Final Report of 2012-13 Citrus Initiative Program

Title: Estimation of citrus fruit drop on the ground using machine vision

PI: Won Suk "Daniel" Lee, Agricultural and Biological Engineering, University of Florida
Co-PI: Reza Ehsani, Citrus Research and Education Center, University of Florida
Graduate Research Assistant: Daeun Choi, Agricultural and Bio. Engr., Univ. of Florida

In this project, a machine vision system for detecting and counting citrus fruit on the ground was developed and tested in order to aid other research projects in the Citrus Initiative program. Specific objectives were to:

1. Complete a hardware system for image acquisition using multiple cameras,
2. Acquire images of citrus fruit drops on the ground in a grove, and develop a software system to identify citrus fruit, and
3. Test the citrus fruit drop estimation system in a citrus grove where other citrus initiative projects are conducted.

A sophisticated classification algorithm was developed to detect dropped citrus fruit from images using logistic classifiers trained by feature information of each object in images. After detecting the citrus fruit using the classifier, a least square circle fitting was applied in order to get the position and the diameter of each citrus fruit individually. Field experiments were conducted in a commercial citrus grove to evaluate the performance of the prototype system.

MATERIALS AND METHODS

Hardware for Image Acquisition: The hardware for image acquisition consisted of two parts: image acquisition equipment and a camera-triggering device, which are shown in Figure 1. To acquire images, the machine vision system had two color CCD cameras with a microprocessor (1772C smart camera, National Instruments Corp., Austin, TX), two VGA monitors, metal mounting frames to a vehicle, and an encoder (CI20, Stegmann Inc., Dayton, OH).

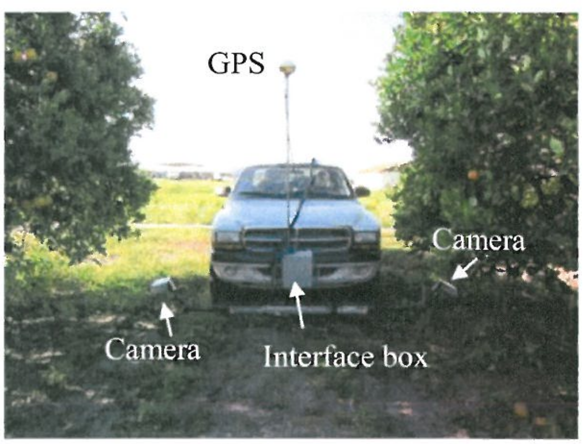

Figure 1. Prototype system for detecting and counting fruit drop on the ground: front view (left), and rear view (right).

The camera had an Intel 1.6 GHz Atom processor and real-time operating system which enabled the camera to acquire digital color images and other information in a simpler way, as opposed to the traditional way of passing data to a computer and then transmitting a trigger signal to the camera. Data from the encoder and a differential GPS receiver (AgGPS 132, Trimble, Sunnyvale, CA) were sent to the camera through a terminal block installed inside an interface box. The encoder was used as an external triggering device for the camera, which helped avoid an overlapped area between images. The DGPS receiver was also triggered to save the position information where images were acquired.

Image Acquisition Software: An executable software to acquire images and GPS coordinate was developed using LabVIEW 2012 (National Instruments Corp., Austin, Texas). This image acquisition software had three main purposes, i.e., displaying images, reading digital input from the encoder, and reading position information in a serial port transmitted from the DGPS receiver.

Field Experiment: The detection and counting algorithm of dropped citrus fruit was developed using images acquired from three field experiments in Duda & Sons grove (Immokalee, FL), Silver strand grove (Immokalee, FL), and Lykes Bros. Inc. grove (Ft. Basinger, FL). The average row spacing for these citrus groves was 24 ft and the tree spacing was 15 ft. Since dropped citrus fruit on the ground were most important in the experiments, images covered a wide area of the ground, especially under the canopy. The clearance between the ground and lowest canopy for hand harvested rows at the Duda grove was less than one foot. While this would be OK for hand harvesting, it turned out to be troublesome for acquiring images by the developed prototype system. For the mechanically harvested rows at the Lykes grove, the canopy was skirted in order to make it accessible by a mechanical harvester, and so the lowest canopy was about 18 inches above the ground.

Machine Vision Algorithm: In total, 1470 images were acquired during the field experiment. Each image had a resolution of 480×640 pixels to make process time faster. Among those, 10% of the images were randomly chosen to be used as a training set and the rest of 90% were designated as a validation set. The image pixels were classified into two classes: citrus fruit and background (non-citrus objects). Direct classification was difficult due to the similarity in the color of the objects and the varying illumination conditions between the images and within an image. This was because the images covered a wide area (3 ft horizontal field of view and 7 ft vertical field of view), which included ground under the canopy and the ground without canopy. The ground had a lot of shadows in some areas, which made the color of objects darker. In contrast, some areas without the shadow resulted in the soil having an excessive amount of white color due to the high sunlight intensity. Therefore, illumination conditions were normalized to diminish the drastic change in intensity level, as defined as Equation 1. After that, multiplying with 255 made citrus fruit more distinguishable among other objects by increasing the difference of the color value.

$$\begin{pmatrix} R' \\ G' \\ B' \end{pmatrix} = 255 \cdot \begin{pmatrix} R/I \\ G/I \\ B/I \end{pmatrix} \tag{1}$$

where I is intensity component of an image; R, G, and B are red, green and blue components, respectively; and $I = 0.2989R + 0.5870G + 0.1140B$.

The normalized images were converted into the hue, saturation and value (HSV) color space and the luminance, blue-difference and red-difference chroma components (YCbCr) color space. These color information was used to train a logistic classifier. Then, an entropy filter was applied to analyze the texture of the image to find boundaries of citrus fruit. After detecting the citrus in the image, the number of citrus fruit and the mass estimation were performed using least square circle fitting. The circle fitting provided the information needed to estimate the mass of the citrus fruit. Based on the calibration data of the size and mass of the citrus, interpolation and extrapolation were performed to estimate the actual mass of the citrus in the image. Figure 2 illustrates an example fruit detection steps.

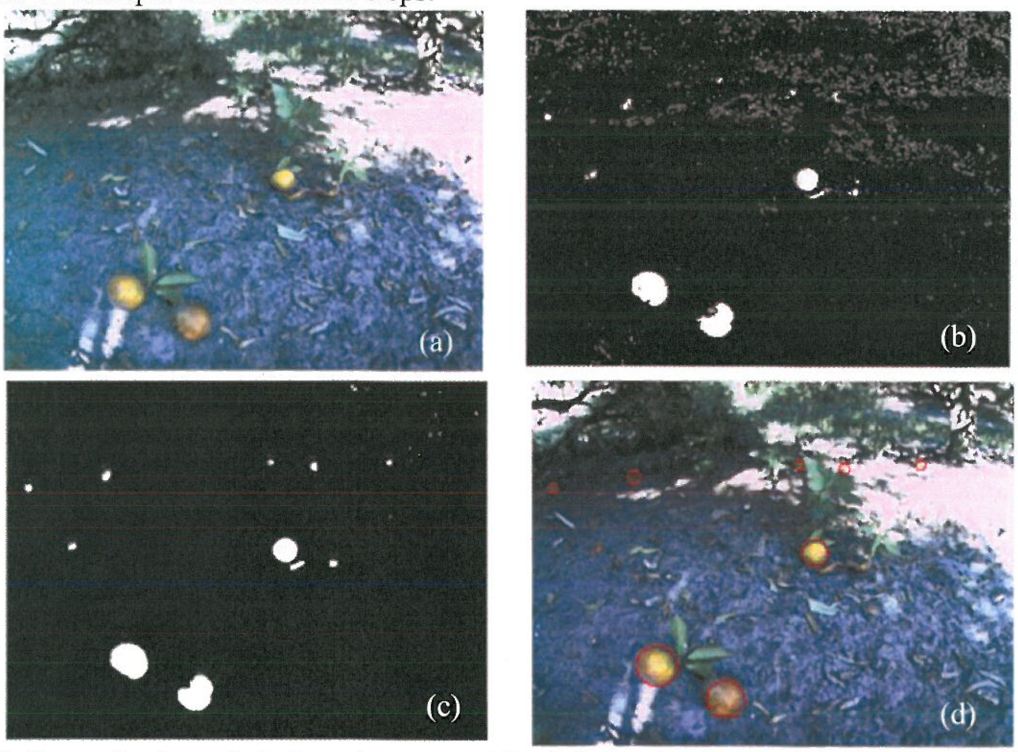

Figure 2. Example citrus fruit detection steps: (a) original color image, (b) after the classification using a logistic regression, (c) morphological operations after entropy filter, and (d) final fruit recognition result with red circles.

FINAL RESULT AND DISCUSSION

The developed citrus fruit algorithm was evaluated by comparing the number of fruit counted by the algorithm and the number of fruit counted manually in the images. Also, weight of dropped fruit on the ground was estimated. These results are summarized in Table 1.

A total of seven trials was validated by comparing manual fruit counting and the number of fruit counted by the algorithm. In manual counting, the actual number of fruit was counted in all of 1,470 images. Additionally, the number of correct count, missing fruit, and false positives (other objects incorrectly identified as citrus) by the algorithm were examined. Trial 1 yielded the most fruit drop (1,650 dropped citrus fruit with an estimated weight of 697 lb) among the seven trials, while Trial 3 showed the least number of dropped fruit. An average number of actual dropped fruit was found to be 1,018 for the seven trials. The percentage of correctly counted fruit by the algorithm was also calculated in every trial. The highest accuracy was in Trial 6 which was 89.5%.

Table 1. Image analysis results of the number of fruit correctly identified by the algorithm, missed fruit, counted by the developed algorithm and false positives, along with the number of actual fruit by manual counting. Estimated weight of dropped fruit is also listed in pound.

Trial number	Number of acquired images	Number of actual fruit by manual counting	Number of fruit correctly identified by the developed algorithm (%)	Number of missed fruit (%)	Number of fruit counted by the algorithm	Number of false positives (%)	Estimated fruit mass in pound
1	220	1650	1322 (80.1)	328 (19.9)	1466	144 (9.8)	697.5
2	222	1448	859 (59.3)	589 (40.7)	881	23 (2.6)	622.1
3	224	430	330 (76.7)	100 (23.3)	473	144 (30.4)	312.8
4	210	1102	784 (71.1)	318 (28.9)	815	31 (3.8)	394.4
5	192	885	707 (80.0)	178 (20.1)	766	59 (7.7)	444.2
6	191	618	553 (89.5)	65 (10.5)	652	99 (15.2)	346.3
7	211	999	782 (78.4)	217 (21.8)	932	150 (16.1)	495.4
Sum	**1470**	**7132**	**5337 (74.8)**	**1795 (25.2)**	**5985**	**650 (10.9)**	**3313.0**

In Trial 6, only 65 fruit (10.5%) were not counted (missed) by the algorithm. This was because the images in Trial 6 were clear and had better contrast compared to the images in other trials. However, Trial 2 had the least accuracy of 59.3%. The missed fruit in Trial 2 was 40.7% which is relatively high. The reason of this high error in Trial 2 was that the images were dark and unclear, which caused the low contrast in color between citrus and background objects. Also, the citrus in the images were located farther than in the other images, and so the size of the citrus were too small to be detected. The mean accuracy of the seven trials was 74.8%.

In addition, false positive counts by the algorithm were evaluated. Most of false positive errors were from the highly saturated area in soil and leaf pixels. They had bright yellowish color which was similar to the citrus pixels. The highest error was in Trial 3. This was because it was unclear to compare the colors between rotten or unhealthy citrus, and healthy fruits under the canopy. While the developed algorithm was counted them as healthy fruit, they were considered as unhealthy fruit by the manual counting.

For the result of the mass estimation, Trial 1 had the highest weight which was 697.5 lb and Trial 3 has the least which was 312.8 lb. The total weight of dropped fruit was estimated to be 3,313 lb, and each trial showed different weight of dropped fruit. This result corresponds to the number of fruit counted by the algorithm, which also showed the highest value in Trial 1 and the lowest value in Trial 3. However, the estimated weight in Trial 4 was less than Trial 5, although the number of fruit count by the algorithm was higher in Trial 4. This error might be because the size of the fruit were different in images between the two trials. The images in Trial 4 were taken in farther distance than in Trial 5, and so the size of the citrus were smaller.

Based on the analysis result, each trial had different number of fruit drop. The possible reason of the variation in trials is that each area had different spatial variability factors such as canopy size, nutrient level, soil pH, and disease infection. However, the impact of the CMNP which was sprayed during the past couple of years was not shown specifically. Trial 6 was sprayed with CMNP, however the number of fruit drop was relatively low compared to other non-sprayed area in the past.

Figure 3 shows spatial distribution of dropped fruit weight at four selected rows in the Lykes grove trial. Total weight of the dropped fruit was 3,313 lb with an average of 2.5 lb estimated from 1,470 images. Spatial variability of fruit weight can be clearly observed. This information can be used to identify potential causes of fruit drop along with other factors, such as degree of disease infection, soil type, tree age, rootstock, and citrus variety.

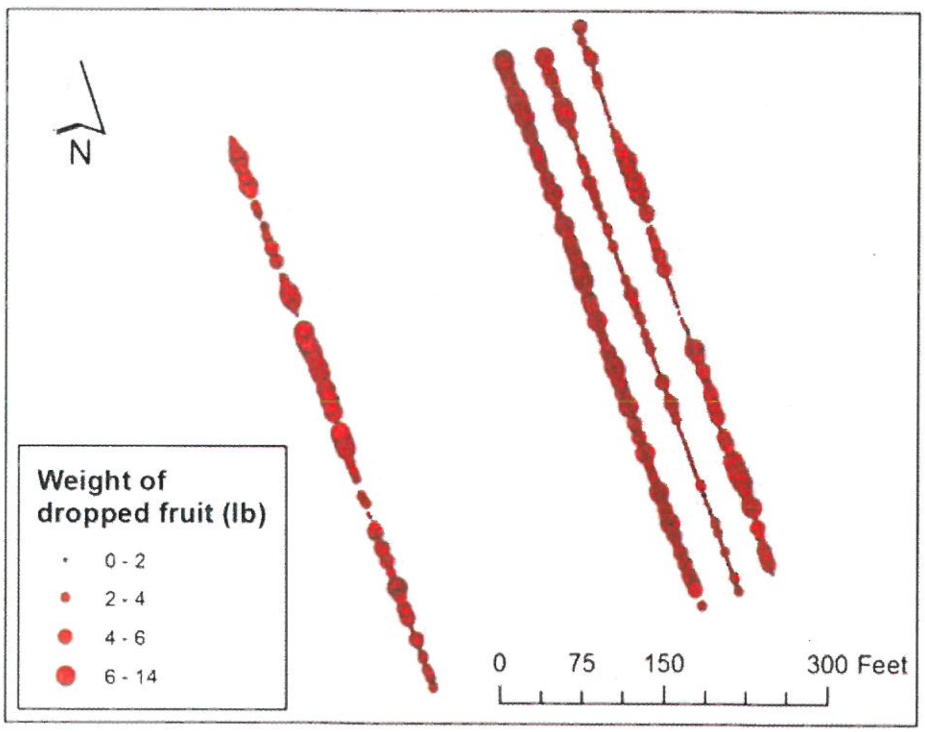

Figure 3. Estimated weight of dropped fruit at four selected rows in Lykes grove.

Output from this project: A master student, Daeun Choi, will graduate at the end of Summer 2013 who were supported by this project. A conference meeting paper and a journal manuscript will be written in the near future.