Automated Strawberry Flower Counting using Machine Vision for Yield Prediction

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Summary

The objective of this phase of the project was to develop an automatic imaging system for counting the number of strawberry flowers using computer vision and image processing. 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 tubing. It was towed by a tractor to move over rows of strawberry plants and configured to capture images at a high frame rate to effectively handle bluring effects of motion. The captured images were analyzed using an improved version of the computer vision algorithm developed during the phase 2 to obtain flower counts. A new algorithm was developed to combine flower counts from multiple images and to integrate GPS coordinates for mapping flower distribution.

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 2018-19 growing season. Eight rows of strawberry plants, each 220 feet long, were used for the experiments. The strawberry cultivar was 'Florida Radiance'.

Hardware Description:

The hardware setup used this year were kept consistent with the setup in year 2. It consisted of four Point Grey Grasshopper (4.1 Megapixel) cameras arranged in such a way as to capture the top and side views of the strawberry plants. The cameras were rearranged this year comparing to the arrangement in year 2 (Fig. 1) to have a better view of flowers located under leaves. Lenses with a focal length of 12 mm were used to cover a field of view of approximately 12 x 12 inches close to the bed. This area was illuminated using LED lights mounted above cameras.

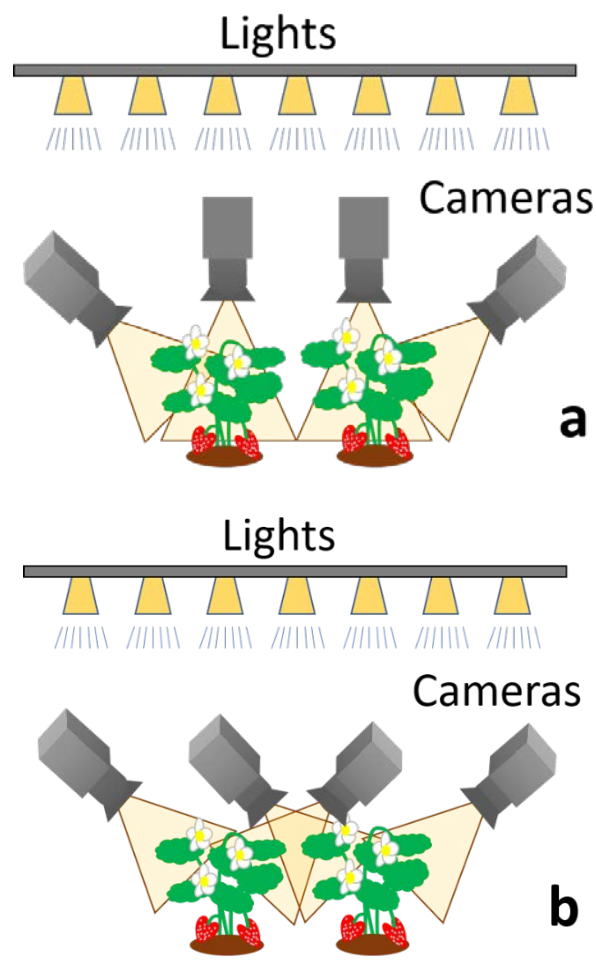

Figure 1. A comparison of camera configurations in year 2 and year 3: (a) positions and angles of the four cameras in year 2, and (b) positions and angles of the four cameras in year 3.

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.

GPS coordinates were acquired along with the images using a Trimble GPS receiver. These were used to create distribution maps of flowers.

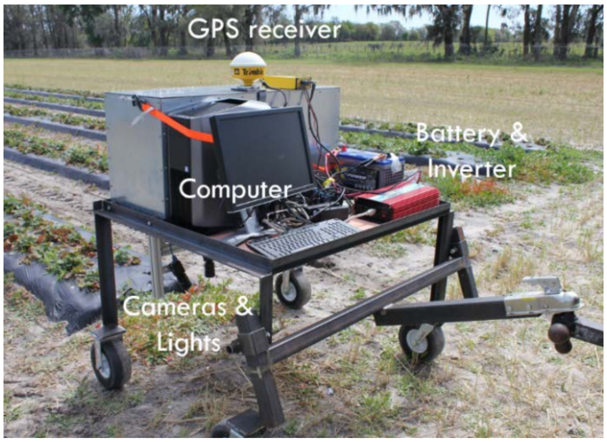

Figure 2. Hardware arrangement: computer, cameras and lights, GPS receiver and power supply.

Experimental Setup:
The overall hardware arrangement used for image capture in the field is shown in Fig. 2. The setup was covered using waterproof and lightproof canvas and towed by a tractor for field experiments as shown in Fig. 3.

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 flower distribution maps can be created. A Python algorithm was written to set up camera parameters, synchronize the cameras and combine the GPS signals with the images acquired by the cameras. The use of this algorithm removed all manual setups in field acquisition and made the post image processing much easier.

During the post-processing, a deep learning model based on Faster R-CNN was trained using this year's data. Five hundred images were labeled and trained for approximately 30 hours. Then, a Python program was written to utilize the trained model for detecting flowers in images. A feature-matching based tracking method was developed 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 flower distribution 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 flower maps automatically.

Results & Observations

Field experiments were conducted once a week from late January to early April, 2019. Acquired images were processed using the developed Python algorithm. Figure 4 shows examples of flowers detected by the algorithm. 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 field. An accuracy of 97% was achieved by the algorithm developed this year. Table 1 shows the detection results in year 3 from row 2 on February 21st, 2019. Maps of strawberry flowers were generated. Figure 5 shows an example distributon map of flowers of the entire field (8 rows) on February 7th, 2019.

Table 1. Flower detection results from row 2 on February 21, 2019. The accuracy was evaluated by total counts by algorithm / manual counts in the images, because manual counts in the field were not accurate. For future studies, much bigger efforts should be made to do field counts. Counting manually in the field is very labor-intensive during major fruit waves which shows the usefulness of the automatic counting system under development.

	Total counts by algorithm	Manual counts in the field	Manual counts in the images	*Accuracy
Flower	619	523	638	0.97

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

Figure 4. Example images of correctly identified flowers in red boxes in year 3. Flowers hidden under leaves were also successfully detected by the algorithm.

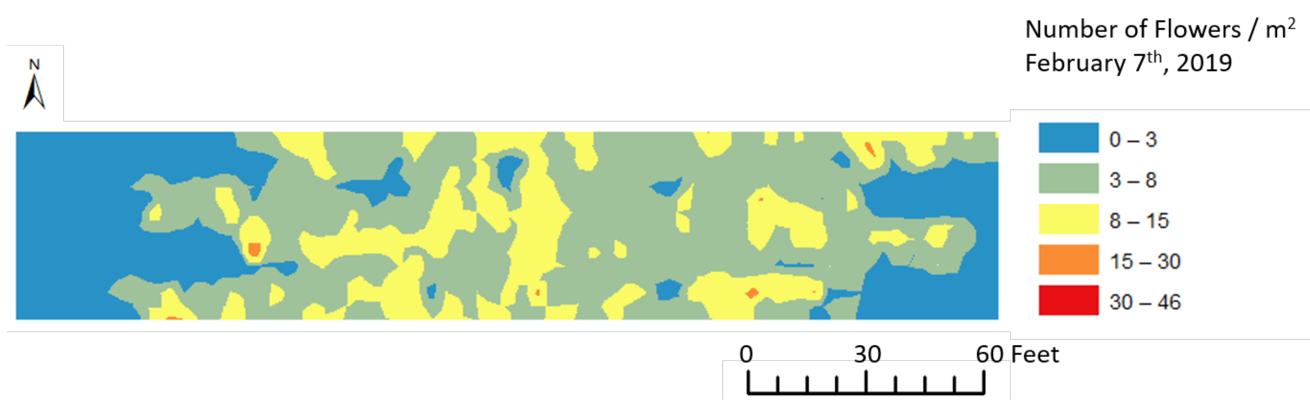

Figure 5. Distribution map of strawberry flowers on February 7th, 2019. The number of flowers was calculated in each unit area. The map shows the variability of flowers in the strawberry field. The total number of flowers on February 7th was 6558.

Conclusions

In this phase of the project, a hardware system was refined and used for automatic image data acquisition from a strawberry field using machine vision cameras and a lighting system. The collected data were then analyzed using a newly developed deep object detection neural network to detect and count flowers in multiangle images. The developed method and algorithm accurately identified strawberry flowers with a 97% accuracy in the images acquired from the field. Flower discribution maps showing the total number of flowers and variations in the number of flowers 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 developed in year 3 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. 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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