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Detecting and counting citrus fruit on the ground using machine vision

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Abstract. *A machine vision system for estimating number of citrus fruit drop was developed in this study. The objectives of this study were to design rugged hardware, to develop an image processing algorithm for accurate estimation of fruit count and to conduct field experiments. Image acquisition hardware was developed to be used in a commercial citrus grove specifically for unfavorable imaging conditions. The image processing algorithm included normalization of intensity, citrus fruit detection by a logistic classifier, and least square circle fitting. Accuracy of the algorithm was analyzed using two different methods. Firstly, the ability of detecting citrus fruit by the algorithm without any missed fruit was analyzed. The accuracy varied within three trials, and the highest was 89.5 percent. The second analysis was for the ability to avoid false positives which represent incorrect detection of the background object as a citrus. The percentage of false positive detection also varied between the trials. The highest error was 16.2 percent and the lowest error was 9.8 percent. Result of the experiments showed that each trial had different number and mass of citrus fruit drop. This was because each area in the images had different site-specific variable factors such as nutrient level, soil pH, disease, canopy size etc. The machine vision algorithm can be modified for more advanced application such as immature citrus fruit drop detection and counting during mechanical harvesting and early yield estimation.*

Keywords. *Citrus fruit drop, CMNP, HLB*

Introduction

Huanglongbing (HLB) is considered one of main reasons of early citrus fruit drop. Consequently the disease has resulted in a loss of yield. According to the Citrus forecast (United States Department of Agriculture - National Agricultural Statistics Services, 2012, 2013), there was a 9 percent production drop in non-Valencia and an 11 percent drop in Valencia for a total loss of 10 percent. To estimate an impact and loss resulting from HLB, accurate estimation of the amount of fruit drop is most important. Once the accurate estimation of the fruit is obtained, efficient management of HLB can be achieved by creating a fruit yield (loss) map and a prescription map for pesticides.

However, due to acreage of citrus production in Florida, manual estimation of the citrus fruit drop is considered as a time consuming and labor intensive task. Therefore, developing automatic estimation is essential. Automation of fruit drop counting can be developed using machine vision. Machine vision is a tool consisting of imaging devices and image processor to produce output for automatic inspection applications.

Therefore, the overall objective of this research was to develop an automation system for identifying fruit drop count using machine vision. To achieve the overall goal, the specific objectives are as follows.

1. To build a rugged hardware system for image acquisition in a citrus grove,
2. To develop a machine vision algorithm that will successfully estimate count of dropped citrus fruit, and
3. To conduct field experiments and evaluate the performance of the developed system.

Similar research was done by Annamalai and Lee (2003, 2004). They developed an automatic citrus yield mapping system using machine vision. The objective was to develop a machine vision system for detecting citrus and to count the total number of citrus fruit in the images to effectively provide an estimated yield map. The algorithm consisted of thresholding the Hue-Saturation plane and counting the number of citrus pixels. Also, Patel et al. (2012) developed automatic segmentation for yield estimation of various fruit such as oranges apple, pomegranate, peach, and plum. They suggested the algorithm using both color and shape information which is often circular shape for fruits. Firstly, the images were acquired in the RGB color space and then they were transformed into the L, a and b color space. The color information of ‘a’ component plane was used to achieve the fruit region in the images. With the edge information, circle fitting was performed to find fruits in the image.

These studies were conducted in outdoor conditions and images included the fruits on the trees. The images were acquired with close and narrow field of view so that the fruits are big enough to be easily detected. However, the research in this study dealt with distant citrus fruits in the images which were very small. Additionally, the images included more complicated the background containing many objects such as soil, grass and irrigation pipe.

Materials and Methods

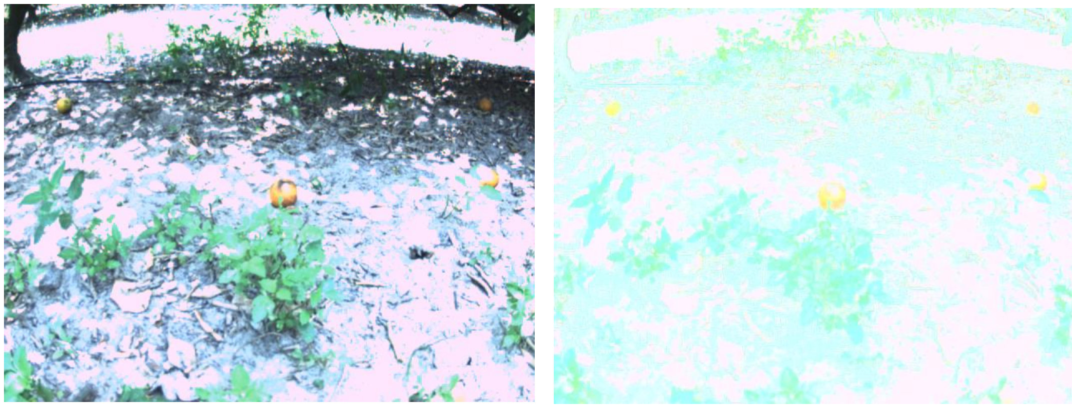
A machine vision system was developed with two color CCD cameras with a processor, two VGA monitors, metal mounting frames for vehicle and an encoder. The cameras used were smart cameras (NI-1772C, National Instruments Corporation, Austin TX), which contained its own processor (1.6GHz). The cameras had a 1/3” CCD sensor to generate regular RGB color images. It also had a rugged metal frame that is water and dust-proof, which were the main reasons for being used in this study. The encoder was used as an external triggering device for the camera, which helped avoid an overlapped area between images. Images were acquired every 0.9 m.

Images were taken in outdoor conditions at a citrus grove under varing illumination conditions. The varying illumination causes dramatic change in color values in the images. Figure 1a shows an example image used in this experiment. The ground had a great deal of shadows in some areas, which made the color of objects darker. In contrast, areas without the shadow resulted in the soil having an excessive amount of white color due to the high intensity. Consequently, different illumination conditions of the images made more difficult to identify citrus from the background because colors of objects in the images were changing. Therefore, a process for removing effect of illumination conditions denoted as normalization of illumination condition was applied before identifying citrus fruit. Normalization of illumination condition was developed to diminish the drastic change in intensity level within an image and between images. Normalization of illumination condition is defined as Equation (1).

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

where, $I = 0.2989R + 0.5870G + 0.1140B$.

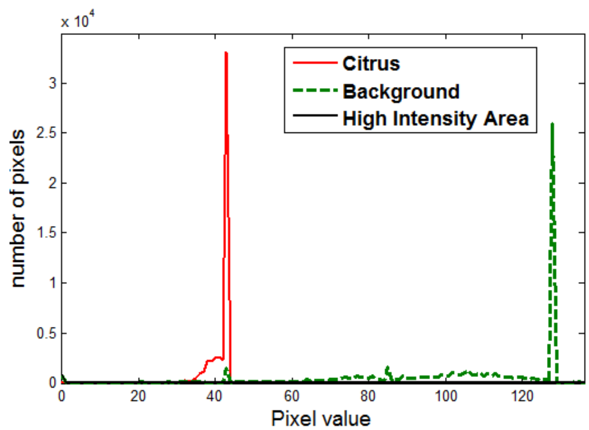
By Equation (1), the effect of different illumination level of pixels is normalized. In Figure 1b, the illumination level throughout the image became approximately uniform so the citrus fruits had identical yellow color rather than different colors depending on the illumination.



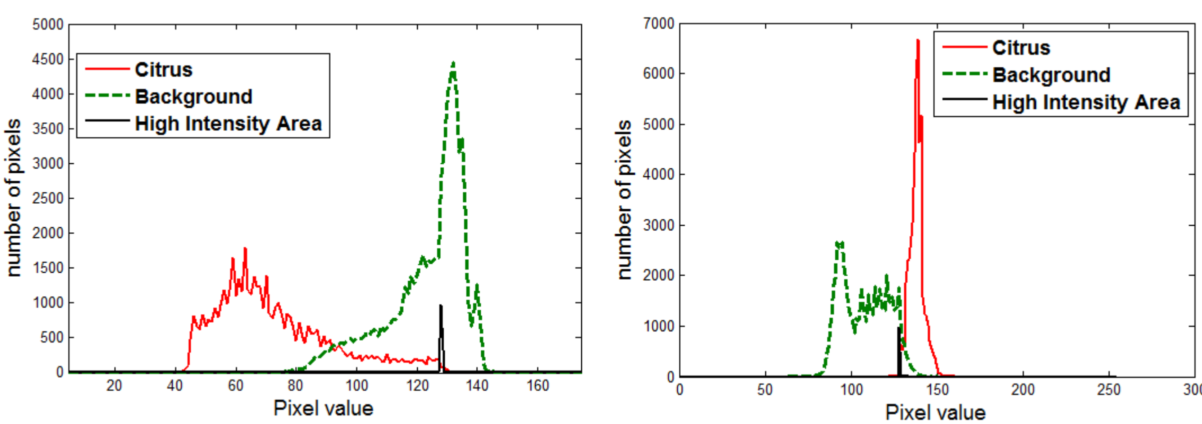
(a) (b)

Figure 1. Example of normalization of illumination condition: (a) original image of varying illumination. Under the shadow objects had darker color and without the shadow, the pixels are highly saturated, and (b) normalized image. Citrus pixels had distinctive color from background.

Then, normalized images were converted into Hue, Saturation and Value (HSV) color space and Luminance, blue-difference and red-difference chroma components (YCbCr) color space. To differentiate color space conversion with normalized intensity RGB values from regular HSV and YCbCr with regular RGB values, notations of H'S'V' and Y'Cb'Cr were introduced. Figure 2 shows histograms of H',Cb' and Cr' components. In Figure 2a, the H' component had distinctive variation between citrus and background objects including leaf, dead leaf, twig, soil and trees. In the Cb' component histogram in Figure 2b, the high intensity area (highly saturated area) was distinguishable among other classes. In Figure 2c, the citrus class is distinguishable from tree, twig, dead leaf and soil classes.



(a)



(b) (c)

Figure 2. Histogram of color values of objects. (a) H' (b) Cb', and (c) Cr' components.

The H' component along with the Cb' and Cr' color information were chosen to compose training information for a logistic classifier. The logistic regression classifier processed each pixel in the image and the output value from the classification was assigned in every single pixel. The confidence level was set to 0.95 so that the classifier assigned citrus class to the pixel if and only if the pixel has the probability equal or greater than 0.95. (c)

Figure 3a shows an original image in a validation set and (c) (d)

Figure 3b shows the image after the classification and most of the citrus pixels were classified as citrus class compared to the original image. However, not only citrus pixels were detected but also highly saturated pixels in leaf, tree and twig were also classified as citrus.

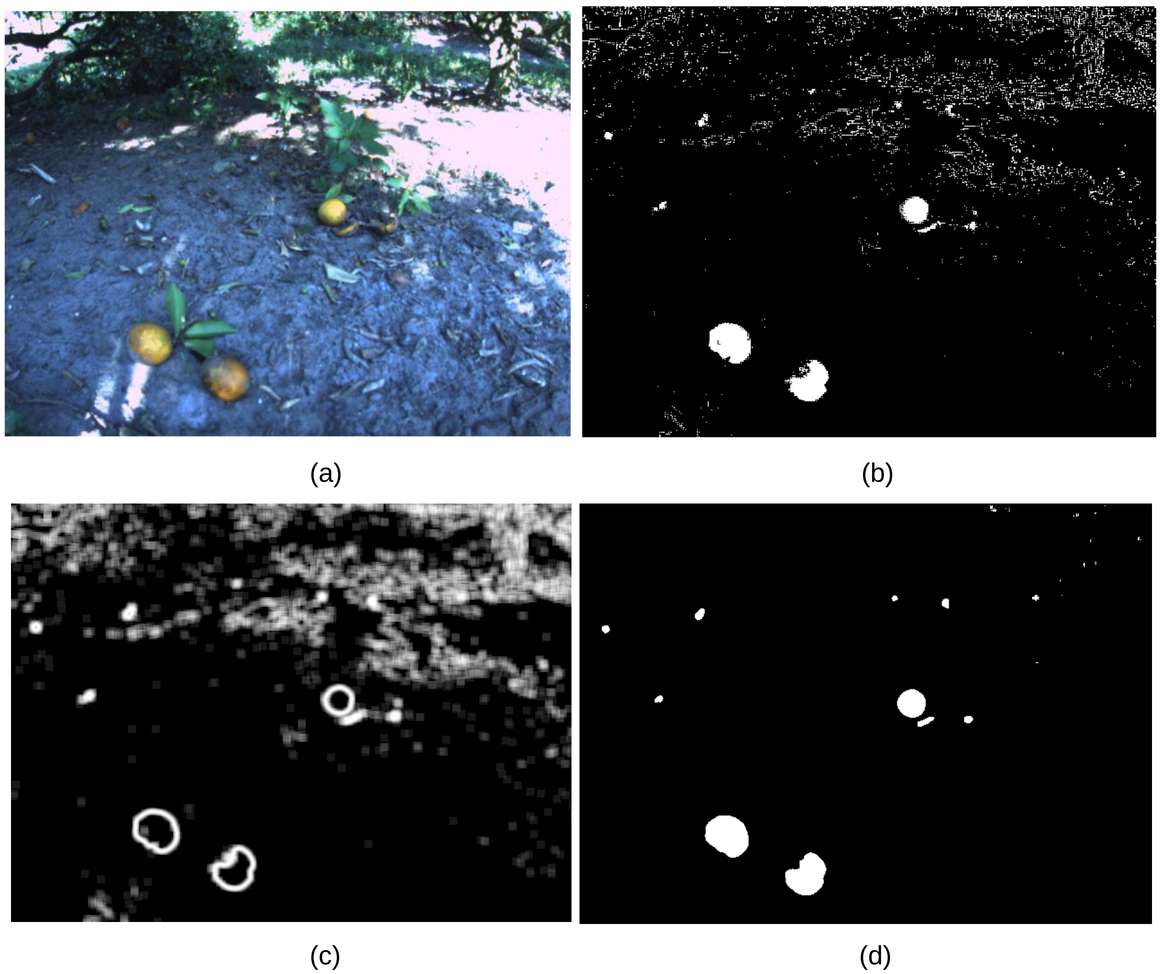


Figure 3. Example of citrus fruit detection: (a) original Image, (b) after the classification using logistic regression, (c): visualization of entropy value, brighter pixel represents higher value, and (d) after threshold with entropy value and morphological operations.

Using entropy texture analysis, only citrus pixels were extracted. Entropy of a pixel in the image represents randomness of the pixel with its neighborhood. If there are white objects in the black background which have heavy contrast, the boundary pixels of the objects will have high entropy value. In (c)
(d)

Figure 3b, the citrus pixels had solid texture which had great contrast to the background. However, noise pixels were scattered so their texture did not have great contrast as the texture of citrus pixels. The visualization of the entropy values is shown in (c) (d)

Figure 3c. The brighter pixel had higher entropy. A 95% confidence level was used to make an entropy filter. The image had only pixels with an entropy value equal or greater than 0.95, which means great contrast to the background. (c) (d)

Figure 3d shows the result after the filter and the morphological operations such as filling holes inside of citrus pixels and remove small noise objects. After detecting the citrus in the image, edge information was used for least square circle fitting. The number of fitted circle became the number of detected citrus fruit.

Result and Discussion

Figure 4 shows an example of the final result of fruit count. Detected citrus are marked as red circles. The total number of detected citrus was eight in this image because the algorithm was programmed to ignore the unhealthy, crushed or immature citrus fruit. The performance of the algorithm was analyzed by two different comparisons between manual counting of fruit in images and count by the algorithm. Firstly the ability of detecting citrus in the images without missed fruit was analyzed. This was done by comparing the number of actual fruit counted manually by human with the number of correctly identified fruit counted by the machine vision algorithm. Missed fruit by the algorithm was analyzed by comparing with manual counting. The missed fruit is which exists in the image but failed to be detected by the algorithm. A total of three trials were performed in Lykes grove (Ft. Basinger, FL) for the experiment. Among 622 images acquired in three trials, 582 images were used as a validation set. The analysis for missed and correctly identified fruit of the trials is shown in Table 1. The highest accuracy was in trial 2 which was 89. 5 percent. In trial 2, the missed fruit were 10.5 percent. This was because the images in trial 2 were clear and had better contrast compared to images in the other trials. The mean accuracy of all trials was 81.3 percent.

Figure 4. Final result. The number of fruit count is eight.

Table 1. Performance of the algorithm for detecting fruit.

	Number of Images	Number of Validation Images	Number of Fruit by Manual Counting	Correctly Identified Fruit by Algorithm (%)	Missed Fruit Count (%)
Trial1	220	193	1650	1322 (80.1)	328 (19.9)
Trial2	191	178	618	553 (89.5)	65 (10.5)
Trial3	211	211	999	782 (78.3)	217 (21.7)
Sum	622	582	3267	2657	610
Mean	-	-	1089	885.7 (81.3)	203.3 (18.7)

The second analysis is for the ability to avoid the false positive detection. False positive detection is incorrectly detected background object as citrus by the algorithm. This analysis was achieved by comparing the number of detected citrus with false positive objects identified by the algorithm. Fourth and fifth columns in Table 2 show the number of false positive and its percentage. The percentage was calculated by dividing the false positive count by the total count by the algorithm. The highest error rate was 16.1 percent in trial 3. This is because images had unclear color variation between unhealthy and healthy citrus under the canopy. Most of false positive errors were from the highly saturated area in soil and leaf pixels. The highly saturated soil and leaf pixels had bright yellowish color which is similar to the citrus pixels.

Table 2. Performance analysis for ability to avoid false positive error.

	Number of fruit Counted by algorithm	Correctly identified fruit by algorithm	False Positive Count (%)
Trial1	1466	1322	144 (9.8)
Trial2	652	553	99 (15.2)
Trial3	932	782	150 (16.1)
Sum	3050	2657	393
Mean	-	885.7	131.0 (12.9)

Based on the result, each trial had different number of fruit drop. The possible reason of the variation in the trials is because each area had different spatial variability factors such as canopy size, nutrient level, soil pH, HLB, and CMNP (5-Chloro-3-Methyl-4-Nitro-1H-Pyrazole) sprayed in this year. CMNP is an abscission agent sprayed before harvesting to loosen fruit so that the fruits can be removed from trees with less force. However, the impact of the CMNP which was sprayed during the past couple of years was not shown specifically. Trial 2 was sprayed with the CMNP, however, the number of fruit drop was relatively low compared to the other non-sprayed area in the past years.

Conclusion

A rugged hardware system was developed for outdoor commercial citrus groves. The system included two cameras with a processor, an encoder and mounting frames. The cameras were mounted on a moving truck and triggered by the encoder to measure distance between the positions where the images were taken. This method avoided overlapping area between images. Taking images on a moving vehicle significantly reduced the amount of time for the image acquisition. However, it had also a disadvantage of less clear vision.

The machine vision algorithm included normalization of illumination, classification using a logistic regression method, and least square circle fitting. The normalization of the illumination reduced the color variation due to the different illumination. After normalization, color space conversion was done in H'S'V' and Y'Cb'Cr' color spaces. Then, a logistic classifier identified objects in the images as citrus if the object had a probability greater than 0.95. The filter using entropy value successfully removed the background objects which were incorrectly detected as citrus. Detected citrus was fitted to a circle using the least square circle fitting in order to provide the number of citrus in the image.

Field experiments were conducted in Lykes Bros. Inc. grove (Ft. Basinger, FL). The citrus fruit dropped on the ground during the harvesting was considered in the experiments. The performance of the algorithm was tested in two ways. Firstly, accuracy which represents ability to detect citrus fruit without missed fruit is analyzed. Secondly, false positive was analyzed to identify incorrectly detected background noise. Both ways were compared with the manual counting by human. The average accuracy was 81.3 percent. For false positive error, percentage also varied among the trial sets while the average error was 12.9 percent.

The performance of machine vision algorithm can be improved by alternative imaging devices. In the experiments, two cameras were used and each camera covered entire area under citrus tree canopy to expedite image acquisition and processing time. Consequently, field of view of the cameras was wide and resulted in considerably small size of citrus fruit in images. This problem can be improved using a higher resolution camera or using multiple cameras so that objects in images can have enough amount information such as color or shape.

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