaluated manually after each field experiment to ensure that all four cameras were synchronized, and the images were not blurred. Based on pre-tests, the four cameras had a maximum time difference of 0.03s between the 1st image and the 4th image. The typical time difference was under 0.01s. Given the tractor's speed of only 0.5 m/s, images from the four cameras aligned very well. Figure 5 shows example images taken by the four cameras under the same trigger.

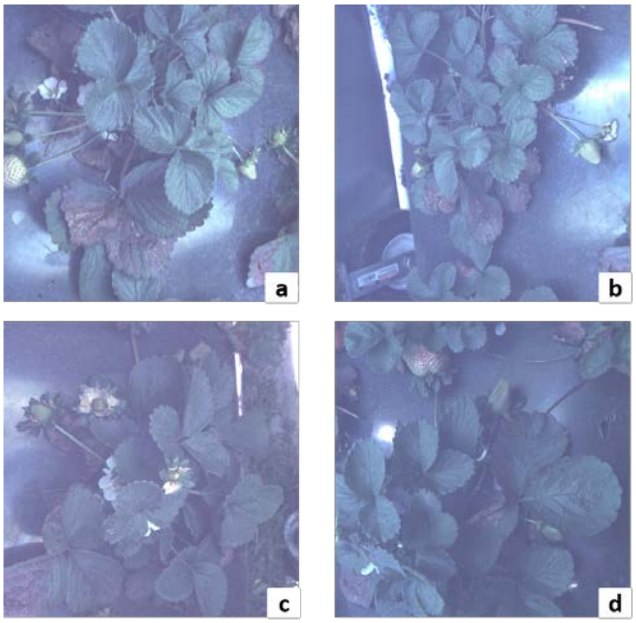

Figure 5. Examples of images acquired by the four cameras under the same trigger. (a) and (b) are images of the same plant, and (c) and (d) are images of the same plant.

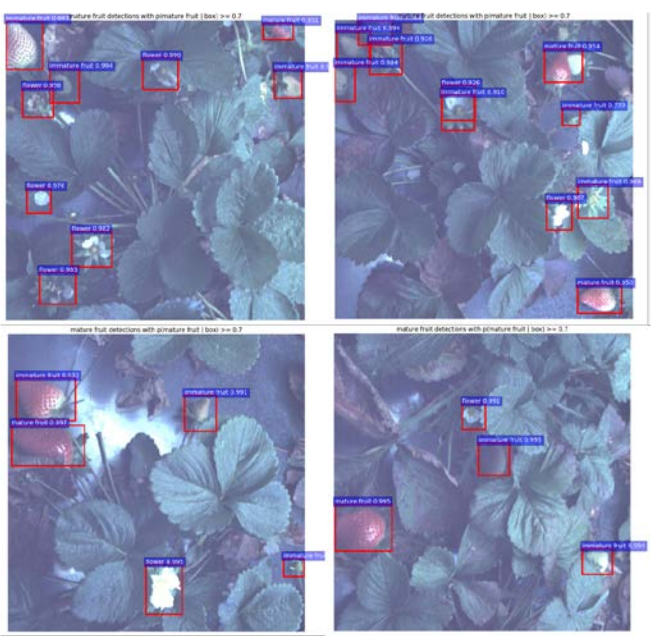

Figure 6. Examples flowers and fruit detected by the Python algorithm using trained Faster R-CNN model.

Flower and Fruit Detection and Counting.
Acquired images were processed using the developed Python algorithm. Figure 6 shows examples of flowers and fruit detected by the algorithm. The average precision (mAP from Faster R-CNN) for flower, immature and mature fruit were 0.83, 0.85, and 0.86, respectively (Table 1). The main causes of errors were the misclassifications in transition stages, including the stages that flowers were turning to immature fruit and immature fruit was turning to mature fruit. There was not a clear cut difference between flower and immature fruit, and between immature fruit and mature fruit.

Table 1. Average precision in detection of flower, immature fruit and mature fruit evaluated by Faster R-CNN

Class Label	**Average Precision (mAP)**
Flower	0.83
Immature fruit	0.85
Mature fruit	0.86

The detecting, tracking and counting algorithm was applied to images of entire rows and the results of detected flowers were compared with manual counts in the videos (overlapped images). Accuracies of 0.97, 0.95, 0.98 were achieved by the algorithm in counting flowers, immature fruit and mature fruit, respectively. Table 2 shows the results of flower and fruit counting in the 2018-19 season from row 2 on February 21st, 2019. The output of flower and fruit counts and their associated GPS locations were stored in a CSV file. ArcMap (ESRI 2010. ArcGIS Desktop: Release 10. Redlands, CA: Environmental Systems Research Institute) was used to create distribution maps of flowers and immature fruit and yield map of mature fruit. Figure 7 shows examples of the distribution maps and fruit yield map of the entire field (8 rows) on February 21st, 2019.

Table 2. Results of flower, immature fruit and mature fruit counts by the Python algorithm.

Class Label	**Total counts by algorithm**	**Manual counts in the images**	***Accuracy**
Flower	619	638	0.97
Immature fruit	2126	2243	0.95
Mature fruit	1244	1266	0.98

*Accuracy = Total counts by algorithm/Manual counts in the image

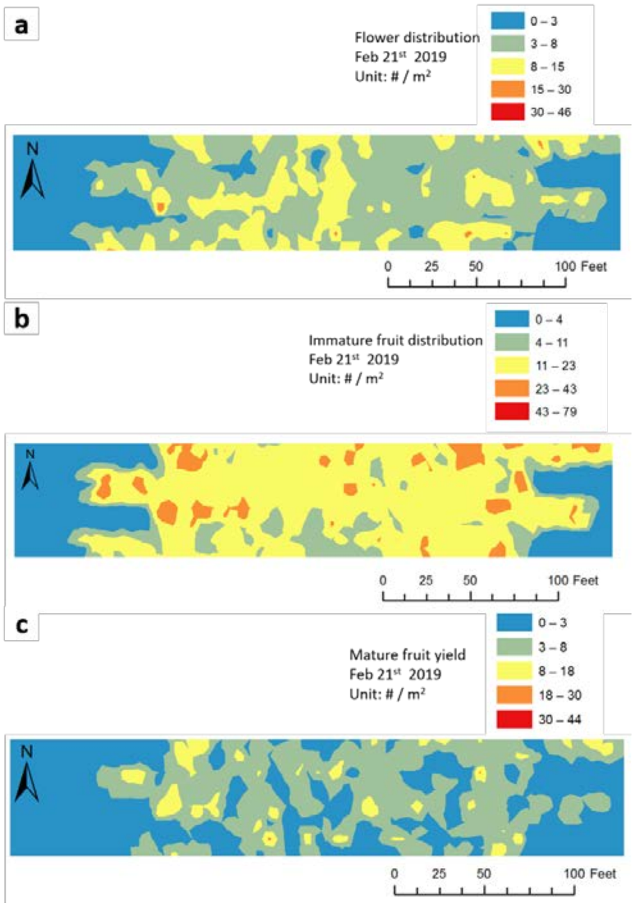

Figure 7. Distribution and yield maps of strawberry flowers and fruit for the entire experimental field (8 rows) on Feb 21st 2019. (a) flower distribution map; (b) immature fruit distribution map; (c) mature fruit yield map.

Conclusion

In this study, a hardware system was designed for automatic image data acquisition from a strawberry field using a multi-angle imaging system. The configurations were refined through experiment and evaluations in the 2017-18 and 2018-19 strawberry seasons. The collected data were then analyzed using Faster R-CNN to detect and count flowers and fruit from multi-angle images. The developed method and algorithm accurately identified strawberry flowers with a 97% accuracy in the images acquired from the field, and 95% and 98% accuracies for immature and mature fruit counting, respectively. Distribution and yield maps showing the total number of flowers and fruit and their variations in the field were generated.

Future Work

During the next phase of this project, a new compact platform will be developed to prepare the system for commercial usage. The system will be upgraded by replacing the computer with a mini-computer which can be powered by a 12-volt power supply. All components will be integrated together and installed in a cubic metal enclosure. A metal frame with a simpler structure will be designed to replace the previous frame. New programs will be developed to be compatible with the new system. The developed system is expected to be more robust and reliable and to allow easy field setup and maintenance.

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References

Brown, M. (2003). Florida strawberry production and marketing. The strawberry: a book for growers, others. Dr. Norman F. Childers Publications, Winter Park, FL, 31-42.

Chen, Y., Lee, W. S., Gan, H., Peres, N., Fraisse, C., Zhang, Y., & He, Y. (2019). Strawberry Yield Prediction Based on a Deep Neural Network Using High-Resolution Aerial Orthoimages. Remote Sensing, 11(13), 1584.

Gan, H., Lee, W. S., Alchanatis, V., Ehsani, R., & Schueller, J. K. (2018). Immature green citrus fruit detection using color and thermal images. Computers and electronics in agriculture, 152, 117-125.

Himelrick, D. G., Dozier Jr, W. A., & Akridge, J. R. (1993). Effect of mulch type in annual hill strawberry plasticulture systems. Acta Hortic. 348, 207-212. DOI: 10.17660/ActaHortic.1993.348.32

Linker, R., Cohen, O., & Naor, A. (2012). Determination of the number of green apples in RGB images recorded in orchards. Computers and Electronics in Agriculture, 81, 45-57.

MacKenzie, S. J., & Chandler, C. K. (2009). A method to predict weekly strawberry fruit yields from extended season production systems. Agronomy journal, 101(2), 278-287.

Salamé-Donoso, T. P., Santos, B. M., Chandler, C. K., & Sargent, S. A. (2010). Effect of high tunnels on the growth, yields, and soluble solids of strawberry cultivars in Florida. International Journal of Fruit Science, 10(3), 249-263.

Tan, K., Lee, W. S., Gan, H., & Wang, S. (2018). Recognising blueberry fruit of different maturity using histogram oriented gradients and colour features in outdoor scenes. Biosystems engineering, 176, 59-72.